A Closing Call's Impact on Market Quality at Euronext Paris

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Abstract

The Paris Bourse (currently Euronext Paris) refined its trading system to include electronic call auctions at market closings in 1996 for its less-liquid "Continuous B" stocks, and in 1998 for its more actively traded "Continuous A" stocks. This paper analyzes the effects of the innovation on market quality. Our empirical analysis of price behavior for two samples of firms (50 "B" stocks, and 50 "A" stocks) for the two different calendar dates (1996 and 1998) indicates that introduction of the closing calls has lowered execution costs for individual participants and sharpened price discovery for the broad market. We further observe that market quality is improved at market openings as well, albeit to a lesser extent. We suggest that a positive spillover effect explains the closing call's more pervasive impact.

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I. Introduction

On May 13, 1996, the Paris Bourse (currently Euronext Paris) changed its market structure by introducing a closing call auction for the less-liquid stocks (the "Continuous B" stocks) in its continuous, electronic CAC market. Two years later, on June 2, 1998, the Exchange introduced the closing call auction for its more actively traded "Continuous A" stocks. This paper seeks to assess the impact that the call auction has had on price determination at the close of trading on the Paris Bourse.

A call auction differs from continuous trading in the following way. In a continuous market, a trade is made whenever a bid and offer match or cross each other.[1] In contrast, in a call auction, the buy and sell orders are cumulated for each stock for simultaneous execution in a multilateral, batched trade, at a single price, at a predetermined point in time. By consolidating liquidity at specific points in time, a call auction is intended to reduce execution costs for individual participants and to sharpen the accuracy of price discovery for the broad market.

Closing call auctions were introduced at the Paris Bourse specifically because of customers' demands for improved price discovery at market closings. Most importantly, derivatives trading was being adversely affected by the ease with which only a few, relatively small orders could change closing prices in the equity market.[2] The situation was making it difficult for traders to unwind their positions at appropriate prices, and for positions to be marked-to-market at appropriate prices. Other European bourses have also taken steps to improve the quality of closing prices. Closing as well as opening calls are now incorporated into the market models of, among other European exchanges, Deutsche Börse, the London Stock Exchange, and the Swiss Exchange.[3]

The paper's importance is threefold. First, evaluating the efficiency of the electronic call auction is important in its own right, as the call auction is the least understood of the three major trading regimes (the other two generic market structures are the continuous order book market and the quote driven, dealer market). Second, a crisp, ceteris paribus assessment of any market structure

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[1] In a continuous, order driven market, public limit orders set the quotes and a trade is made whenever a public market order arrives. The market order executes at the best price set by a previously placed limit order.

[2] Senior officials at the Paris Bourse have advised us that this was the motivation for introducting the closing calls.

[3] Call auctions have historically been a standard part of the German exchanges' market model; currently, Deutsche Börse holds four calls a day for its large cap stocks.

feature is extremely difficult to obtain. Fortunately, the specific way in which the closing auction was introduced in Paris has availed us with an especially clear test of the power of a call market. Third, the paper develops a new and different methodology for assessing market quality. Specifically, we use the well-known market model in an event study context to infer the quality of price discovery at market closings and openings.

Regarding the importance of the call market, call auctions have long been used in European equity markets both before and after they introduced automated continuous trading systems, and calls are also the standard procedure for opening the electronic order book markets of Canada and the Far East.[4] They are neither widely used nor well understood in the U.S., however. The New York Stock Exchange opens with a non-electronic call, and Nasdaq has no special opening facility at all. Because of the importance of a single price opening procedure, Arthur Levitt, then chairman of the U.S. Securities and Exchange Commission, pressured Nasdaq in May, 2000 to introduce call auction trading.[5] Nasdaq responded by establishing a special committee to consider the procedure but, thus far, has announced no plans introduce it into their market model.[6]

Regarding our assessment of the impact of a specific market structure design feature, by introducing the closing call at two different dates for two different sets of companies, the Paris Bourse has availed us with an exceptionally rigorous ceteris paribus environment for assessing the efficiency of call auction trading. We have also been given the opportunity to test the robustness of our analysis through replication. Additionally, we are able to contrast changes in the quality of the market at closing with changes in the quality of the Paris Bourse's market opening.[7] Consequently, we have reasonable assurance that our findings are not attributable to the particular time period used or stocks selected.

Further, we have confidence that our statistical findings are indeed attributable to the call itself, rather than to some other factor. Interpretability is extremely important, but not always clearly achieved. For instance, Amihud and Mendelson's (1987) finding that volatility is greater at

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[4] For further discussion, see Schwartz (2001).

[5] In a letter dated May 16, 2000 to Frank Zarb, then Chairman and Chief Executive Officer of the National Association of Securities Dealers, Arthur Levitt wrote, "I urge the NASD to pursue a unified opening procedure, and in the interim, to press forward with measures to make the opening process more reliable and fair to investors."

[6] One of the authors of the current paper served on that committee.

[7] As we explain below, improving the efficiency of the closing procedure could also have a positive spillover effect on the open, and indeed we find evidence that this is the case.

NYSE call market openings than at NYSE continuous market closes could be interpreted, not as evidence of the inferiority of the call, but of the greater difficulty of price discovery at the open. In a recent paper, Muscarella and Piwowar (2001) found that market quality deteriorates at the Paris Bourse for stocks that are moved from their continuous market to call market only trading (or vice versa) during 1995-1999, and that market quality increases for stocks that are moved from their call market to their continuous market trading. The authors attribute these findings to the superiority of the continuous market. However, "call market only trading" is used in Paris for the less liquid, less frequently traded stocks, and moving to the call market is equivalent to being delisted from the continuous market. For this reason, the finding may be interpreted as reflecting the impact of delisting and listing, rather than market structure, per se.[8] As we shall see in later sections, our results are robust to the possible confounding effect of Paris Bourse stocks being moved from call auction to continuous trading (or vice versa).

In a recent paper that focuses on Israeli stocks that moved to a new continuous trading system on the Tel Aviv Stock Exchange during the period 1997 - 1999, Kalay, Wei and Wohl (2002) present evidence of investor preference for continuous trading. This is consistent with the Paris experience where the preponderance of trading (roughly 95%) has remained in the continuous market despite the existence of opening and closing calls. However, investors could nevertheless benefit collectively from the improved liquidity provision and price discovery at key points during a trading session (e.g., at the open and at the close) that is attributable to the inclusion of the periodic call auctions.

A key part of any study of market structure is the measure of market quality employed. Our innovation in this paper is to infer market quality from the synchronicity of price changes across a set of stocks. We do this using the well-known market model. Inaccuracies in price discovery for individual stocks and non-synchronous price adjustments across stocks are related phenomena, and we can gain insight into the former by studying the latter. Drawing on earlier work by Cohen, Hawawini, Maier, Schwartz and Whitcomb (CHMSW, 1983a, 1983b), we use the market model to contrast the short-run and long-run relationships between individual stock returns and broad market

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[8] Other papers have used analogous settings to hold relevant factors constant so as to infer the impact of a market structure change. Amihud, Mendelson, and Lauterbach (1997) considered the effect on price performance of moving shares in batches from call market to continuous market trading on the Tel Aviv Stock Exchange during 1987-1994. Other researchers have contrasted price behavior for stocks before and after a change in the market where the shares are listed (see, e.g., Barclay (1997), Bessembinder (1998), and Elyasiani, Hauser, Lauterbach (2000) for studies of the effect of changing a firm's listing from Nasdaq/Amex to the NYSE).

index returns.[9] This methodology provides the basis for our event study, where the event is the introduction of the closing call.[10]

We employ measurement intervals ranging from 1 day up to 20 days to contrast the short-period relationships between individual stock returns and the returns on a broad market index. Factors such as bid-ask spreads, market impact, and inaccuracies in price discovery affect the very short interval returns. Fleming and Remolona (1999), in their analysis of the U.S. Treasury market, demonstrate that protracted surges in volume and price volatility, and relatively wide spreads attend the release of major macroeconomic announcements. They attribute these protracted effects to "differential private views that take time for the market to reconcile" (page 1912). In so doing, the authors link the volume, volatility and spread affects to protracted price discovery. If price discovery for individual equity shares is similarly a protracted process, then the synchronicity of short-term stock price adjustments across a set of stocks is also expected to be perturbed.

Further, if inaccuracies in price discovery compound as the measurement interval is lengthened, it is possible for trading frictions to distort the relationships between individual stock returns and market index returns, not only for very short intervals (i.e., intra-day), but also for fairly substantial intervals (e.g., ten days or more). Our methodology is designed to capture this. We further assess the methodology by running a variety of more standard tests with the Paris data. For the most part, the findings for these alternative tests are qualitatively similar, but not as robust.

Our market model tests clearly indicate that price adjustments, for the stocks in our sample, are more synchronized after the closing call's implementation. The results are consistent for two independent events and two different samples of stocks using the beta and R^2 measures, as well as for other measures that are frequently cited in the literature. The replication of our findings over two different time periods gives us further confidence in our inference about the improvement in market quality at the market close.

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[9] For simplicity, we have used a single factor model for the analysis.

[10] Using the CHMSW methodology, we are able to find clearer evidence of the impact of the introduction of the call auction. For our purposes, some of the more conventional tests gave results that were not as unambiguous. See the appendix for further discussion.

We have been advised that improving market quality at the close has had a beneficial effect for the derivatives markets. However, the innovation could have broader impacts on the cash market, and these too should be considered. If a substantial number of orders are directed to the closing call only, spreads could widen and liquidity could dry up in the continuous market immediately preceding the call. The Paris Bourse has advised us, and our own analysis suggests, that this has not been the case.

Nevertheless, trading in the closing calls is meaningful, and has succeeded in attracting institutional orders that would otherwise not have been executed in the continuous market in a given day, but would have been carried over to the next day.[11] Consequently, we further consider the impact the closing calls have had on the quality of price formation at next day openings. We find that market quality has improved at the open, but to a lesser extent than at the close. Thus, comprehensively viewed, our results underscore the importance of the microstructure innovation.

The results are robust to the possible confounding effects of sample-wide changes in return volatility and trading volume during the periods surrounding the closing call's two implementation dates. Our findings are supported further by the lack of any material changes in the test statistics for two control samples for both opening and closing prices. We used the Continuous B stocks as a control sample for the Continuous A stocks' event date, and vice versa. Tests on both of these control samples show far less significant change in the synchronicity of price adjustments across stocks. This gives confidence that our results are not attributable to the specific sample of stocks, time period, or methodology that we have used.

The remainder of the paper is organized as follows. Section II discusses the relevant literature. Section III describes the call auction procedure used by the Paris Bourse, and Section IV describes several econometric tests that examine our hypotheses. Section V describes the data. Section VI presents the broad picture of intraday effects on percentage spreads, returns volatility, and trading volume measured over hourly intervals. Sections VII - IX present the empirical results for, respectively, tests based on closing prices, tests focused on three other times of the day (the

[11] In an attempt to control market impact, institutions commonly slice their orders into smaller tranches that they feed to the market over extended periods of time (a day or so). The process results in unfilled orders which "hang over" the market. The bunching of orders at a closing call makes it easier for the institutions to bring their orders forward and to execute them with minimal market impact. As a consequence, market overhang is reduced.

closing minutes of continuous trading, market openings, and the overnight return), and robustness tests. Section X presents our conclusions. Additional tests are reported in an Appendix.

II. Market Structure, Asset Pricing and Trading Costs

Consistent with the goal of promoting an efficient, liquid market, all modifications proposed by an exchange should, a priori, be expected to reduce the overall level of "frictions" in the market and hence lower trading costs. Recent theoretical and empirical research such as that found in Barclay, Christie, Harris, Kandel, and Schultz (1999), Amihud, Mendelson, and Lauterbach (1997), and Pagano and Roell (1996) suggest that changes in an exchange's microstructure can affect the market's liquidity, trading costs, informational efficiency, and transparency. In addition, Stoll (2000), Schultz (2000), Lesmond, Ogden, and Trzcinka (1999), Chordia and Swaminathan (2000), and Madhavan and Panchapagesan (2000) shed light on the impact of a market's microstructure on liquidity and informational efficiency by proposing new statistical measures and performing related empirical tests. In addition, Ko, Lee, and Chung (1995) find that the implementation of a closing call procedure at the Korea Stock Exchange has improved the price discovery process in terms of stock price volatility. Earlier work of Fisher (1966), Schwartz and Whitcomb (1977), Scholes and Williams (1977), and Dimson (1979) should also be noted in this context.

More recently, Venkatamaran (2001) uses conventional spread measures to examine the relative effective costs of trading in an automated market (proxied by the Paris Bourse) versus a floor-based exchange (proxied by the NYSE); the quoted and effective spreads for the two markets are quite similar despite differences in trading system automation. Contrary to earlier tests based on variance ratio tests, George and Hwang (2001) find similarities in the variance of returns at the open and the close of trading for NYSE stocks. Employing an extension of Hasbrouck's (1993) model based on vector autoregression and generalized method of moments estimation techniques, George and Hwang use opening and closing prices to determine whether or not variances at the NYSE's opening and closing are significantly different. Their findings suggest that the return volatility of a call mechanism (such as the one used by NYSE at the open) is not significantly different than the volatility of a continuous trading system (such as that used at the NYSE's close).

III. The Euronext Paris's Call Auction

The closing call recently instituted by the Paris Bourse has the same structural design as the Exchange's opening call. At the market opening during our sample period, the system receives orders from 8:30 am until 10:00 am, at which point the books are set and the opening clearing prices are established. Trading in the continuous market proceeds from 10:00 am until 5:00 pm, at which point the market is closed and the books are opened to receive orders for the closing call. Book building for the closing continues for 5 minutes. At 5:05 pm, the books are again set and the closing clearing prices are established.[12]

During the book building periods at the open and close, indicated clearing prices are displayed along with indicated volume. In addition, cumulated orders on the book are displayed, with buy orders aggregated from the highest to the lowest buy limit price, and sell orders aggregated from the lowest to the highest sell limit price. The indicated clearing price is the value that maximizes the number of shares that trade. At the time of the auction, the indicated clearing price becomes the actual execution price. Buy orders at this price and higher execute, as do sell orders at this price and lower.[13]

IV. Empirical Methodology

We test the hypothesis that the introduction of the closing call improved market quality at the Paris Bourse.[14] To this end, useful techniques are described in CHMSW (1983a, 1883b), Roll (1984), Hasbrouck and Schwartz (1988), Amihud et al. (1997), Lesmond et al. (1999), Chordia and Swaminathan (2000), and Stoll (2000). In the current analysis, we make major use of the CHMSW model in an event study context. In this section, we describe two market model-related statistics and their respective tests. We focus on these statistics, giving particular emphasis to one of them, the market model R^2, because of its capacity to capture a broad set of frictions that are present in a market. We have also employed several other statistical measures and econometric tests that are summarized in the Appendix.

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[12] Currently, Euronext Paris opens earlier (9:00 am) and closes later (5:35 pm) than during our period of analysis (i.e., 1996-1998). However, the current market microstructure of the Exchange is the same as it was during 1996-1998.

[13] Because of lumpiness in the order flow, aggregate buys generally do not equal aggregate sells exactly at the clearing price. When there is an inexact cross, orders on the bigger side of the market are rationed according to their time of arrival, with the orders that arrived first executing first.

[14] By "market quality" we are referring to the accuracy of price discovery that can be impaired by the magnitude of trading costs, as discussed earlier in the paper.

Bid-ask spread tests are inapplicable to our study because the introduction of a call auction, by definition, eliminates the spread. Variance ratio test statistics and other microstructure-related empirical measures can yield ambiguous results because they are influenced differentially by the specific patterns of autocorrelation (positive and negative) found in security returns.[15] Alternatively, we use the market model regression approach to focus on the closing call's effect on market quality. The market model tests are more robust in the face of correlation patterns that can be either positive or negative; all that is required is that lead/lag price adjustments attributable to market frictions exist in security returns. The sample we have used is predominantly comprised of stocks that are thinner than those in the CAC-40 Stock Index. For this reason, our stocks should predominantly lag the market. As Fisher (1966), Scholes and Williams (1977), Dimson (1979), and CHMSW (1983a, 1983b) have shown, lagged responses by a stock to a market index bias the stock's beta estimate downward and depress its market model R^2.[16]

We use the CHMSW single index market model regression technique as follows.[17] Given an event date (e.g., the date when the closing call auction was introduced), we split our data set into pre- and post-event periods and estimate the market model for each of these subsets using, respectively, 12 measurement intervals: 1- to 10-day, 15-day, and 20-trading day returns (defined as L = 1-10, 15, or 20).[18] A stock's 12 beta estimates are obtained by performing 12 market model regressions (one for each of the 12 return intervals). Using CHMSW's terminology, we refer to these estimates as the "first-pass" betas. That is, 12 market model regressions (corresponding to L = 1-10, 15, 20 days) are run for each of the 100 stocks and over our entire sample period (both the pre- and post-event periods). Thus, 1,200 regressions (12 return intervals x 100 stocks) and their related beta estimates are used to study the impact of the closing call. The downward bias in the beta

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[15] For example, tests such as the variance ratio test described in Hasbrouck and Schwartz (1988) and Lo and Mackinlay (1988) are affected in different ways by momentum trading (which introduces positive correlation) and contrarian trading (which is associated with negative correlation). Further, autocorrelated returns over long measurement intervals can affect variance ratio test statistics in ways that are difficult to interpret (see Lo and Mackinlay, 1997). Nevertheless, we have performed variance ratio analysis, and it has provided some additional confirmation that the introduction of the closing call has improved market quality (see Section VII below).

[16] We also perform beta-related tests based on lagged and concurrent market returns using Chordia and Swaminathan's (2000) *DELAY* variable and obtain results that are similar to, but statistically weaker than, those based on the method described here. See the Appendix for more details on the *DELAY* variable.

[17] Note that our results are still valid even if the true model of the return-generating process contains multiple factors as long as the market factor we employ is orthogonal to the true model's additional factors.

[18] The CAC-40 Stock Index is used as a proxy for the market portfolio in the market model regressions.

estimates due to the generally small stocks that comprise our sample should be found most clearly when short return intervals are used. As Schwartz (1991) notes, the first-pass beta is expected to reach its true value asymptotically as the measurement interval, L, approaches infinity.

To test this expectation, our 12 market model beta estimates, obtained from standard single-index regressions, for each stock (i.e., the first-pass betas) are used as the dependent variable in a "second-pass" set of stock-specific regressions based on an explanatory variable first employed by Fung, Schwartz, and Whitcomb (1985). The variable, denoted as $ln(1+L^{-1})$ in Equation (1) below, is a transformation of the length of the return interval, L, used in the estimations of the set of first-pass betas for each stock. Because the first-pass beta approaches its true value asymptotically, the first-pass beta cannot be linearly related to L. However, as CHMSW and Fung et al. (1985) point out, the first-pass beta could be a linear function of the *inverse* of L. Equation (1) measures the statistical relation between these first-pass betas ($b_{j,1LE}$ in Equation 1's notation) and the transformed return interval, $ln(1+L^{-1})$.[19]

Our event study tests are operationalized by an interaction variable that equals $1 \cdot ln(1+L^{-1})$ for the post-event period and 0 for the pre-event period. This variable is included in Equation (1) to capture any changes in the relation between L and the first-pass betas after the closing call was introduced. The regression, which is estimated for *each stock* in the sample over the 12 different L-day return time series, is specified as,

$$b_{j,1LE} = a_{j,2} + b_{j,2}ln(1+L^{-1}) + c_{j,2}(Dummy_{jE} \cdot ln(1+L^{-1})) + e_{jLE} \qquad (1)$$

where,

$b_{j,1LE}$ = "first-pass" beta estimate for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event,

$a_{j,2}$ and $b_{j,2}$ and $c_{j,2}$ = "second-pass" parameter estimates where, according to CHMSW, $a_{j,2}$ can be interpreted as the asymptotic level of the stock's beta (i.e., the stock's beta estimate when L increases to infinity),

L = the length of the holding period, in days, for which the stock returns were calculated,

$Dummy_{jE}$ = a binary variable equal to 1 if the "first-pass" beta is estimated using the *post*-event data (i.e., E = A) and 0 if the "first-pass" beta is estimated using the *pre*-event data (E = B).

e_{jLE} = a stochastic disturbance term.

[19] This function provides the best linear fit between the first-pass betas and the return interval, L.

As first noted in CHMSW (1983a), the first-pass beta estimates based on regressions of returns over shorter intervals (e.g., L = 1-5 days) are expected to be biased *downward* for stocks that lag the overall market. Consequently, we expect the slope coefficient, $b_{j,2}$, of Equation (1) to be *negative* because this equation regresses the first-pass beta on the inverse of L. A negative relation is predicted because as the return interval is lengthened, the beta estimates are expected to *increase* while the transformed interval function, $ln(1+L^{-1})$, *decreases*.

If the closing call has, by reducing market frictions, increased the synchronicity of price adjustments across stocks, a stock's price reactions will follow the market more closely in relatively short measurement intervals during the post-event period. This expectation is tested by examining the sign and significance of the dummy's parameter estimate ($c_{j,2}$). As noted above, for lagging stocks (which predominate in our sample), the sign on $b_{j,2}$ is expected to be negative. Consequently, any improvement in price efficiency brought about by the market structure change is expected to be reflected in $c_{j,2}$ being *positive* (although not greater than $b_{j,2}$ in absolute magnitude).[20] In the Empirical Results section, we refer to the parameter estimate of $b_{j,2}$ as the pre-event second-pass parameter, BETA2, and define the post-event BETA2 parameter as the sum of $b_{j,2}$ and $c_{j,2}$.

Non-synchronous price adjustments to changes pertaining to the broader market also cause market model R^2s to be depressed for short-period returns. Thus, similar to beta estimates, market model R^2s can be influenced by the choice of return interval. We therefore examine how the explanatory power of the market model changes as the return interval is lengthened. The procedure is equivalent to that used for analyzing beta in Equation (1). First, we measure the R^2 of the "first-pass," standard market model regressions for each return interval.[21] If informational efficiency increases, as we expect, then the post-event period's R^2 should be higher than the pre-event period's R^2 for the various return intervals we have used. Accordingly, we use the R^2 statistics from 2,400 market model regressions (12 return intervals x 100 stocks x 2 periods) to estimate two pooled regressions where the post-event explanatory power of the market model is compared to its pre-event explanatory power for the Continuous A and B stocks, respectively.[22] Unlike the beta tests,

[20] We expect $|c_{j,2}|$ to be less than $|b_{j,2}|$ because the introduction of the closing call should mitigate, but not reverse, the intervalling effect.

[21] The R^2 we are referring to here (and throughout the paper) is the adjusted R^2 statistic.

[22] Note that we perform 1,200 regressions to estimate the second-pass betas in Equation (1) because we can add a dummy variable to account for differences in the parameters during the pre- and post-event periods. However, we cannot use a dummy variable to account for differences in R^2 between the two periods. Thus, we perform two sets

we expect a stock's short period R^2 to be depressed regardless of whether or not its price adjustments generally lead or lag the market index. We thus expect short period R^2 across all stocks to increase if market structure becomes more efficient.

Similar to the logic of the second-pass beta regression of Equation (1), the above R^2 analysis can be summarized by the following specification:[23]

$$AdjRsq_{jLE} = r_j + s_j ln(1+L^{-1}) + t_j(DummyRsq_{jE}) + u_j(DummyC_{jE}) + v_{jLE} \quad (2)$$

where,

$AdjRsq_{jLE}$: adjusted R^2 statistic from the market model regression for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event,

r_j and s_j and t_j and u_j = parameter estimates,

L = the length of the return interval, in days, for which the stock returns are calculated,

$DummyRsq_{jE}$: a dummy variable for the slope which is equal to $1 \cdot ln(1+L^{-1})$ if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B).

$DummyC_{jE}$: a dummy variable for the intercept which is equal to 1 if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B).

v_{jLE} = a stochastic disturbance term.

The expectation for Equation (2) is that the R^2 statistic will *increase* for relatively short intervals after the closing call's introduction. Following the logic of CHMSW (1983b), the intercept in (2) can be interpreted as the asymptotic level of the R^2 statistic when L approaches infinity. Accordingly, we expect both u_j and t_j to be *positive* as the closing call's introduction shifts the market model's observed explanatory power for all measurement intervals higher towards its asymptotic level. This is a direct, explicit test of the closing call's impact on market quality. If the R^2 statistics do not rise significantly, then our hypothesis that market quality improved after the introduction of the closing call is rejected. However, as noted in the Introduction, it is unclear

of runs (i.e., 1,200 regressions for the pre-event period and another 1,200 for the post-event period in order to obtain a total of 2,400 R^2 estimates).

[23] As was the case with the beta estimates, we expect an *inverse* relation between the dependent variable (the adjusted R^2 statistic; referred to as $AdjRsq_{jLE}$ in Equation 2) and the transformed interval function $ln(1+L^{-1})$ because the market model's R^2 should increase as L is lengthened (and $ln(1+L^{-1})$ decreases). Accordingly, we expect the parameter for the transformed interval function, s_j, to be negative.

whether or not a decrease in market frictions and an improved price discovery process will cause R^2 statistics to increase proportionately more for the shortest measurement intervals (e.g., 1 or 2 day return intervals) than for the longer intervals (e.g., 15 or 20 days). Whether or not they do is an empirical issue that we address in a later section of the paper. In the Empirical Results section, we refer to the intercept and slope parameters of Equation (2) (r_j and s_j) as the pre-event R2CONSTANT and R2SLOPE variables. We define the post-event R2CONSTANT and R2SLOPE variables as (r_j plus u_j) and (s_j plus t_j), respectively.

V. Data

The data used for this analysis are daily opening and closing stock prices as well as daily trading volume for the period 1995-1999. All data were obtained directly from the Paris Bourse's research department. Two subsets of the sample were used to account for the two closing call events that occurred during the sample period. On May 13, 1996, the Paris Bourse first introduced the closing call auction for the less-liquid, Continuous B stocks. Later, on June 2, 1998, the Bourse introduced the closing call for the more actively traded, Continuous A stocks. We took random samples of 50 stocks for each of the two types of securities.[24] Thus, we used a total of 100 stocks that have daily return data for the 500 trading days surrounding the relevant event.[25] Accordingly, we were able to perform our tests on two different samples of 50 stocks over two different time periods. This replication of the closing call's introduction provides useful verification of whether or not the "A" stocks' results corroborate the "B" stocks' results. In effect, the two event dates create a natural means of replicating our analysis in order to make stronger inferences. It also enables us to perform tests on control samples for both event dates. Specifically, we examined two *Pseudo-Events:* the returns behavior for (i) the A stocks around the B stocks' event date (May 13, 1996), and (ii) the B stocks around the A stocks' event date (June 2, 1998).

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[24] Our sample of 50 continuous A stocks includes no stocks that are part of the CAC-40 index, the index that we used for our market model regressions. The large cap stocks on the Paris Bourse are in this index. Cohen, Hawawini, Maier, Schwartz and Whitcomb (1983a) have shown that one-day beta estimates tend to be biased upward for the largest cap stocks that generally lead other stocks in adjusting to new information and, accordingly, our expectation about the impact of the closing calls on the beta estimates for these stocks is ambiguous. Additionally, with only 40 stocks in the index, the individual stock returns are to some extent correlated with the index returns simply because of their inclusion in the index. Nevertheless, we did undertake some limited testing of the CAC-40 stocks (see footnote 34).

[25] The names of the firms that comprise our sample can be found in the Appendix.

For our primary tests, we employed a 500-trading day window (i.e., +/- 250 trading days around the event). This window, which represents approximately two years of daily trading activity, was used for the market model regression tests. By necessity, a relatively long calendar period is needed for this estimation method to obtain reliable parameter estimates. Thus, following the regression technique described above, the pre- and post-event beta estimates are obtained using the 250 days that precede and follow the event, respectively.[26]

We used the daily returns on the CAC-40 Stock Index as our proxy for the returns on the market portfolio in the market model regressions. None of the stocks in our sample are part of this index for the reason that the inclusion of stocks in the CAC-40, given the relatively small number of stocks in the index, would have introduced spurious correlation between individual stock returns and index returns. One might expect the A stocks to be more highly correlated with the CAC-40 index because they are more similar to the CAC-40 stocks than are the B stocks in terms of size and trading volume.[27] Consequently, we expect the market model regression R^2 statistics to be higher for the A stocks than the B stocks.

VI. Intra-Day Effects

VI. A. The Broad Picture

Before turning to a focused assessment of the quality of price determination in the call auctions, we present the broad picture of the intra-day effects that introduction of the closing calls has had on three common market characteristic measures: percentage spreads, returns volatility, and trading volume. To analyze these measures, we have divided the trading day into seven hourly periods.[28] For each of the hourly periods, we compute the average value of each of the three variables for the month preceding the event date (the introduction of the closing call) and for the month following the event date.[29]

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[26] Other sample sizes around the event period (e.g., 120, 150, and 250 days) were also tested and yielded results that are qualitatively similar to those reported here for the 500-day trading window.

[27] One can view our sample of A stocks as a set of second tier stocks and the B stocks as a third tier.

[28] At the times the closing calls were introduced, the continuous market opened at 10:00 am and closed at 5:00 pm.

[29] We also assessed the three variables (spread, volatility, and volume) for the first and last 15-minute intervals of the continuous trading period. The results for these first and last 15-minute intervals are very similar to the first and last hourly intervals of the continuous trading period, and the results are not reported here. This finding is not

Volatility is measured as the standard deviation of the returns, where the return for each one-hour period is measured as the log of the mid-spread value recorded at the end of the period divided by the log of the mid-spread value recorded at the beginning of the period. The findings for spreads, volatility and volume, along with the differences between their pre-event and post-event values, are presented in Table 1. The table also presents the average trading volume in the opening and closing calls.

Overall, introduction of the closing calls appears to have had no meaningful effect on the intraday spread, volatility, and volume measures, as the pre- and post-event differences are, almost without exception, numerically small and statistically insignificant. Only three changes are statistically significant at the .05 level, and they are all for the B stocks: percentage spreads increased in the first hour of continuous trading and decreased in the last hour of continuous trading, and trading volume decreased in the last hour.

It may be hazardous to attribute importance to three significant results out of forty-four tests, but the findings for the B stocks are intriguing and could be explained as follows. The existence of a non-trivial spread in an order driven market has been attributed by Cohen, Maier, Schwartz and Whitcomb (CMSW, 1981) to the "gravitational pull" that a posted quote has on a newly arriving, contra-side order. According to CMSW, the bid-ask spread will be wider, the more attractive it is to newly arriving participants to: (a) trade with certainty by market order at an already posted quote, rather than (b) place limit orders on the book. A reduction of the spread and an increase in trading volume in the final hour of the continuous market preceding a closing call could be understood in this light.

Presumably, the opportunity to place a limit order in a closing call if it has not executed in the continuous market, results in participants being more willing to post limit orders in the final hour of trading, instead of trading with certainty by market order. In other words, the option of paying the spread and trading with certainty at a contra-side quote is less compelling when a call auction exists as a "backup." This would explain two of the three statistically significant findings: a tightening of the spread and a decrease of trading volume at the end of the continuous market. The third statistically significant finding, an increase of spreads in the

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surprising given that quote revision and trading is comparatively infrequent for the relatively thin stocks in our sample.

first hour of the continuous market, may itself be attributed to more orders in the neighborhood of the opening prices having been "cleared out" by trades in the two back-to-back call auctions (the previous night's closing auction and the current day's opening auction).

VI. B. The Final Fifteen Minutes of the Continuous Market and the Opening Call

Demarchi and Thomas (2001) examine the closing call's impact on trading during the final ten minutes of the day including the closing call itself (the volume for which is not separately broken out). They report that participation by institutional investors did in fact increase after the closing call was introduced in 1996 and 1998. Specifically, they observed that order size at the close jumped by roughly fifty percent, and that both trading volume and the aggressiveness of orders (proxied by the number of orders placed "at market") increased significantly.[30]

Our own analysis of trading volume and block trading activity at the end of the trading day provides another perspective on the effect of the closing call beyond that reported by Demarchi and Thomas (2001). The Paris Bourse does not have a standard definition of block trades for all stocks; therefore, we chose 5,000 shares as a reasonable criterion for block activity because, given typical share prices in France, a 5,000 share trade is of considerable size.[31] The following summarizes our findings for relatively large trades during March-August, 1996 and May-July, 1998.

During the last 15 minutes of continuous trading, for the two real events, share volume (as a proportion of total daily trading volume) fell 2.4 percentage points (from 7.8% to 5.4%) for the A stocks, and 1.4 percentage points (from 5.4% to 4.0%) for the B stocks.[32] Concurrently, daily volume at the closing calls averaged approximately 3% for the A stocks and 2% for the B stocks. This suggests that the introduction of the closing call has lead to some redirection of trading away from the continuous market at the end of the day, but also that additional volume has been attracted to the calls. The additional volume implies a reduction of market overhang. We also observe that

[30] Technically, the Paris Bourse refers to these market orders as "at any price" orders.

[31] Very few trades of 10,000 shares or more were observed during the sample period so 5,000 shares was used as our benchmark for block trading activity. At an average stock price of 170 French francs, a 5,000-share trade translates into smaller block trades than those seen in the U.S. (i.e., 5,000 versus 10,000 shares). However, such a trade still represents a sizeable amount of capital (850,000 francs) and is far larger than the typical trade of a Continuous A or B stock, which normally ranges from 100 to 300 shares.

[32] To conserve space, we do not report these volume-related statistics here but they are available from the authors upon request. The pseudo-events also indicate an increase in total trading volume, but the share of trading at the end of the continuous market does not change appreciably. We do not compute significance tests for changes in the pre- and post-event periods due to the relatively few months of data that we have.

block trades at the close as a percentage of total daily block trades rose 6.4% for the A stocks and 35.3% for the B stocks after the closing calls were introduced. For the "pseudo-event" periods, block trading activity at the close for the A stocks appears to have been unaffected by the introduction of the B stocks' closing call in 1996 (the ratio changed only slightly from 8.4% to 8.6%), while the B stocks' closing block trades actually decreased when the A stocks' closing call was implemented in 1998 (i.e., the ratio fell from 4.8% to 3.3%).[33]

For both the A and B stocks, the overall share of trading during the last 15 minutes of continuous trading *including* the closing call increased from 7.8% to 8.4% (for the A stocks) and from 5.4% to 6.3% (for the B stocks). In addition, the changes in these shares of trading volume for the pseudo-events show no meaningful increase. These results suggest that the introduction of the closing calls helped bring in trades that might not have otherwise been executed because the share of trading at the end of the day increased for both A and B stocks' real events. Interestingly, the opening call volume also increased as a share of total trading volume once the closing calls were introduced. Specifically, the opening call volume's share of total trading rose from 1.1% to 1.5% for the A stocks and from 2.8% to 3.0% for the B stocks.

Comprehensively viewed, the evidence suggests that a win-win situation may have resulted. Namely, that the re-direction of orders into the closing calls has been light enough to have had no appreciable impact on the preceding continuous market, but substantial enough to sharpen the accuracy of price discovery at the close. Presumably, a concentration of 2% to 3% of daily trading volume at the single point in time that the market closes has produced more meaningful prices than was the case when the closing prices could have been set by only a few small orders. We examine this further in the next section of the paper.

VII. Empirical Results of Market Model Tests

VII. A. The Market Model R^2 and Beta Statistics

Our tests are organized according to the two sets of stocks for which the closing call auction was introduced (the B stocks on May 13, 1996 and the A stocks on June 2, 1998). We first consider the market model R^2 regression statistic. Panel A of Table 2 shows sample average R^2s for the two sets of stocks (the B and the A shares), with the results presented for the Actual Events and the

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[33] The picture is reversed at the open for the A stocks' pseudo-event (the ratio rose from .001 to .009) while, for the B stocks' pseudo-event, there were no block trades at all at the open in either period.

Pseudo-Events, two times of the day (close and open), the two shortest return intervals (1 and 2 days), the two longest return intervals (10 and 20 days), and the average of all 12 return intervals. Panel A of Table 2 also reports R^2 regression statistics based on the returns from yesterday's close to today's open. These close-to-open (C/O) results are presented to provide an additional perspective on how the closing call affected the quality of opening and closing prices. The open-to-open and close-to-open results are discussed further in Section VIII. Panel B of Table 2 displays the cross-sectional average beta estimates from the market model regressions for the same return intervals shown in Panel A of the table. The beta estimates reported in Panel B are the "first-pass" betas described earlier in Section IV. They are the average betas for the 50 stocks that comprise each of our two key sub-samples for A and B stocks based on market model regressions using 1-10, 15, and 20-day return intervals.

The average R^2s, shown at the bottom of Panel A, provide a good overview of the change associated with the introduction of the closing call. For the Actual Events, the pre- and post-event percentage jump in the average R^2 ranges from 31% (for the A stocks' close-to-open return) to 101% (for the B stocks' close-to-close return), and four of the six jumps are significant at the .01 level. While the actual changes in the level of the R^2 statistics are typically small, on a percentage basis the changes are generally quite sizable. Since the closing mechanism for the A stocks and the B stocks was not affected by each other's movement to a closing call, we expect the market quality of each to be *unaffected* by the other's event. We find that, for the Pseudo-Events, the average jumps are indeed clearly less; they range from 1.9% (for the A stocks' open) to 42% (for the B stocks' close), and only the largest value is significant at the .01 level.[34]

The individual R^2s shown in Table 2 display considerable variation across measurement intervals, between the open and the close, and between the various samples. A number of patterns can be seen. Most noteworthy, the post-event R^2s are greater than their pre-event values for 14 of

[34] First pass regression tests based on a more limited data set for the CAC-40 stocks yielded R^2s for the 1996 pseudo-event that were consistent with those we have reported for the Continuous A stocks. That is, there is no statistically significant change in adjusted R^2 from the pre- to post-event periods (the cross-sectional average R^2 rose only slightly from .24 to .27). For the 1998 real event, R^2 decreased from .39 to .30. However, this result was driven in part by two of the CAC-40 stocks that exhibited large positive returns during the 1998 post-event, a time when the CAC-40 index actually declined 1%. With these two stocks omitted from the sample, the cross-sectional average R^2 declined insignificantly from .38 to .31.

the 16 matched sets in the four Actual Events columns (the two exceptions are the 1-day A-Open and the 2-day B-Open). For the most part, the differences are substantial.

As expected based on CHMSW (1983b), for each of the eight columns, the 10- and 20-day R^2s are substantially greater than the 1- and 2-day R^2s. Importantly, for the 1-day interval through the 10-day interval, the pre- to post-event *differences* are substantial for the Actual Events (and 10 of the 12 values are positive), but are small for the Pseudo-Events (and 7 of the 12 values are negative).[35] Further, for the Actual Event test for the A stocks (but not the B stocks), the pre- to post-event percentage jump in R^2 is consistently greater for the close than for the open. Also, the actual changes in the level of R^2 are typically higher for the close-to-close returns than for the open-to-open or the close-to-open returns.[36]

It should be noted that our results could potentially be attributed, in part at least, to other changes at the Paris Bourse at the time the closing calls were introduced in 1996 and 1998. For example, Muscarella and Piwowar (2001) examine Paris Bourse stocks that switched during 1995-1999 between the continuous trading system and a "fixed" time-specific call auction. As noted earlier, Muscarella and Piwowar (2001) reports statistically significant abnormal returns around the time these stocks were switched from one system to the other. Thus, any stocks in our sample that were involved in the switching might have contaminated our results.

Six B stocks, but no A stocks in our sample were in the list of companies used in Muscarella and Piwowar's study. We omitted these six stocks from our sample and re-estimated our first- and second-pass regressions. The omission had virtually no effect on our results. The average R^2, beta, and second-pass parameter estimates of the reduced sample of

[35] For the 1-day return interval, the percentage changes for the Actual Event (versus the Pseudo-Event) for the B-Close, A-Close, B-Open, and A-Open returns, respectively, are 140.0% (vs. 6.7%), 18.8% (vs. –5.6%), 166.7% (vs. –43.9%), and –7.2% (vs. –6.1%).

[36] Another interesting aspect of Panel A of Table 2 is that R^2 statistics for the A stocks' during their pseudo-event in 1996 are lower than those reported for their "real" event in 1998. The B stocks' R^2 statistics also exhibit a reversal between real and pseudo-event results, except that in the B stocks' case the pseudo-event R^2s of 1998 are greater, on average, than those reported for the B stocks' real event in 1996. The results for both the A and B stocks can be reconciled and explained by the fact that, over time, market linkages between the market portfolio proxy (the CAC-40 index) and both the A and B stocks improved. That is, the R^2 statistics reported for both A and B stocks during the 1998 sample period were higher than those reported for the 1996 period. Thus, if the Paris stock market has become more tightly integrated due to improvements in information dissemination, technological innovation, and other factors over time, we would expect R^2 statistics to rise as time passes (regardless of whether the event we study was a real or a pseudo-event). Indeed, this is exactly the pattern we observe in the data. We suggest that by focusing on the few months surrounding the event we limit the possible confounding effect of time variation in market linkages between the A and B stocks and the market portfolio proxy we have used.

stocks are qualitatively and quantitatively very similar to the ones reported in Tables 2-4 for the full sample (and are not included here to conserve space). In addition, private communications with senior Paris Bourse officials confirm that no other microstructure changes were made at the exchange during our sample period.

The percentage change in the R^2s remains substantial in each of the six Actual Events columns, as we increase the measurement interval from 1 day to 20 days. One might expect that non-synchronicity in price adjustments caused by trading frictions such as spreads and market impact would depress primarily the short measurement interval R^2s and, consequently, that they might increase proportionately more than the longer-interval R^2s with a decrease in market frictions. However, as noted in footnote 15, momentum trading may accentuate the synchronicity of price movements across stocks in relatively brief trading periods. If so, and if price discovery errors tend to compound as the measurement interval is lengthened, then the longer interval R^2s can also be distorted. In such a case, sharper price discovery can result in the *longer*-interval R^2s rising proportionately more than the short-interval R^2s. The values reported in Panel A of Table 2 suggest that this is indeed the case.

The cross-sectional averages of the first-pass beta estimates reported in Panel B of Table 2 are consistent with the findings described above for the average R^2s presented in Panel A. As we have previously noted, the stocks in our sample are smaller and less-liquid than those that comprise the market portfolio proxy (i.e., the CAC-40 stocks). Thus, we expect to find short period betas that are depressed (closer to zero), but that these first-pass beta estimates will be less depressed then they would otherwise have been in the period after the closing call's implementation.[37] We also expect the B stocks' betas to be more depressed than those estimated for the A stocks, because the B stocks are smaller and less-liquid than the A stocks.

Panel B of Table 2 shows that nearly all of the changes in beta estimates are positive and, on average, that they are appreciably larger for the real events than the pseudo-events. Interestingly, the average beta estimates based on all three return measures (close-to-close, open-to-open, and

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[37] It should be noted that Levhari and Levy (1977) demonstrated that the first-pass beta from a market model is non-monotonic in the return interval, L, whenever this interval is either longer or shorter than the "true" length of the unobservable holding period of market participants. However, we use relatively short return intervals of 1-20 days in our analysis that, in most likelihood, are all shorter than the true holding period of market participants. As Levhari and Levy (1977) note, when L is strictly below the true holding period (or strictly above it) then the first-pass beta is a monotonic function of L. Indeed, the relation between L and beta suggested by Levhari and Levy is consistent with CHMSW's (and our) hypothesis of a monotonic increasing function when the measurement interval is less than the true holding period.

close-to-open) are relatively close to each other for both the A and the B stocks. That is, the choice of the type of return used to estimate beta does not radically alter our beta estimates for the various return intervals. Also, average beta estimates nearly always increase as the return interval increases, and the B stocks' betas are always lower than those reported for the A stocks for each return interval.

However, due to the relatively high cross-sectional variation in betas for each return interval across our total sample of 100 stocks, few of the changes in the average beta estimates are statistically significant. This observation suggests that a multivariate test such as the "second-pass" beta regression described by Equation (1), vis-à-vis the univariate *t*-tests, will better remove the confounding factor of the high cross-sectional variability of the betas within each sub-sample, and hence will more effectively isolate the impact of the closing call on beta estimates. As noted above, Panel B of Table 2 does corroborate our R^2 results of Panel A. The statistics indicate that the closing call's introduction has had a direct effect on both the observed betas and the R^2 statistics.

Although Table 2 provides a useful description of the closing call's impact on the information content of opening and closing prices, we use regression analysis on the market model R^2 and beta statistics in order to assess the statistical significance of the findings we have thus far discussed. Tables 3 and A1 report the empirical results for the Continuous A stocks and Tables 4 and A2 show the test results for the Continuous B stocks. Each table contains pre- and post-event comparisons of opening and closing prices, where the event is the introduction of the closing call auction. The last three columns show how the difference between closing and opening price behavior changes with the introduction of the closing call.

Tables 3 and 4 also report changes in average daily trading volume for each stock (VOLUME), and changes in the variances of 1-day and 2-day returns (VAR1 and VAR2). None of these variables experienced statistically significant changes during the 90-trading day sample period. Although the cross-sectional average of daily trading volume shows a decline for the A and B stocks, there are large standard deviations around these point estimates. Due to the limited number of observations and the sizable variability in trading volume figures, it is difficult to find any meaningful patterns in the volume changes. Because of the lack of significance in these volume estimates, we do not examine possible explanations for this change in volume (although the aggregate trading volume for all B stocks does decline during the period surrounding the 1996 closing call introduction) and therefore do not pursue this issue further. Overall, the test results reported below do not appear to have been induced by major sample-wide changes in trading volume or returns volatility.[38] The volatility statistics are interesting for a second reason: in and of themselves, they give no insight into the impact the closing call has had on price formation. In fact, whereas one might anticipate that the call auction would result in enhanced price stability, for both the A and the B stocks, both VAR1 and VAR2 increased somewhat following the stocks' event dates.

Of course, one would expect volatility itself to fluctuate because of any number of factors in addition to the introduction of the closing call. Both the systematic (market related) and the idiosyncratic components of volatility may each separately fluctuate for a spectrum of reasons. This underscores the difficulty of capturing the impact of the market design change by a direct variance calculation. For this reason, and recognizing that the closing calls could result in price changes across stocks being more synchronous, we have considered the relationship *between* residual variance and total variance, as given by the R^2 statistic, where:[39]

$$1 - R^2 = \frac{MSE(N-k)}{\sigma^2(N-1)},$$

MSE = variance of the residual from the market model regression,
σ^2 = total variance of individual stock returns,
N = number of observations used in the regression, and
k = number of independent variables used in the regression plus one (for the constant).

The R^2 results reported in Table 2 suggest that introduction of the closing call has indeed sharpened the accuracy of price discovery at the close. We consider the statistical significance of these findings further in the next sub-section.

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38 As can be seen in the last three columns of Tables 3 and 4, the variances of close-to-open returns for both A and B stocks exhibit insignificant changes in 1-day return volatility similar to those reported for the close-to-close and open-to-open returns.

39 We consider market quality in terms of the synchronicity of individual stock returns with respect to the returns on the broader market, and take an increase in R^2 as evidence that the market microstructure innovation has improved the informational efficiency of the market. This is based on CHMSW's (1983) argument that microstructure-related frictions generate lead/lag relations between individual stock returns and the broader market which reduce the explanatory power of the market model. This effect of microstructure-related frictions is captured by the formula for R^2. Note that in the formula if the residual variance (MSE) from a market model regression decreases due to, for example, a reduction in market frictions, then R^2 will increase when total variance remains unchanged.

VII. B. Assessment of Market Model Parameter Estimates Using Closing Prices

Tables 3 and 4 report the results of the market model tests described by Equations (1) and (2) for the A and B stocks, respectively. Columns 1-3 of each table pertain to closing prices, columns 4-6 report results for the opening prices, and columns 7-9 show the results for the close-to-open, or overnight, returns. Both tables show that the key parameters of the first- and second-pass regressions (i.e., R2CONSTANT and R2SLOPE from Equation 2 and BETA2 from Equation 1) are statistically significant for the pre- and post-event periods. In addition, nearly all of these parameters changed significantly in the expected direction after the closing call was introduced for both the A and B stocks. The sole exception is the second-pass regression parameter, BETA2, for the closing prices of A stocks; the change is in the expected direction, but it is not statistically significant.

The results for both the A and B stocks presented in Tables 3 and 4 provide two independent sets of tests that confirm our expectation that the explanatory power of the market model would improve after the closing call was introduced. As noted earlier in the discussion of Table 2, nearly all return intervals had higher post-event R^2 statistics, with the A stocks reporting R^2s greater than those for the B stocks.[40] For example, all but two of the 32 changes in the R^2 statistic for the A's and B's opening and closing prices were positive (with 17 of them statistically significant at the .10 level or better).[41] The higher R^2s for both groups of stocks indicate that the returns based on closing prices followed the market returns more closely after the introduction of the closing call. These findings suggest that price discovery was indeed sharpened for both the A and the B stocks.

The results reported in Tables 3 and 4 for the R^2 analysis of the first-pass regressions based on closing prices provide strong evidence in support of our hypothesis about the improvement in market quality. The R2CONSTANT parameter reports statistically significant increases of 0.1069 (+69.8%) in column 3 of Table 3 and 0.0409 (+114.6%) in column 3 of Table 4 for the A and B stocks, respectively. In addition, the R2SLOPE parameter shows a significant change of –0.13639 (-126.9%) for the A stocks and –0.07423 (-139.5%) for the B stocks. As can be seen from the R^2 statistics of the first-pass regressions based on closing prices, the parameter changes for the B

[40] The generally lower R^2 estimates for the B stocks might be due to the fact that these stocks are not as similar to our choice of market proxy (the CAC-40 index) because the B stocks are in a different market segment than the CAC-40 stocks.

[41] By Bernoulli tests, the likelihood of finding 30 of 32 changes to be positive by chance is less than 1%.

stocks' closing prices are statistically significant but not as large in absolute magnitude as those for the A stocks. Consistent with the A stocks, the changes in R2CONSTANT and R2SLOPE confirm the improvement in R^2 across nearly all of the B stocks' return intervals. As we will discuss in more detail within Section VIII. B., the results based on close-to-open returns reported in Tables 3 and 4 also corroborate the results obtained using the close-to-close and open-to-open returns.

As noted in Section IV, the average BETA2 parameter should be *less* negative when market frictions are less. So, we expect a positive change in BETA2 when the closing call is introduced. The test results of Tables 3 and 4 provide support for this, albeit not as strongly as the R^2 results. The strongest support for the positive change in BETA2 is found in the closing prices of the B stocks. These findings provide further evidence consistent with our expectation that the closing call reduced trading costs and sharpened price discovery at the Paris Bourse. Our results are consistent with Cushing and Madhavan's (2000) findings that closing prices in a continuous trading environment can be distorted and that the introduction of a closing call auction system might reduce some of the end-of-day return anomalies they observe for NYSE stocks.

VII. C. Test Results for Control Samples

To further test the robustness of our results, we used our two control samples to determine whether the A stocks were affected by the B stocks' event in 1996, and whether the B stocks were affected by the A stocks' event in 1998. A priori, we expect any changes in the key market model variables (BETA2, R2CONSTANT, and R2SLOPE) to be insignificant for the "pseudo-events." Results for these control samples are presented in Table 5 with Panel A for the 1996 pseudo-event and Panel B for the 1998 pseudo-event. Consistent with Table 2, Table 5 shows, for all of the market model statistics, that the changes for the pseudo-events are only a fraction of the changes observed for the real events. Further, the changes are all insignificant. The generally insignificant findings reported in Table 5 for the pseudo-events further indicate the statistical significance of the real events (see Tables 3-4). That is, it is unlikely that our findings are a statistical artifact of the specific time period, sample, or test procedure that we have used.

Section VIII. The Closing Call's Broader Impacts

Our analysis of the hour-by-hour, intra-day effects that introduction of the closing call had on percentage spreads, returns volatility, and trading volume is reported in Section VI. While the effects were predominantly insignificant, we did observe significant changes for the B stocks in the last hour of continuous trading (percentage spreads and trading volume decreased after the introduction of the closing call) and in the first hour of continuous trading (percentage spreads increased). In this section, we look more closely at the impact introduction of the closing call has had on: (1) the synchronicity of open-to-open returns, and (2) the synchronicity of overnight (close-to-open) returns. Sharper price discovery at the close and a reduction in market overhang (resulting from institutional customers entering more of their unexecuted orders into the closing calls) can improve the accuracy of opening prices and the meaningfulness of the overnight return. On the other hand, a re-direction of orders from the continuous market to the closing calls could cause spreads to widen, liquidity to dry up, and price volatility to increase in the continuous market.

VIII. A. Tests of Opening Prices

We focus on the impact the closing call has had on the quality of price discovery at another important time in the trading day: at the open. Tables 3 and 4 report the R^2 analysis of the first-pass regressions (R2CONSTANT and R2SLOPE) and the second-pass regression parameter estimates (BETA2) for the opening prices of the A and B stocks. These tables present evidence from the R^2 analysis that the explanatory power of the market model regression is higher for the post-event period for *both* the closing and the opening prices. For the Continuous A stocks' opening prices, R2CONSTANT shows a statistically significant increase of 0.09415, while R2SLOPE shows a significant change of -0.16722 (see column 6 of Table 3). Similar to the closing price results, the parameter changes for the B stocks' opening prices are 0.04635 and -0.09307 for the two parameters, respectively, which are also statistically significant, but not as large in magnitude as those reported for the A stocks. Similar to the results for the closing prices, the changes in R2CONSTANT and R2SLOPE show that R^2 increases for nearly all return intervals. With regard to BETA2, the parameter increased by 0.06715 for the A stocks and 0.22245 for the B stocks. These results suggest that a decrease in the intervalling effect occurred with the introduction of the closing call facility.

We also note that percentage changes in the empirical measures based on opening prices are generally smaller than those reported for the closing prices (i.e., the spillover effect is smaller than the closing call's direct effect on closing prices). The reduced effect for the opening prices (relative to the closing prices) is no doubt also partially explained by the fact that the closing call's introduction eliminated the close's bid-ask spread, whereas the opening prices did not benefit from the removal of a bid-ask spread because the opening call auction was already in existence.[42]

VIII. B. Close-to-Open Returns

We next examine the impact of the closing calls on close-to-open returns. If closing and opening prices are both being set with greater precision, one would expect greater synchronicity between the close-to-open returns of different stocks.

The last two columns of Panel A of Table 2 for the actual and the pseudo-events show sample average R^2s for the two sets of stocks based on returns measured using the closing price on one day, and the opening price on, respectively, the following day, two days later, 19 days later and 20 days later. We wish to determine the impact that more precise closing prices have on the relation between pricing at the close and at next day openings. Of course, only the "one-day" measure is a pure overnight (close-to-open) return.

For the array of measurement intervals that we have used, the open-to-open, close-to-close, and close-to-open returns are the most independent of each other when the measurement interval is one-day. As the return interval is lengthened to two days and more, the close-to-close, open-to-open, and close-to-open returns become increasingly similar. For instance, one 2-day close-to-close return will have in common one close-to-open return, while one 3-day close-to-close return will have in common one one-day open-to-open return and two close-to-open returns. As the measurement interval is lengthened beyond three days, an even greater proportion of the component returns are the same across the three types of return measures. Thus, we expect to observe larger differences in the closing call's impact on the three alternative return measures when a 1-day return interval is used.

The R^2s for the close-to-open returns show a pattern that is similar to the ones observed for the close-to-close and open-to-open returns. For the one-day close-to-open return, we observe a 350% increase in R^2 in the post-event period for the B stocks. Curiously, however, the one-day close-to-open R^2 is an unusually high .234 for the A stocks in the pre-event period, and this statistic decreases 45.3% to .128 for the post-event period. Interestingly, we also observe a decrease in the

[42] In contrast to the changes in the R^2 statistics for the closing and opening prices, the relative difference in the R^2 statistics between the opening and closing prices shows no significant change. This result can be seen in the final three columns of Tables 2 and 4 for the R2CONSTANT and R2SLOPE parameters.

average beta for this return interval (from 0.651 to 0.508 in Panel B of Table 2). For the average R^2 across all measurement intervals, we observe 94.5% and 31.3% increases in explanatory power for the B and the A stocks respectively, during the actual event periods. While the average R^2 and beta statistics typically increase for the close-to-open returns as they do for the close-to-close returns, the variability of R^2 across firms is considerably greater for the close-to-open returns and, consequently, the differences we have observed are not as statistically significant.[43]

As is the case with the returns based on close-to-close and open-to-open prices, we expect the market quality of each set of stocks (A and B) to be *unaffected* by the other's event. Indeed, we find that, for the Pseudo-Events, the average R^2 changes are much lower (they are 4.0% for the B stocks, 12.5% for the A stocks, and both are statistically insignificant).

While Table 2 provides a useful description of the closing call's impact on the information content of opening and closing prices, we use regression analysis on the market model R^2 statistics using the second-pass technique of Equation (1) to assess the statistical significance of the findings. Similar to Tables 3, 4, and 5, we estimate Equations (1) and (2) using the close-to-open returns for the Continuous A stocks and Continuous B stocks. These results are qualitatively similar to those reported in Tables 3, 4, and 5 and are presented in columns 7-9 of these tables. As suggested by the Table 2 results, the R2CONSTANT parameter increases significantly after the actual event occurs, but does not increase for the pseudo-events.

The only difference between the close-to-open results and those reported in Tables 3-5 for the close-to-close and open-to-open returns is the lack of significance in the changes for the R2SLOPE and BETA2 parameters. As noted earlier, the variability of the R^2s and second-pass beta estimates is greater for the close-to-open. This appears to be the main reason why the close-to-open results generally show less statistical significance but are otherwise consistent with our other findings.

In sum, the 1-day returns analysis indicates that the behavior of the close-to-close returns, in terms of both sign and magnitude, conforms most closely to our predictions about changes in R^2 and beta. The results based on open-to-open and close-to-open returns are generally similar in terms of

[43] The range of the R^2 statistics for each return interval is not reported in Table 2 in order to conserve space. To note one contrast, for the 50 A stocks' actual event, the 1-day close-to-open returns R^2 statistics had a range of .448 (from .019 to .467); the comparable range of R^2 for this same set of stocks based on close-to-close returns was a substantially smaller .305 (from .009 to .314). As noted earlier, the average betas also exhibit a wide degree of cross-sectional variation with individual stock betas ranging from below zero to above 1.0.
Investigating the cause of the greater cross-sectional variability in the overnight R^2 and beta statistics would be an interesting subject for future analysis.

the sign of the changes in R^2 and beta, but they are neither as consistently large or as significant. It is not surprising that the close-to-close returns would yield the strongest results because the introduction of the closing call has, of course, directly affected the closing prices.

IX. Further Tests of Market Quality

This section reports the results of additional measures of market quality that are described in greater detail in the Appendix. These tests serve as a robustness check on our market model results.

As noted above, other empirical measures of trading costs have been considered in the literature.[44] Variance ratio test statistics such as Hasbrouck and Schwartz's (1988) market efficiency coefficient, MEC, are of limited use for our purpose. The primary shortcoming of MEC is that momentum trading introduces positive autocorrelation in security returns while other factors introduce negative autocorrelation (mean-reversion), and the two patterns tend to offset each other. However, as noted in the Appendix, the range of MEC should in any event decrease if the closing call's impact is consistent with our hypothesis. Indeed, we find that the range of stock-specific MEC statistics does decrease for both the A and B stocks during the post-event periods. The range of MEC for the closing prices declined from 1.203 to 1.067 for the A stocks, and from 0.917 to 0.875 for the B stocks.

A simple, intuitive approach for examining the relative volatility of opening versus closing prices can be based on the absolute differences between opening and closing prices. In fact, Stoll (2000) uses such a measure to estimate changes in stock price volatility (referred to as "*OV*" and defined in our Appendix). We report the results of tests based on pre- and post-event estimates of *OV* in Tables A1 and A2. The results indicate that there is no significant excess volatility during our sample period.

The spread measures of Roll (1984) and Lesmond, et al. (1999) are not directly applicable to our problem because there is no bid-ask spread for the Paris Bourse's opening prices or post-event closing prices. Lesmond, et al. (1999) use a limited dependent variable model and the tobit estimation technique to infer the spread associated with trading stocks on the NYSE and American Stock Exchange (Amex). Using daily return data, the authors derive their inference from the relative frequency of trading days that have zero returns for a particular security. This approach is relevant to our analysis if we interpret their estimation technique as a method to estimate the overall

[44] See the Appendix for further discussion of these measures.

round-trip cost of trading in a security. Thus, we apply their model and tobit analysis to daily returns on the Paris Bourse to obtain pre- and post-event estimates of the exchange's Lesmond-type average spread. We expect both the Roll- and Lesmond-type spread measures to *decrease* after the closing call is implemented. To conserve space, we simply note here that a post-event decline in round-trip trading costs did occur that would be consistent with improved price discovery. These results, however, are not statistically significant.

In addition to the quantitative measures reported in Tables 3 and 4, we draw some casual inferences from the information presented in Figures 1 and 2. These graphs display the frequency distribution of 1-day returns for the sub-sample of stocks that are most likely to benefit from a closing call auction, namely, the most volatile and least liquid shares (i.e., the most volatile quartile of the B stocks).[45] The findings in Figures 1 and 2 are supportive of our hypothesis in that the 1-day returns for both the closing and the opening prices become more tightly distributed after the closing call's introduction.[46]

Lastly, we employ the procedure of Amihud, et al. (1997) to measure the effect on security returns of a major change in the market microstructure on the Tel Aviv Stock Exchange. Not surprisingly, when the Tel Aviv stocks were moved to a more liquid trading environment, positive abnormal returns were generated. In our case, we do not expect large abnormal returns because the market microstructure change we study (i.e., the closing call) is a modification of the Paris Bourse's trading system that may not have been widely recognized or understood at the time it occurred. Based on Amihud, et al.'s method, we estimate Equation (A4) and find that the average cumulative abnormal return (SUMCAR) is not significantly different from zero in any of our tests.[47]

X. Conclusion

In response to investors' needs for a more orderly, efficient means of closing the market for individual securities, the Paris Bourse refined its trading system in 1996 and 1998 to include electronic call auctions at market closings to complement its electronic call auction openings.

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[45] In this test, volatility is measured using pre-event returns.

[46] The closing call's effects on other sub-groups of the A and B stocks is less clear than those discussed above for the most volatile quartile of B stocks. This might be due to the fact that the effects of the closing call on more-liquid, less-volatile stocks are not as easily detected via graphs such as Figures 1 and 2. Nevertheless, other statistical tests noted earlier confirm the improvement in market quality for a wider variety of stocks.

[47] There are also no significant CARs for the sub-periods related to the 10 days prior to and the 10 days after the event (as well as the event period itself, days 0 and +1).

Closing calls are now being used in London, Germany, and other major markets in Europe, and our empirical findings indicate that this innovation significantly improves market quality at the close. We suggest that the call auction is a market structure feature that should receive more attention in the academic literature.

Our key assessments of market quality have been made using a new methodology that is based on the well-known market model. That is, we have inferred the quality of price discovery for individual stocks by studying the non-synchronous price adjustments that occur across stocks in short intervals of time (our return measurement intervals range from one day up to twenty days). One of our more intriguing findings is that the closing call's introduction has increased the market model R^2s for all of our measurement intervals. Observing that R^2s increased substantially for the 20-day interval suggests that inaccuracies in price discovery are not simply an intra-day phenomenon. Further investigation of the possibility that price discovery errors can compound over time would be desirable.

The results using Paris Bourse data are confirmed for two independent test periods and two different sets of securities. Further, we examined two control samples based on two "pseudo-events" (the A stocks' event date for the B stocks and the B stocks' event date for the A stocks). That no meaningful changes were detected for the pseudo-events, indicates that our findings for the real events are not a spurious consequence of our specific time period, sample, or test procedure. We also find that changes in the listing venue for some of the stocks in the Paris market, actions that were first analyzed by Muscarella and Piwowar (2001), have not perturbed our results.

As expected, in terms of percentage changes, the positive effects on market quality of the closing call's introduction are greatest for closing prices, while the behavior of opening price and overnight returns signal similar, yet smaller, improvements in market quality. In addition, an investigation of trading volume and return volatility surrounding the closing call's introduction yields no statistically significant changes, and suggests that these factors have not influenced our results.

The Paris Bourse has advised us that no appreciable, negative liquidity effects have occurred in the continuous market leading up to the calls, and our own empirical assessment of intra-day spreads, volume, and volatility measures for the continuous market suggests that this is indeed the case. On the contrary, we have observed that the closing call's constructive impact on market quality extends beyond the close itself. First, improved price discovery at the close is believed to have increased the efficiency of the derivatives markets by making the marking-to-market of French stock options more orderly and by making it easier for options traders to unwind their positions at appropriate prices. Second, improved price discovery at the close and a likely reduction in the overhang of unfilled orders after the close, have further sharpened price discovery at market openings, albeit to a lesser extent. Third, if closing prices and opening prices are both established with greater precision, one would expect the synchronicity of close-to-open returns to be improved, and our empirical results suggest that this has indeed been the case.

While our analysis has focused primarily on the quality of price discovery, introduction of the closing calls also appears to have affected participant order placement decisions. For instance, we have observed that, on average, spreads tightened during the last half-hour of the trading day after the closing calls were introduced, and we have hypothesized that the existence of the closing calls has provided more encouragement for traders to place limit orders rather than market orders as the continuous market nears its close. More generally, one might expect the impact of the closing call to be complex, and that further analysis of its impact on the order flow would be desirable.

Additional attention should also be given to the broader impacts of market structure on the quality of price discovery. Unfortunately, inaccuracies in price discovery cannot be directly measured because equilibrium values are unobservable. However, our analysis indicates that the quality of price discovery can be inferred, and that the impact a market structure change has on the dynamic process of price formation can be assessed in this light.

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Appendix

A1. Additional Test Statistics

This section provides details on several other market quality statistics and their related tests. These statistics provide a robustness check for the empirical measures described in the body of the text. For example, to test our hypothesis in terms of the closing call's impact on trading costs, we must construct estimates of these costs because the true costs of execution are not directly observable. We can do this by estimating a "market efficiency coefficient" (MEC) as described in Hasbrouck and Schwartz (1988) using the variance of 1- and 2-day returns, as follows:

$$MEC = \frac{VAR(R_{2DAY})}{2[VAR(R_{1DAY})]} \tag{A1}$$

where,

VAR(R_{2DAY}) = sample variance of 2-day returns, and

VAR(R_{1DAY}) = sample variance of 1-day returns.

A MEC equal to 1.0 indicates that there are no net intervalling effects on the return's variance. However, in practice, MECs can differ from these "frictionless world" values. MECs less than 1.0 indicate negative correlation in returns data that is attributable to cost factors such as the bid-ask spread, market impact, and overshooting in price discovery. MECs greater than 1.0 indicate positive correlation in returns data that is attributable to cost related factors such as the sequential dissemination of information, momentum trading, and undershooting in price discovery.

We can test the effectiveness of the closing call system by studying the changes in the *range* of MEC from the pre-event to the post-event period. As noted in the Empirical Methodology section, the MEC statistic can be influenced by momentum trading and mean-reversion tendencies in security return time series. Thus, the actual level of the MEC statistics might not be the best way to measure the effect of the closing call on market quality. However, the extreme values of MEC well above or below 1.0 should be ameliorated if the closing call had a positive impact on market quality. According to our hypothesis, we expect a measure of these extreme values (e.g., the *range* of MEC) to *decline* after the closing call was implemented. Since the range is sensitive to extreme values, it is an ideal measure to capture the potential effect of the closing call mechanism on the MEC statistic.

Amihud, et al. (1997) demonstrate another way to measure a market's trading efficiency. They note that the "relative return dispersion" (RRD) of a particular market can be calculated using the residuals from a conventional market model. The RRD should *decrease* as market frictions decline. This prediction is based on the premise that a market model should become a more descriptive model of an exchange's securities when the exchange's trading costs are lower. Thus, we would expect RRD to decline for our post-event period (i.e., the *average* of all securities' post-event RRD's should be significantly lower than the average of pre-event RRD's). This statistic can be calculated for time-*t* as follows:

$$RRD_t = \Sigma_j \varepsilon_{jt}^2 / n \tag{A2}$$

where,

RRD_t = relative return dispersion for the entire sample of securities at time-*t*,

ε_{jt}^2 = squared market model residual for security-*j* at time-*t*,

n = number of securities in the sample at time-*t*.

The relative return dispersion examines market frictions from a different perspective than the R^2 statistic test described by (1). RRD depicts the level of *cross-sectional* dispersion in market model residuals whereas the R^2 statistic captures the magnitude of market model residuals for each stock's time series. Thus, RRD explicitly considers the covariation in the residuals across our stock sample whereas the R^2 statistic analysis focuses on the residuals for each stock across time. Together, the two measures provide complementary methods for examining changes in a market's trading costs. We expect RRD to *decrease* after the closing call's implementation since less-severe market imperfections should result in less-correlated, and smaller, residuals across our sample on any given day.

Additional tests of a market's trading efficiency include a measure of the responsiveness of a stock's returns to fluctuations in the market portfolio's returns (denoted here as DELAY and described in Chordia and Swaminathan, 2000). This statistic is defined below:

$$DELAY = \frac{1}{1+e^{-X}}; \quad \text{where, } X = \frac{\sum_{k=1}^{5} \beta_{j,t-k}}{\beta_{j,t}} \tag{A3}$$

and,

$\beta_{j,t}$ = the beta parameter estimate for the *j*-th security from a Dimson-type (1979) regression using the relevant return on the market portfolio for the *t*-th day (i.e., based on the contemporaneous and five lagged market returns).

Note that if there are no market frictions affecting security returns, then DELAY should equal 0.5. Thus, large deviations from 0.5 would suggest market frictions are affecting the observed return data.

In addition to the above regression analyses, a comparison of the tails of the distribution for 1-day returns during the pre- and post-event periods can help provide another perspective on informational efficiency and the closing call. For example, we expect that the introduction of a closing call might decrease market frictions which, in turn, should lead to less uncertainty about the true price of security and ultimately result in less extreme fluctuations in daily security returns. Thus, we expect that the tails of the return distributions of illiquid, volatile stocks should become smaller. That is, there should be fewer observations of large returns (e.g., +/- 5%) once the closing call is implemented. We can test this hypothesis by examining the effect of the closing call on the stocks that are most likely to need "improvement" in terms of market imperfections (i.e., the most illiquid and volatile stocks). A visual inspection of a security's return distribution (such as those displayed in Figures 1 and 2) can be used to provide us with some casual evidence regarding the closing call's impact.

As implied by our hypothesis, significant changes in trading costs associated with a market microstructure change could also be reflected in stock returns around the time of the change. Thus, following Amihud, et al. (1997), we perform an event study using a market model regression that includes dummy variables for the period surrounding the closing call's introduction date.

$$R_{jt} = a_j + b_j(R_{mt}) + c_j(Dummy1_t) + d_j(Dummy2_t) + e_j(Dummy3_t) + u_{jt} \qquad \text{(A4)}$$

where,

R_{jt} = natural logarithm of the price relative ($ln(p_t / p_{t-1})$) for security-*j* at time-*t*,

a_j and b_j and c_j and d_j and e_j = parameter estimates,

R_{mt}=natural logarithm of the price relative, $ln(p_t / p_{t-1})$, for a value-weighted market portfolio at time-*t*,

$Dummy1_t$ = 1 if time t is 1 - 10 days *prior* to the event,

$Dummy2_t$ = 1 if time t is 0 - 1 days *after* the event,

$Dummy3_t$ = 1 if time t is 2 - 11 days *after* the event,

u_{jt} = a stochastic disturbance term.

Note that the summation of the dummy parameters equals the cumulative abnormal return ($SUMCAR_j$) for security-*j* during its 22-day event window. This $SUMCAR_j$ can then be averaged over all stocks in the sample in order to verify whether or not the closing call's introduction coincided with positive stock price reactions.

In addition to the above tests directly related to closing prices, we can study the effect of the closing call mechanism in relation to the Bourse's opening prices because the exchange already had an opening call auction system in existence for several years. This provides us with a natural experiment where we can not only examine the behavior of the closing prices but also study the trading efficiency of closing prices *relative to* opening prices. For example, if the closing call helps reduce trading costs at the close, then the opening call during the following day might also be affected in a positive manner. Thus, we can test the effects of the introduction of the closing call on not only closing prices but also opening prices. Further, the relative difference in opening versus closing prices can be studied.

One measure of relative performance between opening and closing prices is presented below. Specifically, we can use Stoll's (2000) measure of "excess volatility" (OV) between opening and closing prices:

$$OV_{j,t} = \left|OPEN_{j,t} - OPEN_{j,t-1}\right| - \left|CLOSE_{j,t} - CLOSE_{j,t-1}\right| \qquad \text{(A5)}$$

where,

$OPEN_{j,t}$ = opening price of the j-th security on the t-th day, and

$CLOSE_{j,t}$ = closing price of the j-th security on the t-th day.

If the opening and closing prices behave similarly, then the average OV should not be significantly different from zero over our sample period. In particular, we can test whether or not OV moves closer to zero after the closing call is implemented.

In sum, the above sections (and the Appendix) have described several different types of tests that can be used to analyze the impact of the closing call auction on Paris-based stocks. These tests enable us to study the closing call's effects on two important attributes of any financial market: trading costs and price discovery.

Empirical Results of the Additional Test Statistics:

To test the measures described above, we used a 90-trading day window surrounding the event date. That is, we used the 45 trading days prior to the closing call's introduction as our pre-event period for these tests. For the post-event period, we used the event date plus the 44 trading days after the event. Both periods cover roughly two months of trading activity. The event window is designed to be long enough to measure adequately the test statistic, yet short enough to avoid incorporating other unrelated, confounding effects. Other event windows of up to 250 trading days exhibited results qualitatively similar to those reported here. To conserve space, we focus on the 90-trading day window in our presentation of the additional tests.

One exception to the above 90-day sample size pertains to the abnormal return estimates obtained for each stock using Equation (A4). For these estimates we used the 250 trading days preceding and following the event to estimate the market model regression described by (A4). The abnormal return estimates were then calculated from this regression based on the 22-day event window, as noted earlier.

In addition to the CHMSW-type market model results described in the body of the text, Tables A1 and A2 present further evidence that is generally supportive of our hypothesis based on alternative measures of market quality. For example, results for the DELAY measure are consistent with our hypothesis in the majority of tests for both the A and B stock groups. As expected, the DELAY measure decreases during the post-event period (most significantly for A's closing prices). Tables A1 and A2 also show that Amihud, et al.'s (1997) measure of the average cross-sectional level of the market model residuals for the A and B stocks, RRD, declines slightly in a majority of the tests. These results provide a cross-sectional perspective on the explanatory power of the market model and corroborate the earlier findings of reduced market frictions described for the BETA2 and R^2 statistics.

We repeat the additional tests for the opening prices, and for the differences in the relevant statistics between the opening and closing prices. Tables A1 and A2 contain the results.

The DELAY measure provides mixed support for our hypothesis with some evidence in support of our expectation reported for the A's opening prices but not for the B's. Tables A1 and A2 also indicate that the average cross-sectional level of the market model residuals for the A and B stocks, RRD, declines slightly in a majority of the tests with the biggest drop found in the B's opening prices. Interestingly, the decrease is more pronounced in the opening prices when compared with the closing prices. This is contrary to our expectation about the closing call's impact on market quality. However, for nearly all of the differences reported in columns 7-9 of the two tables, the changes are not statistically significant. The one exception is the RRD statistic for the B stocks in Table A2.

In contrast to DELAY, the tests comparing pre- and post-event periods find that Stoll's (2000) measure of "excess volatility", OV, is not significantly different from zero in either period. Further, the change in OV is insignificant although it does move in the correct direction (i.e., OV moves towards zero for both the A and B stocks). The OV results confirm that excess volatility does not appear to be a problem at the Paris Bourse and provides some additional, yet statistically weaker, support for our hypothesis.

A2. List of Stocks Used in the Analysis

Presented below are the 50 Continuous A and 50 Continuous B stocks included in our analysis.

50 Continuous A Stocks:	**50 Continuous B Stocks:**
ATOS	ADA
BERTRAND FAURE	AFE
BOUYGUES	ARBEL
BULL	BAINS MER MONACO
CASINO GUICHARD	BIOBLOCK SCIENT.
CASTORAMA DUBOIS	CAOUTCHOUCS PADANG
CEGID	CEGEDIM
CHARGEURS	CHAINE TRAME
CHRISTIAN DIOR	CIPE France
CLUB MEDITERRANEE	DASSAULT AVIATION
COFLEXIP	DAUPHIN
COLAS	EMIN-LEYDIER
CPR	EURO.EXTINCTEURS
CREDIT LYONNAIS CI	FIDEI
DASSAULT-ELECTRO.	FONCIERE LYONNAISE
DE DIETRICH	GEL 2000
ECIA	GROUPE GUILLIN
EIFFAGE	GUERBET
EURO DISNEY SCA	ICBT GROUPE
GRANDVISION	IMMOB.MARSEILLAISE
GROUPE GTM	INDUSTRIE (CENT.)
HAVAS	KINDY
IMETAL	MANITOU BF
ISIS	MATUSSIERE FOREST
LEGRIS INDUSTRIES	MGI COUTIER
MARINE WENDEL	MORS
METALEUROP	PENAUILLE POLYSCES
METROLOGIE INTL	PRIMIST.REYNOIRD
MOULINEX	RALLYE
NATEXIS	SAGEM ADP
NRJ	SALVEPAR
PECHINEY	SECURIDEV
PERNOD-RICARD	SFIM
PRIMAGAZ	SILIC
REMY COINTREAU	SMOBY
SCOR	SUCR.PITHIVIERS
SEB	TROUVAY CAUVIN
SEITA	VILMORIN ET CIE
SIDEL	BURELLE

SIMCO	CARBONE LORRAINE
SKIS ROSSIGNOL	FINACOR
SOGEPARC	GFI INDUSTRIES
SOMMER-ALLIBERT	IMMOBAIL
SOPHIA	IMMOBANQUE FIN.
SYNTHELABO	INFOGRAMES ENTERT.
TECHNIP	LEBON
TF1	MICHEL THIERRY
UIF	POCHET
UNION ASSUR.FDAL	SADE
VALLOUREC	UIS

Table 1. Intraday Tests of Spreads, Volatility, and Volume

This table presents hourly average estimates of the Bid-Ask Spread to Mid-Quote ratio, hourly Return Volatility, and hourly Trading Volume for the two-month periods surrounding the 1998 event (Panel A for the 50 Continuous A stocks) and the 1996 event (Panel B for the 50 Continuous B stocks). The averages are based on the 50-stock cross-sectional samples of A and B stocks. The Trading Volume measure is defined as the ratio of trading volume during the designated time period divided by the day's total trading volume. The table also presents trading volume statistics for the morning and closing call auctions (denoted as A.M. CALL and P.M. CALL, respectively).

Panel A. Hourly Results for A Stocks during the Two Months Surrounding the Event Date (May 1998 - June 1998)

	Bid-Ask Spread / Mid-Quote				Return Volatility				Trading Volume		
Time Period	Before	After	Diff.		Before	After	Diff.		Before	After	Diff.
10:02 – 10:59 Avg.	**0.00924**	**0.00942**	0.00018	Avg. Volatility	**0.00233**	**0.00229**	-0.00004	Avg. Volume	**0.2057**	**0.2483**	0.0426
S.D.	0.00482	0.00548	0.00730	S.D.	0.00251	0.00268	0.00367	S.D.	0.0693	0.1086	0.1288
t-statistic	23.63	21.26	0.30	Wald statistic	130.98	111.71	0.00	t-statistic	14.24	11.66	1.66
				p-value	0.0001	0.0001	0.9991				
11:00 – 11:59 Avg.	**0.00848**	**0.00858**	0.00010	Avg. Volatility	**0.00179**	**0.00176**	-0.00003	Avg. Volume	**0.1635**	**0.1392**	-0.0243
S.D.	0.00457	0.00464	0.00651	S.D.	0.00143	0.00120	0.00187	S.D.	0.0859	0.0329	0.0920
t-statistic	22.88	22.87	0.19	Wald statistic	238.16	329.12	0.00	t-statistic	9.13	21.57	-1.28
				p-value	0.0001	0.0001	0.9993				
12:00 – 12:59 Avg.	**0.00842**	**0.00848**	0.00006	Avg. Volatility	**0.00170**	**0.00155**	-0.00015	Avg. Volume	**0.0972**	**0.1004**	0.0032
S.D.	0.00431	0.00474	0.00641	S.D.	0.00146	0.00101	0.00178	S.D.	0.0547	0.0667	0.0863
t-statistic	24.09	22.13	0.12	Wald statistic	206.08	360.34	0.02	t-statistic	8.52	7.68	0.18
				p-value	0.0001	0.0001	0.9899				
1:00 - 1:59 Avg.	**0.00812**	**0.00834**	0.00022	Avg. Volatility	**0.00157**	**0.00159**	0.00002	Avg. Volume	**0.0566**	**0.0548**	-0.0018
S.D.	0.00413	0.00459	0.00617	S.D.	0.00120	0.00114	0.00166	S.D.	0.0172	0.0316	0.0360
t-statistic	24.24	22.47	0.44	Wald statistic	260.18	297.63	0.00	t-statistic	15.78	8.84	-0.25
				p-value	0.0001	0.0001	0.9986				
2:00 - 2:59 Avg.	**0.00822**	**0.00814**	-0.00008	Avg. Volatility	**0.00150**	**0.00155**	0.00005	Avg. Volume	**0.1077**	**0.0925**	-0.0152
S.D.	0.00422	0.00446	0.00614	S.D.	0.00106	0.00106	0.00150	S.D.	0.0538	0.0416	0.0680
t-statistic	24.01	22.58	-0.16	Wald statistic	304.38	326.53	-1.18	t-statistic	9.60	11.34	-1.10
				p-value	0.0001	0.0001	0.5547				

Note: Values in bold face denote the statistic is significant at the .01 level. Values in italics denote significance at the .05 or .10 levels.

Table 1. (continued)

Panel A.	Bid-Ask Spread / Mid-Quote				Return Volatility				Trading Volume		
Time Period	Before	After	Diff.		Before	After	Diff.		Before	After	Diff.
3:00 - 3:59 Avg.	**0.00819**	**0.00838**	0.00019	Avg. Volatility	**0.00147**	**0.00169**	0.00022	Avg. Volume	**0.1360**	**0.1267**	-0.0093
S.D.	0.00401	0.00473	0.00620	S.D.	0.00107	0.00125	0.00165	S.D.	0.0381	0.0517	0.0642
t-statistic	25.18	21.91	0.38	Wald statistic	286.89	279.67	-0.12	t-statistic	17.12	12.50	-0.72
				p-value	0.0001	0.0001	0.9437				
4:00 - 4:59 Avg.	**0.00916**	**0.00928**	0.00012	Avg. Volatility	**0.00235**	**0.00217**	-0.00018	Avg. Volume	**0.2117**	**0.1887**	-0.0230
S.D.	0.00421	0.00502	0.00655	S.D.	0.00170	0.00204	0.00266	S.D.	0.0611	0.0831	0.1031
t-statistic	26.82	22.87	0.23	Wald statistic	290.46	173.12	-0.03	t-statistic	16.62	11.58	-1.11
				p-value	0.0001	0.0001	0.9873				
								A.M. CALL	**0.0216**	**0.0168**	-0.0048
								S.D.	0.0243	0.0227	0.0333
								t-statistic	4.26	3.77	-0.71
								P.M. CALL	--	**0.0326**	--
								S.D.	--	0.0224	--
								t-statistic	--	7.42	--

Panel B. Hourly Results for B Stocks during the Two Months Surrounding the Event Date (April 12, 1996 - June 13, 1996)

	Bid-Ask Spread / Mid-Quote				Return Volatility				Trading Volume		
Time Period	Before	After	Diff.		Before	After	Diff.		Before	After	Diff.
10:02 - 10:59 Avg.	**0.01815**	**0.02080**	*0.00265*	Avg. Volatility	**0.00312**	**0.00440**	0.00128	Avg. Volume	**0.2799**	**0.3005**	0.02060
S.D.	0.01068	0.01218	0.01620	S.D.	0.00376	0.00545	0.00662	S.D.	0.0757	0.0503	0.0909
t-statistic	19.75	20.13	1.92	Wald statistic	92.95	90.60	-0.11	t-statistic	15.69	28.02	0.99
				p-value	0.0001	0.0001	0.9487				
11:00 - 11:59 Avg.	**0.01916**	**0.02020**	0.00104	Avg. Volatility	**0.00354**	**0.00469**	0.00115	Avg. Volume	**0.1823**	**0.1736**	-0.00870
S.D.	0.01318	0.01184	0.01772	S.D.	0.00363	0.00450	0.00578	S.D.	0.0964	0.0513	0.1092
t-statistic	16.89	20.11	0.69	Wald statistic	128.39	150.99	-0.19	t-statistic	8.02	15.87	-0.35
				p-value	0.0001	0.0001	0.9107				

Table 1. (continued)

Panel B.	Bid-Ask Spread / Mid-Quote				Return Volatility				Trading Volume		
Time Period	Before	After	Diff.		Before	After	Diff.		Before	After	Diff.
12:00 - 12:59 Avg.	**0.01883**	**0.01991**	0.00108	Avg. Volatility	**0.00491**	**0.00477**	-0.00014	Avg. Volume	**0.0634**	**0.0777**	0.01430
S.D.	0.01283	0.01133	0.01712	S.D.	0.00412	0.00420	0.00588	S.D.	0.0401	0.0191	0.0444
t-statistic	17.05	20.72	0.74	Wald statistic	191.74	179.29	-0.03	t-statistic	6.71	19.08	1.39
				p-value	0.0001	0.0001	0.9854				
1:00 - 1:59 Avg.	**0.01931**	**0.01945**	0.00014	Avg. Volatility	**0.00444**	**0.00473**	0.00029	Avg. Volume	**0.0413**	**0.0361**	-0.00520
S.D.	0.01386	0.01110	0.01776	S.D.	0.00365	0.00398	0.00540	S.D.	0.0158	0.0137	0.0209
t-statistic	16.19	20.66	0.09	Wald statistic	199.76	196.32	-0.03	t-statistic	11.09	12.36	-1.10
				p-value	0.0001	0.0001	0.9834				
2:00 - 2:59 Avg.	**0.01917**	**0.01952**	0.00035	Avg. Volatility	**0.00495**	**0.00517**	0.00022	Avg. Volume	**0.0825**	**0.0877**	0.00520
S.D.	0.01382	0.01059	0.01741	S.D.	0.00482	0.00467	0.00671	S.D.	0.0471	0.0269	0.0542
t-statistic	16.12	21.73	0.23	Wald statistic	142.38	170.36	0.03	t-statistic	7.43	15.29	0.42
				p-value	0.0001	0.0001	0.9831				
3:00 - 3:59 Avg.	**0.01924**	**0.01928**	0.00004	Avg. Volatility	**0.00465**	**0.00506**	0.00041	Avg. Volume	**0.1521**	**0.1279**	-0.02420
S.D.	0.01297	0.01067	0.01679	S.D.	0.00542	0.00403	0.00675	S.D.	0.1257	0.0354	0.1306
t-statistic	17.24	21.30	0.03	Wald statistic	99.37	219.13	0.01	t-statistic	5.13	16.95	-0.79
				p-value	0.0001	0.0001	0.9936				
4:00 - 4:59 Avg.	**0.02006**	**0.01673**	*-0.00333*	Avg. Volatility	**0.00467**	**0.00638**	0.00171	Avg. Volume	**0.1681**	**0.1372**	*-0.0309*
S.D.	0.01281	0.01078	0.01674	S.D.	0.00441	0.00408	0.00601	S.D.	0.0487	0.0471	0.0678
t-statistic	18.19	18.30	-2.32	Wald statistic	151.39	339.89	1.04	t-statistic	14.64	13.66	-2.03
				p-value	0.0001	0.0001	0.5934				
								A.M. CALL	**0.0304**	**0.0331**	0.00270
								S.D.	0.0140	0.0121	0.0185
								t-statistic	9.21	12.83	0.64
								P.M. CALL	--	**0.0262**	--
								S.D.	--	0.0121	--
								t-statistic	--	10.16	--

Note: Values in bold face denote the statistic is significant at the .01 level. Values in italics denote significance at the .05 or .10 levels.

Table 2. Comparison of Adjusted Coefficients of Determination over Different Return Intervals before and after Implementation of the Closing Call Auction Mechanism

The table presents the 50-stock averages of the adjusted R^2 statistics (Panel A) and Beta estimates (Panel B) from conventional market model regressions of 1, 2, 10, and 20-day returns of individual stocks on returns of the CAC-40 Stock Index. For the *Actual Events* columns, the averages are computed for the A and B stocks' opening prices, closing prices, and close-to-open returns (C/O) during the 500 days surrounding the introduction of the closing call facility (pre- and post-event). For the *Pseudo Events* columns, we compute averages of a sample of A stocks during the B stocks' closing call introduction (*A – Open, A – Close,* and *A – C/O*) as well as a sample of B stocks during the A stocks' closing call introduction (*B – Open, B – Close,* and *B – C/O*). The final 3 rows report simple averages of the adjusted R^2 and Beta estimates for all 12 return intervals (*Overall*). An asterisk (*) denotes the differences between the pre- and post-event average R^2 and betas are significant at the .01 level.

Panel A.	Actual Events						Pseudo-Events					
Average R^2	B - Close	A - Close	B - Open	A - Open	B – C/O	A – C/O	B - Close	A - Close	B - Open	A - Open	B – C/O	A – C/O
Pre-event 1-day	0.005	0.101	0.003	0.180	0.002	0.234	0.030	0.072	0.041	0.066	0.068	0.057
Post-event 1-day	0.012	0.120	0.008	0.167	0.009	0.128	0.032	0.068	0.023	0.062	0.018	0.082
Change in R^2 level	0.007*	0.019	0.005	-0.013	0.007*	-0.106*	0.002	-0.004	-0.018	-0.004	-0.050*	0.025
Pctg. Difference	140.0%	18.8%	166.7%	-7.2%	350.0%	-45.3%	6.7%	-5.6%	-43.9%	-6.1%	-73.5%	43.9%
Pre-event 2-day	0.009	0.092	0.013	0.141	0.007	0.141	0.024	0.077	0.050	0.085	0.049	0.078
Post-event 2-day	0.016	0.159	0.012	0.185	0.022	0.184	0.045	0.080	0.045	0.080	0.038	0.080
Change in R^2 level	0.007	0.067*	-0.001	0.044	0.015	0.043*	0.019	0.003	-0.005	-0.005	-0.009	0.002
Pctg. Difference	77.8%	72.8%	-7.7%	31.2%	114.3%	30.5%	87.5%	3.9%	-10.0%	-5.9%	-22.4%	2.6%
Pre-event 10-day	0.038	0.155	0.026	0.178	0.037	0.168	0.071	0.123	0.068	0.116	0.074	0.127
Post-event 10-day	0.058	0.268	0.063	0.282	0.052	0.282	0.086	0.117	0.086	0.111	0.076	0.113
Change in R^2 level	0.020	0.113*	0.037	0.104*	0.015	0.114*	0.015	-0.006	0.018	-0.005	0.002	-0.014
Pctg. Difference	52.6%	72.9%	142.3%	58.4%	40.5%	67.9%	21.1%	-4.9%	26.5%	-4.3%	2.7%	-11.0%
Pre-event 20-day	0.050	0.177	0.047	0.192	0.064	0.196	0.051	0.101	0.068	0.086	0.062	0.107
Post-event 20-day	0.094	0.275	0.115	0.281	0.109	0.305	0.142	0.135	0.159	0.152	0.128	0.139
Change in R^2 level	0.044	0.098	0.0068	0.089	0.045	0.109*	0.091*	0.034	0.091	0.066	0.066	0.032
Pctg. Difference	88.0%	55.4%	144.7%	46.4%	70.3%	55.6%	178.4%	33.7%	133.8%	76.7%	106.5%	29.9%
Pre-event (Overall)	0.025	0.131	0.025	0.164	0.025	0.167	0.053	0.104	0.060	0.100	0.059	0.092
Post-event (Overall)	0.050	0.209	0.049	0.223	0.048	0.219	0.075	0.106	0.073	0.106	0.062	0.103
Change in R^2 level	0.025*	0.078*	0.024*	0.059*	0.023	0.052	0.022*	0.002	0.013	0.006	0.003	0.011
Pctg. Difference	101.7%	59.9%	97.7%	36.3%	94.5%	31.3%	41.5%	1.9%	21.8%	5.8%	4.0%	12.5%

Table 2. (continued)

Panel B.	Actual Events						Pseudo-Events					
Average *Beta*	B – Close	A - Close	B - Open	A - Open	B – C/O	A – C/O	B - Close	A - Close	B - Open	A - Open	B – C/O	A – C/O
Pre-event 1-day	0.120	0.481	0.135	0.562	0.160	0.651	0.242	0.408	0.220	0.380	0.330	0.398
Post-event 1-day	0.231	0.515	0.180	0.571	0.230	0.508	0.222	0.480	0.196	0.462	0.212	0.528
Change in *Beta* level	0.111*	0.034	0.045	0.009	0.070	-0.143*	-0.020	0.072	-0.024	0.082	-0.118*	0.130*
Pctg. Difference	92.5%	7.1%	33.3%	1.6%	43.8%	-22.0%	-8.3%	17.6%	-10.9%	21.6%	-35.8%	32.7%
Pre-event 2-day	0.180	0.449	0.216	0.481	0.211	0.501	0.223	0.430	0.256	0.471	0.277	0.425
Post-event 2-day	0.259	0.570	0.238	0.613	0.273	0.601	0.266	0.526	0.263	0.529	0.244	0.540
Change in *Beta* level	0.079	0.121*	0.022	0.132	0.062	0.100	0.043	0.096	0.007	0.058	-0.033	0.115
Pctg. Difference	43.9%	26.9%	10.2%	27.4%	29.4%	20.0%	19.3%	22.3%	2.7%	12.3%	-11.9%	27.1%
Pre-event 10-day	0.384	0.641	0.378	0.652	0.335	0.638	0.414	0.531	0.400	0.519	0.417	0.536
Post-event 10-day	0.479	0.700	0.581	0.673	0.524	0.681	0.393	0.718	0.370	0.719	0.358	0.702
Change in *Beta* level	0.095	0.059	0.203	0.021	0.189	0.043	-0.021	0.187	-0.030	0.200	-0.059	0.166
Pctg. Difference	24.7%	9.2%	53.7%	3.2%	56.4%	6.7%	-5.1%	35.2%	-7.5%	38.5%	-14.1%	31.0%
Pre-event 20-day	0.512	0.658	0.510	0.684	0.493	0.665	0.451	0.698	0.439	0.592	0.438	0.642
Post-event 20-day	0.625	0.732	0.687	0.683	0.712	0.779	0.555	0.759	0.563	0.848	0.579	0.807
Change in *Beta* level	0.113	0.074	0.177	-0.001	0.219	0.114	0.104	0.061	0.124	0.256	0.141	0.165
Pctg. Difference	22.1%	11.2%	34.7%	-0.1%	44.4%	17.1%	23.1%	8.7%	28.2%	43.2%	32.2%	25.7%
Pre-event (Overall)	0.290	0.559	0.301	0.582	0.292	0.578	0.353	0.542	0.335	0.504	0.359	0.518
Post-event (Overall)	0.410	0.646	0.422	0.637	0.435	0.641	0.363	0.627	0.350	0.639	0.353	0.637
Change in *Beta* level	0.120	0.087	0.121	0.055	0.143	0.063	0.010	0.085	0.015	0.135	-0.006	0.119
Pctg. Difference	41.4%	15.6%	40.2%	9.5%	49.0%	10.9%	2.8%	15.7%	4.5%	26.8%	1.7%	23.0%

Table 3. Comparison of Market Efficiency Measures before and after Implementation of the Closing Call Auction Mechanism

This table reports the relevant parameter estimates for the first- and second-pass regressions of CHMSW (1983), R2CONSTANT, R2SLOPE, and BETA2. The average 1- and 2-day return variance (VAR1 and VAR2) and daily trading volume (VOLUME) are also reported. R2CONSTANT and R2SLOPE are derived from the following regression equation (Equation 2 in the text):

$$\mathrm{AdjRsq}_{jLE} = r_j + s_j ln(1+L^{-1}) + t_j(\mathrm{DummyRsq}_{jE}) + u_j(\mathrm{DummyC}_{jE}) + v_{jLE}$$

where, AdjRsq_{jLE} is the adjusted R^2 statistic from the market model regression for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event, The terms, r_j and s_j and t_j and u_j are parameter estimates while v_{jLE} is a stochastic disturbance term. The variable, L, denotes the length of the return interval, in days, for which the stock returns are calculated. $\mathrm{DummyRsq}_{jE}$ is a dummy variable for the slope which is equal to $1 \cdot ln(1+L)^{-1}$ if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B). DummyC_{jE} is a dummy variable for the intercept which is equal to 1 if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B). We denote the intercept and slope parameters of Equation (2) (r_j and s_j) as the *pre-event* R2CONSTANT and R2SLOPE variables. We define the *post-event* R2CONSTANT and R2SLOPE variables as (r_j plus u_j) and (s_j plus t_j), respectively.

BETA2 is derived from regression estimates based on Equation (1):

$$b_{j,1LE} = a_{j,2} + b_{j,2} ln(1+L^{-1}) + c_{j,2}(\mathrm{Dummy}_{jE} \cdot ln(1+L^{-1})) + e_{jLE}$$

where, $b_{j,1LE}$ = “first-pass” beta estimate for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event. The terms $a_{j,2}$ and $b_{j,2}$ and $c_{j,2}$ are “second-pass” parameter estimates where, according to CHMSW, $a_{j,2}$ can be interpreted as the asymptotic level of the stock’s beta (i.e., the stock’s beta estimate when L increases to infinity). The variable, e_{jLE}, is a stochastic disturbance term. Similar to Equation (2) noted above, L equals the length of the holding period, in days, for which the stock returns were calculated. Dummy_{jE} is a binary variable equal to 1 if the “first-pass” beta is estimated using the *post*-event data (i.e., E = A) and 0 if the “first-pass” beta is estimated using the *pre*-event data (E = B).

Table 3. (continued)

Based on Full Sample of Continuous A Stocks

	Closing Prices			Opening Prices			Close-to-Open Returns		
	Before	After	Difference	Before	After	Difference	Before	After	Difference
R2CONSTANT*	**0.15307**	**0.25997**	**0.10690**	**0.16497**	**0.25912**	**0.09415**	**0.14518**	**0.27217**	**0.12699**
S.D.	0.13035	0.18806	0.22882	0.14102	0.19096	0.23739	0.14126	0.18045	0.22916
t-statistic	8.30	9.77	3.30	8.27	9.59	2.80	7.27	10.67	3.92
Avg. R2SLOPE*	**-0.10772**	**-0.24411**	**-0.13639**	**-0.00685**	**-0.17407**	**-0.16722**	**0.07615**	**-0.24361**	**-0.31976**
S.D.	0.20334	0.30576	0.36720	0.18720	0.31589	0.36719	0.24698	0.31660	0.40154
t-statistic	-3.75	-5.65	-2.63	-0.26	-3.90	-3.22	2.18	-5.44	-5.63
Avg. BETA2*	**-0.40222**	**-0.28306**	0.11915	**-0.26967**	**-0.20252**	0.06715	-0.03633	**-0.32621**	**-0.28988**
S.D.	0.69725	0.56790	0.77745	0.67785	0.54807	0.76765	0.52592	0.57876	0.78202
t-statistic	-4.08	-3.52	0.94	-2.81	-2.61	0.54	-0.49	-3.99	-2.62
Avg. VAR1	**0.00050**	**0.00056**	0.00006	**0.00049**	**0.00057**	0.00008	**0.00023**	**0.00021**	-0.00002
S.D.	0.00029	0.00033	0.00041	0.00032	0.00036	0.00049	0.00023	0.00017	0.00004
Wald statistic	147.37	140.52	-0.14	117.07	122.63	-0.208	50.00	73.67	0.02
p-value	0.0000	0.0000	0.9322	0.0000	0.0000	0.9013	0.0000	0.0000	0.9913
Avg. VAR2	**0.00095**	**0.00106**	0.00011	**0.00095**	**0.00105**	0.00011	n.a.	n.a.	n.a.
S.D.	0.00055	0.00060	0.00073	0.00059	0.00069	0.00087	n.a.	n.a.	n.a.
Wald statistic	148.00	154.88	0.92	128.10	115.59	-0.088	n.a.	n.a.	n.a.
p-value	0.0000	0.0000	0.6324	0.0000	0.0000	0.9571	n.a.	n.a.	n.a.
Avg. VOLUME	**86,105**	**59,907**	(26,198)						
S.D.	147,095	84,449	166,096						
t-statistic	4.14	5.02	-1.09						

Note: Values in bold face denote the statistic is significant at the .05 level. Values in italics denote significance at the .10 level. “n.a.” denotes not applicable for the 2-day return variance based on close-to-open returns because these returns are effectively “overnight” returns.
* = These statistics are based on market model betas estimated over a 500-trading day interval surrounding the event date (i.e., +/- 250 days around 6/2/98). The other statistics reported in this table are based on a 90-trading day interval (+/- 45 days around 6/2/98).

Table 4. Comparison of Market Efficiency Measures before and after Implementation of the Closing Call Auction Mechanism

This table reports the relevant parameter estimates for the first- and second-pass regressions of CHMSW (1983b), R2CONSTANT, R2SLOPE, and BETA2. The average 1- and 2-day return variance (VAR1 and VAR2) and daily trading volume (VOLUME) are also reported. R2CONSTANT and R2SLOPE are derived from the following regression equation (Equation 2 in the text):

$$AdjRsq_{jLE} = r_j + s_j ln(1+L^{-1}) + t_j(DummyRsq_{jE}) + u_j(DummyC_{jE}) + v_{jLE}$$

where, $AdjRsq_{jLE}$ is the adjusted R^2 statistic from the market model regression for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event, The terms, r_j and s_j and t_j and u_j are parameter estimates while v_{jLE} is a stochastic disturbance term. The variable, L, denotes the length of the return interval, in days, for which the stock returns are calculated. $DummyRsq_{jE}$ is a dummy variable for the slope which is equal to $1 \cdot ln(1+L)^{-1}$ if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B). $DummyC_{jE}$ is a dummy variable for the intercept which is equal to 1 if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B). We denote the intercept and slope parameters of Equation (2) (r_j and s_j) as the *pre-event* R2CONSTANT and R2SLOPE variables. We define the *post-event* R2CONSTANT and R2SLOPE variables as (r_j plus u_j) and (s_j plus t_j), respectively.

BETA2 is derived from regression estimates based on Equation (1):

$$b_{j,1LE} = a_{j,2} + b_{j,2} ln(1+L^{-1}) + c_{j,2}(Dummy_{jE} \cdot ln(1+L^{-1})) + e_{jLE}$$

where, $b_{j,1LE}$ = “first-pass” beta estimate for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event. The terms $a_{j,2}$ and $b_{j,2}$ and $c_{j,2}$ are “second-pass” parameter estimates where, according to CHMSW, $a_{j,2}$ can be interpreted as the asymptotic level of the stock’s beta (i.e., the stock’s beta estimate when L increases to infinity). The variable, e_{jLE}, is a stochastic disturbance term. Similar to Equation (2) noted above, L equals the length of the holding period, in days, for which the stock returns were calculated. $Dummy_{jE}$ is a binary variable equal to 1 if the “first-pass” beta is estimated using the *post*-event data (i.e., E = A) and 0 if the “first-pass” beta is estimated using the *pre*-event data (E = B).

Table 4. (continued)

Based on Full Sample of Continuous B Stocks

	Closing Prices			Opening Prices			Close-to-Open Returns		
	Before	After	Difference	Before	After	Difference	Before	After	Difference
R2CONSTANT*	**0.03571**	**0.07663**	**0.04092**	**0.03278**	**0.07913**	**0.04635**	**0.03791**	**0.07409**	*0.03618*
S.D.	0.10038	0.10366	0.14430	0.07913	0.09237	0.12163	0.09045	0.09484	0.13106
t-statistic	2.52	5.23	2.01	2.93	6.06	2.69	2.96	5.52	1.95
Avg. R2SLOPE*	**-0.05320**	**-0.12743**	*-0.07423*	**-0.04885**	**-0.14192**	**-0.09307**	**-0.06497**	**-0.12871**	*-0.06374*
S.D.	0.18593	0.20372	0.27581	0.17302	0.18321	0.25200	0.17556	0.19211	0.26025
t-statistic	-2.02	-4.42	-1.90	-2.00	-5.48	-2.61	-2.62	-4.74	-1.73
Avg. BETA2*	**-0.62378**	**-0.29049**	**0.33329**	**-0.60980**	**-0.38735**	0.22245	**-0.48744**	**-0.63597**	-0.14853
S.D.	0.63032	0.71015	0.93776	0.72696	0.68921	0.95201	0.81721	0.77084	1.12340
t-statistic	-7.00	-2.89	2.48	-5.93	-3.97	1.57	-4.22	-5.83	-0.93
Avg. VAR1	**0.00046**	**0.00049**	0.00003	**0.00057**	**0.00056**	-0.00001	**0.00030**	**0.00025**	-0.00005
S.D.	0.00031	0.00029	0.00047	0.00041	0.00036	0.00062	0.00024	0.00017	0.00004
Wald statistic	107.44	137.08	0.10	94.84	121.55	0.001	78.13	108.13	0.087
p-value	0.0000	0.0000	0.9518	0.0000	0.0000	0.9996	0.0000	0.0000	0.9574
Avg. VAR2	**0.00091**	**0.00096**	0.00004	**0.00103**	**0.00103**	0.00000	n.a.	n.a.	n.a.
S.D.	0.00071	0.00064	0.00105	0.00081	0.00073	0.00124	n.a.	n.a.	n.a.
Wald statistic	83.38	113.03	0.33	81.08	99.10	0.000	n.a.	n.a.	n.a.
p-value	0.0000	0.0000	0.8469	0.0000	0.0000	1.0000	n.a.	n.a.	n.a.
Avg. VOLUME	**2,742**	**1,741**	(1,001)						
S.D.	5,323	2,403	5,844						
t-statistic	3.64	5.12	-1.21						

Note: Values in bold face denote the statistic is significant at the .05 level. Values in italics denote significance at the .10 level. "n.a." denotes not applicable for the 2-day return variance based on close-to-open returns because these returns are effectively "overnight" returns.
* = These statistics are based on market model betas estimated over a 500-trading day interval surrounding the event date (i.e., +/- 250 days around 5/13/96). The other statistics reported in this table are based on a 90-trading day interval (+/- 45 days around 5/13/96).

Table 5. Control Sample Results for 1996 and 1998 Events

This table reports the parameter estimates for the first- and second-pass regressions of CHMSW (1983b) for two control samples (or "pseudo-events"). Panel A reports the results of a sample of 50 Continuous A stocks using the B stocks' event date (May 13, 1996). Panel B's results are based on a sample of 50 B stocks using the A stocks' event date (June 2, 1998). R2CONSTANT and R2SLOPE are derived from the following regression equation (Equation 2 in the text):

$$AdjRsq_{jLE} = r_j + s_j ln(1+L^{-1}) + t_j(DummyRsq_{jE}) + u_j(DummyC_{jE}) + v_{jLE}$$

where, $AdjRsq_{jLE}$ is the adjusted R^2 statistic from the market model regression for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event, The terms, r_j and s_j and t_j and u_j are parameter estimates while v_{jLE} is a stochastic disturbance term. The variable, L, denotes the length of the return interval, in days, for which the stock returns are calculated. $DummyRsq_{jE}$ is a dummy variable for the slope which is equal to $1 \cdot ln(1+L)^{-1}$ if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B). $DummyC_{jE}$ is a dummy variable for the intercept which is equal to 1 if the first-pass adjusted R^2 statistic is estimated using the *post*-event data (i.e., E = A) and 0 if the first-pass adjusted R^2 statistic is estimated using the *pre*-event data (E = B). We denote the intercept and slope parameters of Equation (2) (r_j and s_j) as the *pre-event* R2CONSTANT and R2SLOPE variables. We define the *post-event* R2CONSTANT and R2SLOPE variables as (r_j plus u_j) and (s_j plus t_j), respectively.

BETA2 is derived from regression estimates based on Equation (1):

$$b_{j,1LE} = a_{j,2} + b_{j,2} ln(1+L^{-1}) + c_{j,2}(Dummy_{jE} \cdot ln(1+L^{-1})) + e_{jLE}$$

where, $b_{j,1LE}$ = "first-pass" beta estimate for security-*j* based on L-day stock returns for the time period, E, where E = A or B, and denotes either the period before (B) or after (A) the event. The terms $a_{j,2}$ and $b_{j,2}$ and $c_{j,2}$ are "second-pass" parameter estimates where, according to CHMSW, $a_{j,2}$ can be interpreted as the asymptotic level of the stock's beta (i.e., the stock's beta estimate when L increases to infinity). The variable, e_{jLE}, is a stochastic disturbance term. Similar to Equation (2) noted above, L equals the length of the holding period, in days, for which the stock returns were calculated. $Dummy_{jE}$ is a binary variable equal to 1 if the "first-pass" beta is estimated using the *post*-event data (i.e., E = A) and 0 if the "first-pass" beta is estimated using the *pre*-event data (E = B).

Table 5. (continued)

A. 1996 Event with Cont. A Stocks	Closing Prices			Opening Prices			Close-to-Open Returns		
	Before	After	Difference	Before	After	Difference	Before	After	Difference
Avg. R2CONSTANT*	**0.12058**	**0.12913**	0.00855	**0.11487**	**0.12979**	0.01492	**0.12405**	**0.12551**	0.00146
S.D.	0.13216	0.13890	0.19173	0.12696	0.13135	0.18268	0.15747	0.13540	0.20768
t-statistic	6.45	6.57	0.32	6.40	6.99	0.58	5.57	6.55	0.05
Avg. R2SLOPE*	**-0.08028**	**-0.11120**	-0.03092	**-0.07135**	**-0.11564**	-0.04429	**-0.10059**	**-0.08830**	0.01229
S.D.	0.16978	0.24755	0.30018	0.17111	0.22708	0.28433	0.19534	0.24208	0.31106
t-statistic	-3.34	-3.18	-0.73	-2.95	-3.60	-1.10	-3.64	-2.58	0.28
Avg. BETA2*	**-0.49900**	**-0.30557**	0.19343	**-0.50084**	*-0.25824*	*0.24260*	**-0.31827**	**-0.40703**	-0.08876
S.D.	0.63394	0.68901	0.93628	0.62919	0.74095	0.97205	0.85906	0.64471	1.07407
t-statistic	-5.57	-3.14	1.46	-4.29	-1.88	1.76	-2.62	-4.46	-0.58
B. 1998 Event with Cont. B Stocks									
Avg. R2CONSTANT*	**0.06872**	**0.09965**	0.03093	**0.07157**	**0.10436**	0.03279	**0.06847**	**0.09710**	0.02863
S.D.	0.08678	0.10593	0.13694	0.09011	0.10791	0.14059	0.08494	0.10309	0.13358
t-statistic	5.60	6.65	1.60	5.62	6.84	1.65	5.70	6.66	1.52
Avg. R2SLOPE*	**-0.07704**	**-0.11880**	-0.04176	**-0.03636**	**-0.09942**	**-0.06306**	-0.02150	**-0.13106**	**-0.10956**
S.D.	0.15308	0.16960	0.22847	0.10887	0.14151	0.17854	0.16654	0.17656	0.24271
t-statistic	-3.56	-4.95	-1.29	-2.36	-4.97	-2.50	-0.91	-5.25	-3.19
Avg. BETA2*	**-0.40989**	**-0.47314**	-0.06325	**-0.40065**	**-0.46351**	-0.06286	**-0.21936**	**-0.40667**	*-0.18731*
S.D.	0.51959	0.54276	0.75137	0.58553	0.48336	0.75926	0.54443	0.57487	0.79176
t-statistic	-5.58	-6.16	-0.60	-3.68	-5.16	-0.59	-2.85	-5.00	-1.67

Note: Values in bold face denote the statistic is significant at the .05 level. Values in italics denote significance at the .10 level.
* = These statistics are based on Beta parameters estimated over a 500-trading day interval surrounding the event date (i.e., +/- 250 days around 5/13/96 or 6/2/98).

Table A1. Comparison of Additional Market Efficiency Measures before and after Implementation of the Closing Call Auction Mechanism

Additional tests described by Equations (A2) – (A5) in the Appendix are reported here as a robustness check on the results presented in Table 2 for the Continuous A stock sample.

Based on Full Sample of Continuous A Stocks

	Closing Prices			Opening Prices			Diff. Between Closing and Opening		
	Before	After	Difference	Before	After	Difference	Before	After	Difference
Avg. DELAY*	**0.63759**	**0.52958**	*-0.10801*	**0.62535**	**0.56774**	-0.05761	0.01224	-0.03816	-0.05040
S.D.	0.27602	0.29054	0.38954	0.26626	0.26784	0.39330	0.38351	0.39516	0.55067
t-statistic	16.33	12.89	-1.96	16.61	14.99	-1.04	0.23	-0.68	-0.65
RRD	**0.00043**	**0.00044**	0.00001	**0.00045**	**0.00042**	-0.00003	-0.00002	0.00002	0.00004
S.D.	0.00017	0.00019	0.00025	0.00014	0.00017	0.00022	0.00022	0.00026	0.00034
t-statistic	18.43	16.61	0.39	22.25	17.43	-0.82	-0.65	0.55	0.84

Summary Measures Across Event Periods:	Close	Open	Difference
SUMCAR*	-0.00509	-0.00671	-0.00162
S.D.	0.09110	0.09000	0.12806
t-statistic	-0.40	-0.53	-0.09
	Before	After	Difference
Excess Volatility (OV)	-0.24083	0.10547	0.3463
S.D.	1.1251	1.6236	1.97533
t-statistic	-1.51	0.46	1.24

Note: Values in bold face denote the statistic is significant at the .05 level. Values in italics denote significance at the .10 level.
* - These statistics are estimated for a 500-trading interval surrounding the event date (+/- 250 days).
The other statistics are based on a 90-trading day interval surrounding the event date (+/- 45 days).

Table A2. Comparison of Additional Market Efficiency Measures before and after Implementation of the Closing Call Auction Mechanism

Additional tests described by Equations (A2) – (A5) in the Appendix are reported here as a robustness check on the results presented in Table 2 for the Continuous B stock sample.

Based on Full Sample of Continuous B Stocks

	Closing Prices			**Opening Prices**			**Diff. Between Closing and Opening**		
	Before	After	Difference	Before	After	Difference	Before	After	Difference
Avg. DELAY*	**0.57100**	**0.53382**	-0.03718	**0.51126**	**0.53550**	0.02424	0.05974	-0.00168	-0.06142
S.D.	0.35720	0.37500	0.51790	0.38021	0.38555	0.54149	0.52168	0.53784	0.74928
t-statistic	11.30	10.07	-0.51	9.51	9.82	0.32	0.81	-0.02	-0.58
RRD	**0.00047**	**0.00044**	-0.00003	**0.00059**	**0.00047**	**-0.00012**	**-0.00012**	-0.00004	0.00008
S.D.	0.00013	0.00020	0.00024	0.00019	0.00019	0.00027	0.00023	0.00028	0.00036
t-statistic	25.51	15.38	-1.01	22.28	17.58	-3.09	-3.65	-0.90	1.63

Summary Measures Across Event Periods:	Close	Open	Difference
SUMCAR*	0.00310	0.01022	0.00712
S.D.	0.10135	0.10548	0.14628
t-statistic	0.22	0.69	0.34
	Before	After	Difference
Excess Volatility (OV)	0.20365	0.15705	-0.0466
S.D.	1.10578	1.4084	1.79063
t-statistic	1.30	0.79	-0.18

Note: Values in bold face denote the statistic is significant at the .05 level. Values in italics denote significance at the .10 level.
* - These statistics are estimated for a 500-trading interval surrounding the event date (+/- 250 days).
The other statistics are based on a 90-trading day interval surrounding the event date (+/- 45 days).

Figure 1. Return Distribution for Most Volatile B Stocks - Closing Prices

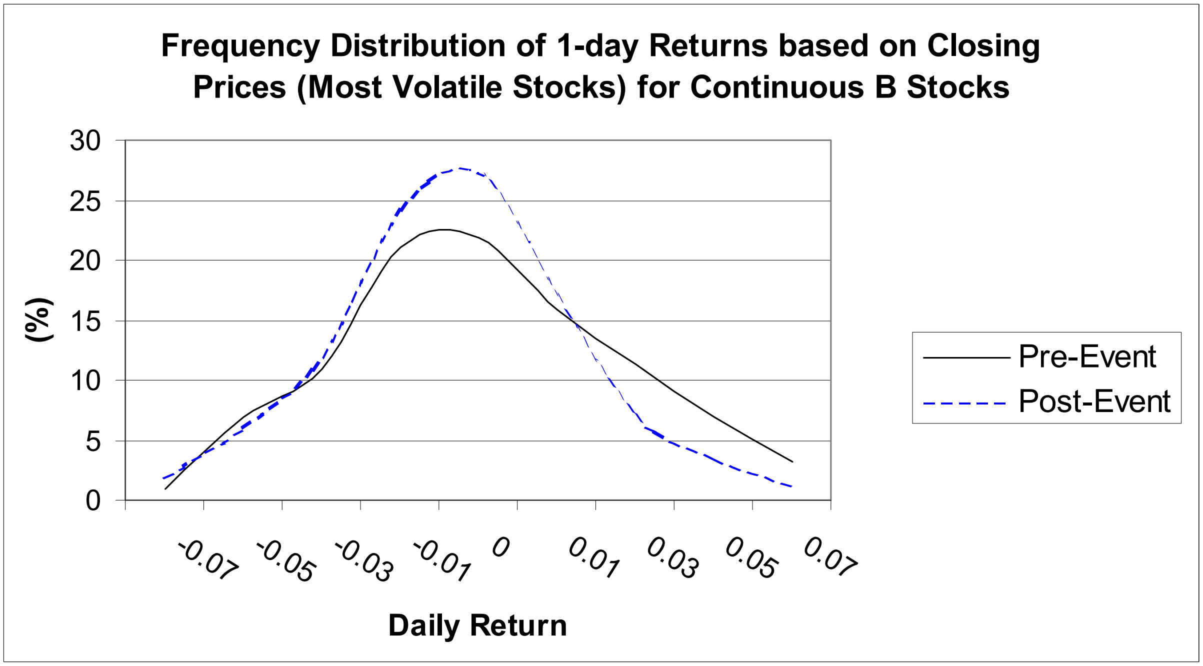

Figure 2. Return Distribution for Most Volatile B Stocks – Opening Prices