Overnight volatility when overnight trading can be observed

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Abstract

It is well known that volatility during trading periods (daytime) is higher than volatility during daily non-trading periods (overnight) or over the weekend in virtual all markets. Economic reasoning attributes these volatility patterns to two main factors: the inflow of new relevant information and trading activity itself, especially noise trading. However, distinguishing between these two causes is challenging, as trading generally occurs during the day when most relevant information is released to the market.

The unique organizational structure of derivatives on the Korean KOSPI 200 index, which are traded on the Korean KRX during the daytime and on the German Eurex during Korean nighttime, with several hours of trading breaks between the trading periods, allows for separate consideration of information inflow and trading as sources of volatility patterns.

We decompose the KOSPI 200 volatility within a 24-hour cycle into the daily contributions of trading and non-trading periods. We measure the impact of global information by examining spillover effects from the S&P 500 index and consider specific Korean (idiosyncratic) information that enters the market during the daytime. This approach allows us to simultaneously analyze the impact of information inflow and noise trading on volatility.

Understanding and calculating the factors that create intraday volatility patterns is important for several reasons: (a) measuring and managing intraday market risk, (b) developing trading strategies based on volatility, and (c) optimizing trading schedules for exchanges. The extension of the trading period for the KOSPI 200's underlying stocks from 6.5 to 12 hours a day, expected with the opening of the Alternative Trading System Nextrade in 2025, could impact future volatility patterns.

We find that (i) more than half of the daily price variance originates from the 7 hours of trading at KRX, and less than a quarter from the ten to eleven hours of overnight trading at Eurex, i. e. while trading positively impacts volatility, the extent is low without inflow of new information; (ii) trading without the inflow of new information has a lower impact on volatility than the inflow of new information without trading opportunity; (iii) volatility during weekends is lower than during Korean holidays, thereby indicating the strong relevance of global information in comparison to specific national information; (iv) we find evidence that a small part of the 24-hour volatility is attributed to intraday auto-correlation.

JEL Classification: D47, G14, G15

1 Introduction

Intraday seasonal volatility patterns are a well-documented feature of most financial markets (cf. Dacorogna et al. (1993); Andersen and Bollerslev (1997), among others). Such

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intraday patterns can be observed during trading hours, however, it is also well-known that volatility varies between trading (daytime) and non-trading (nighttime, weekend, holiday) phases as emphasized in the seminal paper by French and Roll (1986).

We refer to such periodic patterns as deterministic seasonal volatility components which might be overlaid by a stochastic component. Economic theory implies that volatility in a certain market is driven by (i) the inflow of new relevant information (news) and (ii) noise trading. Trading by informed investors mainly reflects the impact of incoming news, while speculative trading can cause arbitrary price movements, making noise trading a separate cause for volatility.

Differentiating between the impacts of incoming news and noise trading can be a difficult task because exchanges for obvious reasons set their trading times during the day when the majority of news will be released to the particular market. Separating the impacts of the two factors usually requires capturing news (single news items, sentiment indices etc.) and/or incorporating trade-by-trade information regarding the investor type (e. g. Ryu (2015) for the KOSPI market), i. e. elaborate microstructural studies requiring a comprehensive and detailed data set.

We follow a much simpler approach by making use of the particular and rather unique trading schedule of derivatives on the Korean stock index KOSPI 200. KOSPI 200 futures are traded during Korean daytime at the Korea Exchange (KRX), and after a break of $2^1/_4$ hours, trading is continued at the German exchange Eurex. After trading closes at Eurex another break of 4 to 5 hours applies before trading starts again at KRX. The KOSPI 200 futures thus have two daily trading phases, the first to happen when domestic (Korean) news will enter the market, the second during Korean nighttime with almost no specific Korean news to occur. Also the two non-trading periods differ in the amount of Korean news that are released to the markets. This “natural” separation allows us to analyze the impact of news vs. (noise) trading.

We contribute to the literature by providing a structured view on intraday volatility and its causes. Such insights are important for measuring and forecasting intraday market risk and espcially for exchanges that seek to optimize their trading schedules. Especially in the case of Korean market the launch of an Alternative Trading System (ATS) in 2025 will extend the daily trading period for Korean stocks from $6^1/_2$ to 12 hours which likely will impact the intraday volatility patterns of the KOSPI 200 index (Financial Services Commission (2024)). While the particular figures in this study are specific for the Korean market which exhibits certain characteristics as outlined in Section 3, the general findings apply to all markets.

The remainder of the paper is structured as follows: In Section 2 we review the literature on intraday volatility patterns as well as on the KOSPI 200 futures. Section 3 provides stylized facts on the Korean stock market and the KOSPI 200 futures. Section 4 describes the model and methodology we apply. In Section 5 we present the data sample and descriptive statistics. Section 6 contains the results of our study. Section 7 concludes.

2 Literature Review

Seasonal patterns in volatility are well-documented in the literature. French and Roll (1986) find for the U.S. stock market between 1963 and 1982 that the variance (i. e. squared volatility) is 72 times higher on trading days than over weekends, but for mid-week holidays the factor is only 13. They conclude that the inflow of information, also private information, is a major driver of variance, but also mispricing during trading phases contributes to overall variance. Lockwood and Linn (1990) find for the U.S. market that stock price variance is significantly greater for intraday than for overnight periods.

Dacorogna et al. (1993) find U-shaped intraday volatility patterns in foreign exchange markets and model those by introducing an activity variable representing market presence of traders on various continents. They show that such an approach to modelling trading activity strongly reduces intraday heteroscedasticity of the residual volatility. Andersen and Bollerslev (1997) confirm such U-shaped intraday volatility patterns for the S&P 500 and for the DM-$ foreign exchange during trading periods. Wile they focus on modelling such patterns, they conclude that neglecting intraday patterns may lead to erroneous inference about volatility dynamics. Alemany et al. (2019) find that seasonal patterns in intraday volatility strongly influence the measurement of spillover effects between stock markets, in particular the CAC40, DAX, and FTSE100, and conclude in a similar reasoning that neglecting such seasonality likely leads to spurious causality. Boyarchenko et al. (2023) analyze the intraday returns of the S&P 500 e-mini futures rather than the volatility and show strong intraday patterns caused by European traders entering the market in the morning when it is still nighttime in the U.S.

All such findings led to a growing amount of publications that propose various approaches to model seasonal intraday volatility patterns or integrate those into GARCH-style models, showing the growing awareness for deterministic volatility components.

The Korean market for exchange traded derivatives has shown a remarkable growth since its launch in 1997. Even though it is considered as an emerging market, since more than ten years KOSPI 200 derivatives rank among the TOP 10 as compiled by the World Federation of Exchanges in its annual derivatives report. Kang and Ryu (2010); Yang et al. (2019), besides others, state and provide evidence that the Korean stock and especially the derivatives market enjoys an unusual large participation of individual (private) investors. The latter paper as well as Ryu et al. (2017) find by microstructural approaches find that individual investors in the Korean stock and derivatives markets tend to make less informed trades than (doemstic or foreign) institutional investors. Such results provide considerable evidence for a significant impact of noise traders on prices and volatility. During the nighttime trading at Eurex, roughly two thirds of the trading volume comes from South Korean investors (private or institutional), cf. Eurex (2023b), p. 4.

Kang et al. (2013) find that the KOSPI 200 index as calculated from the spot market and the index derived from KOSPI 200 futures are closely connected by showing bi-directional Granger-causality between both market segments.

Kim and Kim (2010); Han et al. (2015); Song et al. (2018); Chun et al. (2020) provide evidence for a strong dependency of the Korean market on the US market.

These findings are taken into account for designing our model.

3 The KOSPI 200 Index and its Derivatives Market – Stylized Facts

The Korean financial markets are often still classified as emerging markets, e. g. Korean stocks are not included in the MSCI World index. Major reasons for this classification are institutional and regulatory matters rather than market size and liquidity. As of 2024, the Korea Exchange KRX operates three market segments whereof the so-called KOSPI market being the largest with some 800 listed stocks, corresponding to a market capitalization in the magnitude between 1 and 3 trn USD. This segment also includes the large Korean industrial conglomerates often referred to as *chaebol*. The smaller segments are the KOSDAQ market (1,700 stocks, market cap of 250 bln USD) and the KONEX market for SME and start-ups (130 stocks, market cap below 5 bln USD).

Stock indices for the Korean stock market comprise the KTOP 30 for the largest 30 stocks of all market segments, the KOSPI index family and the KOSDAQ indices. Among those indices the KOSPI 200 is the most cited index, and options and futures on the KOSPI 200 belong to the most actively traded derivatives.

The KOSPI 200 index comprises the 200 largest stock weighted based on market capitalization, i. e. dividend payments of its stocks are not re-invested.

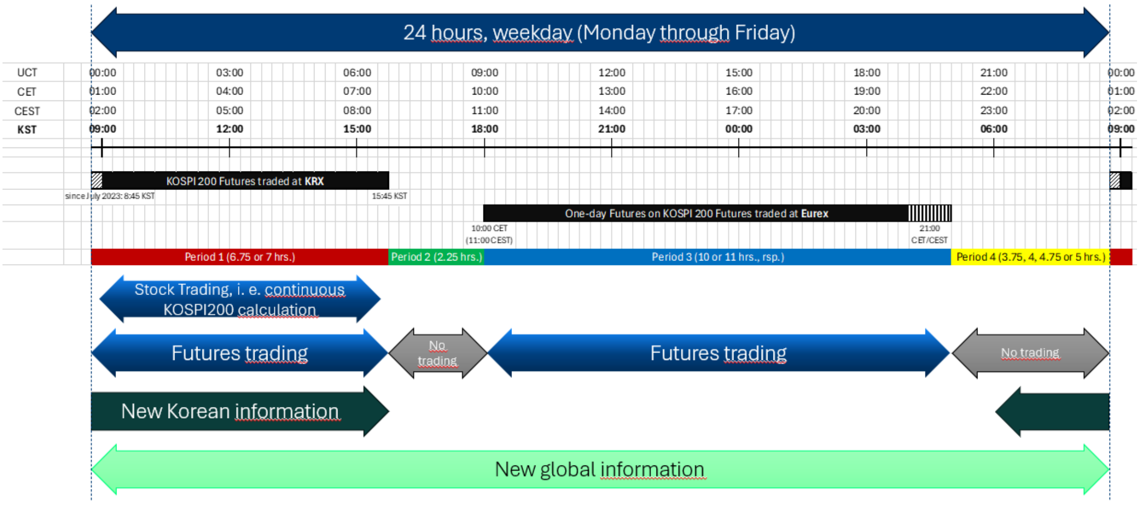

Figure 1: This figure shows how the trading phases of KOPSI 200 mini futures at KRX and Eurex are organized. The trading phases at the both exchanges do not overlap. Formally, at Eurex one-day futures on the KOSPI 200 mini futures are traded, its settlement happens in period 4 as indicated in the figure by delivering the mini futures to KRX's clearing system.

Derivatives on the KOSPI 200 are traded at the Korean exchange KRX each week-day between 8:45 KST (until July 30th, 2023: 9:00 a.m. KST) and 15:45 KST – also referred to as "daytime trading". The exchange is closed on Korean national holidays. On certain days, esp. on the first trading day in January and on the day of the national Korean College Scholastic Ability Test in November, the trading phase is delayed by one hour. The trading of futures starts with an opening auction as the daily initial price discovery process. Market participants can enter orders during a pre-trading phase, and at 8:45 a.m. KST the auction results are disclosed with the continuous trading to commence directly afterwards.

Among the derivatives on the KOSPI 200 listed at KRX there are two futures contracts, besides European option series. The regular KOSPI 200 futures contract was introduced in May of 1996, the smaller, but otherwise equal KOSPI 200 mini futures contract has been listed since July of 2015.

To improve trading of KOSPI 200 derivatives, in 2009 KRX launched the nighttime trading of its index derivatives at CME Globex. However, due to specific U.S. regulations trading in KRX products at CME Globex had to be ceased as of 18 December 2020 (Korea Exchange (2020)). By then, KRX and Frankfurt-based exchange Eurex had already initiated a cooperation known as Eurex-KRX link, allowing for certain KOSPI 200 derivatives to be traded at Eurex during Korean nighttime, see Fig. 1 for more details. All positions traded at Eurex are transferred to KRX each day before trading starts (Eurex (2023a)). On exchange holidays at KRX, KOSPI 200 derivatives cannot be traded at Eurex.

The fraction of traders that use KOSPI 200 derivatives for speculative reasons is known to be rather large. Karagozoglu et al. (2005) conclude from trading data of KOSPI 200 derivatives between 1996–2003 that speculation seems to be a major trading motive. Ham et al. (2023) find that, depending on the situation of the Korean market, individual investors tend to enter opposite positions to those of institutional investors.

Figure 2 shows the development of the trading volumes of the KOSPI 200 futures from January of 2016 until March of 2024, with the Eurex trading having commenced end of November 2016.

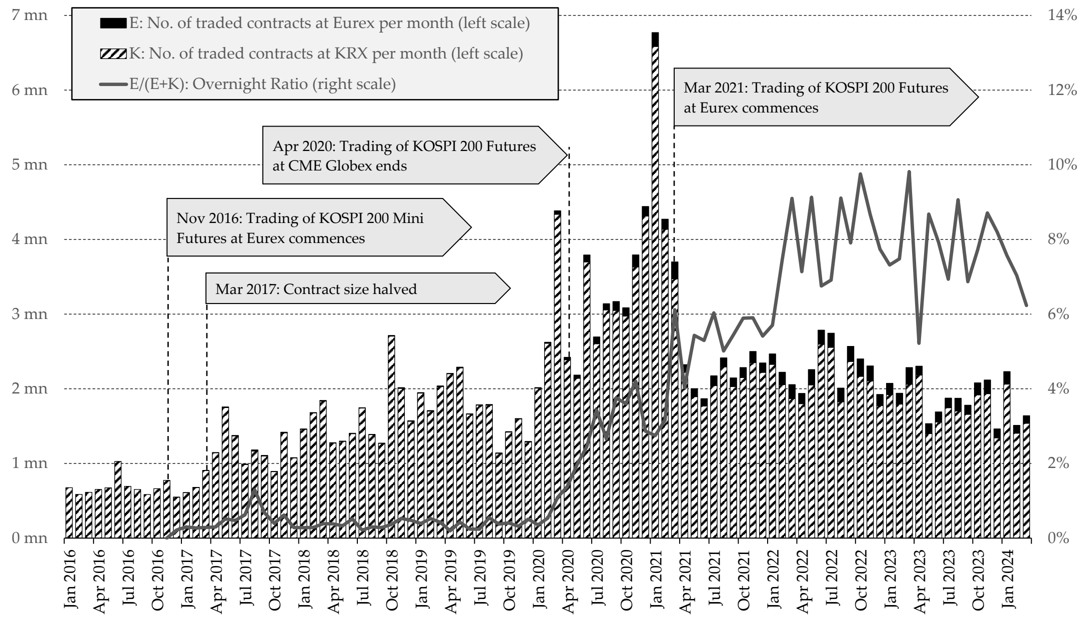

Figure 2: This figure shows the monthly trading volumes (number of contracts) at KRX (grey) and at Eurex (black). The right scale denotes the ratio of Eurex traded contracts to total traded contracts.

4 Methodology

4.1 Model

In our analysis of the volatility of the KOSPI 200, we use the mini futures on the KOSPI 200 rather than the index itself. Such an approach combines several advantages: First, the impact of trading on the volatility can only be observed when taking tradable contracts into account. Second, the KOSPI 200 index itself is only calculated and pulished during the trading time at KRX, but not overnight. Third, by using the futures insted of the index, the necessity to adjust the index for dividend distributions can be neglected as the futures prices will usually reflect such expected dividend.

Our empirical analysis is based on a sample of seven years of daily open and close prices of KOSPI 200 mini futures traded at KRX and Eurex as more closely described in Section 5. We define time periods $(d; P_i)$ with d denoting a particular exchange day at KRX and P_i an intraday period measured in hours or, in case of weekends or holidays, a multi-day period. We denote the periods by P_1, P_2, P_3, P_4, but subclassify P_4 for varying occurrences of holidays, weekends etc. as follows:

- P_1: Trading phase at KRX (usually 6¾ or 7 hours).
- P_2: Trading break after KRX trading closes, but only if Eurex trading will commence at the same day (usually 2¼ hours).
- P_3: Trading phase at Eurex (usually 10 or 11 hours).
- P_{4-std}: Standard trading break after Eurex trading closes, but only if there is a trading phase at KRX on the subsequent calendar day (between 3¾ and 5 hours).
- P_{4-long}: Trading break after KRX trading closes in cases when there is no overnight trading at Eurex on the same day (17 or 17¼ hours).
- P_{4-HO}: Trading break after Eurex closes before a KRX holiday or, in one case, before a two-day holiday period at KRX (usually 28, 28¾, or 29 hours, one case of 53 hours).
- P_{4-WE}: Trading break after closing before a weekend, but only if there is a trading phase at KRX on the subsequent Monday (between 51¾ and 53 hours).
- $P_{4-WE-HO}$: Long trading breaks over a weekend immediately preceeded and/or followed by one or more holidays.

Note that by this notation we map all deviations from a standard trading day to period P_4, also for those days that do not have periods P_2 and P_3 due to a holiday a Eurex.

We refer to one particular trading day d as the time between the opening auction at KRX on that day and the same auction on the subsequent trading day, that is, a sequence of the periods P_1, P_2, P_3 and P_4 of a particular day. We further define t_1 as the start of P_1, i. e. when trading at KRX commences, t_2 as the beginning of P_2 and so forth, cf. figure 1.

The return of a whole trading day d is then defined as log-return between the opening price on day $d + 1$ and day d:

$$r_d = \ln\left(\frac{S_{d+1,t_1}}{S_{d,t_1}}\right) \tag{1}$$

The daily return equals the sum of the single return per period

$$r_d = r_{d,P_1} + r_{d,P_2} + r_{d,P_3} + r_{d,P_4} \tag{2}$$

for such days at which Eurex is open, otherwise Eq. 2 collapses to $r_d = r_{d,P_1} + r_{d,P_4}$. In other words, r_{d,P_1} denotes the intraday return between closing and opening price at KRX, and r_{d,P_3} denotes the intraday return between closing and opening price at Eurex. Note that the intraday returns are of varying duration T. For standard trading days, the relationship $T_d = T_{d,P_1} + T_{d,P_2} + T_{d,P_3} + T_{d,P_4} = 24$hrs. holds, but not for Fridays or trading days followed by a holiday.

If the returns of the KOSPI 200 mini futures follow a random walk, the intraday returns behave independently and are uncorrelated. However, Ham et al. (2023) find evidence for contingent correlation between overnight and daytime returns of Korean stocks. The unconditional variance $\text{Var}(r_d) \equiv \sigma_d^2$ of the daily return in Eq. 2 is then given by

$$\sigma_d^2 = \sigma_{d,P_1}^2 + \sigma_{d,P_2}^2 + \sigma_{d,P_3}^2 + \sigma_{d,P_4}^2 + SoC_d \tag{3}$$

with SoC_d denoting the Sum of Covariances between the intraday returns of day d, which can be positive or negative if not zero.

Eq. 3 in its general form allows that the KOSPI 200 return's variance varies between days and between intraday periods. In general, though, we will not be able to empirically observe each such variance and will apply assumptions. For the trading periods P_1 and P_3 realized variances (RV) based on intra-period high-frequency data could be used as estimates, but not for periods P_2 and P_4.

Note that the variances in Eq. 3 refer to periods of varying duration, implying that e. g. σ_{d,P_2}^2 is supposed to be smaller than σ_{d,P_1}^2 solely because $T_{d,P_2} < T_{d,P_1}$. In order to compare intraday variances, we normalize the effective variances by multiplying with the duration and introduce

$$\bar{\sigma}_{d,P_i}^2 = T_{d,P_i} \cdot \sigma_{d,P_i}^2 \tag{4}$$

as the 24-hour variance.

In order to decompose the daily variance into its various sources – i. e. inflow of global information, inflow of domestic information, and noise trading – we argue that globally relevant information is also reflected in global major indices which then can serve as a proxy. In the empirical literature the strong influence of the S&P 500 index on the KOSPI 200 is well documented, cf. Kim and Kim (2010), Han et al. (2015), Song et al. (2018), Chun et al. (2020), among others. We therefore apply the S&P 500 futures contracts which are traded 23 hours per day at the Chicago-based exchange CME as a proxy for the influence of global information and denote r_d^{SP} as the one-day log-return of the futures contract closest to maturity, and r_{d,P_i}^{SP} as the return during the intraday period P_i on day d analogously to the KOSPI 200 mini futures returns. We assume for each intraday period P_i a linear impact of the S&P 500 on the KOSPI 200:

$$\begin{aligned} r_{d,P_i} = \beta_{SP,P_i} \cdot r_{SP,d,P_i} + r_{id,d,P_i} \quad & \text{where} \\ & r_{id,d,P_i} \sim \mathcal{N}(0; ^2_{id,d,P_i}) \text{ and } \text{Cov}(r_{id,d,P_i}, r_{SP,d,P_i}) = 0 \end{aligned} \tag{5}$$

Since r_{d,P_i} and r_{SP,d,P_i} denote returns of futures prices on indices rather than on indices directly, Eq. 5 describes a CAPM-approach if one accepts the S&P 500 as the (proxy for the) market portfolio. The residual r_{id,d,P_i} then represents the idiosyncratic Korean risk. The unconditional variance of the KOSPI mini futures' returns is then given as

$$\sigma_{d,P_i}^2 = \beta_{SP,P_i}^2 \cdot \sigma_{SP,d,P_i}^2 + \sigma_{id,d,P_i}^2 \tag{6}$$

Note that this approach allows for different β_{SP,P_i} for each period P_i as previous studies have shown that the variance of the S&P 500 futures exhibits intraday seasonality patterns itself (cf. Andersen and Bollerslev (1997); Cho and Daigler (2014) among others) which are unlikely to be synchronous with the KOSPI 200 patterns. Such intraday volatility patterns in the S&P 500 index again might be caused by noise trading and by the inflow of globally relevant information.

4.2 Hypotheses on the information effect

At first we test for the impact of information inflow. As presented in Section 3 we argue that P_1, followed by P_4, are the daily phases during which the inflow of new Korean information is rather large. As P_1 is a trading phase, we compare its variance to the one of P_3. Analogously, we compare the variance of the non-trading phase P_4 to the of P_2. For the test being reasonable we use the time-normalized variances and state the following hypotheses: Information:

$$\begin{aligned} H_1^{I.1} &: \bar{\sigma}^2_{d,P_1} > \bar{\sigma}^2_{d,P_3} \\ H_1^{I.2} &: \bar{\sigma}^2_{id,d,P_4} > \bar{\sigma}^2_{id,d,P_2} \end{aligned} \tag{7}$$

4.3 Hypotheses on the trading effect

In order to test whether trading increases the price variance versus non-trading phases we compare the squared log-returns of the same day in a paired t-test. Specifically, we compare the KRX trading phase P_1 with P_4 as both intraday phases are supposed to exhibit the inflow of domestic news. Second, we compare the Eurex trading phase P_3 to P_2 as in both phases domestic news is unlikely to flow into the market. We therefore state the hypotheses $T.1$ and $T.2$ with regards on trading as follows:

$$\begin{aligned} H_1^{T.1} &: \bar{\sigma}^2_{d,P_3} > \bar{\sigma}^2_{d,P_3} \\ H_1^{T.2} &: \bar{\sigma}^2_{d,P_4} > \bar{\sigma}^2_{d,P_1} \end{aligned} \tag{8}$$

4.4 Analysis of the idiosyncratic volatility

After having the linear regression in Eq. 5 applied to all four daily phases, we calculate the residual (idiosyncratic) variances r^2_{id,d,P_i}. We apply a linear regression to evaluate the contribution of trading and of domestic (idiosyncratic Korean) news on the volatility. Note that this analysis is performed in-sample in order to explain the composition of the volatility; however, significant results from the in-sample analysis do not necessarily ensure that they help improving forecasting. We apply the following variables for trading:

- $TRAD_{d,P_i}$ is a dummy variable that is equal to 1 for trading periods, i. e. for P_1 and P_3.
- VOL_{d,P_i} is the trading volume (traded quantity) in the particular trading phase P_1 (KRX) or P_3 (Eurex) an a day d.
- $EUXHO_{d,P_4}$ is a dummy variable set to 1 if there is a German exchange holiday at Eurex, but not at KRX, i. e. a day with regular flow of domestic news, but without trading, meaning that one could expect a negative impact from $EUXHO$.

For the inflow of domestic news, we apply the following variables

- $NEWS_{d,P_i}$ is a dummy variable that is set to 1 for the periods P_1 and P_4 to reflect that domestic news often are released to the market between 6:00 and 15:00 KST.
- WE_{d,P_4} is a dummy variable set to 1 for P_{4-WE} and $P_{4-WE-HO}$ in order to reflect the reduced amount of news during weekends. Note that the phase P_{4-WE} ends on Monday morning, so for such cases the previous dummy $NEWS$ will also be set to 1 by definition.
- HO_{d,P_4} is a dummy variable for exchange holidays at KRX (and thus also at Eurex). Analogously to weekends one might expect a reduced amount of domestic news on such days.

In order to avoid biases from the different durations of the phases, we again normalize the derived idiosyncratic volatility by $\bar{\sigma}_{id,d,P_i} = \sigma_{id,d,P_i} \cdot \sqrt{24/T_{P_i}}$. Since we are interested in the impacts of trading and news, we want to eliminate stochastic and transient components of the volatility. We therefore divide $\bar{\sigma}_{id,d,P_i}$ by the level of the implied volatility of that day, given by the VKOSPI index, and define $\xi_{d,P_i} = \bar{\sigma}_{id,d,P_i} \cdot \sqrt{365}/VKOSPI_d$.

The regression equation is then as follows:

$$\begin{aligned}\xi_{d,P_i} = c + \gamma_{TRAD} \cdot TRAD_{d,P_i} + \gamma_{VOL} \cdot VOL_{d,P_i} + \gamma_{EUXHO} \cdot EUXHO_{d,P_i} \\ + \gamma_{NEWS} \cdot NEWS_{d,P_i} + \gamma_{WE} \cdot WE_{d,P_i} + \gamma_{HO} \cdot HO_{d,P_i}\end{aligned} \tag{9}$$

5 Data sample and descriptive statistics

The KOSPI 200 mini futures were introduced for overnight trading at Eurex in December of 2016. Active trading at Eurex started on day one, but the average trading volume was below 100 contracts per day in the first months until March 2017. To exclude potential biases from low liquidity, the altered contract size in March 2017 and/or mistrades in the very beginning we set April 1st, 2017, as starting date of our sample. To circumvent a bias of potential annual seasonal effects we let or sample end on March 31st, 2024, i. e. set our sample duration to exactly seven years. We divide our sample period into 12-months subsamples, each lasting from April 1st to March 31 of the subsequent year. Table 1 provides annual trading volumes of the front month KOSPI 200 mini futures for our sample. As already shown in fig. 2, the trading volume at Eurex has increased significantly from April 2020 onwards due to the reasons discussed before. Still, even during the first three subsamples the KOPSI 200 mini futures were actively traded at Eurex, so we do not exclude those subsamples.

	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	total
KRX								
Total vol.	15 853 309	20 304 460	24 096 468	42 051 028	25 227 881	25 017 738	20 443 245	172 994 129
Trading days	254	254	261	258	259	261	256	1 803
Avg. daily vol.	62 415	79 939	92 324	162 988	97 405	95 853	79 856	95 948
Eurex								
Total vol.	79 274	81 098	122 580	1 409 137	1 572 431	2 212 193	1 651 277	7 127 990
Trading days	234	239	245	243	244	246	240	1 691
Avg. daily vol.	339	339	500	5 799	6 444	8 993	6 880	4 215

Table 1: Traded volume of the front month KOSPI 200 Mini Futures in number of traded contracts at KRX and at Eurex in total and on average per trading day. Eurex exhibits less trading days because of European holidays and of certain trading suspensions in 2017 due to technical issues. Each time period (column) refers to the 12 months ranging from April 1st to March 31st of the following year.

Tables 2 and 3 provide descriptive statistics on the intraday log-returns for the various periods, determined from some 6,900 open and close prices at KRX and Eurex.

From the yearly statistics as shown in Table 2 we find patterns that are well-known from virtually all financial markets such as (i) mostly negatively skewed returns (Ekholm and Pasternack (2005); Neuberger and Payne (2020)), (ii) an increase in volatility and kurtosis during the COVID-19 pandemic, (iii) no significant autocorrelation on the first lag. The first lag refers to returns of subsequent periods P_i, P_{i+1} of the same day or between (d, P_4) and $(d+1, P_1)$.

The statistics per period as reported in Table 3 show that the normalized volatility $\bar{\sigma}_{P_i}$ per 24 hours is largest for the trading period at KRX (P_1), amounting to 1.784%. The volatility during trading at Eurex (P_3) is roughly half as large with a value of 0.876%. The smallest volatility occurs during P_2, amounting to 0.558%. For the period P_4 we find the

	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	total
Obs.	952	962	988	978	982	990	968	6 820
Avg.	+0.012%	−0.012%	−0.017%	+0.061%	−0.012%	−0.012%	+0.015%	+0.005%
Min.	−3.801%	−2.065%	−9.138%	−3.823%	−4.049%	−3.262%	−2.737%	−9.138%
Median	+0.030%	+0.007%	+0.007%	+0.061%	+0.014%	−0.013%	+0.006%	+0.013%
Max.	+2.523%	+2.421%	+6.252%	+3.205%	+2.252%	+2.859%	+3.574%	+6.252%
σ_{P_i}	0.416%	0.482%	0.868%	0.733%	0.515%	0.586%	0.479%	0.604%
Avg. T_{P_i}	9.18h	9.08h	8.89h	8.96h	8.92h	8.90h	9.02h	8.99h
$\bar{\sigma}_{P_i}$	0.764%	0.893%	1.564%	1.353%	0.940%	1.051%	0.869%	0.863%
Skew.	−1.252	−0.299	−1.494	−0.369	−0.797	−0.166	+0.274	−0.884
Kurt.	12.44	3.75	28.96	5.16	7.48	3.46	6.69	22.38
AR(1)	+0.018	−0.038	+0.029	−0.010	−0.059	+0.015	+0.040	+0.007

Table 2: Summary statistics of intraday log-returns. AR(1) denotes the autocorrelation of lag 1, JB is the Jarque-Bera statistic for the test on the log-returns for normal distribution.

lowest volatility during weekends. For combinations of weekends and domestic holidays ($P_{4-WE-HO}$, the volatility is larger

	P_1	P_2	P_3	P_4 (all)	P_{4-std}	P_{4-WE}	$P_{4-WE-HO}$	P_{4-HO}	P_{4-long}
Obs.	1719	1691	1691	1719	1309	310	54	31	15
Avg.	−0.011%	+0.003%	+0.030%	−0.002%	−0.006%	−0.009%	+0.129%	−0.149%	+0.348%
Min.	−9.318%	−1.256%	−5.514%	−5.247%	−2.232%	−5.247%	−3.446%	−1.690%	−0.871%
Median	0%	+0.006%	+0.064%	+0.012%	0%	+0.027%	+0.153%	+0.024%	+0.388%
Max.	+6.252%	+1.682%	+4.670%	+2.742%	+2.742%	+1.403%	+2.361%	+1.776%	+1.453%
σ_{P_i}	0.946%	0.171%	0.581%	0.433%	0.348%	0.529%	0.980%	0.768%	0.493%
Avg. T_{P_i}	6.77h	2.25h	10.41h	16.45h	4.56h	52.56h	89.02h	30.43h	17.23h
$\bar{\sigma}_{P_i}$	1.784%	0.558%	0.876%	0.739%	0.811%	0.359%	0.501%	0.691%	0.581%
Skew.	−0.552	+0.198	−0.962	−1.205	+0.356	−3.647	−0.684	+0.115	−0.106
Kurt.	10.27	11.80	13.87	20.12	8.86	32.24	3.18	0.54	2.67
JB	7648	9818	13823	29407	4309	14125	26.9	0.449	4.48

Table 3: Summary statistics of the KOSPI 200 mini futures intraday returns per period.

	r_{d,P_1}	r_{d,P_2}	r_{d,P_3}	r_{d,P_4}	$r_{d,P_{4-std}}$	$r_{d,P_{4-WE}}$
r_{d-1,P_1}	−0.077					
r_{d-1,P_2}	+0.046	−0.004				
r_{d-1,P_3}	−0.037	−0.033	−0.087			
r_{d-1,P_4}	**+0.024**	+0.014	+0.002	−0.109	−0.171	+0.101
$r_{d-1,P_{4-std}}$	**−0.034**	+0.007	−0.005	−0.042	−0.119	+0.081
$r_{d-1,P_{4-WE}}$	**+0.150**	+0.082	+0.092	−0.287	−0.335	
r_{d,P_1}	1	**+0.001**	+0.067	−0.146	−0.138	−0.272
r_{d,P_2}		1	**+0.052**	−0.055	−0.009	−0.318
r_{d,P_3}			1	**−0.018**	−0.026	+0.088
r_{d,P_4}				1	1	1

Table 4: Correlations between the log-returns of the various intraday phases. Correlations in boldface are those of subsequent intraday periods.

Table 4 provides correlations between the returns of the intraday periods of the same day or lagged by one day. Without providing more detailed data we state that the correlations are rather unstable. Removing the three months of March to May 2020, i. e. the high-volatile beginning of the COVID-19 pandemic, reduces the correlations drastically.

6 Results

6.1 Test on the impact of information

We apply a paired t-test on the hypotheses $H^{I.1}$ and $H^{I.2}$. Table 5 provides the results. We find clear evidence that the variance, measured as the squared return $r^2_{d,P_i} \cdot {}^{24}/_{T_{P_i}}$ of a particular trading phase normalized to 24 hours, is larger for intraday periods that are associated with higher inflow of information. This holds for trading phases ($H^{I.1}$) as well as for non-trading phases ($H^{I.2}$). We do not provide separate test statistics for single 12-months periods as the relation is very robust across all years.

$H_0^{I.1}: \bar{\sigma}^2_{d,P_1} \leq \bar{\sigma}^2_{d,P_3}$	$\bar{\sigma}^2_{d,P_1}$	$\bar{\sigma}^2_{d,P_3}$	$H_0^{I.2}: \bar{\sigma}^2_{d,P_4} \leq \bar{\sigma}^2_{d,P_2}$	$\bar{\sigma}^2_{d,P_4}$	$\bar{\sigma}^2_{d,P_2}$
Obs.	1691	1691	Obs.	1691	1691
Avg.	$9.02 \cdot 10^{-5}$	$3.39 \cdot 10^{-5}$	Avg.	$1.85 \cdot 10^{-5}$	$2.93 \cdot 10^{-6}$
t-value	7.651		t-value	7.431	
p-value	<0.0001		p-value	<0.0001	

Table 5: Test statistics of paired t-tests for the hypotheses $H_0^{I.1}$ and $H_0^{I.2}$ as defined in Section 4. The test is applied on the whole sample. Days that do not have phases P_2 and P_3 are omitted, i. e. holidays at Eurex.

6.2 Test on the impact of trading

As in the previous subsection we provide test results for paired t-tests on the hypotheses $H^{T.1}$ and $H^{T.2}$. Table 6 contains the results. Again we find unambigiuous test results and conclude that trading does have a positive impact on volatility.

$H_0^{T.1}: \bar{\sigma}^2_{d,P_3} \leq \bar{\sigma}^2_{d,P_2}$	$\bar{\sigma}^2_{d,P_3}$	$\bar{\sigma}^2_{d,P_2}$	$H_0^{T.2}: \bar{\sigma}^2_{d,P_4} \leq \bar{\sigma}^2_{d,P_1}$	$\bar{\sigma}^2_{d,P_4}$	$\bar{\sigma}^2_{d,P_1}$
Obs.	1691	1691	Obs.	1719	1719
Avg.	$3.39 \cdot 10^{-5}$	$2.93 \cdot 10^{-6}$	Avg.	$8.96 \cdot 10^{-5}$	$1.88 \cdot 10^{-5}$
t-value	9.662		t-value	9.801	
p-value	<0.0001		p-value	<0.0001	

Table 6: Test statistics of paired t-tests for the hypotheses $H_0^{T.1}$ and $H_0^{T.2}$ as defined in Section 4. The test is applied on the whole sample. Days that do not have phases P_2 and P_3 are omitted for the test of hypothesis $H_0^{T.1}$, i. e. holidays at Eurex.

6.3 The effect of global news

The estimation of the CAPM-style Eq. 5 allows to understand the impact of global news on the KOSPI 200 volatility. As outlined in Sec. 4, we apply a separate regression for each of the four intraday trading phases. Table 7 presents the results.

	P_1	P_2	P_3	P_4
Obs.	1719	1691	1691	1719
β_{SP,P_i}	1.549	0.482	0.565	0.582
t-value	34.908	62.611	80.189	55.125
p-value	<0.0001	<0.0001	<0.0001	<0.0001
Adj. R^2	0.414	0.698	0.791	0.638

Table 7: The results for the CAPM estimations, whereby the β represents the influence of the S&P 500 index as the market portfolio. We apply the estimation separately for each $P_i, i = 1, \ldots, 4$.

The β_{SP} is obviously the largest by far for the trading phase at KRX, P_1, even though it exhibits the lowest R^2 of all four regressions.

6.4 Idiosyncratic volatility

We conduct the regression in Eq. 9 on the whole sample and provide the regression results Table 8.

	coefficient	std. err.	t-value	p-value
c	+0.00137945	0.000099690	+13.84	<0.0001***
TRAD	+0.00210054	0.000182702	+11.50	<0.0001***
VOL	$+4.07588 \cdot 10^{-8}$	$4.12827 \cdot 10^{-9}$	+9.873	<0.0001***
EUXHO	−0.00113105	0.000913003	−1.239	0.2155
NEWS	+0.00274797	0.000187536	+14.65	<0.0001***
WE	−0.00133246	0.000503162	−2.648	0.0081***
HO	−0.00109085	0.000481005	−2.268	0.0234**

mean dep. var.	0.004830	std. dev. dep. var.	0.006237
sum of quared red.	0.184920	std. err. regression	0.005210
R^2	0.302791	Adj. R^2	0.302177
$F(6, 6813)$	234.5307	P-value(F)	<0.000001
Log-Likelihood	26180.51	Durbin–Watson	1.907937

Table 8: Coefficient estimators and statistics for the regression as defined in Eq.9. Heteroscedasticity and autocorrelation consistent estimators are applied.

Among the three variables representing the impact of trading on volatility, we find that the dummy variable $TRADE$, indicating whether the realized return occurred during a trading phase or not, is highly significant with a positive coefficient estimator. Also the trading volume VOL of a particular trading day at KRX or Eurex (being 0 for non-trading phases) shows a significant positive coefficient. As shown in Fig. 2, trading volume at Eurex is clearly lower than at KRX, and so is the volatility. The dummy for exchange holidays only at Eurex, but not at KRX, $EUXHO$, has a negative, but not significant coefficient. This meets expectations, however, with only 31 of such days in the whole 7-year sample, the impact is too low to reach statistical significance.

For the inflow of news the dummy $NEWS$ shows a positive, highly significant impact as expected. The dummy for weekends, WE, has a significantly negative impact, again meeting expectation as over weekends the amount of incoming news is supposed to be low. To a lesser extent this also applies to Korean holidays as measured by the dummy HO on a 5% significance level. As not only public holidays, but also Korean election days are exchange holidays, it is reasonable that the inflow of news on holidays is not as much lowered as on weekends.

The constant in the regression is positive and significant. We argue that this "base" volatility rather contributes to inflow of new information than to trading as it applied to all phases during a day.

Aggregating all results and de-normalizing to the actual durations of the daily trading phases, we find that approx. 54% of the price variance is caused by global news represented by the S&P 500 index. 13 % of the price variance in the KOSPI 200 futures are caused by trading, thereby referring to the common impact measured by $TRADE$, VOL and $EUXHO$. Another 11% is attributed to the inflow of domestic or idiosyncratic Korean information. The remaining 22% cannot be explained by the presented model setting. The sum of all sub-components of the price variance is 1.3% smaller than the total variance of daily returns, indicating that a slight positive autocorrelation (SoC as defined in Eq. 3) between the intradaily phases effect exists.

7 Conclusion

We used the unique trading schedule of the KOSPI 200 futures being traded at KRX during Korean daytime and at Eurex during Korean nighttime to distinguish between (noise) trading and the inflow of new information as the main causes of volatility or price variance, rsp. We find that the major share of daily price variance – more than 50 % – is caused by global relevant information, proxied by the S&P 500 index, but only 11% are caused by domestic Korean information, while 13% are attributed to trading. Based on these results, the extension of the daily trading time as planned for the Korean stock market for the year 2025 will therefore lead to a rather weak increase of daily volatility.

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