Hedging demand and market intraday momentum

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Abstract

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JEL Classification: G12, G15, G40, Q02.

Keywords: Return momentum; Futures trading; Hedging demand; Return Predictability; Indexing.

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1 Introduction

During the last week of February 2020, as the coronavirus surged outside China, the US stock market crashed by more than 10% and market volatility soared. According to market participants, hedging by traders with short gamma position has been a big contributor to the increase in the volatility.[1] Gamma measures how much the price of a derivative accelerates when the underlying security price moves. Market makers in products with gamma exposure, such as options and leveraged ETFs, are commonly net short these products. Consequently, they have to buy additional securities when prices are rising and sell when prices are falling in order to ensure their positions are delta-neutral. Trading in the direction of the market price movement will exacerbate market swings and thereby result in "market intraday momentum."

Similar hedging activities are carried out by other market participants and have existed for a long time. For example, dynamic hedging programs like portfolio insurance (Leland and Rubinstein, 1976), and the hedging of variable annuities products by insurers. Indeed, portfolio insurance was a popular portfolio protecting strategy during the 1980s, achieving a market cap of $70 billion in the US around 1987, and is commonly blamed to be one of the drivers of the October 19th, 1987 crash in the equity futures market, accounting for up to 24% of the market's short volume on that day (Tosini, 1988). More recently, popular volatility targeting strategies (for example, risk parity portfolios), variance swaps and levered or inverse ETFs, all conduct similar hedging trades.[2] These hedging activities all contribute to market intraday momentum.

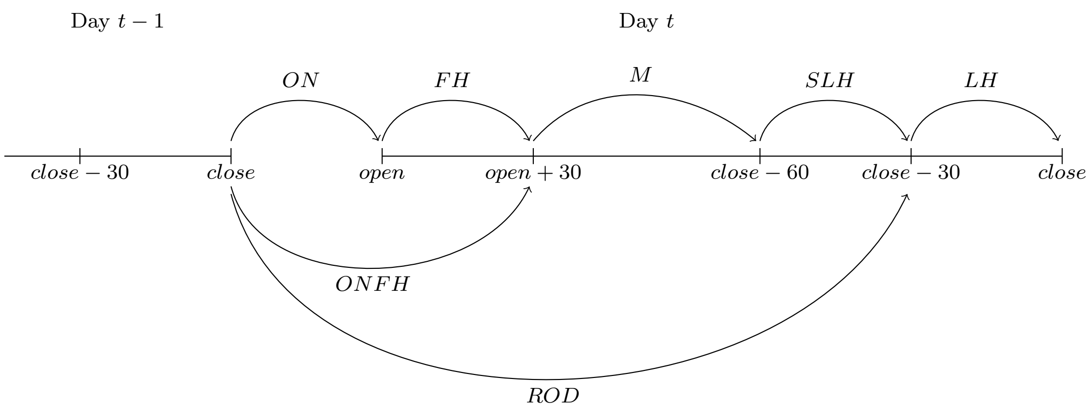
In this paper, we extensively study market intraday momentum, or time series momentum at the market level at the intraday frequency, across all major asset classes going back to the 1970s. The comprehensive coverage is made possible by examining intraday trading of futures contracts. Specifically, our data consists of 17 developed markets equity index futures (6 North American, 8 European, 3 Asian or Australian); 16 developed market bond futures (6 North American, 7 European, 3 Asian or Australian); 21 commodity futures (5 metals, 4 energies, 12 softs), and 8 currency futures. Our sample period covers almost 45 years from December 1974 to

[1] See https://www.wsj.com/articles/the-invisible-forces-exacerbating-market-swings-11582804802. JP Morgan Chase estimated that more than $100 billion in stock selling during the first two days of the week was due to such hedging activities.

[2] Anecdotal evidence of this channel is covered in several news paper articles, including Jason Zweig, "Will Leveraged ETFs Put Cracks in Market Close?", Wall Street Journal, April 18,2009, and Tom Lauricella, Susan Pulliam and Diya Gullapalli, "Are ETFs Driving Late-Day Turns?", December 15, 2018, and more recently Gunjan Banerji, "The Invisible Forces Exacerbating Market Swings", Wall Street Journal, Feb 27, 2020, Gunjan Banerji, "The 30 Minutes That Can Make or Break the Trading Day", Wall Street Journal, March 11, 2020, and Gunjan Banerji and Gregory Zuckerman, "Why are Markets so Volatile? It's not just the Coronavirus", Wall Street Journal, March 16, 2020.

May 2020. We present novel evidence that market intraday momentum appears "everywhere" (i.e., robustly across asset classes and time periods) and that gamma hedging is an important driver.

To facilitate our discussion, we define a trading day as the 24-hour-period from the market close on day $t-1$ to the market close on day t. We select the open and close time to match the "common" trading hours of the market. The time line below then partitions the trading day into five parts: overnight (ON, from close to open); first half-an-hour (FH, the first 30 minutes after the market open); middle-of-the-day (M, from the end of FH to an hour before the market close); second-to-last-half-an-hour (SLH, the second-to-last 30 minute interval); last half-an-hour (LH, the last 30 minutes before the market close). The combination of the first two partitions is labelled as "ONFH" ($ONFH = ON + FH$). The combination of the first four partitions is labelled as "rest-of-the-day" ($ROD = ON + FH + M + SLH$) and will be the focus of our paper.



We start by documenting a robust stylized fact: the rest-of-day return (r_{ROD}) positively and significantly predicts the last half-an-hour return (r_{LH}) across all major asset classes and markets. This effect is robust over time across our sample period of 1974 to 2020, and distinct from cross-sectional intraday return seasonality of Heston et al. (2010). A simple market intraday momentum trading strategy produces consistent returns over time, translating into high and attractive (annualized) Sharpe ratios between 0.87 and 1.73 at the asset class level.

Note that our result differs from that obtained by Gao et al. (2018) who find r_{ONFH} to predict r_{LH} for nine ETFs on equity indices and one ETF on a bond index. While we also confirm that r_{ONFH} positively and significantly predicts r_{LH} in other markets and asset classes, its predictive power is weaker than r_{ROD}. First, r_{ROD} has higher out-of-sample R-squares than r_{ONFH}. Second, when r_{ROD} and r_{ONFH} differ in signs, r_{ROD} in general does a better job predicting r_{LH}. Gao et al. (2018) also find r_{SLH} to predict r_{LH}. We find the predictive power of r_{SLH} does not extend to other asset classes such as commodities and currencies. In contrast, r_M seems to predict r_{LH} better than r_{SLH}. We further show that these results are robust over time and markets, and generally also show up in the returns of simple trading strategies. All in all, using data across multiple asset classes and markets in an extended sample period, we conclude that r_{ROD} positively and significantly predicts r_{LH} and this robust pattern better describes market intraday momentum everywhere.

Next, we provide two novel pieces of empirical evidence linking hedging demand to the market intraday momentum. The first is based on S&P 500 index options. Option market makers need to trade in the same direction as the underlying movement of the S&P 500 index if they have negative gamma exposure. The more negative their gamma exposure is, the more aggressively they have to trade. Using a direct proxy of their negative gamma exposure (NGE), we confirm that market intraday momentum is present for the index when NGE is negative and becomes stronger when NGE becomes more negative.

The second piece of evidence is based on leveraged ETFs (LETF). LETFs seek to deliver a multiple of the daily market return of their underlying. As of the end of February 2009, Cheng and Madhavan (2010) estimated that LETF rebalancing made up 16.8% (50.2%) of the market-on-close volume on a day when the market moved 1% (5%). Shum et al. (2015) argue that market-on-close orders have fill risk, such that the hedging could start as early as 30 minutes before close. This fits nicely into our reasoning of r_{ROD} predicting r_{LH}. Hedging demand on a particular LETF can be directly measured using its market capitalization and leverage and this hedging demand varies considerably in the cross-section and over time. We find strong cross-sectional and time-series evidence that LETFs hedging demand on a particular index drives the magnitude of its market intraday momentum pattern.

What's so special about the end of a trading day? While we do find evidence that large price jumps during the day predict subsequent returns, consistent with intraday hedging activities, the bulk of the hedge seems to take place towards the end of the day. We conjecture that there are at least five reasons for this decision. First, from a theoretical point of view, Clewlow and Hodges (1997) show that, in the presence of partially fixed transaction cost, it is optimal to hedge only partially after a large price movement, implying that additional hedging is required afterwards. Second, the additional hedging may be deferred to the end of the trading day for liquidity reasons. The U-shape intraday volume pattern across the equity, bond, commodity and currency markets in Figure 1 confirms that liquidity tends to be high right after open and before close. Further, spreads are generally lower and market depth higher when trading towards the close. This is another reason why investors may not fully hedge their positions immediately after a jump during the day and will leave the bulk of hedging to be done in the last half hour when liquidity is generally better, especially for trading larger quantities.

Third, while hedging is partial during the day, it tends to be complete at the end of the day to protect against overnight risk. Brock and Kleidon (1992) and Hong and Wang (2000) show that lower liquidity and higher price risk overnight makes it optimal for market makers to close delta positions before overnight. Fourth, holding positions overnight typically incurs higher capital needs and investment frictions. For example, BIS capital requirements are driven by deltas at close. Further, margin requirements generally increase for overnight positions, while lending fees and margin interest are typically charged only on positions held overnight (Bogousslavsky, 2020). As a consequence, holding risky positions overnight not only comes with higher price risks, but also with higher capital requirements. Market participants therefore have an incentive to reduce delta at the end of the day to free up capital and save cost. Finally, as we have demonstrated, market makers of index products such as LETFs have little discretion but to hedge at the end of the day.[3]

Besides hedging demand, other factors may also contribute to the market intraday momentum. Gao et al. (2018) discuss two: infrequent portfolio rebalancing and late informed trading. Under the infrequent rebalancing explanation, some institutional investors effectively choose to rebalance their portfolios in the first half hour and others in the last half hour. Rebalancing in the same direction can thus generate momentum intraday. Under the late informed trading explanation, traders who are informed late trade in the last 30 minutes. Hence, the same information is incorporated into prices during both the first and the last 30 minutes, resulting in momentum. Both explanations hinge on the strong U-shape intraday trading volume pattern, as informed trading and rebalancing are expected to primarily take place at the start and end of the trading session when liquidity is high (Admati and Pfleiderer, 1988; Bogousslavsky, 2016). The fact that r_{ROD} better predicts r_{LH} than r_{ONFH} suggests that returns during the day also

[3]The same holds for market makers of variance swaps, as payoff of a variance swap is calculated based on the closing levels of the underlying index.

matter, and that hedging is an important driver of market intraday momentum.

We conduct two additional tests that further differentiate hedging demand from informed trading. We first notice that under the hedging explanation, the predictability of r_{LH} reflects transitory price pressure and should therefore be reverted in the future. In contrast, the informed trading explanation builds upon the arrival of fundamental information, which should cause permanent price impact, and hence no reversal in predictability. Empirically, in all four asset classes, returns in the next three days are opposite to those of r_{LH}. For equities, bonds and commodities there is a highly significant mean-reversion, consistent with transitory price pressure, which arise from hedging.

For another piece of evidence supporting the hedging channel instead of informed trading, we turn to the underlying market for S&P 500, which closes at 4pm ET, at which time most related options and Levered ETFs also settle. Yet futures contracts on the S&P 500 index still trade actively at substantial volume for another 15 minutes until the futures settles at 4:15pm ET, and as such, informed trading at sufficient liquidity can well take place after 4pm ET. We find the return predictability of r_{ROD} does not extend to the futures return beyond 4pm ET, which seems hard to reconcile with the informed trading channel.

Our paper contributes to the voluminous literature on return momentum. In the cross-section, winners in the past six months to one year earn higher returns up to one year in the future (see Jegadeesh and Titman, 1993, amongst others). Similarly in the time series, the past one-year returns of an asset positively predict its future returns across many asset classes (see Moskowitz et al., 2012, amongst others). Instead, we focus on market momentum within a trading day. In this regard, our paper is most closely related to Gao et al. (2018) but differs in several aspects. Our analysis is much more comprehensive in its coverage, spanning indices and futures contracts across all major asset classes between 1974 and 2020. The market intraday momentum effect we document is also different from theirs. And most importantly, we discover a novel underlying economic force, which seems increasingly prominent. Related, Elaut et al. (2018) show intraday momentum in the RUB/USD currency pair since 2005, which they attribute to dealers closing positions overnight.

Our paper also relates to a growing literature on intraday price patterns. Recently, Lou et al. (2019) document strong overnight and intraday return continuation and an offsetting cross-period reversal at individual stock level and in equity return factors (see also Bogousslavsky, 2020 and Hendershott et al., 2020). Related, Muravyev and Ni (2019) and Goyenko and Zhang

(2019) document strong intraday and overnight differences in option returns. Further, Heston et al. (2010) find evidence of intraday return seasonality in the cross-section of stocks: returns continue during the same half-hour intervals as previous trading days, lasting from one day up to 40 trading days. While these studies focus on individual stocks and their options, our paper focuses on indices across a broad range of asset classes.[4] We also find market intraday momentum to be distinct from intraday return seasonality, with r_{ROD} continuing to predict r_{LH} even after controlling for r_{LH} from previous days.

Our results reveal that hedging demand coming from options and LETFs amplify price changes and affect market return dynamics over several days. Related, several other recent studies link the rise in indexing products (like ETFs) to side effects such as the amplification of fundamental shocks (Hong et al., 2012), excessive co-movement (Barberis et al., 2005; Greenwood, 2005, 2008; Da and Shive, 2018), a deterioration of the firm's information environment (Israeli et al., 2017), increased non-fundamental volatility in individual stocks (Ben-David et al., 2018) and VIX and commodity futures markets (Todorov, 2019), and non-fundamental shocks at the market level that result in price reversals (Baltussen et al., 2019). Intraday gamma hedging demand effects may contribute to short-term negative market reversals documented in the latter paper. Related, Bogousslavsky and Muravyev (2019) argue that an increase in indexing is associated with an increase in market close volumes and distortions in closing price. These results are broadly consistent with the view in Wurgler (2011) that indexing can affect the general properties of markets.

The rest of the paper is organized as follows. Section 2 describes our data and provides summary statistics. Section 3 documents the main stylized facts about the market intraday momentum pattern across the various asset classes. Section 4 presents evidence supporting the gamma hedging demand channel. Section 5 concludes. The Appendix contains additional descriptions of the data and various robustness results.

2 Data

To examine intraday momentum effects, we collect data for the world's largest, best traded, and most important stock and government bond futures or indices in developed markets around the

[4] In addition, several studies utilize intraday price data to examine intraday volatility (Chang et al., 1995) or the efficiency of volatility estimators. Example include Bollerslev et al. (2000); Martens and Van Dijk (2007); Bollerslev et al. (2018).

world, as well as for commodity and currency futures. We obtain historical tick-by-tick data on the major equity index, government bond, commodity and currency futures from Tick Data LLC [5]. The data consists of 17 developed markets equity futures (6 North American, 8 European, 3 Asian or Australian), 12 of which are also covered by data on their underlying equity indices, 16 developed markets bond futures (6 North American, 7 European, 3 Asian or Australian), 21 commodity futures (5 metals, 4 energies, 12 softs) and 8 currency futures with the sample period ranging from December 1974 to May 2020.

We retrieve one-minute intervals containing the corresponding open price, close price and trade volume. Volume data is available from 2003 onwards. We consider the most liquid contract (generally the nearest-to-delivery contract) and roll it over when the daily tick volume of the next back-month contract exceeds the current contract. Following the procedure for intraday data filtering by Barndorff-Nielsen et al. (2008), we filter the data by subsequently (i) removing all observations with non-positive prices, (ii) removing all non-business days, (iii) removing all days where the exchange closed earlier (such as Memorial Day), and (iv) removing all days where the total traded volume is less than 100 contracts. This procedure ensures that the sample consists of regular trading days. Appendix A provides a detailed overview of the included futures contracts.

To determine ON, FH, M, SLH and LH hours, we have to determine the opening and closing times of markets, which we determine using the following procedure. We select the observations that correspond with the "common" trading hours of the market (i.e., the openings hours of the cash (and ETF market) in line with Gao et al. (2018)), which typically differ from futures' trading hours (futures trade for extended time periods, nowadays often close to 24 hours a day). Our motivation for this choice is that futures are derivatives and are expected to follow their underlying instruments in behavior, and as such these are the moments at which positions are most likely rebalanced. This corresponds to the trading hours of the underlying for equity futures; e.g., we select the observations of the S&P E-Mini between 09:30 and 16:00, as these are the trading hours of the S&P 500. Futures are traded nearly round the clock, but most of the trading happens during the hours the underlying is trading. Trading volume outside of these hours is typically substantially lower. By contrast, the highest levels of trading volume clearly happen around open and close of the underlying equity index. As equity markets have clear trading hours, it is straightforward to select the trading hours of the equity index itself.

[5] www.tickdata.com

We correct for changes in trading hours over our sample, as for example the S&P 500 opened 30 minutes later before 1985.[6]

For futures on non-equity assets it is not that straightforward to select the trading hours, as for example government bonds are generally traded over-the-counter. Following the patterns in equity markets, we select trading hours of government bond futures based on volume plots and selecting “open” and “close” times based on spikes in volume. These spikes consistently happen on preset times, signaling their suitability as opening and closing times. For all but Australian and Japanese bond futures this results in using the regular opening hours of the futures as open, and the end of the daily settlement period as close. We use the regular trading hours of Australian and Japanese futures as trading hours.

The currency futures we use are all US listed. These futures show volume spikes at 8:21 and 15:00, which correspond to the open outcry hours of options on those futures. 15:00 also happens to be the end of the daily settlement period for these futures.

The commodity futures in our sample have been subject to several changes in trading hours. Nowadays most of these futures trade almost 24 hours a day, but this used to be different. Before the futures trade continuously, we consider the actual trading hours of the futures as our trading hours. After the introduction of continuous trading, we select trading hours based on volume plots, as for government bond futures and currency futures.

For each of the asset classes, a more detailed description of the sample, along with trading hours at the end of our sample, can be found in Appendix A. The trading hours we consider over time and average volume plots are available upon request.

To examine the presence of intraday return predictability, we calculate the return of buying at previous day’s $(t-1)$ close (c) and selling 30 minutes after today’s (t) opening (o) for each futures or index,

$$r_{ONFH,t} = \frac{P_{o+30,t}}{P_{c,t-1}} - 1 \tag{1}$$

and every following half-hour return until close.

We argue that the return until the last half hour, the return of buying at previous day’s

[6] For several equity index futures, the standard contracts were quickly outgrown in terms of traded volume by their mini versions. To obtain the largest sample, we first consider the standard contracts and replace them with the mini versions after its introduction.

close and selling 30 minutes before today's close,

$$r_{ROD,t} = \frac{P_{c-30,t}}{P_{c,t-1}} - 1 \tag{2}$$

predicts the last half-hour return. To investigate the added value of considering the return until last half-hour over the first half-hour return, we also consider the return between the end of first half-hour and the last hour and the second-to-last half hour,

$$r_{M,t} = \frac{P_{c-60,t}}{P_{o+30,t}} - 1 \tag{3}$$

$$r_{SLH,t} = \frac{P_{c-30,t}}{P_{c-60,t}} - 1 \tag{4}$$

We remove all observations outside of the trading hours we consider a trading day. This way the overnight return, which is contained in the first half-hour return, is computed using the price at our closing time on the previous day: e.g., a German future usually trades between 08:00 and 22:00. When adjusting the time frame to 08:00-17:15, r_{ONFH} is computed over the closing price at 17:15 yesterday and the closing price of the first half hour today, 08:30.

For each asset class we construct various groups, one of which containing all futures belonging to that asset class. Within equity index and bond futures we consider geographical groups for U.S. based futures ("USA"), futures from Europe ("EU") and futures from Australia or Asia ("Australasia"). Commodity futures are not country specific, such that we consider categorical groups for metals, energies and softs.

Table 1 lists the tickers and trading hours for all the futures contracts we used in the paper.

3 Market Intraday Momentum Everywhere

In the section, we document a robust market intraday momentum effect in all four asset classes we examine.

We consider several regression specifications for predicting the last half-an-hour return(r_{LH}). In the first specification, the only predictor is the return from previous close to the end of the first half-an-hour (r_{ONFH}) as in Gao et al. (2018):

$$r_{LH,t} = \alpha + \beta_{ONFH} \cdot r_{ONFH,t} + \varepsilon_t \tag{5}$$

In the second specification, we consider multiple predictors. In addition to r_{ONFH}, we also include the return during the middle of the day (r_M) and the return in the second-to-last-half-an-hour (r_{SLH}):

$$r_{LH,t} = \alpha + \beta_{ONFH} \cdot r_{ONFH,t} + \beta_M \cdot r_{M,t} + \beta_{SLH} \cdot r_{SLH,t} + \varepsilon_t \tag{6}$$

In the third specification, we combine the returns from all three periods into the return during the rest of the day (r_{ROD}):

$$r_{LH,t} = \alpha + \beta_{ROD} \cdot r_{ROD,t} + \varepsilon_t \tag{7}$$

We also compute the out-of-sample (OOS) R^2 to measure the out-of-sample predictability for each individual market. A positive OOS R^2 implies that the model makes better forecasts, i.e., lower mean squared prediction error (MSPE), than using the recursive historical mean as prediction for the last half-hour return. For each individual market we make forecasts using an expanding window, requiring at least 500 observations, or about two years of data.

We then define the OOS R^2 as follows:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}(r_{LH,t} - \hat{r}_{LH,t})^2}{\sum_{t=1}^{T}(r_{LH,t} - \bar{r}_{LH,t})^2} \tag{8}$$

where $\hat{r}_{LH,t}$ is the predicted last half-hour return on day t and $\bar{r}_{LH,t}$ is the historical average last half-hour return until $t-1$ (expanding window).

To see whether the MSPE is significantly lower than using the recursive historical mean, we perform a Clark and West (2007) test. First define f_t,

$$f_t = (r_{LH,t} - \bar{r}_{LH,t})^2 - ((r_{LH,t} - \hat{r}_{LH,t})^2 - (\bar{r}_{LH,t} - \hat{r}_{LH,t})^2) \tag{9}$$

or the test statistic follows from regressing f_t on a constant. A significant positive constant implies that predictor $\hat{r}_{LH,t}$, the first half-hour return or return until the last half hour before close, results in a significantly lower MSPE than using $\bar{r}_{LH,t}$, the recursive historical mean.

3.1 Baseline Results

In our analyses, we first pool together futures contracts in the same asset class and the regressions results are provided in Table 2. Panels A through D report the results for equity, bond, commodity, and currency futures, respectively.

To our best knowledge, there is no pooled out-of-sample R^2 measure, so we define a measure that represents a pooled OOS R^2. Define F_t as the futures available at day t and $n(F_t)$ the number of futures available on day t. We define $r_{LH,f,t}$ as the last half-hour return for future $f \in F_t$ on day t, $\hat{r}_{LH,f,t}$ our prediction for the last half hour, and $\bar{r}_{LH,f,t}$ the historical average last half-hour return until $t-1$. Then R^2_{OOS} is defined as:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T} \frac{\sum_{f \in F_t} (r_{LH,f,t} - \hat{r}_{LH,f,t})^2}{n(F_t)}}{\sum_{t=1}^{T} \frac{\sum_{f \in F_t} (r_{LH,f,t} - \bar{r}_{LH,f,t})^2}{n(F_t)}} \tag{10}$$

Gao et al. (2018) examine for 10 equity ETFs and one bond ETF how the return in each of the 30-minute intervals during the day predicts the return in the last half-an-hour. They find r_{ONFH} to have the strongest predictive power, followed by r_{SLH}. Panel A of Table 2 confirms this pattern in an extended sample period and across different stock markets. Column (1) finds a strong predictive power in r_{ONFH} on a stand-alone basis. Column (2) presents the results for equation (6). r_{ONFH} is again highly significant (t-value = 6.46), followed by r_{SLH} (t-value = 4.82). Interestingly, the returns in other 30-minute intervals, when combined into one r_M variable, is also significant in predicting r_{LH} (t-value = 4.43). In other words, all returns during the day (prior to the last half-an-hour) have predictive power on r_{LH}.

In column (3) of Panel A, we find that combining all returns during the day (prior to the last half-an-hour) into r_{ROD} generates the strongest predictive power. First, r_{ROD} has the highest t-value of 7.29. In addition, r_{ROD} has the highest out-of-sample R-squared (R^2_{OOS}) of 2.88%. In contrast, in this extended equity futures index sample, r_{ONFH} has a negative R^2_{OOS} of -1.71%. Interestingly, the R^2_{OOS} of r_{ROD} is also higher than that of the case when r_{ONFH}, r_M, and r_{SLH} are used separately.

Panels B to D document similar patterns in bond, commodity, and currency futures markets. While r_{ONFH} always positively and significantly predicts r_{LH}, r_{ROD} has generally stronger predictive performance. In almost all asset classes, r_{ROD} has the highest t-value and the highest R^2_{OOS}. The only exception is in the currency futures market (panel D) where r_{ONFH} has a slightly higher t-value and R^2_{OOS} than r_{ROD}. This is probably due to the fact that the U-shape intraday volume pattern is the least pronounced in the currency futures market. Figure 1(d) shows that the first half-an-hour dominates and the volume drops afterwards.

The four tables in Appendix B report the predictive regression results for each individual futures contract in equities (Table B1), bonds (Table B2), commodities (Table B3), and currencies (Table B4). In each of the four tables, Panel A first reports the pooled results by regions (USA, Europe, Australasia). Panel B then reports the results contract by contract.

The four tables present overwhelming evidence that r_{ROD} positively and significantly predicts r_{LH}. Focusing on the R^2_{OOS} of r_{ROD} in the equity futures market (Table B1), out of a total of 17 contracts, the R^2_{OOS} is positive and significant for 14 contracts. In addition, r_{ROD} has a higher R^2_{OOS} than r_{ONFH} for 10 contracts. In Appendix C, we show these results are very similar for stock market indices included in our sample instead of index futures. This is not surprising given the no-arbitrage relation between the index futures and the underlying index.

In the bond futures market (Table B2), out of a total of 16 contracts, the R^2_{OOS} is positive and significant for 11 contracts. r_{ROD} has a higher R^2_{OOS} than r_{ONFH} for 13 contracts. The results are slightly weaker for commodity futures (Table B3) and currency futures (Table B4). Still, for about 40% to 50% of the contracts, r_{ROD} has a positive and significant R^2_{OOS}. Its performance, however, is more comparable to that of r_{ONFH} in these two asset classes.

Based on the evidence across multiple asset classes and markets in an extended sample period, we conclude that the rest-of-day return (r_{ROD}) positively and significantly predicts the last half-an-hour return (r_{LH}) and this robust pattern better describes market intraday momentum everywhere.

3.2 Horse Race between r_{ONFH} and r_{ROD}

The fact that returns during all intervals of the day matter for predicting r_{LH} suggests a new driver of market intraday momentum: market makers' hedging demand. To the extent that market makers want to hedge their exposure right before the market close (i.e., during the LH period) and their exposure tends to be opposite to the return during the rest of the day (or they are short gamma), their hedging activity will push r_{LH} in the same direction as r_{ROD}, resulting in the market intraday momentum we documented so far.

Under this hedging-based explanation, r_{LH} should be best predicted by r_{ROD}, not just

r_{ONFH}. To test this conjecture directly, we estimate:

$$r_{LH,t} = \alpha + \beta_{ONFH} \cdot r_{ONFH,t} + \beta_{ROD} \cdot r_{ROD,t} + \varepsilon_t \tag{11}$$

We also estimate Equation 11 separately for the cases where r_{ROD} and r_{ONFH} are of the same or different sign. The results are presented in Table 3 for the four asset classes separately in Panels A through D.

The evidence in Table 3 is clear. When r_{ROD} and r_{ONFH} are of the same sign, r_{ROD} tends to be the better predictor of r_{LH}, in terms of both t-value and R-squared. When r_{ROD} and r_{ONFH} are of the opposite sign, r_{ROD} is also clearly better, apart from the result for currencies. The only reason r_{ROD} and r_{ONFH} can be of opposite sign is that $\big|(r_M + r_{SLH})\big| > \big|(r_{ONFH})\big|$. In equity, bond and commodity futures markets, the coefficient on r_{ONFH} has the wrong sign but the coefficient on r_{ROD} is still positive and highly significant. The currency futures market is again the exception with the coefficients for both r_{ROD} and r_{ONFH} positive but insignificant.

In general the result supports the negative gamma hedging hypothesis where r_{ROD} should be more relevant than r_{ONFH} in determining the hedging demand towards the end of the trading hours. Also for the full sample, i.e., without conditioning, we see clearly that r_{ROD} is the strongest predictor for r_{LH} for equities, bonds and commodities, leaving r_{ONFH} insignificant.

3.3 Intraday Seasonality

Heston et al. (2010) documents a striking intraday seasonality in the cross-section of individual stock returns. The return of a stock over a half-hour trading interval today positively and significantly predicts its return during the same interval tomorrow and on subsequent days, potentially up to 40 days. They attribute this seasonality to systematic trading and institutional fund flows. How does market intraday momentum compare against such an intraday seasonality? We examine this question in Table 4 where we repeat the regressions in Table 2 after including yesterday's last half-hour return ($r_{LH_{t-1}}$) as an additional predictor.

We do not find positive and significant coefficients on $r_{LH_{t-1}}$ except in the case of currency futures. In fact, the coefficients are negative and significant among equity index futures, suggesting that intraday seasonality in the cross-section of individual stocks does not aggregate up to time-series intraday seasonality at the market level. One possible explanation is that the former effect is a cross-sectional effect, hence largely ignoring general market movements, while the latter effects is a time-series effect that especially captures general market movements. More importantly, including $r_{LH_{t-1}}$ hardly changes the conclusions regarding market intraday momentum we reached in Table 2. Coefficients on r_{ROD} in Table 4 are almost identical to those in Table 2. We have confirmed (unreported for the sake of brevity) that these results remain similar even when five up to 40 lags of r_{LH} are included. In other words, market intraday momentum seems distinct from intraday seasonality in the cross-section. The results further support the negative gamma hedging channel where only intraday returns during day-t should matter.

3.4 Intraday Momentum over Time

In this section we show the pooled regression results for the subsamples: 1974-1999, and 2000-2020. Table 5 shows the results for equity index (Panel A), government bond (Panel B), commodity (Panel C) and currency futures (Panel D). The results are similar in the first- and second-half of our sample. In addition to r_{ONFH}, r_M and r_{SLH} also predict returns in the last half hour. As a result, r_{ROD} generally has higher adjusted R^2 than r_{ONFH} in both subsamples. Results also confirm that r_{ROD} wins the direct horse race against r_{ONFH} in both subsamples, especially when they differ in signs, as shown in Appendix D.

Overall, intraday momentum as predicted by r_{ROD} is present in both subsamples, indicating there always have been hedgers who have to trade in the same direction as the market has moved. For example, portfolio insurance was very popular during the first period (Tosini, 1988), option activity increased a lot since the end of the first period, while leveraged ETF activity strongly gained traction as of 2006 (Cheng and Madhavan, 2010).

3.5 Economic Significance Market Intraday Momentum

Next, we examine the economic significance of market intraday momentum in futures markets. To this end, we examine a market timing strategy that uses the predictor variables as timing signals and evaluate their trading profits. We look at both $r = r_{ONFH}$ and $r = r_{ROD}$ as predictors. If the predictor return is positive we will earn the last half-hour return, r_{LH}, otherwise we will earn $-r_{LH}$. Hence the timing returns are:

$$\eta(r) = \begin{cases} r_{LH}, & \text{if } r > 0. \\ -r_{LH}, & \text{otherwise.} \end{cases} \tag{12}$$

We use two different benchmark strategies to compare the timing strategies. The first benchmark, *Always Long*, has a long position during the last half hour irrespective of the sign of the signal. The other benchmark buys at the start of the sample and sells at the end of the sample, May 2020.

The trading strategy results are presented in Table 6, showing annualized returns, volatilities, and Sharpe ratios, as well as daily success rates. We find overall positive returns, very high Sharpe ratios and success rates well above 0.50 on the timing strategies. Further, r_{ROD} produces higher average returns and Sharpe ratios than r_{ONFH} in all asset classes but currencies. Moreover, the market timing strategies based on r_{ROD} outperform passive benchmark strategies in terms of Sharpe ratios.

Figure 2 provides a visual illustration of the strategy returns and its consistency over time. We plot the cumulative (log) performance of the market intraday momentum strategy based on r_{ROD} (solid line) and the benchmark *Always Long* strategy (dashed line). Clearly, conditioning positions in LH to equal r_{ROD} outperforms a passive *Always Long* strategy. This outperformance is generally consistent over time, as evident from the upward sloping solid lines. Focusing on the equity asset class, the market intraday momentum strategy also performs strongly during the last four months of our sample (February to May, 2020), consistent with the anecdotal evidence cited in the beginning of the paper.

Note that we do not consider transaction cost. Given that trading on market intraday momentum requires frequent rebalancing, the strategy as presented might not be exploitable to many investors after accounting for transaction costs. That said, this is definitely not to say that market intraday momentum is not exploitable for investors. In fact, several investors in especially the most liquid markets are known to trade at very limited cost, and exploiting the effect in the S&P 500 futures yields a positive net Sharpe ratio when we assume transaction cost equal to a tick (a cost level faced commonly by advanced investors in the S&P 500 futures market). Further, market intraday momentum may be exploited in other manners that limit turnover or additional trading cost, for example via the timing of already planned trades. we leave a detailed study of the best way to exploit market intraday momentum for future research.

4 New Evidence on Hedging Demand

In this section, we provide more evidence supporting market makers' hedging demand as a novel driver of the market intraday momentum phenomenon. The first two tests provide direct evidence for the hedging channel, while the last two tests allow us to differentiate hedging activities from late informed trading.

4.1 Hedging Demand of Option Market Makers

Hedging demand of option market makers hinges on their net gamma positions. So far we assumed that option market makers are on average net short gamma, and as a result they need to trade in the direction of the market to rebalance their delta hedges. It is well known that institutional investors buy index puts as portfolio insurance (Bollen and Whaley (2004)). Similarly, Garleanu et al. (2008) find that end users have a net long position in S&P 500 index options with large net positions in out-of-the-money puts. Since there are no natural counter-parties to these trades, market makers must step in to absorb the imbalance. By contrast, index call options are typically shorted by market participants, for example via call overwriting strategies. Goyenko and Zhang (2019) provide evidence supporting positive net demand pressures by end users for S&P 500 index puts, and negative net demand pressures for S&P 500 index calls. Cici and Palacios (2015) study mutual fund holdings in options, finding that for mutual funds using options, written calls and long (mostly index) put options represent the majority of option positions. As a result, option market makers are typically net short (index) put options, and net long call options, and as a result often net short gamma on average.

By contrast, if option market makers are net long gamma (which happens for example with net short put and long call positions and markets drifting up) they will have to trade against the market. As such, they may offset the effects of information and rebalancing trades, potentially resulting in no market intraday momentum or even intraday reversals. Hence if hedging demand is a key driver of market intraday momentum, the market intraday momentum may be virtually absent in periods that option market makers are not net short gamma, but stronger the more gamma they short.

For the S&P 500 index, we proxy the Net Gamma Exposure (NGE) of option market makers based on all the open interest in S&P 500 index options using OptionMetrics data. Specifically we assume that (i) all traded options are facilitated by delta-hedgers; (ii) call options are sold by investors, and bought by option market makers; (iii) put options are bought by investors, and sold by option market makers; and (iv) option market makers hedge precisely their option deltas.

For a call (C) option on day t with strike price $s \in S_t^C$ and maturity $m \in M_t^C$ the NGE is computed as:

$$NGE_{s,m,t}^C = \Gamma_{s,m,t}^C \cdot OI_{s,m,t}^C \cdot 100 \cdot P_t, \tag{13}$$

where $\Gamma_{s,m}^C$ is the option's gamma, $OI_{s,m}^C$ is the option's open interest, and 100 is the adjustment from option contracts to shares of the underlying. P_t is equal to the level of the S&P 500 index on day t.

For a put (P) option on day t with strike price $s \in S_t^P$ and maturity $m \in M_t^P$ the NGE is computed as:

$$NGE_{s,m,t}^P = \Gamma_{s,m,t}^P \cdot OI_{s,m,t}^P \cdot (-100) \cdot P_t, \tag{14}$$

where we use the adjustment of -100 as this represents short gamma for option market makers and P_t the level of the S&P 500 index on day t.

The NGE of the S&P 500 index is then computed by summing all NGE at every strike price in every available contract and dividing by the market value of the S&P 500 index (MV_t):

$$NGE_t = \frac{\sum_{s \in S^C} \sum_{m \in M^C} NGE_{s,m}^C + \sum_{s \in S^P} \sum_{m \in M^P} NGE_{s,m}^P}{MV_t}. \tag{15}$$

Using data from OptionMetrics, we compute the NGE measure from 1996 until the end of 2017. We use data from SqueezeMetrics to extend the sample until May 2020.[7] Figure 3 shows the NGE for the S&P 500 over time. In the period from 1996 until May 2020 there have been 2930 days with a negative NGE and 3158 with a positive one.[8]

[7] We have verified the computations of SqueezeMetrics using OptionMetrics data over the 2002 to 2017 period, yielding virtually identical results.

[8] Note that NGE is on average positive for most days. One possible explanation is that market makers are net short put and long call positions but markets on average drift up over time in such a manner that the net gamma of the puts drop and the net gamma of calls rise. Another explanation for more positive NGE days could also be the choice of data. We like to stress that the data used in this section is limited to listed cash options

A negative NGE_t implies that option market makers will delta hedge in the same direction as the market has moved, in line with market intraday momentum. Therefore, we regress the r_{LH} on r_{ROD} conditional on the sign of the NGE. Table 7 shows that indeed intraday momentum is much more pronounced on negative NGE days. On days with positive NGE, however, there is no significant intraday momentum. This provides strong support for our hedging demand hypothesis, i.e., that intraday momentum is partially driven by option hedging demand. As discussed in the introduction, rebalancing and information traders may also show up to trigger the market intraday momentum. However, we show that market intraday momentum is only present when, according to our proxy, option market makers are net short gamma. But when they are net long gamma market intraday momentum is no longer present. This suggests that hedging demand then seems to offset the intraday momentum effects triggered by rebalancing and information traders. Unreported analyses show that the results in Table 7 also hold when using the overnight return plus first half hour (r_{ONFH}) used in Gao et al. (2018) or the return between the first half our and last half hour (r_M).

Furthermore, we include the S&P 500 NGE into Equation 7. We include NGE_t and NGE_t multiplied by $r_{ROD,t-1}$ into Equation 7. Table 8 contains the results. Confirming the earlier results, intraday momentum is especially pronounced when NGE is negative (i.e., option market makers are net short gamma) or when their net short gamma position is stronger. The last two columns confirm that these results are not driven by a time trend shared by intraday momentum and NGE by running a difference-in-difference regression. Further, unreported robustness checks confirm that these results also hold when only considering puts (and no calls).

4.2 Hedging Demand from Leveraged ETFs

Next, we present direct evidence for the hedging-based explanation in the market for leveraged ETFs (LETF). Note that direct data on dynamic hedging demand is generally not available or very noisy. Option data across asset classes is also limited. On the other hand, data on leveraged

available from OptionMetrics, and we assume option market makers are short all puts and long all calls. We do not have data on, for example, OTC option positions and precise end-user option positions. This means our sample misses many long puts and short calls typically done OTC by institutional investors (for example, many institutional investors buy index puts as portfolio insurance and insurers buy puts to hedge insurance books) and proxies end-user demand. Portfolio insurance and insurer hedging practices create structural option demand, in line with studies showing net long end-user demand to index put options (Bollen and Whaley, 2004; Garleanu et al., 2008). Further, net short option position of option market makers is believed to cause them to demand a volatility risk premium as compensation for exposure to volatility risk (Bollen and Whaley, 2004), a finding consistently observed across most of the markets we study. Industry estimates from for example JP Morgan Chase suggest short puts are by far the most dominant positions of option market makers.

ETFs is readily available and generally accurate. Leveraged ETFs seek to deliver a multiple of their underlying market's daily returns. There are two types of leveraged ETFs: bull/ultra ETFs that promise a positive multiple (usually two or three times) of the underlying index's daily return, and inverse/bear ETFs that promise an (leveraged) inverse of their underlying market's return. Both ETF types need to rebalance daily in the same direction as the underlying index's daily performance. This is caused by the fact that on an up (down) day, bull ETFs need to increase (decrease) their exposure to the underlying, while bear ETFs have to close (open) some shorts.

Consequently, market makers of the ETF providers need to rebalance exposure to the market near or at the market close (which these investors typically do using total return swaps and futures contracts), as these indexing products essentially offer a multiple of the daily close-to-close return of the underlying index (see also Bogousslavsky and Muravyev, 2019, for the use of close prices). This hedging behavior causes price pressures near the end of the trading day. Cheng and Madhavan (2010) derive that the rebalancing demand on day t is equal to:

$$NAV_{t-1}(x^2 - x)r^{c,t}_{c,t-1} \tag{16}$$

where NAV_t are the net asset values on day t for a leveraged ETF and x is the leverage factor (e.g., -2,-1,2,3).

As of the end of February 2009, Cheng and Madhavan (2010) estimated that leveraged ETF rebalancing made up 16.8% (50.2%) of the market-on-close (MOC) volume on a day the market moved 1% (5%).[9] Shum et al. (2015) argue that MOC orders have fill risk, such that the hedging could start as early as 30 minutes before close. This fits nicely into our reasoning of r_{ROD} predicting r_{LH} .

We obtain historical daily NAV data of leveraged ETFs on markets underlying the futures contracts used from Bloomberg. Not all markets used in this research have leveraged ETF data available. For markets with LETF data available, we sum the NAVs multiplied by $x^2 - x$ (where x is the leverage factor) and express it as a percentage of the underlying index's market capitalization (akin to Baltussen et al., 2019). We denote this market share of leveraged ETFs by $Indexing_{LETF}$. Market sizes for government bonds are per maturity bucket. Due to duration requirements, they show seasonality that we solve by using a three-month rolling average. For

[9] Related, Todorov (2019) shows that leveraged ETFs rebalancing demand substantially influence price changes in the VIX futures, natural gas, silver, gold and oil commodity futures markets).

commodities we cannot compute market shares, as we do not have data on the size of the market.

If hedging activity on these products drive market intraday momentum, we would expect more pronounced market intraday momentum in markets with more leveraged ETF activity. To examine this relationship, we first examine such a relationship in the cross-section. To this end, we plot the average leveraged ETF share per market against the t-statistics of β_{ROD}. As leveraged ETFs are introduced in 2006, we make scatterplots over the subsample 2006-2020. As we do not have market sizes for commodities, we rank the LETF market sizes and plot these ranks against the t-statistics. Figure 4 shows a significant upward sloping line for all three asset classes, indicating a positive relationship between LETF market shares and intraday momentum.

Next, we examine the relationship in a time series. To this end, we expand the regression of r_{LH} on r_{ROD} with $Indexing_{LETF}$ and this measure multiplied by r_{ROD} (the hedging demand):

$$r_{LH,t} = \alpha + \beta_1 \cdot r_{ROD,t} + \beta_2 \cdot Indexing_{LETF,t} \cdot r_{ROD,t} + \beta_3 \cdot Indexing_{LETF,t} + \varepsilon_t \tag{17}$$

We run this regression for equity index and government bond futures, as we lack dynamic LETF data for the other asset classes. The first columns of Table 9 show that the hedging demand has additional predictive power for the last half-hour return in both equity index and government bond futures. Further, in order to remove any index-specific time trend (indexing of LETFs has increased over time, and profits on intraday momentum might share a similar time component) we also run difference-in-difference regressions. The results confirm the earlier findings. In summary, LETF's hedging demand drives the magnitude of market intraday momentum patterns, providing unique evidence supporting the hedging channel.

4.3 Intraday vs. End-of-day Hedging

In a frictionless Black-Scholes world, hedging is done continuously to ensure delta-neutrality all the time. With transaction costs, it is optimal to hedge only discretely during the day. Yet if hedging is complete so the delta goes back to zero at the end of each discrete interval, then the return prior to the hedge should not predict the return after the hedge, as demonstrated by Leland (1985).

In Table 10, we examine such intraday hedging activities. We conjecture that while small price movements during the day may not trigger hedging due to transaction cost, large price jumps probably will. If the gamma is negative, then hedging will further push the price in the direction of the jump. Hence, cumulative return up to and including the jump should positively predict the return after the jump when hedging takes place. In addition, if the jump occurs early during the day and the hedge is timely and complete, then the cumulative jump return should not predict the return in the last half an hour (r_{LH}).

The results in Table 10 confirm that cumulative jump returns positively predict subsequent returns during the day ($r_{Postjump}$). A jump is defined as each daily half hour in which the return from close to that half-hour interval is below (above) the 10% (90%) percentile of the full-sample daily returns distribution of that asset (we have verified that results are comparable when using 5% (95%) or 2.5% (97.5%) percentiles). We run a pooled regression of $r_{Postjump}$ on a constant and the return from the previous day's close until jump. Next, we decompose $r_{Postjump}$ into two parts: the return from post-jump to the end of SLH ($r_{PostjumptoSLH}$) and the return in the last half hour (r_{LH}). We find the cumulative jump returns to positively predict $r_{PostjumptoSLH}$ for all four asset classes and significantly for commodities and currencies. We interpret the pattern as evidence for intraday hedging after large jumps. Nevertheless, for all four asset classes, the cumulative jump returns still positively and significantly predict r_{LH}, suggesting that intraday hedging is incomplete and a significant portion of the hedge is still carried out towards the end of the day.

We conjecture that there are at least five reasons why hedging activity is more intensive towards the end of the day. First, from a theoretical point of view, Clewlow and Hodges (1997) show that, in the presence of partially fixed transaction costs, the optimal trade-off between delta risk and costs results in two bandwidths around a delta-neutral hedge. If the outer bandwidth is breached, it is optimal to trade towards the inner bandwidth, not back to delta-neutral. Simply put, it is optimal to hedge only partially after a large price movement, implying that additional hedging is required afterwards (see also Sepp, 2013).

Second, the additional hedging may be deferred to the end of the trading day for liquidity reasons. The U-shape intraday volume pattern across the equity, bond, commodity and currency markets in Figure 1 confirms that liquidity tends to be high right after open and before close. Further, spreads are generally lower and market depth higher when trading towards the close. Improved liquidity is another reason why investors may leave the bulk of hedging to the last half hour, especially when they have larger quantities to trade.

Third, while hedging is partial during the day, it tends to be complete at the end of the day to protect against overnight risk. Brock and Kleidon (1992) and Hong and Wang (2000) show that lower liquidity and higher price risk overnight makes it optimal for market makers to close delta positions before overnight.

Fourth, holding positions overnight typically incurs higher capital needs and investment frictions. For example, BIS capital requirements are driven by deltas at close. Further, margin requirements generally increase for overnight positions, while lending fees and margin interest are typically charged only on positions held overnight (Bogousslavsky, 2020). As a consequence, holding risky positions overnight not only comes with higher price risks, but also with higher capital requirements. Market participants therefore have an incentive to reduce delta at the end of the day to free up capital and save cost. Several studies empirically show that dealers in stocks, bonds, commodities or currencies are indeed reluctant to hold delta positions overnight and tend to close them before the end of the day (Lyons, 1995; Manaster and Mann, 1996; Ferguson and Mann, 2001; Bjønnes and Rime, 2005). Related, (Gerety and Mulherin, 1992) provide evidence consistent with dealers unloading their delta positions before the close and reopening them on the following day.

Finally, as we have demonstrated, index products such as LETF seek to deliver a multiple of their underlying market's daily returns benchmarked at closing prices. Market makers in these index products have little discretion but to rebalance daily and around the close in the same direction as the underlying index's daily performance. A similar mechanism holds for market makers of variance swaps, as the payoff of a variance swap is calculated based on the closing levels of the underlying index.

4.4 Price Pressure vs. Informed Trading

Gao et al. (2018) presents late informed trading as another potential driver of market intraday momentum. Under this explanation, traders who are informed late trade in the last 30 minutes. Hence, the same information is incorporated into prices during both the first and the last 30 minutes, resulting in momentum. A major difference between hedging and informed trading lies in their price impact. Generally speaking, hedging activities should only result in transitory price pressure (as there is no news), while fundamental information is expected to cause a permanent price impact (as news is incorporated in prices). In case the market intraday momentum is caused by price pressure from hedging demands, the price should revert back after the hedging activity has ceased. In case market intraday momentum is caused by informed traders delaying their trades to benefit from liquidity, the last half-hour return should reflect delayed incorporation of new information and should not revert back the next days. In other words, under the hedging explanation, we expect mean-reversion in the near future, while we do not expect mean-reversion under the informed trading explanation.

Figure 5 examines whether market intraday momentum persists beyond the current trading day. Throughout this paper we use the intervals overnight, first half-an-hour, middle-of-day, second-to-last-half-an-hour and last half-an-hour. To find out when momentum disappears, in Figure 5, we extend the last half hour with the previously mentioned intervals. Starting at our standard setting of regressing the last half-hour return (r_{LH}) on the return until the last half-hour (r_{ROD}), we progressively add those intervals until we regress the return from 30 minutes before today's close until 30 minutes before close three days later ($r_{c-30,t}^{c,t+3}$) on the return until 30 minutes before today's close ($r_{ROD,t}$).

Figure 5 clearly shows that the market intraday momentum does not persist for long. The predictive power of r_{ROD} reverts to zero in the next day in the currency futures market (Figure 4D), in two days in the equity and commodity futures markets (Figures 4A and 4C), and in three days in the government bond futures markets (Figure 4B).

In Figure 5, we focus on the relation between the predictor of the last half hour, r_{ROD}, and the cumulative return from the last half hour on the same day. Table 11 shows the results of regressing the next day return ($r_{c,t}^{c,t+1}$), the next two days return ($r_{c,t}^{c,t+2}$), and the next three days return ($r_{c,t}^{c,t+3}$) on a constant and today's last half-hour return ($r_{LH,t}$). In all four markets, we observe reversals, although this effect is not significant in currency futures. Such a return reversal is consistent with the price pressure caused by market makers' hedging activities.

For another piece of evidence for the hedging demand, we turn to the S&P 500 underlying market. The market closes at 4:00pm ET, the time at which most options and levered ETFs on the index are settled. Market makers for these index-related instruments have strong incentives to hedge their positions before 4:00pm in the underlying market.

On the other hand, the futures trades well until at least 4:15pm ET when the futures market has its settlement. This is evident in Figure 6, which plots the average 15-minute trading volume of the S&P 500 E-Mini futures. We observe very active trading during the 15-minute interval from 4:00pm ET to 4:15pm ET, suggesting that informed traders can trade on their information at sufficient liquidity even after 4:00pm ET in the futures market.

Table 12 examines the return predictability during the last half-an-hour before close in both the S&P 500 cash index market (Panel A) and the futures market (Panel B). Empirically, Panel A shows that r_{ROD} strongly predict r_{LH} in the cash index market (we have verified similar results in the futures market over the same time interval). In contrast, in Panel B, we find the predictability of r_{ROD} does not extend to the futures return beyond 4:00pm ET. The evidence is again consistent with hedging demand channel, and seems hard to reconcile with the late informed trading channel.

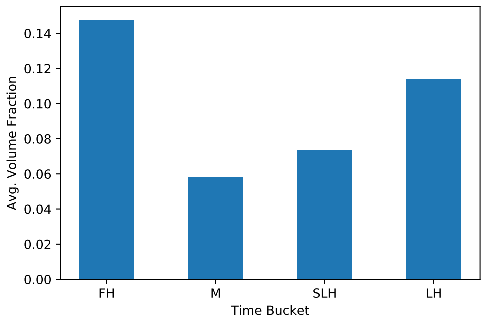
5 Conclusion

Using intraday price data on more than 60 futures contracts on equity indices, bonds, commodities, and currencies over the past 45 years, we document a strong market intraday momentum across the main markets in the major asset classes. The futures return during the last 30 minutes before the market close is positively predicted by the futures return during the rest of the day (from previous market close to just before the last 30 minutes). The predictive power is both statistically and economically highly significant, yielding Sharpe ratios between 0.87 and 1.73. Market intraday momentum is robustly present across markets and over time, reverts over the next days and is distinct from intraday seasonality effects.

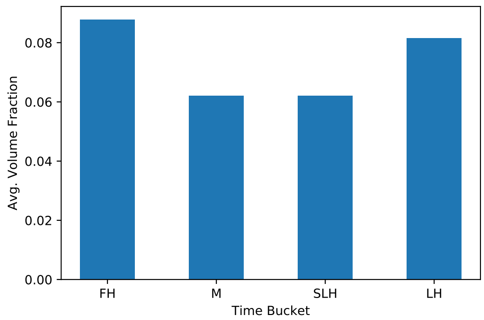
More importantly, we identify a novel economic force that drives market intraday momentum: market participants' hedging demand coming from short gamma exposure. Our tests link both cross-sectional and time-series variation in market intraday momentum to such hedging demand. Our evidence suggests that concentrated trades of groups of investors - like portfolio insurers, option market makers and leveraged ETFs - can have substantial, non-fundamental price impact, amplifying price changes and impacting market dynamics around the times they trade. Paradoxically, these dynamics may even lead to leveraged (including short) ETFs to underperform their underlying index, as the hedging impact of their trades tend to revert. At the same time, market dynamics are strongly predictable intraday, and as such, proactive investors can benefit, for example by providing liquidity opportunistically in anticipation of hedging flows, or a smart timing of planned trades.

Figures

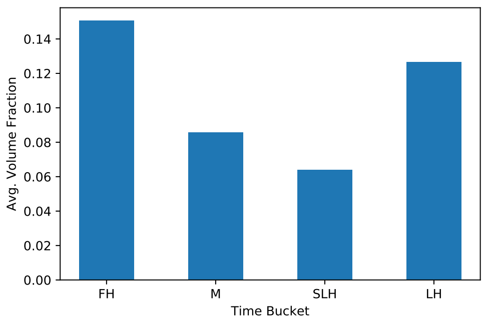
Figure 1: This figure shows the average trading volume as fraction of total daily volume per time bucket for each asset class. The time buckets are (1) the "first half-an-hour" (FH, the first 30 minutes after the market open), (2) the "middle-of-the-day" (M, from the end of FH to an hour before the market close), (3) the "second-to-last-half-an-hour" (SLH, the second-to-last 30 minute interval), and (4) the "last half-an-hour" (LH, the last 30 minutes before the market close). Since bucket M contains more than 30 minutes, we divide its volume by the number of minutes in the bucket and multiply by 30, such that all buckets represent volume per 30 minutes. Per market we divide the buckets' volumes by the daily volume and average over time to get the average volume fractions per market. For each asset class, we then take the average over the markets belonging to that asset class. Shown are the results for equity index futures (Panel (a)), government bond futures (Panel (b)), commodity futures (Panel (c)), and currency futures (Panel (d)). Samples range from July 2003 to May 2020.



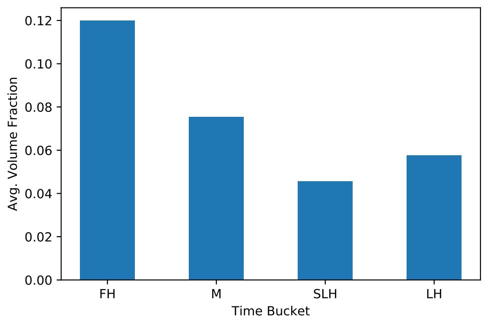
(a) Equity Index Futures



(b) Bond Futures

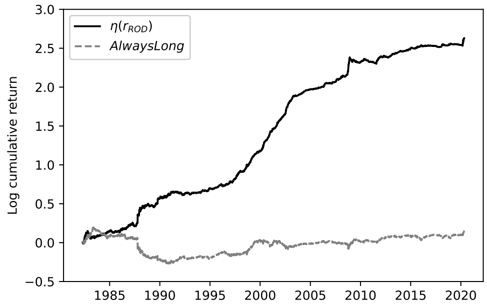


(c) Commodity Futures

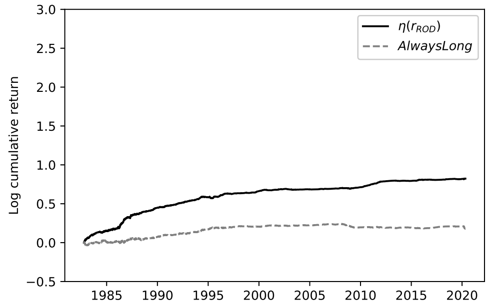


(d) Currency Futures

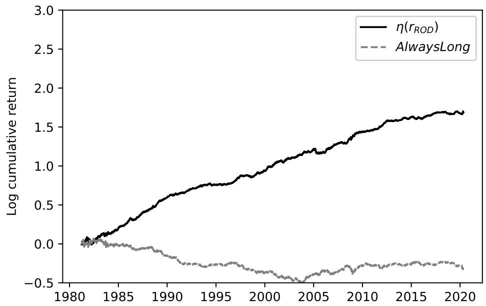
Figure 2: This figure shows the cumulative performance (on a log-scale) of the $\eta(r_{ROD})$ timing strategy and the *Always Long* benchmark strategy per asset class. Timing strategy $\eta(r_{ROD})$ takes a long position when the return until 30 minutes before close r_{ROD} is positive and a short position otherwise. The benchmark strategy *Always Long* is always long during the last half hour. Shown are the results for equity index futures (Panel (a)), government bond futures (Panel (b)), commodity futures (Panel (c)), and currency futures (Panel (d)). Samples range from December 1974 to May 2020. For each asset class a 1/N portfolio is used to combine the various futures belonging to the same asset class into one portfolio.



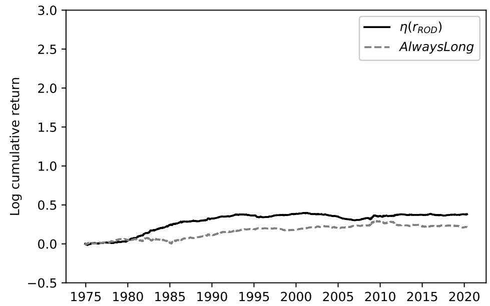
(a) Equity Index Futures



(b) Government Bond Futures



(c) Commodity Futures



(d) Currency Futures

Figure 3: This figure shows the Net Gamma Exposure (NGE) for the S&P500 between January 1996 and May 2020.

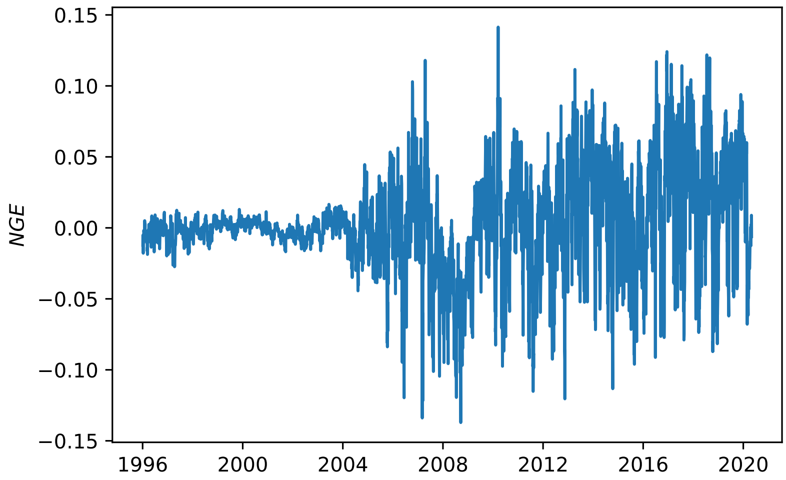
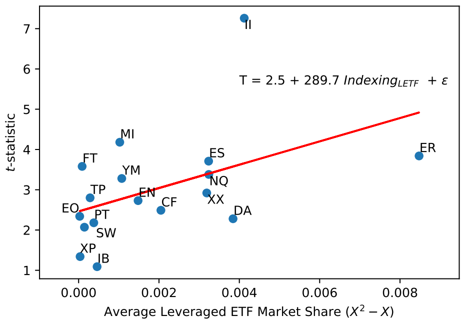
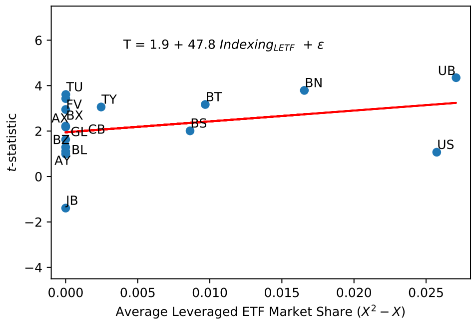


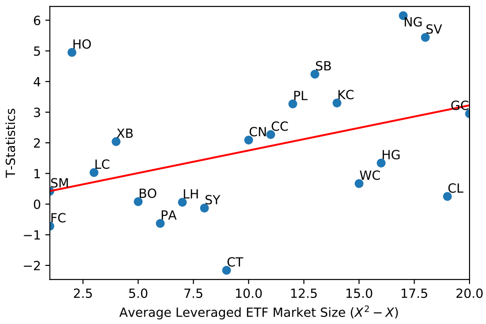
Figure 4: This figure plots the average Leveraged ETF (LETF) market share against the Newey and West (1986) robust t-statistic of regressing its futures' last half-hour return (r_{LH}) on the return until 30 minutes before close (r_{ROD}) for equity index futures (Panel (a)), government bond futures (Panel (b)), and commodity futures (Panel (c)). The market share measure is computed as the total market value of all LETFs on the market multiplied by $x^2 - x$, where x is the leverage factor, divided by the index market value. For government bond futures we use three-month rolling average market sizes. Currencies are missing as we do not have LETF data on those markets. Commodity futures have no market size data available, therefore we rank the LETF market sizes. Samples range from June 2006 to May 2020.



(a) Equity Index Futures

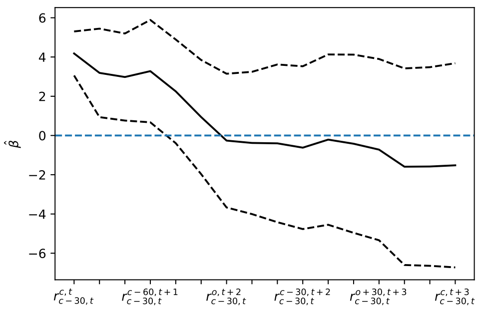


(b) Government Bond Futures

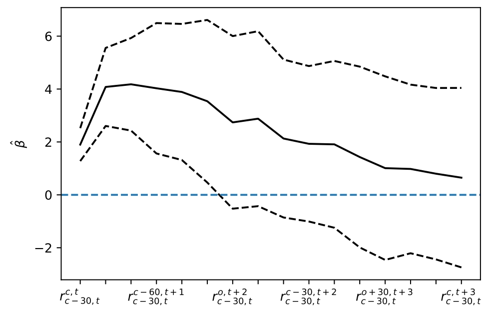


(c) Commodity Futures

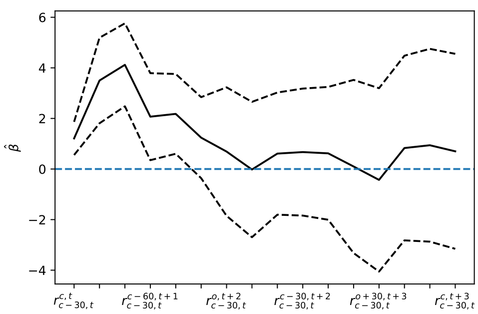
Figure 5: This figure shows the regression coefficients and corresponding confidence bounds of using the return until last half-hour today, r_{ROD}, to predict today's last half-hour return, r_{LH}, and progressively adding intervals: overnight, first half-an-hour, middle-of-the-day, second-to-last-half-an-hour and last half-an-hour, until close three days later, $r^{c,t+3}_{c-30,t}$. Shown are the results for equity index futures (Panel (a)), government bond futures (Panel (b)), commodity futures (Panel (c)), and currency futures (Panel (d)). Samples range from December 1974 to May 2020.



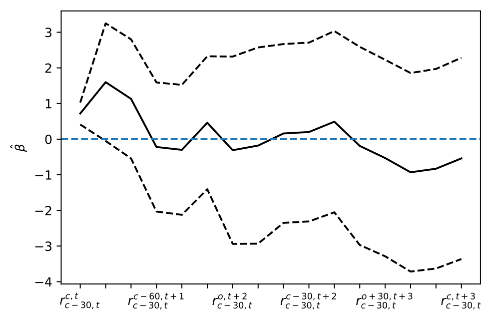
(a) Equity Index Futures



(b) Government Bond Futures

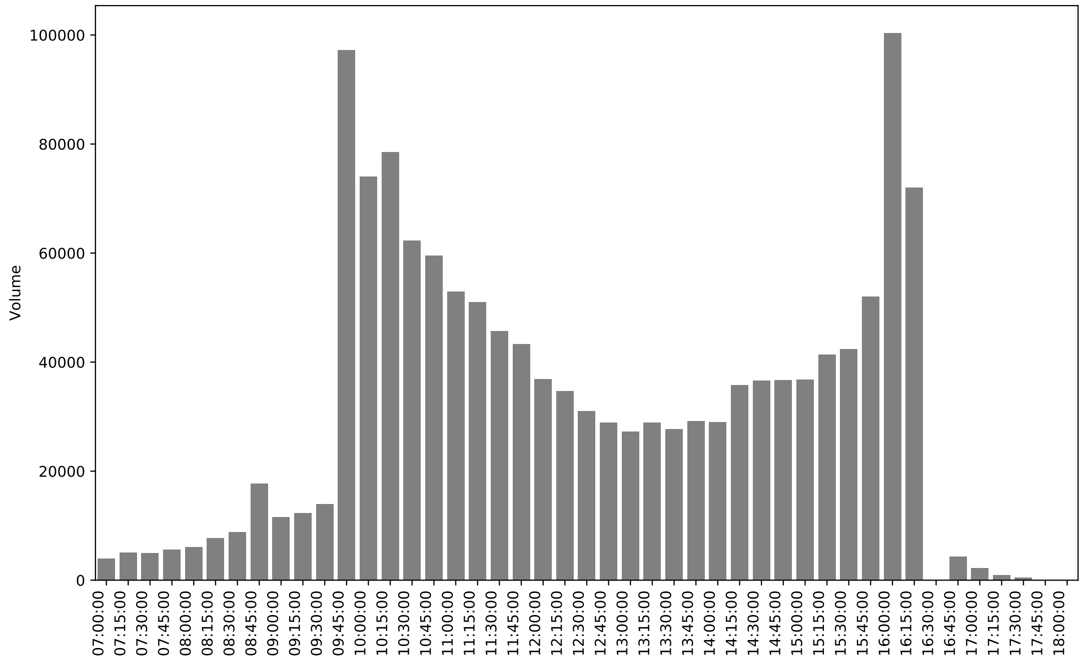


(c) Commodity Futures



(d) Currency Futures

Figure 6: This figure shows the average 15-minute trading volume of the S&P 500 E-Mini futures over the period ranging from July 2003 to May 2020.



Tables

Table 1: Overview of futures used. Trading hours are based on underlying trading hours (equity index futures) or on volume patterns. Trading hours are expressed in the local exchange time zone. US listed futures are expressed in Eastern Standard Time (EST). A * indicates futures where sample period is extended by considering the regular future before the mini contract was introduced.

Future	Symbol	Trading Hours	Future	Symbol	Trading Hours
Equity Index Futures			Commodity Futures		
Dow Jones Futures*	YM	9:30 - 16:00	Gold Futures COMEX	GC	8:20 - 13:30
S&P 500 Futures*	ES	9:30 - 16:00	Copper High Grade Futures COMEX	HG	8:10 - 13:00
NASDAQ 100 Futures*	NQ	9:30 - 16:00	Silver Futures COMEX	SV	8:25 - 13:25
Russell 2000 ICE/CME*	ER	9:30 - 16:00	Palladium Futures NYMEX	PA	8:30 - 13:00
S&P 400 MidCap Futures*	MI	9:30 - 16:00	Platinum Futures NYMEX	PL	8:20 - 13:05
Amsterdam AEX Index Futures	EO	9:00 - 17:30	Light Crude Oil Futures NYMEX	CL	9:00 - 14:30
DAX Index Futures	DA	9:00 - 17:30	Heating Oil #2 Futures NYMEX	HO	9:00 - 14:30
Swiss Market Index Futures	SW	9:00 - 17:30	Natural Gas Futures NYMEX	NG	9:00 - 14:30
EURO STOXX 50 Index Futures	XX	9:00 - 17:30	RBOB Gasoline Futures NYMEX	XB	9:00 - 14:30
CAC 40 Index Futures	CF	9:00 - 17:30	Soybean Oil Futures	BO	8:30 - 13:20
IBEX 35 Index Futures	IB	9:00 - 17:30	Corn Futures	CN	8:30 - 13:20
FTSE MIB Index Futures	II	9:00 - 17:30	Soybean Meal Futures	SM	8:30 - 13:20
FTSE 100 Index Futures	FT	8:00 - 16:30	Soybean Futures	SY	8:30 - 13:20
Nikkei 225 Futures SGX	EN	8:00 - 14:00	Wheat Futures CBOT	WC	8:30 - 13:20
TOPIX Futures JPX	TP	9:00 - 15:00	Cocoa Futures	CC	9:45 - 18:30
ASX SPI 200 Index Futures	XP	10:00 - 16:00	Cotton #2 Futures	CT	2:00 - 19:20
S&P Canada 60 Futures	PT	9:30 - 16:00	Coffee 'C' Futures	KC	9:15 - 18:30
			Sugar #11 Futures	SB	8:30 - 18:00
Government Bond Futures			Feeder Cattle Futures	FC	8:30 - 13:05
US 2-Year T-Note Futures	TU	8:20 - 15:00	Live Cattle Futures	LC	8:30 - 13:05
US 5-Year T-Note Futures	FV	8:20 - 15:00	Lean Hogs Futures	LH	8:30 - 13:05
US 10-Year T-Note Futures	TY	8:20 - 15:00			
US 30-Year T-Bond Futures	US	8:20 - 15:00	Currency Futures		
Ultra T-Bond Futures	UB	8:20 - 15:00	Australian Dollar Futures	AD	7:20 - 14:00
Euro-Schatz 2-Year Futures	BZ	8:00 - 17:15	British Pound Futures	BP	7:20 - 14:00
Euro-Bobl 5-Year Futures	BL	8:00 - 17:15	Canadian Dollar Futures	CD	7:20 - 14:00
Euro-Bund 10-Year Futures	BN	8:00 - 17:15	Euro FX Futures	EC	7:20 - 14:00
Euro-Buxl 30-Year Futures	BX	8:00 - 17:15	Japanese Yen Futures	JY	7:20 - 14:00
Short-Term Euro-BTP Futures	BS	8:00 - 17:15	Mexican Peso Futures	ME	7:20 - 14:00
Long-Term Euro-BTP Futures	BT	8:00 - 17:15	New Zealand Dollar Futures	NZ	7:20 - 14:00
Long Gilt Futures	GL	8:00 - 16:15	Swiss Franc Futures	SF	7:20 - 14:00
Australian 3-Year Bond Futures	AY	8:30 - 16:30			
Australian 10-Year Bond Futures	AX	8:32 - 16:30			
Japanese 10-Year Bond Futures JPX	JB	8:45 - 15:00			
Canadian 10-Year Futures	CB	8:20 - 15:00			

Table 2: This table shows the pooled regression results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), and the return until the last half-hour (r_{ROD}), for equity index futures (Panel A), government bond futures (Panel B), commodity futures (Panel C) and currency futures (Panel D). Trading hours of equity futures are based on the trading hours of their underlying markets, for other futures trading hours are matched to their volume patterns. The intercept is not reported. T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Samples range from December 1974 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	Panel A Equity Futures			Panel B Bond Futures		
β_{ONFH}	4.86*** (6.52)	4.72*** (6.46)		1.59*** (4.65)	1.66*** (4.99)	
β_M		2.92*** (4.43)			1.97*** (5.93)	
β_{SLH}		9.08*** (4.82)			3.11* (1.68)	
β_{ROD}			4.18*** (7.29)			1.90*** (5.97)
R^2(%)	1.49	2.74	2.45	0.2	0.66	0.64
R^2_{OOS}(%)	-1.71	2.22	2.88	-0.05	0.56	0.60
	Panel C Commodity Futures			Panel D Currency Futures		
β_{ONFH}	1.33*** (3.04)	1.29*** (3.02)		0.91*** (4.58)	0.91*** (4.61)	
β_M		0.85*** (2.73)			0.37 (1.60)	
β_{SLH}		2.24 (1.16)			0.62 (0.33)	
β_{ROD}			1.21*** (3.63)			0.72*** (4.57)
R^2(%)	0.09	0.15	0.15	0.19	0.21	0.19
R^2_{OOS}(%)	-0.01	-0.14	0.07	0.28	0.03	0.26

Table 3: This table reports the pooled regressions results for equation (11), conditioned on whether the first half hour return (r_{ONFH}) and the return until the last half hour (r_{ROD}) have (i) the same sign (row "Equal Sign"), (ii) have a different sign (row "Different Sign"), and (iii) without conditioning (row "Full Sample"). Results are shown for equity index futures (Panel A), government bond futures (Panel B), commodity futures (Panel C) and currency futures (Panel D). T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Samples range from December 1974 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	β_{ONFH}	$R^2(\%)$	β_{ROD}	$R^2(\%)$	β_{ONFH}	β_{ROD}	$R^2(\%)$
	Panel A: Equity Index Futures						
Equal Sign	5.75*** (6.78)	2.67	4.26*** (7.19)	3.13	1.80 (1.44)	3.23*** (3.39)	3.21
Different Sign	−3.71*** (−2.76)	0.28	3.59*** (3.54)	0.80	−0.46 (−0.33)	3.44*** (3.09)	0.79
Full Sample	4.86*** (6.52)	1.49	4.18*** (7.29)	2.45	1.14 (1.39)	3.65*** (5.28)	2.49
	Panel B: Government Bond Futures						
Equal Sign	1.94*** (5.04)	0.41	2.00*** (6.43)	0.91	−1.29*** (−2.77)	2.73*** (5.91)	0.97
Different Sign	−1.35 (−1.39)	0.04	1.32* (1.84)	0.14	−0.23 (−0.19)	1.25 (1.48)	0.14
Full Sample	1.59*** (4.65)	0.20	1.90*** (5.97)	0.64	−0.41 (−1.04)	2.07*** (5.17)	0.65
	Panel C: Commodity Futures						
Equal Sign	1.47*** (3.23)	0.14	1.19*** (3.50)	0.18	0.23 (0.36)	1.06** (2.09)	0.18
Different Sign	−0.47 (−0.56)	0.00	1.32*** (3.12)	0.09	0.94 (0.96)	1.52*** (3.07)	0.09
Full Sample	1.33*** (3.04)	0.09	1.21*** (3.63)	0.15	0.17 (0.39)	1.13*** (3.02)	0.15
	Panel D: Currency Futures						
Equal Sign	0.90*** (4.41)	0.24	0.74*** (4.73)	0.25	0.42 (1.03)	0.45 (1.46)	0.26
Different Sign	1.05 (1.33)	0.05	0.46 (0.69)	0.02	1.86** (2.18)	1.09 (1.46)	0.14
Full Sample	0.91*** (4.58)	0.19	0.72*** (4.57)	0.19	0.52 (1.51)	0.39 (1.45)	0.21

Table 4: This table shows the pooled regression results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), the return until the last half-hour (r_{ROD}), and the last half-hour return of the previous day ($r_{LH_{t-1}}$) for equity index futures (panel A), government bond futures (panel B), commodity futures (panel C) and currency futures (panel D). Trading hours of equity futures are based on the trading hours of their underlying markets, for other futures trading hours are matched to their volume patterns. The intercept is not reported. T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Samples range from December 1974 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	Panel A Equity Futures			Panel B Bond Futures		
β_{ONFH}	4.76*** (6.66)	4.63*** (6.55)		1.59*** (4.68)	1.66*** (5.02)	
β_M		2.97*** (4.54)			1.98*** (6.00)	
β_{SLH}		8.83*** (4.95)			3.13* (1.69)	
β_{ROD}			4.14*** (7.50)			1.90*** (6.01)
$\beta_{LH_{t-1}}$	−6.68*** (−2.66)	−6.56*** (−2.71)	−6.81*** (−2.75)	2.22 (1.36)	2.24 (1.36)	2.24 (1.35)
R^2(%)	1.94	3.17	2.91	0.25	0.71	0.69
R^2_{OOS}(%)	-1.40	2.51	2.77	0.00	0.61	0.66
	Panel C Commodity Futures			Panel D Currency Futures		
β_{ONFH}	1.33*** (3.03)	1.29*** (3.01)		0.93*** (4.66)	0.94*** (4.70)	
β_M		0.85*** (2.74)			0.37 (1.57)	
β_{SLH}		2.27 (1.18)			0.57 (0.30)	
β_{ROD}			1.21*** (3.63)			0.73*** (4.62)
$\beta_{LH_{t-1}}$	−1.04 (−0.99)	−1.09 (−1.03)	−1.07 (−1.02)	3.05*** (3.43)	3.03*** (3.42)	2.98*** (3.37)
R^2(%)	0.10	0.16	0.16	0.28	0.30	0.28
R^2_{OOS}(%)	0.17	0.03	0.24	0.25	0.00	0.22

Table 5: This table shows the pooled regression results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), and the return until the last half-hour (r_{ROD}), for equity index futures, government bond futures, commodity futures and currency futures for the subsamples 1974-1999 (Panel A) and 2000-2020 (Panel B). Trading hours of equity futures are based on the trading hours of their underlying markets, for other futures trading hours are matched to their volume patterns. The intercept is not reported. T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	β_{ONFH}	$R^2(\%)$	β_{ONFH}	β_M	β_{SLH}	$R^2(\%)$	β_{ROD}	$R^2(\%)$
				Panel A: 1974-1999				
Equity	3.73*** (2.74)	0.53	3.81*** (2.70)	6.94*** (4.25)	9.46*** (4.35)	3.74	5.96*** (4.80)	3.41
Bonds	1.65*** (3.49)	0.17	1.89*** (4.14)	3.71*** (7.46)	9.40*** (4.75)	1.68	3.19*** (8.38)	1.28
Commodity	0.83 (1.45)	0.03	0.72 (1.29)	2.08*** (4.06)	4.13*** (3.14)	0.31	1.59*** (3.92)	0.23
Currency	1.79*** (7.54)	0.68	1.84*** (7.66)	0.97*** (2.99)	−4.05 (−1.55)	0.95	1.31*** (6.48)	0.61
				Panel B: 2000-2020				
Equity	4.97*** (6.06)	1.67	4.83*** (6.02)	2.42*** (3.82)	8.89*** (4.11)	2.73	3.98*** (6.65)	2.34
Bonds	1.56*** (3.63)	0.21	1.60*** (3.79)	1.52*** (4.16)	1.00 (0.35)	0.47	1.53*** (3.61)	0.47
Commodity	1.58*** (3.22)	0.13	1.57*** (3.25)	0.34 (1.08)	0.86 (0.28)	0.14	1.04*** (2.86)	0.12
Currency	0.38 (1.29)	0.03	0.37 (1.27)	−0.04 (−0.12)	3.44 (1.41)	0.17	0.33 (1.45)	0.04

Table 6: This table shows annualized average returns, standard deviations and Sharpe Ratios (SR) together with the success rates of our three timing strategies; $\eta(r_{ONFH})$, $\eta(r_{ONFH}, r_{ROD})$, $\eta(r_{ROD})$ and two benchmark strategies; *Always Long* and *Buy & Hold*. Timing strategies $\eta(r_{ONFH})$ ($\eta(r_{ROD})$) take a long position when the first half hour return r_{ONFH} (return until 30 minutes before close r_{ROD}) is positive and a short position otherwise. Timing strategy $\eta(r_{ONFH}, r_{ROD})$ takes a long (short) position when both the first half hour return and the return until 30 minutes before close are positive (negative) and does not trade when signs differ. The benchmark strategy *Always Long* is always long during the last half hour, and *Buy & Hold* opens a position at the start of each futures sample and closes this at the end of the sample (May 2020). For each asset class a 1/N portfolio is used to combine the various futures belonging to the same asset class into one portfolio. Shown are the results for equity index futures (Panel A), government bond futures (Panel B), commodity futures (Panel C) and currency futures (Panel D). Samples range from December 1974 to May 2020.

	Avg ret(%)	Std dev(%)	SR	Success	Avg ret(%)	Std dev(%)	SR	Success
	Panel A: Equity Index Futures				Panel B: Government Bond Futures			
$\eta(r_{ONFH})$	4.21	3.95	1.07	0.55	1.08	1.33	0.81	0.53
$\eta(r_{ONFH}, r_{ROD})$	5.47	3.42	1.60	0.61	1.57	1.10	1.42	0.58
$\eta(r_{ROD})$	6.86	3.96	1.73	0.55	2.16	1.33	1.62	0.55
Always Long	0.44	4.20	0.11	0.53	0.48	1.42	0.34	0.53
Buy & Hold	8.76	17.29	0.51	0.54	4.07	5.96	0.68	0.53
	Panel C: Commodity Futures				Panel D: Currency Futures			
$\eta(r_{ONFH})$	2.48	3.03	0.82	0.54	0.93	0.97	0.96	0.54
$\eta(r_{ONFH}, r_{ROD})$	3.29	2.56	1.29	0.56	0.89	0.86	1.03	0.54
$\eta(r_{ROD})$	4.34	3.05	1.42	0.56	0.85	0.98	0.87	0.53
Always Long	-0.68	3.50	-0.19	0.51	0.49	1.13	0.43	0.52
Buy & Hold	1.92	13.34	0.14	0.51	0.53	7.27	0.07	0.50

Table 7: This table reports the regressions results of regressing $r_{LH,t}$ on $r_{ROD,t}$, conditioned on the sign of the Net Gamma Exposure (NGE) for the S&P500 futures. Newey and West (1986) robust t-statistics are shown in parentheses. Samples range from January 1996 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, and coefficients are multiplied by 100.

	Intercept	$\beta_{ROD,t}$	$R^2(\%)$
$NGE_{t-1} \geq 0$	0.00 (0.17)	0.82 (1.03)	0.05
$NGE_{t-1} < 0$	-0.01 (-0.63)	6.63*** (4.78)	3.58

Table 8: This table reports the regression results of regressing the last half-hour return (r_{LH}) on a constant, the return until the last half-hour (r_{ROD}), $I_{NGE<0} * r_{ROD,t}$, NGE_t and NGE_t multiplied by r_{ROD} for the S&P500 futures. X_t is computed as Net Gamma Exposure (NGE) divided by the market value of the S&P500 index. Newey and West (1986) robust t-statistics are shown in parentheses. Samples range from January 1996 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, and coefficients are multiplied by 100.

Variable	r_{LH}			Δr_{LH}	
	(1)	(2)	(3)	(4)	(5)
$Intercept$	-0.00	0.00	-0.00	-0.01	-0.01
	(-0.38)	(0.82)	(-0.47)	(-0.80)	(-0.85)
$r_{ROD,t}$	5.08***	1.41*	2.58***		
	(4.72)	(1.72)	(3.86)		
$I_{NGE\leq 0} * r_{ROD,t}$		5.05***			
		(3.04)			
$NGE * r_{ROD,t}$			-123.04***		
			(-3.42)		
NGE_t			0.21		
			(1.34)		
$\Delta r_{ROD,t}$				5.77***	3.33***
				(6.49)	(4.86)
$\Delta NGE * r_{ROD,t}$					-119.79***
					(-4.06)
ΔNGE_t					0.43**
					(2.51)
$R^2(\%)$	2.32	2.75	3.78	3.04	4.63

Table 9: This table reports the pooled regression results of regressing the last half-hour return (r_{LH}) on a constant, the return until the last half-hour (r_{ROD}), $Indexing_{LETF}$ and $Indexing_{LETF}$ multiplied by r_{ROD}, for equity index futures (Panel A) and government bond futures (Panel B). $Indexing_{LETF}$ is computed as the total market value of all Leveraged ETFs on the equity indices or government bond indices multiplied by $x^2 - x$, where x is their leverage factor, divided by their market size. Due to seasonality in government bond market sizes, we use three month rolling averages for this asset class. T-statistics that account for clustering on time and market (in case number of clusters exceeds 10) in parentheses, see Cameron et al. (2011). Samples range from June 2006 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients for r_{ROD} are multiplied by 100.

Panel A: Equity futures	r_{LH}		Δr_{LH}	
	(1)	(2)	(3)	(4)
$Intercept$	0.00 (0.83)	0.00 (0.51)	0.00 (0.01)	0.00 (0.01)
r_{ROD}	2.90*** (4.51)	2.91*** (4.51)		
$Indexing_{LETF} \cdot r_{ROD}$	1.79** (2.20)	1.79** (2.20)		
$Indexing_{LETF}$	0.25 (0.75)	0.71 (1.26)		
Δr_{ROD}			2.42*** (3.49)	2.42*** (3.49)
$\Delta Indexing_{LETF} \cdot r_{ROD}$			2.94*** (3.10)	2.94*** (3.10)
$\Delta Indexing_{LETF}$			−10.09*** (−3.36)	−10.19*** (−3.38)
$R^2(\%)$	1.75	1.76	1.67	1.67
Fixed Effects	No	Yes	No	Yes

Panel B: Bond futures	r_{LH}		Δr_{LH}	
	(1)	(2)	(3)	(4)
$Intercept$	−0.00* (−1.88)	−0.00*** (−2.83)	−0.00* (−1.70)	−0.00** (−2.38)
r_{ROD}	1.07*** (2.85)	1.08*** (2.91)		
$Indexing_{LETF} \cdot r_{ROD}$	0.67* (1.96)	0.67** (1.96)		
$Indexing_{LETF}$	0.03 (0.40)	0.20 (1.64)		
Δr_{ROD}			0.38* (1.65)	0.38* (1.65)
$\Delta Indexing_{LETF} \cdot r_{ROD}$			0.24* (1.77)	0.24* (1.78)
$\Delta Indexing_{LETF}$			−0.86** (−2.51)	−0.92*** (−2.77)
$R^2(\%)$	1.01	1.06	0.34	0.35
Fixed Effects	No	Yes	No	Yes

Table 10: This table shows the pooled regression results of regressing the return post a jump on a constant and the return from the previous day's close until jump. A jump is defined as each daily half hour in which the return from close to that half-hour interval is below (above) the 10% (90%) percentile of daily returns for that asset. The dependent variables are the return in the period post the jump to close ($r_{Postjump}$), the return after the half-hour post jump to the second-to-last half hour ($r_{PostjumptoSLH}$), and the last half-hour return (r_{LH}). The sample includes equity index futures, government bond futures, commodity futures and currency futures, and range from December 1974 to May 2020. Trading hours of equity futures are based on the trading hours of their underlying markets, for other futures trading hours are matched to their volume patterns. The intercept is not reported. T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	$r_{Postjump}$	$R^2(\%)$	$r_{PostjumptoSLH}$	$R^2(\%)$	r_{LH}	$R^2(\%)$
Equity	6.74*** (5.03)	1.83	1.50 (1.40)	0.14	5.16*** (7.51)	4.96
Bonds	1.63 (1.42)	0.14	0.34 (0.36)	0.01	1.58*** (4.64)	0.89
Commodity	3.28*** (3.55)	0.70	2.16*** (3.60)	0.49	1.00** (2.54)	0.24
Currency	1.64** (2.45)	0.27	0.97* (1.72)	0.13	0.80*** (3.89)	0.53

Table 11: This table reports the pooled regression results of regressing the next day return ($r_{c,t}^{c,t+1}$), the next two days return ($r_{c,t}^{c,t+2}$), and the next three days return ($r_{c,t}^{c,t+3}$) on a constant and today's last half hour return ($r_{LH,t}$), for equity index futures (Panel A), government bond futures (Panel B), commodity futures (Panel C) and currency futures (Panel D). Trading hours of equity futures are based on the trading hours of their underlying markets, for other futures trading hours are matched to their volume patterns. T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Samples range from December 1974 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, intercept and slope coefficients are multiplied by 100.

Dep. Variable:	$r_{c,t}^{c,t+1}$	$r_{c,t}^{c,t+2}$	$r_{c,t}^{c,t+3}$	$r_{c,t}^{c,t+1}$	$r_{c,t}^{c,t+2}$	$r_{c,t}^{c,t+3}$
	Panel A: Equity Futures			Panel B: Bond Futures		
Intercept	0.02*	0.05**	0.07***	0.01***	0.03***	0.04***
	(1.95)	(2.55)	(2.98)	(4.53)	(5.30)	(5.79)
$r_{LH,t}$	−14.51*	−29.05***	−27.98***	1.77	−10.68	−19.64**
	(−1.70)	(−3.16)	(−2.61)	(0.41)	(−1.60)	(−2.21)
$R^2(\%)$	0.13	0.27	0.17	0.00	0.03	0.06
	Panel C: Commodity Futures			Panel D: Currency Futures		
Intercept	0.01	0.01	0.02	0.00	0.00	0.01
	(0.76)	(0.94)	(1.01)	(0.54)	(0.74)	(0.89)
$r_{LH,t}$	−0.82	−8.56	−12.22**	−8.06	−8.64	−6.98
	(−0.25)	(−1.61)	(−2.17)	(−1.32)	(−1.14)	(−0.84)
$R^2(\%)$	-0.00	0.03	0.04	0.02	0.01	0.00

Table 12: This table reports the results of regressing the last half-hour return (r_{LH}), last fifteen-minute return ($r^{c,t}_{c-15,t}$) or last five-minute return ($r^{c,t}_{c-5,t}$) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M), second-to-last half hour return (r_{SLH}) and the return until the last half-hour (r_{ROD}) for the S&P 500 index in Panel A (close 16:00 ET) and for the S&P 500 index futures in Panel B (close 16:15 ET). The intercept is not reported. Newey and West (1986) robust t-statistics are shown in parentheses. Sample ranges from April 1982 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	β_{ONFH}	$R^2(\%)$	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	$R^2(\%)$	β_{ROD}	$R^2(\%)$
				Panel A: 16:00 Close				
r_{LH}	5.14***	0.96	4.78***	5.58**	18.47***	3.69	5.98***	3.28
	(3.36)		(3.22)	(2.25)	(3.90)		(4.78)	
$r^{c,t}_{c-15,t}$	2.97***	0.80	2.84***	2.53**	6.90**	1.88	2.83***	1.81
	(3.21)		(3.11)	(2.00)	(2.57)		(3.99)	
$r^{c,t}_{c-15,t}$	2.15***	1.29	2.07**	1.73***	4.01***	2.63	1.94***	2.65
	(2.60)		(2.56)	(4.77)	(3.18)		(5.03)	
				Panel B: 16:15 Close				
r_{LH}	3.98***	0.77	3.68***	1.69	10.10***	1.87	3.28***	1.48
	(3.07)		(2.79)	(1.58)	(4.45)		(5.09)	
$r^{c,t}_{c-15,t}$	0.01	-0.01	0.00	−1.04*	−0.03	0.22	−0.37	0.05
	(0.01)		(0.01)	(−1.89)	(−0.02)		(−0.97)	
$r^{c,t}_{c-15,t}$	0.40	0.06	0.43	−0.92*	−1.02	0.52	−0.28	0.09
	(0.87)		(0.95)	(−1.88)	(−0.94)		(−1.06)	

References

Admati, A. R. and Pfleiderer, P. (1988). A theory of intraday patterns: Volume and price variability. *The Review of Financial Studies*, 1(1):3–40.

Baltussen, G., van Bekkum, S., and Da, Z. (2019). Indexing and stock market serial dependence around the world. *Journal of Financial Economics*, 132(1):26–48.

Barberis, N., Shleifer, A., and Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, 75(2):283–317.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., and Shephard, N. (2008). Designing realized kernels to measure the ex post variation of equity prices in the presence of noise. *Econometrica*, 76(6):1481–1536.

Ben-David, I., Franzoni, F., and Moussawi, R. (2018). Do etfs increase volatility? *The Journal of Finance*, 73(6):2471–2535.

Bjønnes, G. H. and Rime, D. (2005). Dealer behavior and trading systems in foreign exchange markets. *Journal of Financial Economics*, 75(3):571 – 605.

Bogousslavsky, V. (2016). Infrequent rebalancing, return autocorrelation, and seasonality. *The Journal of Finance*, 71(6):2967–3006.

Bogousslavsky, V. (2020). The cross-section of intraday and overnight returns. *Working paper*.

Bogousslavsky, V. and Muravyev, D. (2019). Should we use closing prices? institutional price pressure at the close. *Working paper*.

Bollen, N. P. and Whaley, R. E. (2004). Does net buying pressure affect the shape of implied volatility functions? *The Journal of Finance*, 59(2):711–753.

Bollerslev, T., Cai, J., and Song, F. M. (2000). Intraday periodicity, long memory volatility, and macroeconomic announcement effects in the us treasury bond market. *Journal of Empirical Finance*, 7(1):37–55.

Bollerslev, T., Hood, B., Huss, J., and Pedersen, L. H. (2018). Risk everywhere: Modeling and managing volatility. *The Review of Financial Studies*, 31(7):2729–2773.

Brock, W. A. and Kleidon, A. W. (1992). Periodic market closure and trading volume: A model of intraday bids and asks. *Journal of Economic Dynamics and Control*, 16(3):451 – 489.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2):238–249.

Chang, E. C., Jain, P. C., and Locke, P. R. (1995). Standard & poor's 500 index futures volatility and price changes around the new york stock exchange close. *Journal of Business*, pages 61–84.

Cheng, M. and Madhavan, A. (2010). The dynamics of leveraged and inverse exchange-traded funds. *The Journal of Investment Management*, 7(4):43–62.

Cici, G. and Palacios, L.-F. (2015). On the use of options by mutual funds: Do they know what they are doing? *Journal of Banking & Finance*, 50:157–168.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1):291–311.

Clewlow, L. and Hodges, S. (1997). Optimal delta-hedging under transactions costs. *Journal of Economic Dynamics and Control*, 21(8):1353 – 1376. Computational financial modelling.

Da, Z. and Shive, S. (2018). Exchange traded funds and asset return correlations. *European Financial Management*, 24(1):136–168.

Elaut, G., Frömmel, M., and Lampaert, K. (2018). Intraday momentum in fx markets: Disentangling informed trading from liquidity provision. *Journal of Financial Markets*, 37:35 – 51.

Ferguson, M. F. and Mann, S. C. (2001). Execution costs and their intraday variation in futures markets. *The Journal of Business*, 74(1):125–160.

Gao, L., Han, Y., Li, S. Z., and Zhou, G. (2018). Market intraday momentum. *Journal of Financial Economics*.

Garleanu, N., Pedersen, L. H., and Poteshman, A. M. (2008). Demand-based option pricing. *The Review of Financial Studies*, 22(10):4259–4299.

Gerety, M. S. and Mulherin, J. H. (1992). Trading halts and market activity: An analysis of volume at the open and the close. *The Journal of Finance*, 47(5):1765–1784.

Goyenko, R. and Zhang, C. (2019). Option returns: Closing prices are not what you pay. *Working paper.*

Greenwood, R. (2005). Short-and long-term demand curves for stocks: theory and evidence on the dynamics of arbitrage. *Journal of Financial Economics*, 75(3):607–649.

Greenwood, R. (2008). Excess comovement of stock returns: Evidence from cross-sectional variation in nikkei 225 weights. *The Review of Financial Studies*, 21(3):1153–1186.

Hendershott, T., Livdan, D., and Rösch, D. (2020). Asset pricing: A tale of night and day. *Journal of Financial Economics.*

Heston, S. L., Korajczyk, R. A., and Sadka, R. (2010). Intraday patterns in the cross-section of stock returns. *The Journal of Finance*, 65(4):1369–1407.

Hong, H., Kubik, J. D., and Fishman, T. (2012). Do arbitrageurs amplify economic shocks? *Journal of Financial Economics*, 103(3):454–470.

Hong, H. and Wang, J. (2000). Trading and returns under periodic market closures. *The Journal of Finance*, 55(1):297–354.

Israeli, D., Lee, C. M., and Sridharan, S. A. (2017). Is there a dark side to exchange traded funds? an information perspective. *Review of Accounting Studies*, 22(3):1048–1083.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1):65–91.

Leland, H. and Rubinstein, M. (1976). The evolution of portfolio insurance. *Dynamic Hedging.*

Leland, H. E. (1985). Option pricing and replication with transactions costs. *The Journal of Finance*, 40(5):1283–1301.

Lou, D., Polk, C., and Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, 34(1):192–213.

Lyons, R. K. (1995). Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics*, 39(2):321 – 351.

Manaster, S. and Mann, S. (1996). Life in the pits: Competitive market making and inventory control. *Review of Financial Studies*, 9(3):953–75.

Martens, M. and Van Dijk, D. (2007). Measuring volatility with the realized range. *Journal of Econometrics*, 138(1):181–207.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2):228–250.

Muravyev, D. and Ni, X. C. (2019). Why do option returns change sign from day to night? *Journal of Financial Economics*, page forthcoming.

Newey, W. K. and West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix.

Sepp, A. (2013). When you hedge discretely: Optimization of sharpe ratio for delta-hedging strategy under discrete hedging and transaction costs. *Journal of Investment Strategies*, 3(1):19–59.

Shum, P., Hejazi, W., Haryanto, E., and Rodier, A. (2015). Intraday share price volatility and leveraged etf rebalancing. *Review of Finance*, 20(6):2379–2409.

Todorov, K. (2019). Passive funds actively affect prices: Evidence from the largest etf markets. *Working paper.*

Tosini, P. A. (1988). Stock index futures and stock market activity in october 1987. *Financial Analysts Journal*, 44(1):28–37.

Wurgler, J. (2011). On the economic consequences of index-linked investing. *In: Allen, W.T., Khurana, R., Rosenfeld, G. (Eds.), Challenges to Business in the Twenty-First Century: The Way Forward. American Academy of Arts and Sciences, Cambridge, MA.*

Appendix

This Appendix is divided into four sections. The first section (subsection A) elaborates on the futures contracts used in this research. The second section (subsection B) shows results for the individual markets. The third section (subsection C) shows the results for equity cash indices as opposed to futures contracts. Finally, subsection D shows the horserace results for the different subperiods.

A Details on Futures Contracts

Table A1: Overview of equity index futures used. Symbols as listed on www.tickdata.com, start of the sample period, end of sample period, trading hours we consider as a trading day, number of observations after filtering and the geographical group a future belongs to. A * indicates futures where sample period is extended by considering the regular future before the mini contract was introduced. The symbol given is the Ticker used by Tickdata.com, which is not necessarily the exchange ticker. Trading hours provided are the current trading hours, however some indices have changed over time, for which the data has been adjusted. Trading hours are expressed in the local exchange time zone, with US listed futures being denoted in Eastern Standard Time (EST).

Future	Symbol	Start	End	Obs	Times	Group
Dow Jones Futures*	YM	1997-10-08	2020-05-01	5639	09:30 - 16:00	USA
S&P 500 Futures*	ES	1982-04-23	2020-05-01	9535	09:30 - 16:00	USA
NASDAQ 100 Futures*	NQ	1996-04-12	2020-05-01	6017	09:30 - 16:00	USA
Russell 2000 ICE/CME*	ER	1993-02-08	2020-05-01	6746	09:30 - 16:00	USA
S&P 400 MidCap Futures*	MI	1993-01-06	2020-05-01	6594	09:30 - 16:00	USA
Amsterdam AEX Index Futures	EO	2008-01-04	2020-05-01	3136	09:00 - 17:30	EU
DAX Index Futures	DA	1997-01-06	2020-05-01	5911	09:00 - 17:30	EU
Swiss Market Index Futures	SW	2005-11-21	2020-05-01	3624	09:00 - 17:30	EU
EURO STOXX 50 Index Futures	XX	1998-07-03	2020-05-01	5550	09:00 - 17:30	EU
CAC 40 Index Futures	CF	2000-05-04	2020-05-01	5093	09:00 - 17:30	EU
IBEX 35 Index Futures	IB	2003-07-03	2020-05-01	4275	09:00 - 17:30	EU
FTSE MIB Index Futures	II	2004-10-05	2020-05-01	3951	09:00 - 17:30	EU
FTSE 100 Index Futures	FT	1998-07-03	2020-05-01	5484	08:00 - 16:30	EU
Nikkei 225 Futures SGX	EN	1997-04-03	2020-04-02	5560	08:00 - 14:00	Australasia
TOPIX Futures JPX	TP	2003-07-03	2020-05-01	4118	09:00 - 15:00	Australasia
ASX SPI 200 Index Futures	XP	2001-07-04	2020-03-19	4538	10:00 - 16:00	Australasia
S&P Canada 60 Futures	PT	1999-10-05	2020-05-01	5142	09:30 - 16:00	-

Table A2: Overview of government bond futures used. Symbols as listed on www.tickdata.com, start of the sample period, end of sample period, trading hours we consider as a trading day, number of observations after filtering and the geographical group a future belongs to. The symbol given is the Ticker used by Tickdata.com, which is not necessarily the exchange ticker. Trading hours provided are the current trading hours, however some indices have changed over time, for which the data has been adjusted. Trading hours are expressed in the local exchange time zone, with US listed futures being denoted in Eastern Standard Time (EST).

Future	Symbol	Start	End	Obs	Times	Group
US 2-Year T-Note Futures	TU	1991-01-04	2020-05-01	7153	08:20 - 15:00	USA
US 5-Year T-Note Futures	FV	1988-07-06	2020-05-01	7907	08:20 - 15:00	USA
US 10-Year T-Note Futures	TY	1983-01-05	2020-05-01	9296	08:20 - 15:00	USA
US 30-Year T-Bond Futures	US	1982-10-05	2020-05-01	9366	08:20 - 15:00	USA
Ultra T-Bond Futures	UB	2010-02-03	2020-05-01	2564	08:20 - 15:00	USA
Euro-Schatz 2-Year Futures	BZ	1997-03-11	2020-05-01	5874	08:00 - 17:15	EU
Euro-Bobl 5-Year Futures	BL	1997-01-06	2020-05-01	5921	08:00 - 17:15	EU
Euro-Bund 10-Year Futures	BN	1997-01-06	2020-05-01	5921	08:00 - 17:15	EU
Euro-Buxl 30-Year Futures	BX	2005-09-13	2020-05-01	3720	08:00 - 17:15	EU
Short-Term Euro-BTP Futures	BS	2010-10-21	2020-05-01	2421	08:00 - 17:15	EU
Long-Term Euro-BTP Futures	BT	2010-02-24	2020-05-01	2591	08:00 - 17:15	EU
Long Gilt Futures	GL	1998-07-03	2020-05-01	5485	08:00 - 16:15	EU
Australian 3-Year Bond Futures	AY	2001-07-04	2020-05-01	4738	08:30 - 16:30	Australasia
Australian 10-Year Bond Futures	AX	2001-07-04	2020-05-01	4737	08:32 - 16:30	Australasia
Japanese 10-Year Bond Futures JPX	JB	2003-07-03	2020-05-01	4117	08:45 - 15:00	Australasia
Canadian 10-Year Futures	CB	1990-04-04	2020-05-01	7368	08:20 - 15:00	-

Table A3: Overview of commodity futures used. Symbols as listed on www.tickdata.com, start of the sample period, end of sample period, trading hours we consider as a trading day, number of observations after filtering and the categorical group a future belongs to. The symbol given is the Ticker used by Tickdata.com, which is not necessarily the exchange ticker. Trading hours provided are the current trading hours, however some indices have changed over time, for which the data has been adjusted. Trading hours are expressed in the local exchange time zone, except for CC, CT, KC, SB, which are expressed in London time.

Future	Symbol	Start	End	Obs	Times	Group
Gold Futures COMEX	GC	1984-01-05	2020-05-01	9044	08:20 - 13:30	Metals
Copper High Grade Futures COMEX	HG	1989-12-05	2020-05-01	7608	08:10 - 13:00	Metals
Silver Futures COMEX	SV	1983-12-05	2020-05-01	9064	08:25 - 13:25	Metals
Palladium Futures NYMEX	PA	1994-01-05	2020-05-01	5495	08:30 - 13:00	Metals
Platinum Futures NYMEX	PL	2007-10-03	2020-03-30	2978	08:20 - 13:05	Metals
Light Crude Oil Futures NYMEX	CL	1987-01-06	2020-05-01	8336	09:00 - 14:30	Energies
Heating Oil #2 Futures NYMEX	HO	1984-01-05	2020-05-01	9060	09:00 - 14:30	Energies
Natural Gas Futures NYMEX	NG	1993-01-06	2020-05-01	6824	09:00 - 14:30	Energies
RBOB Gasoline Futures NYMEX	XB	2006-10-04	2020-05-01	3417	09:00 - 14:30	Energies
Soybean Oil Futures	BO	1982-07-06	2020-05-01	9458	08:30 - 13:20	Softs
Corn Futures	CN	1982-07-06	2020-05-01	9462	08:30 - 13:20	Softs
Soybean Meal Futures	SM	1982-07-06	2020-05-01	9458	08:30 - 13:20	Softs
Soybean Futures	SY	1982-07-06	2020-05-01	9462	08:30 - 13:20	Softs
Wheat Futures CBOT	WC	1982-07-06	2020-05-01	9462	08:30 - 13:20	Softs
Cocoa Futures	CC	1986-07-07	2020-05-01	8389	09:45 - 18:30	Softs
Cotton #2 Futures	CT	1987-01-07	2020-05-01	8168	02:00 - 19:20	Softs
Coffee “C” Futures	KC	1987-01-07	2020-05-01	8201	09:15 - 18:30	Softs
Sugar #11 Futures	SB	1986-07-07	2020-05-01	8345	08:30 - 18:00	Softs
Feeder Cattle Futures	FC	1984-08-15	2020-05-01	8164	08:30 - 13:05	Softs
Live Cattle Futures	LC	1984-08-14	2020-05-01	8797	08:30 - 13:05	Softs
Lean Hogs Futures	LH	1981-04-03	2020-05-01	9499	08:30 - 13:05	Softs

Table A4: Overview of currency futures used. Symbols as listed on www.tickdata.com, start of the sample period, end of sample period, trading hours we consider as a trading day and the number of observations after filtering. Trading hours are expressed in the local exchange time zone.

Future	Symbol	Start	End	Obs	Times
Australian Dollar Futures	AD	1987-01-15	2020-04-13	8139	07:20 - 14:00
British Pound Futures	BP	1977-09-06	2020-05-01	10570	07:20 - 14:00
Canadian Dollar Futures	CD	1977-01-05	2020-03-16	10658	07:20 - 14:00
Euro FX Futures	EC	1999-01-06	2020-05-01	5284	07:20 - 14:00
Japanese Yen Futures	JY	1977-03-14	2020-04-23	10553	07:20 - 14:00
Mexican Peso Futures	ME	2002-07-12	2020-04-09	4255	07:20 - 14:00
New Zealand Dollar Futures	NZ	2010-01-06	2020-05-01	2584	07:20 - 14:00
Swiss Franc Futures	SF	1974-12-04	2020-05-01	11233	07:20 - 14:00

B Individual Market Results

Table B1: Equities. This table shows the pooled (Panel A) and individual (Panel B) results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), and the return until the last half-hour (r_{ROD}), for equity index futures. Trading hours based on the trading hours of their underlying markets. Intercepts are not reported. Panel A: T-statistics that account for clustering on time and market (in case number of clusters exceeds 10) in parentheses, see Cameron et al. (2011). Panel B: Newey and West (1986) robust t-statistics in parentheses. Samples range from April 1982 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, R^2_{OOS} and slope coefficients are multiplied by 100.

Panel A: Pooled Regressions

	β_{ONFH}	R^2(%)	R^2_{OOS}(%)	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	R^2(%)	R^2_{OOS}(%)	β_{ROD}	R^2(%)	R^2_{OOS}(%)
Total	4.86*** (6.52)	1.49	-1.71	4.72*** (6.46)	2.92*** (4.43)	9.08*** (4.82)	2.74	2.22	4.18*** (7.29)	2.45	2.88
USA	6.92*** (4.67)	1.80	-0.87	6.50*** (4.49)	4.47*** (4.22)	12.58*** (3.66)	3.84	2.60	5.99*** (6.66)	3.46	3.09
EU	4.62*** (5.62)	1.76	1.60	4.59*** (5.57)	2.33*** (3.99)	5.05*** (2.83)	2.60	2.22	3.48*** (7.41)	2.36	2.50
Australasia	2.97*** (4.30)	1.17	1.03	2.90*** (4.29)	0.39 (0.42)	8.66*** (3.37)	1.73	1.03	2.40*** (5.33)	1.17	0.85

Panel B: Individual Regressions

	β_{ONFH}	R^2(%)	R^2_{OOS}(%)	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	R^2(%)	R^2_{OOS}(%)	β_{ROD}	R^2(%)	R^2_{OOS}(%)
YM	6.07*** (3.28)	1.34	1.31***	5.71*** (3.19)	2.77* (1.91)	13.09** (2.46)	2.75	2.34***	5.02*** (4.12)	2.20	2.18***
ES	5.24*** (3.38)	0.98	-1.68	4.81*** (3.25)	6.06** (2.48)	12.39*** (3.49)	3.74	1.21***	6.18*** (4.97)	3.41	2.29***
NQ	7.45*** (5.33)	2.01	1.83***	6.95*** (5.03)	5.14*** (4.74)	11.54*** (3.26)	4.31	3.58***	6.36*** (7.97)	4.10	3.76***
ER	8.17*** (4.62)	2.38	2.21***	7.79*** (4.54)	3.61*** (3.15)	12.27** (2.17)	3.91	3.33***	6.00*** (5.86)	3.35	3.15***
MI	7.34*** (4.06)	2.41	2.23***	6.99*** (4.09)	3.59*** (3.26)	14.67*** (3.23)	4.46	3.87***	5.85*** (5.53)	3.69	3.46***
EO	3.82*** (2.62)	1.68	-1.91	3.78*** (2.71)	0.62 (0.75)	2.69 (0.69)	1.75	-3.05	2.23** (2.33)	1.24	-1.91
DA	4.57*** (5.45)	1.67	1.19***	4.69*** (5.58)	2.14*** (2.99)	4.97*** (2.72)	2.39	0.42***	3.42*** (6.28)	2.13	0.42***
SW	3.52*** (3.02)	1.11	0.71***	3.41*** (3.01)	0.43 (0.42)	3.80 (1.17)	1.21	0.17***	1.98** (2.26)	0.80	0.37
XX	5.66*** (6.02)	2.30	2.44***	5.73*** (6.13)	4.17*** (5.01)	5.91** (2.42)	4.10	3.26***	4.98*** (7.61)	4.06	3.67***
CF	4.82*** (5.55)	1.89	1.72***	4.81*** (5.63)	3.07*** (3.79)	6.64*** (2.82)	3.30	0.42***	4.07*** (6.37)	3.14	0.85***
IB	2.35** (2.25)	0.50	0.10*	2.27** (2.21)	−0.38 (−0.60)	2.83 (1.05)	0.56	-0.28*	0.93 (1.45)	0.18	-0.21
II	5.39*** (5.42)	2.26	1.94***	5.13*** (5.32)	3.49*** (5.83)	6.53** (2.24)	4.29	3.31***	4.29*** (7.58)	4.15	3.68***
FT	5.76*** (6.91)	2.48	1.70***	5.78*** (7.00)	2.92*** (3.48)	4.41* (1.79)	3.37	1.96***	4.28*** (7.35)	3.09	2.03***
EN	3.31*** (3.13)	1.20	1.26***	3.16*** (3.06)	0.67 (0.74)	9.50*** (2.86)	1.84	1.36***	2.70*** (3.74)	1.30	1.20***
TP	3.92*** (3.59)	2.04	1.76***	3.80*** (3.58)	−0.75 (−0.70)	9.40** (2.17)	2.66	1.78***	2.77*** (3.22)	1.47	1.24***
XP	0.72 (0.94)	0.10	-0.25	0.76 (0.99)	1.59 (1.58)	2.80 (0.83)	0.39	-0.78	1.05* (1.73)	0.36	-0.13*
PT	2.08 (1.50)	0.28	0.09	1.80 (1.34)	1.11 (0.86)	12.18** (2.16)	1.26	0.56*	2.12** (2.36)	0.61	0.48**

Table B2: Bonds. This table shows the pooled (Panel A) and individual (Panel B) results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), and the return until the last half-hour (r_{ROD}), for government bond futures. Trading hours based on volume plots. Intercepts are not reported. Panel A: T-statistics that account for clustering on time and market (in case number of clusters exceeds 10) in parentheses, see Cameron et al. (2011). Panel B: Newey and West (1986) robust t-statistics in parentheses. Samples range from October 1982 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, R^2_{OOS} and slope coefficients are multiplied by 100.

Panel A: Pooled Regressions

	β_{ONFH}	$R^2(\%)$	$R^2_{OOS}(\%)$	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	$R^2(\%)$	$R^2_{OOS}(\%)$	β_{ROD}	$R^2(\%)$	$R^2_{OOS}(\%)$
Total	1.59*** (4.65)	0.20	-0.05	1.66*** (4.99)	1.97*** (5.93)	3.11* (1.68)	0.66	0.56	1.90*** (5.97)	0.64	0.60
USA	1.91*** (3.57)	0.30	-0.11	1.96*** (3.71)	2.77*** (5.23)	5.25 (1.42)	1.13	0.16	2.51*** (6.00)	1.03	0.29
EU	1.85*** (2.95)	0.22	0.04	1.99*** (3.20)	1.47*** (3.44)	2.58 (1.57)	0.57	-0.08	1.69*** (4.78)	0.56	0.29
Australasia	0.00 (0.01)	-0.01	-0.92	0.01 (0.03)	−0.22 (−0.38)	−14.07*** (−6.51)	1.33	0.52	−0.45 (−1.16)	0.04	-0.63

Panel B: Individual Regressions

	β_{ONFH}	$R^2(\%)$	$R^2_{OOS}(\%)$	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	$R^2(\%)$	$R^2_{OOS}(\%)$	β_{ROD}	$R^2(\%)$	$R^2_{OOS}(\%)$
TU	1.37** (2.11)	0.17	0.09*	1.56** (2.44)	2.34*** (3.41)	4.83 (1.52)	0.80	0.26**	2.07*** (4.45)	0.71	0.70***
FV	1.67*** (3.35)	0.27	0.19***	1.82*** (3.72)	2.01*** (3.89)	8.77*** (2.93)	1.56	1.12***	2.33*** (6.25)	1.05	0.93***
TY	1.68*** (3.41)	0.24	0.16***	1.81*** (3.68)	2.60*** (5.21)	7.51*** (4.07)	1.33	0.91***	2.53*** (6.96)	1.06	0.86***
US	1.77*** (3.62)	0.21	0.09***	1.81*** (3.71)	2.59*** (5.03)	0.88 (0.15)	0.65	-0.43***	2.11*** (3.85)	0.64	0.22***
UB	2.46*** (2.79)	0.61	-2.24	2.44*** (2.77)	3.73*** (3.30)	15.06** (2.52)	3.49	-1.92**	3.39*** (4.36)	2.35	-3.40*
BZ	0.55 (0.61)	0.00	-0.12	0.77 (0.84)	1.56*** (2.59)	0.93 (0.38)	0.24	-0.19**	1.28** (2.26)	0.25	0.14**
BL	0.90 (1.23)	0.02	-0.05	1.00 (1.36)	0.91* (1.74)	4.72 (1.44)	0.28	-0.15**	1.19*** (2.70)	0.19	0.11**
BN	1.79** (2.54)	0.16	0.11**	1.97*** (2.78)	1.80*** (3.65)	3.67** (2.18)	0.67	0.36***	1.97*** (5.12)	0.67	0.54***
BX	2.08** (2.37)	0.23	0.02**	2.28*** (2.64)	1.63** (2.37)	−0.16 (−0.06)	0.51	0.01**	1.71*** (3.19)	0.52	0.33***
BS	1.51 (0.73)	0.15	0.12	1.03 (0.51)	1.74 (1.22)	12.47** (1.99)	2.23	0.96	2.02** (2.01)	1.20	1.02
BT	1.56 (1.47)	0.18	-0.11	1.52 (1.41)	1.64** (2.51)	11.13*** (2.95)	1.82	-0.98**	2.04*** (3.17)	1.07	0.81***
GL	2.02*** (3.28)	0.26	0.26***	2.05*** (3.34)	0.74 (1.43)	0.02 (0.01)	0.28	-0.11**	1.16*** (2.92)	0.23	0.02**
AY	−0.41 (−0.60)	0.01	-1.05	−0.38 (−0.54)	−0.38 (−0.58)	−17.25*** (−7.20)	2.01	0.70***	−0.82 (−1.55)	0.15	-0.87
AX	1.03 (0.89)	0.15	-0.56	0.90 (0.91)	2.07* (1.74)	−14.41*** (−2.86)	1.98	0.35*	1.06 (1.08)	0.26	-0.58
JB	1.73 (1.54)	0.17	-0.95	1.68 (1.50)	−1.67 (−1.16)	−3.59 (−0.85)	0.36	-1.15	−0.05 (−0.06)	-0.02	-0.56
CB	0.87* (1.78)	0.05	-0.10	0.93* (1.93)	1.52*** (3.02)	0.77 (0.36)	0.25	-0.07**	1.20*** (3.67)	0.25	0.19***

Table B3: Commodities. This table shows the pooled (Panel A) and individual (Panel B) results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), and the return until the last half-hour (r_{ROD}), for commodity futures. Trading hours based on volume plots. Intercepts are not reported. Panel A: T-statistics that account for clustering on time and market (in case number of clusters exceeds 10) in parentheses, see Cameron et al. (2011). Panel B: Newey and West (1986) robust t-statistics in parentheses. Samples range from April 1981 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, R^2_{OOS} and slope coefficients are multiplied by 100.

Panel A: Pooled Regressions											
	β_{ONFH}	R^2(%)	R^2_{OOS}(%)	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	R^2(%)	R^2_{OOS}(%)	β_{ROD}	R^2(%)	R^2_{OOS}(%)
Total	1.33*** (3.04)	0.09	-0.01	1.29*** (3.02)	0.85*** (2.73)	2.24 (1.16)	0.15	-0.14	1.21*** (3.63)	0.15	0.07
Metals	1.60*** (4.76)	0.28	0.21	1.61*** (4.80)	0.69* (1.77)	0.06 (0.05)	0.31	0.10	1.19*** (4.50)	0.26	0.31
Energies	2.80** (2.43)	0.35	0.03	2.75** (2.49)	1.25 (1.52)	0.73 (0.13)	0.42	-0.07	2.10** (2.34)	0.45	0.20
Softs	0.25 (0.70)	0.00	-0.06	0.19 (0.57)	0.61* (1.70)	3.50*** (2.62)	0.09	-0.14	0.65** (2.16)	0.04	-0.01

Panel B: Individual Regressions											
	β_{ONFH}	R^2(%)	R^2_{OOS}(%)	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	R^2(%)	R^2_{OOS}(%)	β_{ROD}	R^2(%)	R^2_{OOS}(%)
GC	1.43*** (2.98)	0.23	0.18***	1.43*** (2.97)	0.68 (1.20)	0.84 (0.44)	0.26	-0.19	1.09*** (2.95)	0.25	0.08**
HG	0.87* (1.86)	0.08	-0.02	0.92** (1.97)	0.38 (0.60)	−3.56* (−1.70)	0.15	-0.31	0.52 (1.34)	0.04	-0.25
SV	3.17*** (4.14)	0.84	0.73***	3.14*** (4.13)	2.33*** (3.58)	5.59** (2.48)	1.51	0.76***	2.93*** (5.44)	1.42	1.01***
PA	0.74 (1.32)	0.05	-0.15	0.64 (1.13)	−1.49 (−1.60)	−7.72*** (−3.08)	0.53	-0.01***	−0.32 (−0.63)	0.00	-0.16
PL	2.34*** (3.35)	0.95	1.02***	2.33*** (3.37)	0.42 (0.43)	0.89 (0.25)	0.90	0.68***	1.79*** (3.27)	0.79	0.96***
CL	2.00 (0.72)	0.17	-0.48	2.40 (1.12)	−0.06 (−0.03)	−13.95 (−0.99)	1.25	-1.77	0.67 (0.25)	0.03	-1.04
HO	2.25*** (2.76)	0.22	0.04	2.22*** (2.74)	2.24*** (3.15)	5.39** (2.40)	0.59	0.16***	2.40*** (4.95)	0.55	0.44***
NG	3.89*** (5.49)	0.68	0.61***	3.74*** (5.21)	1.80*** (2.58)	9.20*** (3.44)	1.34	0.94***	3.02*** (6.15)	1.04	0.92***
XB	2.90 (1.62)	0.38	-0.14	2.87 (1.60)	0.80 (0.47)	3.40 (0.47)	0.40	-0.83	1.92** (2.04)	0.32	-0.00
BO	−0.80 (−1.40)	0.02	-0.06	−0.86 (−1.48)	1.02 (1.20)	2.80 (1.22)	0.06	-0.36	0.03 (0.08)	-0.01	-0.06
CN	−0.13 (−0.26)	-0.01	-0.05	−0.21 (−0.41)	2.89*** (3.54)	0.79 (0.42)	0.21	0.03***	0.82** (2.09)	0.05	-0.01
SM	−0.95 (−1.58)	0.03	-0.04*	−1.02* (−1.68)	2.49*** (3.22)	−1.35 (−0.54)	0.18	-0.27***	0.18 (0.42)	-0.01	-0.07
SY	−1.17** (−2.17)	0.06	-0.04**	−1.23** (−2.26)	1.68** (2.01)	3.11 (1.19)	0.15	-0.45	−0.05 (−0.13)	-0.01	-0.07
WC	0.48 (0.73)	-0.00	-0.06	0.48 (0.73)	0.49 (0.57)	−1.74 (−0.85)	-0.00	-0.21	0.32 (0.67)	-0.00	-0.07
CC	1.50*** (2.59)	0.11	0.03***	1.44** (2.48)	0.20 (0.59)	2.00 (1.09)	0.12	-0.14**	0.70** (2.27)	0.07	0.02***
CT	−0.20 (−0.26)	-0.01	-0.05	−0.21 (−0.27)	−1.47*** (−2.94)	0.90 (0.45)	0.11	-0.08**	−0.90** (−2.16)	0.07	-0.02**
KC	1.46 (1.55)	0.07	0.00	1.24 (1.31)	1.39** (2.50)	5.65*** (3.07)	0.45	0.23***	1.72*** (3.30)	0.34	0.26***
SB	2.19** (2.26)	0.09	-0.09*	1.89* (1.93)	0.71 (1.11)	9.41*** (4.07)	0.66	0.29***	2.07*** (4.24)	0.29	0.08***
FC	0.06 (0.08)	-0.01	-0.06	0.01 (0.02)	−1.04 (−1.22)	1.99 (0.83)	0.03	-0.19	−0.34 (−0.72)	-0.00	-0.04
LC	−0.01 (−0.01)	-0.01	-0.05	−0.03 (−0.04)	0.01 (0.01)	6.14*** (2.77)	0.19	0.01**	0.42 (1.03)	0.00	-0.05
LH	0.56 (0.87)	0.00	-0.04	0.58 (0.89)	−0.98 (−1.18)	3.30* (1.76)	0.08	-0.06	0.03 (0.06)	-0.01	-0.06

Table B4: Currencies. This table shows the pooled (panel A) and individual (panel B) results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), and the return until the last half-hour (r_{ROD}), for currency futures. Trading hours based on volume plots. Intercepts are not reported. Panel A: T-statistics that account for clustering on time and market (in case number of clusters exceeds 10) in parentheses, see Cameron et al. (2011). Panel B: Newey and West (1986) robust t-statistics in parentheses. Samples range from December 1974 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, R^2_{OOS} and slope coefficients are multiplied by 100.

Panel A: Pooled Regressions

	β_{ONFH}	R^2(%)	R^2_{OOS}(%)	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	R^2(%)	R^2_{OOS}(%)	β_{ROD}	R^2(%)	R^2_{OOS}(%)
Total	0.91*** (4.58)	0.19	0.28	0.91*** (4.61)	0.37 (1.60)	0.62 (0.33)	0.21	0.03	0.72*** (4.57)	0.19	0.26

Panel B: Individual Regressions

	β_{ONFH}	R^2(%)	R^2_{OOS}(%)	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	R^2(%)	R^2_{OOS}(%)	β_{ROD}	R^2(%)	R^2_{OOS}(%)
AD	0.72** (2.27)	0.10	0.03*	0.71** (2.25)	1.23** (2.19)	1.36 (0.45)	0.22	-0.17**	0.89*** (3.25)	0.23	0.17***
BP	1.40*** (4.92)	0.49	0.46***	1.41*** (4.92)	−0.04 (−0.11)	−3.30 (−0.74)	0.59	-0.14***	0.76*** (2.95)	0.23	0.16***
CD	0.36 (0.97)	0.01	-0.05*	0.39 (1.06)	0.90** (2.23)	1.33 (0.52)	0.14	-0.16***	0.65* (1.94)	0.13	0.02***
EC	0.04 (0.12)	-0.02	-0.08	0.01 (0.04)	−0.47 (−1.25)	4.07 (1.44)	0.22	-0.30	−0.04 (−0.17)	-0.02	-0.07
JY	0.45* (1.72)	0.05	-0.01***	0.44* (1.68)	0.19 (0.40)	1.07 (0.41)	0.05	-0.23***	0.39 (1.54)	0.06	-0.01***
ME	1.13 (1.46)	0.18	-0.27	1.17 (1.51)	0.23 (0.31)	−0.08 (−0.03)	0.14	-1.23	0.70 (1.21)	0.10	-0.14
NZ	0.47 (0.94)	0.03	-0.23	0.54 (1.07)	0.84 (0.98)	8.21** (2.11)	0.97	0.07*	0.84** (2.07)	0.25	-0.25
SF	1.66*** (3.93)	0.62	0.55***	1.68*** (3.96)	0.37 (1.14)	−0.50 (−0.30)	0.63	0.38***	1.10*** (3.53)	0.46	0.40***

C Cash Index Results

Table C1: Overview of equity indices used. Symbols as listed on www.tickdata.com, start of the sample period, end of sample period, trading hours we consider as a trading day, number of observations after filtering and the geographical group a future belongs to. Trading hours are expressed in the local exchange time zone, with US listed futures being denoted in Eastern Standard Time (EST).

Index	Symbol	Start	End	#Obs	Trading hours	Group
Dow Jones Industrial Average Index	DJ	1993-04-05	2020-05-01	6757	09:30 - 16:00	USA
S&P 500 Index	SP	1983-02-03	2020-05-01	9312	09:30 - 16:00	USA
NASDAQ 100 Index	ND	1997-01-06	2020-05-01	5807	09:30 - 16:00	USA
S&P 400 MidCap Index	MD	1998-01-06	2020-05-01	5554	09:30 - 16:00	USA
Amsterdam AEX Index	AE	2008-01-04	2020-05-01	3116	09:00 - 17:30	EU
DAX Index	DA	2003-07-03	2020-05-01	4241	09:00 - 17:30	EU
Swiss Market Index	SW	2011-07-01	2020-05-01	2187	09:00 - 17:30	EU
EURO STOXX 50 Index	XX	2003-07-03	2020-05-01	4263	09:00 - 17:30	EU
CAC 40 Index	CF	2003-07-03	2020-05-01	4267	09:00 - 17:30	EU
IBEX 35 Index	IB	2003-07-03	2020-05-01	4248	09:00 - 17:30	EU
Nikkei 225 Index	NE	2003-07-03	2020-05-01	4090	09:00 - 15:00	Australasia
TOPIX Index	TP	2003-07-03	2020-05-01	4093	09:00 - 15:00	Australasia
S&P Canada 60 Index	SC	2003-07-04	2020-05-01	4188	09:30 - 16:00	-

Table C2: Equity indices. This table shows the pooled (panel A) and individual (panel B) results of regressing the last half-hour return (r_{LH}) on a constant and the first-half hour return (r_{ONFH}), return from first half-hour until last hour (r_M) and second-to-last half hour (r_{SLH}), and the return until the last half-hour (r_{ROD}), for equity indices. Intercepts are not reported. Panel A: T-statistics that account for clustering on time and market (in case number of clusters exceeds 10) in parentheses, see Cameron et al. (2011). Panel B: Newey and West (1986) robust t-statistics in parentheses. Samples range from February 1983 to May 2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2, R^2_{OOS} and slope coefficients are multiplied by 100.

Panel A: Pooled Regressions											
	β_{ONFH}	$R^2(\%)$	$R^2_{OOS}(\%)$	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	$R^2(\%)$	$R^2_{OOS}(\%)$	β_{ROD}	$R^2(\%)$	$R^2_{OOS}(\%)$
Total	4.38*** (5.31)	1.29	0.98	4.18*** (5.25)	2.35*** (2.63)	9.70*** (3.69)	2.46	3.3	3.70*** (4.73)	2.05	3.06
USA	6.71*** (5.30)	1.79	1.35	6.24*** (5.03)	4.50*** (4.35)	14.42*** (3.98)	4.32	3.76	6.03*** (7.27)	3.75	3.45
EU	2.82*** (2.83)	0.83	0.32	2.78*** (2.78)	0.67 (1.00)	2.16 (0.93)	0.93	-0.11	1.71*** (3.07)	0.70	0.23
Australasia	3.38*** (4.02)	1.62	1.39	3.31*** (3.88)	0.07 (0.05)	7.02* (1.74)	2.00	1.15	2.50*** (4.52)	1.37	1.19
Panel B: Individual Regressions											
	β_{ONFH}	$R^2(\%)$	$R^2_{OOS}(\%)$	$\beta_{r_{ONFH}}$	β_M	β_{SLH}	$R^2(\%)$	$R^2_{OOS}(\%)$	β_{ROD}	$R^2(\%)$	$R^2_{OOS}(\%)$
DJ	5.68*** (3.19)	1.15	0.97***	5.38*** (3.14)	2.48* (1.85)	12.49** (2.57)	2.41	1.83***	4.63*** (4.16)	1.88	1.69***
SP	6.26*** (3.99)	1.39	1.15***	5.68*** (3.86)	4.20*** (3.05)	15.36*** (4.04)	3.95	3.10***	5.84*** (5.58)	3.23	2.70***
ND	7.34*** (5.38)	2.09	2.09***	6.88*** (5.09)	5.63*** (5.47)	12.68*** (3.61)	4.99	4.07***	6.69*** (8.96)	4.74	4.39***
MD	7.04*** (5.52)	2.57	2.53***	6.53*** (5.47)	4.28*** (3.68)	18.86*** (3.87)	6.19	5.58***	6.21*** (6.65)	4.91	4.87***
AE	3.00** (2.31)	1.04	-1.46	2.97** (2.36)	1.04 (1.23)	2.53 (0.71)	1.19	-2.60	2.04** (2.31)	1.04	-1.70
DA	3.83*** (3.31)	1.37	1.00***	3.81*** (3.35)	0.51 (0.65)	1.60 (0.63)	1.38	0.46**	2.05*** (3.01)	0.89	0.66**
SW	2.27*** (2.60)	0.98	0.93**	2.36*** (2.59)	1.47** (2.33)	−1.82 (−0.63)	1.41	1.16**	1.76*** (2.94)	1.24	1.28**
XX	3.29*** (3.08)	1.03	0.65**	3.24*** (3.11)	1.24 (1.61)	2.99 (1.16)	1.27	0.43**	2.24*** (3.19)	1.12	0.87**
CF	2.44** (2.49)	0.58	0.27*	2.40** (2.53)	0.82 (1.06)	1.89 (0.62)	0.66	-0.13*	1.63** (2.38)	0.59	0.37*
IB	1.80* (1.77)	0.30	-0.14	1.72* (1.72)	−0.21 (−0.35)	2.96 (1.10)	0.35	-0.51	0.78 (1.23)	0.13	-0.28
NE	3.64*** (3.61)	1.84	1.60***	3.55*** (3.52)	0.35 (0.31)	6.72 (1.62)	2.18	1.39***	2.73*** (3.48)	1.62	1.44***
TP	3.09*** (3.49)	1.37	1.14***	3.03*** (3.39)	−0.26 (−0.24)	7.34 (1.64)	1.75	0.87***	2.24*** (3.31)	1.08	0.91***
SC	3.37** (1.98)	0.80	0.29	3.05* (1.87)	0.51 (0.30)	17.68** (2.30)	2.59	0.81**	2.74** (2.42)	1.04	0.41*

D Horserace subsamples

D.1 1974-1999

Table D1: This table reports the pooled regressions results for equation (11), conditioned on whether the first half hour return (r_{ONFH}) and the return until the last half hour (r_{ROD}) have (i) the same sign (row "Equal Sign"), (ii) have different sign (row "Different Sign"), and (iii) without conditioning (row "Full Sample"). T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Samples range from 1974-1999. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	β_{ONFH}	$R^2(\%)$	β_{ROD}	$R^2(\%)$	β_{ONFH}	β_{ROD}	$R^2(\%)$
	Panel A: Equity Index Futures						
Equal Sign	4.72*** (2.79)	1.08	6.13*** (4.68)	4.42	−7.66** (−2.12)	10.06*** (3.87)	5.47
Different Sign	−3.90** (−1.97)	0.20	4.92*** (2.63)	1.07	0.99 (0.61)	5.22*** (2.66)	1.06
Full Sample	3.73*** (2.74)	0.53	5.96*** (4.80)	3.41	−3.45** (−1.98)	7.32*** (4.74)	3.68
	Panel B: Government Bond Futures						
Equal Sign	2.57*** (5.26)	0.58	2.96*** (8.08)	1.44	−2.77*** (−3.16)	4.67*** (6.71)	1.64
Different Sign	−5.66*** (−4.47)	0.66	4.58*** (4.75)	1.08	−2.81* (−1.95)	3.70*** (3.38)	1.19
Full Sample	1.65*** (3.49)	0.17	3.19*** (8.38)	1.28	−2.41*** (−3.67)	4.35*** (7.94)	1.48
	Panel C: Commodity Futures						
Equal Sign	1.15* (1.95)	0.08	1.44*** (3.51)	0.24	−2.14*** (−2.84)	2.73*** (5.33)	0.31
Different Sign	−2.74** (−2.03)	0.08	2.57*** (3.37)	0.25	−0.58 (−0.44)	2.42*** (3.29)	0.24
Full Sample	0.83 (1.45)	0.03	1.59*** (3.92)	0.23	−1.64** (−2.30)	2.40*** (4.88)	0.28
	Panel D: Currency Futures						
Equal Sign	1.83*** (7.66)	0.92	1.46*** (7.47)	0.95	0.84* (1.73)	0.89** (2.23)	0.99
Different Sign	1.14 (0.96)	0.04	−0.42 (−0.39)	0.00	1.09 (1.04)	−0.07 (−0.06)	0.02
Full Sample	1.79*** (7.54)	0.68	1.31*** (6.48)	0.61	1.19** (2.47)	0.59 (1.49)	0.72

D.2 2000-2020

Table D2: This table reports the pooled regressions results for equation (11), conditioned on whether the first half hour return (r_{ONFH}) and the return until the last half hour (r_{ROD}) have (i) the same sign (row "Equal Sign"), (ii) have different sign (row "Different Sign"), and (iii) without conditioning (row "Full Sample"). T-statistics in parentheses are computed using standard errors that account for clustering on time and market (in case number of clusters exceeds 10), see Cameron et al. (2011). Samples range from 2000-2020. Significance at 1%, 5% and 10% level is denoted by ***, **, or *, respectively. Adjusted R^2 and slope coefficients are multiplied by 100.

	β_{ONFH}	R^2(%)	β_{ROD}	R^2(%)	β_{ONFH}	β_{ROD}	R^2(%)
	Panel A: Equity Index Futures						
Equal Sign	5.84*** (6.28)	2.94	4.05*** (6.55)	2.98	3.07*** (2.83)	2.27*** (2.95)	3.21
Different Sign	−3.69** (−2.39)	0.29	3.42*** (3.12)	0.76	−0.67 (−0.43)	3.21*** (2.75)	0.76
Full Sample	4.97*** (6.07)	1.67	3.97*** (6.66)	2.34	1.74** (2.07)	3.16*** (4.70)	2.44
	Panel B: Government Bond Futures						
Equal Sign	1.71*** (3.63)	0.34	1.72*** (4.43)	0.75	−0.99* (−1.80)	2.27*** (4.08)	0.79
Different Sign	0.19 (0.21)	-0.00	0.47 (0.47)	0.02	0.85 (0.68)	0.70 (0.58)	0.03
Full Sample	1.56*** (3.63)	0.21	1.53*** (3.61)	0.47	0.12 (0.26)	1.48*** (2.84)	0.47
	Panel C: Commodity Futures						
Equal Sign	1.15* (1.95)	0.08	1.44*** (3.51)	0.24	−2.14*** (−2.84)	2.73*** (5.33)	0.31
Different Sign	−2.74** (−2.03)	0.08	2.57*** (3.37)	0.25	−0.58 (−0.44)	2.42*** (3.29)	0.24
Full Sample	0.83 (1.45)	0.03	1.59*** (3.92)	0.23	−1.64** (−2.30)	2.40*** (4.88)	0.28
	Panel D: Currency Futures						
Equal Sign	0.34 (1.13)	0.03	0.27 (1.19)	0.03	0.23 (0.40)	0.11 (0.25)	0.03
Different Sign	0.99 (0.96)	0.04	1.11 (1.32)	0.13	2.39** (1.96)	1.94** (1.99)	0.37
Full Sample	0.38 (1.29)	0.03	0.33 (1.45)	0.04	0.15 (0.32)	0.23 (0.64)	0.04