Price Discovery Among the Punters: Using New Financial Betting Markets to Predict Intraday Volatility

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Abstract

The migration of financial betting to prediction market exchanges in the last 5 years has facilitated the creation of contracts that do not correspond to a security traded on a traditional exchange. The most popular of these have been binary options on the closing value of Dow Jones Industrial Average (DJIA). Prices of these options imply expectations of volatility over the very short term, and they can be used to construct an index that has significant incremental predictive power, even after controlling for multiple lags of realized volatility and implied volatility from longer-term options. The index also has significant incremental power in predicting volatility over the next day, week, or month and in predicting trending or mean reversal in the level of the DJIA.

Price Discovery Among the Punters: Using Financial Betting Markets to Predict Intraday Volatility

The United Kingdom's tax on stock exchange and futures transactions has encouraged the development of financial betting as an alternative for short-term speculators. Traditionally, most financial bets corresponded directly to a security traded on a traditional exchange, and thus academic interest in financial betting has typically focused on taxation issues.[1] In the last 5 years, however, the migration of financial betting to prediction market exchanges such as Tradesports and Betfair has facilitated bets that do not correspond to an existing future or option. The most popular of these by far are binary options on daily or, more recently, hourly values of the Dow Jones Industrial Average (DJIA).

This paper studies Tradesports' DJIA daily and intraday binary options, which expire at $10 if the DJIA is up or down by a specified number of points at a specified time, and $0 otherwise. As with all options, traders' valuations of these options imply expectations of future volatility. But whereas the value of DJIA options traded on Chicago Board of Trade (CBOT) or the Chicago Board Options Exchange (CBOE) depend on volatility to an expiry date that is usually at least a few weeks away, the value of Tradesports' options depend on volatility over the next few hours. I construct a measure of intraday implied volatility from the Tradesports options, and find that this measure is both a reasonably accurate predictor of realized volatility over the next few hours and adds a considerable amount of predictive power to a model that includes both

[1] See, for example, Paton, Siegel, and Williams (2002). The most common financial bet is a contract for differences (CFD), which functions like a futures contract (the payment on settlement depends on the difference between the underlying index at a specified time and the contracted price). Financial betting firms quote bid and ask prices for CFDs using current futures market prices, and usually immediately hedge bets in these markets.

multiple lags of realized volatility and implied volatility from CBOE options. This new measure of intraday implied volatility also appears to be a useful input into a model predicting longer-horizon volatility and persistence or mean reversion in DJIA levels.

The fact that meaningful price discovery is occurring in the Tradesports financial options markets may be surprising to some readers. One possible reason for the surprise is that the literature on prediction markets and other non-traditional exchanges has focused on markets on political events such as the Iowa Electronic Markets (Forsythe, et. al. 1992), and these markets have often been fairly illiquid. From 1992 to 2000, the most liquid political prediction markets were the Iowa markets on Presidential election winners, which averaged $13,000 in monthly trading volume (Berg, Nelson and Rietz, 2003).

While recent political markets on Tradesports, particularly those on the Iraq war and the 2004 Presidential election, have attracted more volume, the volume in most is dwarfed by trading in financial contracts, which have received much less academic attention.[2] In my sample period of June 2003 to August 2005, Tradesports' daily and intraday DJIA markets accounted for 25 percent of the exchange's monthly average of $23 million in trading volume, with other financial contracts (tracking longer horizons and/or other assets) accounting for another 12 percent (Table 1). In contrast, contracts on elections accounted for only 5 percent and contracts on other political or economic events (e.g., geopolitical, macroeconomic, legal) accounted for less than 2 percent.[3]

[2] The exceptions I am aware of are Tetlock (2004), who analyzes the comparative efficiency of Tradesports' financial and sports markets, Wolfers and Zitzewitz (2004, Table 4) who examine the efficiency of long-horizon contracts on the S&P 500, and Berg, Neumann, and Reitz (2005) who analyze pre-IPO markets run to estimate the value of Google. Tetlock is discussed more below.

[3] Markets on sporting events, particularly football, baseball, and basketball, account for almost all of the remaining 57 percent.

Indeed, a comparison of the volume of Tradesports options to volumes on the CBOT and CBOE reveals that Tradesports volumes have grown to the point where they are almost within an order of magnitude of volumes on the "real" options exchanges, at least by the second half of the sample period. Table 2 reports monthly volumes for the Tradesports daily DJIA binary options, for CBOT DJIA futures and options on futures, and for CBOE DJIA options. In terms of the number of contracts traded, the Tradesports markets have volumes that are comparable to the CBOT futures and are larger than either the CBOE or CBOT options markets. The economic size of the Tradesports contracts is smaller, however. While the notional value of a binary option is not well defined (since the derivative of its value with respect to the underlying is either zero or infinite), one can approximate the economic size of the risk transfer embodied by these contracts with the standard deviation of their daily change in value time the square root of their average holding period in days.[4] Doing so reveals that while CBOT futures volumes exceed Tradesports by a factor of about 191, CBOT and CBOE options volumes do so by factors of only 14 and 26, respectively.

The literature on political markets has found that despite their relatively low volumes, the markets provide prices that are reasonably efficient. Wolfers and Zitzewitz (2006a) provide a theoretical justification for why binary option prices should approximate the mean of market participants' beliefs, and Berg, et. al., (2003), Berg, Nelson, and Rietz (2003), Tetlock (2004), and Wolfers and Zitzewitz (2004, 2006b) provide some empirical evidence that prices are good predictors of expiry values in practice. Past studies have also found that changes in political market prices help explain

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[4] I estimate average holding period as the ratio of open interest and daily volume. For the Tradesports contracts, which expire on a daily basis, I use the standard deviation of the contract value to expiry instead of the daily return standard deviation, and I set the holding period equal to one day.

changes in the prices of affected assets. Slemrod and Greimel (1999) find that movements in the probability of the nomination of flat-tax-advocate Steve Forbes in 1996 were reflected in the prices of municipal bonds. Wolfers and Zitzewitz (2005) likewise find that changes in the probability of war with Iraq accounted for a large share of pre-war volatility in oil and equity markets. Knight (2006) finds that changes in the probability of a Bush victory in 2000 differently affected the value of “Bush” and “Gore” stocks. Snowberg, Wolfers, and Zitzewitz (2007) use high frequency data from Election night 2004 to show that election news was incorporated promptly into stock, bond, and oil futures.

In each of these examples, the existence of a prediction market measuring the probability of a particular event helps market participants understand the source of changes in asset prices affected by that event. Understanding the source of market movements can be a useful input into a trading strategy. For example, if one believes that the stock market is overreacting to the risk of war in Iraq, a stock market decline accompanied by an increase in the probability of war might lead one to buy. But normally the prediction market price does not imply a trading strategy on its own. Indeed, Wolfers and Zitzewitz (2005) and Snowberg, Wolfers, and Zitzewitz (2007) find that political news was incorporated more rapidly in financial markets than into prediction markets, a fact which would frustrate attempts to trade financial markets using prediction market price movements. In contrast, this paper’s results about intraday implied volatility being predictive of mean reversion in DJIA levels imply that prediction market prices can be used to both understand contemporaneous market movements and to predict future ones.

The remainder of the paper is organized as follows. The next section provides institutional background on the Tradesports DJIA markets, along with some tests of their efficiency. The following section discusses the construction of an implied volatility measure from the binary option prices, and tests whether this measure adds to existing models predicting high frequency volatility. A discussion follows.

The Tradesports DJIA Markets

The data for this project consist of every trade in Tradesports' daily and intraday DJIA markets from June 2003 to August 2005. The data are time stamped and were paired with the most recent prior values from minute-by-minute data on CBOT DJIA near-month future transaction prices and the CBOE's VXD index of 30-day-horizon implied volatility in DJIA options, as collected by CQG data factory.[5]

Tradesports binary options pay $10 if the DJIA is up or down from its prior close by a specified number of points at a specified time. By the end of the sample in August 2005, options were available with expiry times of 10 am, 1 pm, and 4 pm Eastern time, and with strike prices ranging from 150 points below to 150 points above the prior close, spaced in 25-point intervals. Since August 2005, options have been added with expiry times of 11 am, 12 pm, 2 pm, and 3 pm. Trading is concentrated on near-the-money options with the nearest expiry time (Table 3).

Participants trade at prices ranging from 0 to 100 percentage points. The minimum tick size declined from 1.0 to 0.1 percentage points about halfway through the sample period (September 13, 2004). Each percentage point represents 10 cents of

[5] Trading in the CBOE's DJIA volatility futures began in April 2005, but trading on the June and August 2005 expiry contracts was fairly limited, with volume on only about half of trading days. Given this limited liquidity, I chose not to make use of this indicator in this study.

contract value, so purchasing an option at 60 (or $6) yields a position that will yield a profit of either +$4 or -$6 on expiry. Traders can take either long or short positions in these options, and they must maintain account balances with the exchange sufficient to cover their worst-case losses. Traders place limit orders and can observe the 5-15 best priced outstanding orders on each side. If they choose, they can place a "market" order by entering a limit price at or above/below the current best ask/bid.

The exchange does not take positions, but instead charges fees on each trade and on contract expiry. These fees declined during the sample period. At the beginning of the sample, Tradesports charged both buyer and seller a fee of 4 cents (0.4 percentage points) per trade and charged an expiry fee of 4 cents on open positions. Therefore, a trader taking a position and holding it to expiry would have paid total fees of 8 cents per contract. In September 2004, trading fees were reduced to 2 cents for contracts with prices less than 5 or greater than 95, and in November 2004, trading fees were eliminated for limit orders that were not immediately filled.

One or more traders usually plays the role of a market maker, submitting simultaneous bid and ask prices that are usually separated by 2 to 5 percentage points (i.e., by 20 to 50 cents per contract). In the DJIA markets, there are reportedly 30-40 traders who trade regularly using an application programming interface (API). These traders have trading algorithms that observe recent market movements using a real-time data feed, calculate estimates of the options' value, and then submit orders based on differences between their estimate of value and existing orders. They currently account for over 95 percent of orders on the exchange; a majority of these are limit orders that are not immediately matched with an existing order. Prices on Tradesports can therefore be viewed as an aggregation of information from these traders' pricing models along with the beliefs of non-programmatic traders, most of whom trade by hand using the exchange's website.

For most traders, it is difficult to imagine a "liquidity" motive for trading binary options that expire in a few hours.[6] Therefore, it seems reasonable to assume that traders are motivated by a combination of entertainment seeking and a belief that they are differentially informed. Of course, given that profits from trading these contracts must sum to zero before fees, the latter belief must be mistaken, at least on average.

Table 4 reports average prices by time to expiry and moneyness, as measured by the log difference between their strike price and the most recent CBOT futures price, corrected for the spot-futures difference.[7] To make prices easier to interpret, prices and expiry values for contracts with a bearish frame (i.e., "will the DJIA close below X") are replaced with the implied data for the complementary bullishly framed contract.[8] As one would expect, prices of in-the-money (out-of-the-money) options are higher (lower) closer to expiry.

Table 5 examines the efficiency of these prices by examining returns to expiry (defined as the percentage point difference between a contract's price and its expiry value) by time and moneyness. Although point estimates are not significant for every cell, contracts expiring at 10 AM or 1 PM appear to have earned positive returns when

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[6] The exception to this would be financial betting firms, who do reportedly use the exchange to hedge positions taken by their customers.

[7] Corrected futures prices are used as an indicator of the current value of the DJIA instead of spot index values due to potential staleness in the latter. The spot-futures difference is calculated as the average of the difference between the prior-day Dow close and most recent CBOT futures trade as of 4:00 pm and that implied by the difference between the risk-free rate and dividend yield (as reported by Optionmetrics' Ivy DB). The correlation between the results from these two methods is 0.85 and the standard deviation of the difference is 3 basis points.

[8] Tests for whether a contract's frame affects its pricing are conducted below.

purchased in-the-money and negative returns when purchased out-of-the-money.[9] A similar pattern, albeit a weaker one, exists in the expiry returns of the 4 PM contracts.

It is not uncommon for the implied volatility of traditional options to slightly overestimate future realized volatility (Day and Lewis, 1992; Canina and Figlewski, 1993), and these return patterns suggest that the Tradesports markets are no exception. The time-unadjusted implied volatility of binary options can be calculated as $IVT = ln(s - k)/\Phi^{-1}(p)$, where s is the current spot price, k is the strike price, p is the binary option price (scaled 0 to 1), and Φ^{-1} is the inverse of the standard normal cumulative distribution function. Implied volatility is best measured for options that are neither very close nor very far from the money. For both close-to-the-money and far-from-the-money options, the derivative of IVT with respect to price is high, and thus IVT is very sensitive to errors in prices (due to, e.g., bid-ask bounce or any timing lag between the option and prior DJIA futures trade used to calculate s).

Table 6 plots the average time-adjusted implied volatility for each option trade falling in a specific time*moneyness cell. Implied volatilities are not calculated for options that are within 25 DJIA points of the money (about 25 basis points given the DJIA's range of 8,850 to 10,940 during the sample period) and for trades within 15 minutes of expiry. The implied volatilities in each row are compared with the moments of the actual DJIA futures changes between the option trade and expiry times. It again appears that the Tradesports markets are slightly overpredicting volatility, especially in the hour before expiry and for the 10 AM and 1 PM contracts. Consistent with what has

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[9] The standard errors used for calculating significance are adjusted for heteroskedasticity and for return correlations (of any form) within expiry day. This adjustment was done using the "cluster" option in Stata, which is based on Froot (1989). Since all trades of a given contract have the same expiry day, this also adjusts for the use of multiple observations of the same contract. All other regression analyses in this paper that use multiple observations from the same contract or expiry day make similar adjustments.

been found for longer-term options, implied volatities are higher for deeper out-of-the-money than near-the-money options, especially close to expiry. This steepening "volatility smile" is consistent with higher kurtosis in actual future DJIA changes.[10] Likewise, the absence of a "volatility smirk" (i.e., an asymmetry in the IV-moneyness relationship) is consistent with a lack of skewness in realized volatility.

Tables 7 and 8 directly test market efficiency by attempting to predict returns to expiry using variables known at the time of an options trade. In Table 7, I replicate the most common test of binary option market efficiency by testing whether price alone predicts returns. Given the evidence in Table 6, I separately examine the efficiency of the 4 PM expiry DJIA markets from the 10 AM and 1 PM expiry markets, and I also run the tests for other types of contracts traded on Tradesports. To compare the efficiency of Tradesports and traditional options markets, I also test the efficiency of the pricing of spread positions that approximate binary options constructed from adjacent CBOE DJIA options.[11]

I run the tests two different ways. In Panels A and B, I measure average returns to expiry conditional on a contract trading within a certain price range. For all contract

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[10] Some of the kurtosis reported in Table 6 results from the aggregations of observations with slightly different times to expiry. However, the conclusion that expected kurtosis to expiry increases as expiry gets closer is robust to eliminating this aggregation.

[11] Specifically, for each pair of (European) put or call options with the same expiry date and adjacent strike prices, I calculate the future value of a bullish spread position paying between 0 and 1 as $e^{r\tau}(mid_0 - mid_1)/(strike_1 - strike_0)$, where r is the risk-free rate, τ is time to expiry, *mid* is the bid-ask midpoint of the call option (or the implied call option using put-call parity) and option 0 is the one with the lower strike price. I do not mix puts and calls in constructing these spreads. Unlike true binary options, these spread positions do occasionally have values at expiry between 0 and 1 (i.e., when the underlying is between $strike_1$ and $strike_0$ at expiry). Daily option price data are taken from Optionmetrics' *Ivy DB* for the September 1997 to June 2005. Like all other regressions in the paper, standard errors adjust for clustering of returns within expiry day (and thus within contract as well). To insure the independence of returns for observations with different expiry days, only options 0 to 30 days from expiry were included in the sample. To avoid distortions due to minimum tick sizes, spreads whose values are less than 0.01 or greater than 0.99 are dropped from the sample (using different cutoffs, such as 0.1 and 0.9, does not materially affect the results).

types examined, I find, like other authors, evidence of a favorite-longshot bias, where higher returns are earned on contracts with prices greater than 0.5, although the difference is not always statistically significant.[12] For all Tradesports contract types taken together, the bias does not appear large enough to allow for trading profits once typical bid-ask spreads (2-4 percentage points) and trading and expiry fees (0.4-0.8 percentage points) are taken into account. The 10 AM and 1 PM-expiry DJIA binary options do appear less efficiently priced than the 4 PM-expiry binaries. Interestingly, the 4 PM Tradesports options appear more efficiently priced than the binary option approximations constructed using CBOE midpoints, although the precision of the estimates for the CBOE options is limited by the fact that their longer term means we only have 92 unique expiry days in the approximately 8 years of data available since the options' introduction in September 1997.

As discussed above, a favorite-longshot bias could arise from investors overestimating future volatility. Panel C presents a specification that tests for this more explicitly. Suppose that instead of observing m (the moneyness of a binary option) and σ (the standard deviation of the change in the underlying between now and expiry), investors observed $m + e$ and σ /b, and suppose that future changes in the underlying are normally distributed. These investors would price a binary as $p' = \Phi[b*(m+e)/\sigma]$ rather than $p = \Phi(m/\sigma)$, where $\Phi()$ is the standard normal cumulative distribution function. The

[12] Tetlock (2004, Table VI) conducted a related test of whether the returns to expiry of Tradesports financial contracts were higher or lower conditional on their trading above or below 0.5. He concluded that the returns for "new favorites" was 0.95 percentage points (SE = 2.56) higher than for "new underdogs," whereas I compare all favorite and all underdogs and conclude that returns are 2.60 percentage points higher for favorites (SE = 0.84). I have more statistical power largely due to a larger sample size (739,438 trades versus 2,389 for Tetlock, and 27 months of data versus 6.5 in Tetlock). Other studies that test non-financial binary option pricing efficiency by examining returns-to-expiry conditional on an option transacting in a given price range include Wolfers and Zitzewitz (2004 and 2006b), Gurkaynak and Wolfers (2005), and Borghesi (2006). Of these, Wolfers and Zitzewitz (2006b) and Borghesi (2006) find evidence of favorite-longshot biases in IEM political markets and Tradesports NFL markets, respectively.

probability that a binary priced at *p'* would payoff would be $p = \Phi[-be + b\Phi^{-1}(p')]$, and a probit regression of the binary option payouts on $-be + b\Phi^{-1}(p')$ would recover estimates for $-be$ and b. Panel C runs these regressions and finds that pricing is consistent with investors slightly overestimating volatility in most domains, although not always by a statistically significant margin. For the DJIA options, volatility appears overestimated by 13% for pre-4PM expiry options and 2% for 4PM-expiry options, with only the former estimate being significant.[13]

The functional form of the probit regressions appears to approximate reasonably well the results of the more flexible regressions in Panel A. The probit functional form implies that volatility misestimation should create the largest percent point return predictabilities for contracts priced in the 20s and 70s, and this appears to match the results in Panel A. Furthermore, if the 10 Panel A indicator variables are added to the regressions in Panel C (dropping the constant), their coefficients are jointly insignificant for all subsamples of the data examined in Table 7.

The regressions in Table 8 add control variables to better understand the source of the return predictabilities. Regressions predicting returns to expiry using price alone find a positive relationship and that this relationship gets stronger once the price change from the last tick is added to control for bid-ask bounce. It survives adding a control for whether the contract is bearishly framed, but not adding a control for moneyness. In-the-money contracts are more profitable to purchase than out-of-the-money contracts, whether or not one conditions on price.

[13] For the CBOE spreads, about 5 percent of spreads have expiry values that are neither zero nor one (the cases where the expiry value of the index is between the strike prices spanned by the spread). In these cases, I randomly changed these dependent variables to 0 or 1 in a way that does not change their expected value (if the original value was p, the probability of being reassigned to one is p). Multiple repetitions of this randomization yielded results that differed only trivially from the ones reported.

Returns could be predicted by moneyness for a variety of reasons. First, prices could be underreacting to recent changes in the DJIA, perhaps due to some traders observing the changes with a lag. Second, prices could underreflect the futures-spot difference if some traders were comparing DJIA futures prices with the prior-day spot close without adjusting for the spot-futures difference. Third, traders may be overestimating future volatility. I test for the first two issues by adding controls for recent DJIA futures movements and for the spot-futures difference used for that day (calculated as described in footnote 6). The results suggest that Tradesports prices do not under reflect recent market movements but do under reflect the spot-futures difference, and that this explains much of the predictive power of moneyness.

To examine the third issue, I add a measure of realized volatility over the last 24 trading hours and an interaction of realized volatility with moneyness. The realized volatility measure is the square root of the sum of squared minute-by-minute log changes in the DJIA futures between now and 24 trading hours ago (i.e., the same calendar time on the most recent trading day). For simplicity, I include squared log futures changes with gaps between observations that are longer than one minute without any weighting to compensate for the additional noise in these observations of underlying volatility.[14] This measure has a mean of 0.70 percentage points and a standard deviation of 0.17, so the coefficients in Table 8 imply that moneyness is partially correlated with positive binary

[14] In subsequent analyses (Table 13), I allow squared log DJIA changes over longer time periods to have lower weights due to the fact that they represent a noisier measure of integrated volatility, as suggested by Hanson and Lunde (2005a). When I do so, I find that the optimal weight is not very different from one. This is probably due to the fact that on weekdays the overnight period for the DJIA futures is 3 hours (5 pm to 8 pm Eastern Time), compared with 17.5 hours (4 pm to 9:30 am the next day) for the DJIA component stocks analyzed by Hanson and Lunde.

option returns, albeit to a lesser extent when recent volatility has been high.[15] This suggests that in addition to slightly overestimating future volatility on average, the Tradesports binary options prices also under react to recent changes in volatility.

Constructing an intraday implied volatility measure

The results in the prior section suggest that while the Tradesports binary option markets are not perfectly efficient, they do not appear less efficiently priced than analogous spreads constructed from CBOE options markets. This is especially true of the more liquid 4-PM-expiry markets. Given this, constructing an intraday implied volatility measure with Tradesports' options prices seems a reasonable undertaking. This section describes the construction of such a measure, and then provides some tests of its predictive power. In describing the construction of the index, I focus on the more liquid 4-PM-expiry options, but also construct and test implied volatility measures for the earlier expiry times.

My goal in this section is more to demonstrate the existence of a useful intraday volatility measure than to find the optimal one. To some extent these goals conflict, as fine tuning the measure might raise reader concerns of data snooping, even if all testing is done out of sample. Given this, I will attempt to keep the design of the measure simple, at the cost, of course, of leaving open the possibility that it might be subsequently refined.

The first design choice one faces in constructing an implied volatility measure is whether to rely on a parametric distributional assumption about future returns or to construct a so-called "model-free" measure (Britten-Jones and Neuberger, 2000; Jiang

[15] Volatility trended downward during my sample period (June 2003 to August 2005), so I verified that this result was robust to including controls for time and the interaction of time and moneyness.

and Tian, 2005). A model-free measure of implied volatility is constructed by combining options at different strike prices to construct a position with payoff proportional to the square of the log difference between the current value of the underlying and its value on expiry. The CBOE's (2003) redesigned VIX index of longer-horizon implied volatility takes the "model-free" approach, whereas the original VIX (described in Whaley, 1993) did not. The new VIX begins by "buying" the first out-of-the-money call and put on either side of the current value of the underlying. This yields a position with a V-shaped payoff (i.e. a payoff that is roughly proportional to the absolute log difference between the current value of the underlying index and its value on expiry). Further out-of-the-money calls and puts are then added to the index to give the position an approximately parabolic shape (i.e., so that its payoff is proportional to the square of this log difference).

This approach was considered but rejected for two reasons. The first reason is that the distance between strike prices, relative to the expected volatility over the life of the contracts, is larger for the Tradesports options. Even after the introduction of the additional strike prices in April and May 2004, Tradesports options are spaced 25 DJIA points apart (about 25 basis points), whereas the standard deviation of DJIA returns between 2 and 4 PM was about 41 basis points. Given this discreteness, one would have to rely on distributional assumptions anyway when deciding how to approximate a parabolic position. The second reason is that binary options are not as well suited as vanilla options to constructing an approximately parabolic position, given that the payoff to any option is capped. One needs large positions of the deep out-of-the-money options, which makes the volatility measure sensitive to any pricing errors for these options, which are usually the most thinly traded.

Given these issues, I take an older approach of constructing an average of the volatility implied by individual binary options trades, assuming that future returns are expected to be (conditionally) log-normally distributed. Given this, a second design choice is how to weight the implied volatilities of different options. Latane and Rendelmen (1976) suggest weighting options by their vegas (the derivative of their Black-Scholes (1973) value with respect to volatility), the inverse of which is sensitivity of implied volatility to option price measurement error. For standard options, vega is highest for at-the-money options, which also happen to be the most liquid. For binary options, assuming log normally distributed future returns, vega is maximized (and thus sensitivity to pricing errors is minimized) for options that are one standard deviation of returns to expiry from the money, which corresponds to prices of 0.16 or 0.84.[16] In contrast, the sensitivity of $IVT = m/\Phi^{-1}(p)$ to measurement in moneyness is maximized as $|z|$ approaches infinity. This implies that measurements of IVT from options with $|z| > 1$ would be least subject to the combination of price and moneyness measurement error. Unfortunately, these options are less frequently traded than at-the-money options.

Tables 9 and 10 examine how the relative predictive power of options' implied volatilities varies with their distance from the money. Each option trade is assigned to a moneyness category based on its distance from the money at the time of the trade. In order to make the moneyness measure comparable for options with different time to expiry, each option is assigned a z score, which is calculated as $z = m/\sigma(\tau)$, where $m = ln(s) - ln(k)$ is (log) moneyness, and $\sigma(\tau)$ is the standard deviation of price changes in the

[16] The value of a binary option is $p = \Phi(z)$, where Φ is the standard normal c.d.f. and $z = m/IVT$, where m is log moneyness and IVT is time-unadjusted implied volatility. The option's vega is $z*\varphi(z)/IVT$. For a given IVT, this is maximized at $z = 1$, and this the sensitivity of an estimate of $IVT = m/\Phi^{-1}(p)$ to measurement error in price is minimized at this point.

τ hours between now and expiry. Whereas $\sigma(\tau)$ is usually assumed to be proportional to $\tau^{1/2}$ for longer horizon options, given the well-known higher levels of volatility during certain hours of days, non-parametric estimation of $\sigma(\tau)$ is more appropriate in this case.

Figure 1 plots average future realized volatility for different times. Three measures are used: 1) the sum of squared minute-by-minute log futures changes, 2) the sum of squared changes corrected for first-order autocorrelation as proposed by Hanson and Lunde (2005b),[17] and 3) the square of the log difference between the current futures price and its price at expiry. The three measures are very close during regular trading hours, although of course the third is more noisy than the first two. For simplicity and to avoid using a non-monotonic function, I use the average sum of squared minute-by-minute changes during the entire sample as an estimate of $\sigma(\tau)$.[18]

Table 9 examines how the predictive power of the implied volatility of a binary option varies with its z score. Each observation is an options trade in a given time window. The IVT from that trade is used to predict future realized volatility from the time of the trade to 4 PM, and the coefficient on IVT and constant term are allowed to vary with the absolute value of the option's z-score. Table 10 aggregates the time periods but varies the measure of future volatility being predicted. It also includes the VXD index of longer-horizon implied volatility and lagged realized volatility are included as controls in some specifications to distinguish between absolute and relative predictive power.

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[17] The Hanson and Lunde (2005b) estimator of integrated variance allowing for AR(1) microstructure noise is the sum of $(p_t - p_{t-1})^2 + 2(p_t - p_{t-1})(p_{t-1} - p_{t-2})$, where p_t is log price, as opposed to the standard $(p_t - p_{t-1})^2$ (French, Schwert, and Stambaugh, 1987 also derived this measure for the AR(1) case). The AR(1) coefficient for minute-by-minute changes in the DJIA future is about -0.06. The Hanson-Lunde correction therefore lowers realized variance by about 6 percent. Higher-order autocorrelation in the DJIA futures data is minimal; so making the correction allowing for more lags yields very similar results.

[18] All results that follow are qualitatively similar if one uses the more conventional $\sigma(\tau) = \sigma^*\tau^{1/2}$.

In general, coefficients are higher for options with z scores between 0.5 and 2 and lower for options outside this range. While the results suggest one might want to differentially weight options based on their z score, for simplicity and to prevent the possible introduction of a data snooping bias, I will use equal weights for all options with z scores between 0.5 and 2 and exclude all other observations of IVT.[19]

I can now specify the procedure I use to calculate an implied volatility index:

1. I estimate a $\sigma(\tau)$ for each different expiry time (e.g., 4 PM) as the square root of the sum of squared minute-by-minute log futures changes between τ and the time of expiry over the entire sample period.
2. For the time at which I am interested in calculating implied volatility, I calculate IVT using up to the last N options trades that had z-score between 0.5 and 2.
3. I scale each IVT_n up by $\sigma(\tau_n)/ \sigma(\tau)$, where τ_n is the time to expiry at the time of the trade and τ is current time to expiry.
4. I construct a weighted average of the IVT_n, weighting each by the geometrically decaying weight $w_n = \exp[-d^*(\tau_n - \tau)]$. This yields a measure of time-unadjusted implied volatility (i.e., of expected future volatility from now to expiry, however long that might be).

Somewhat arbitrarily, I use N = 10, 25, and 50 for the 10 AM, 1 PM, and 4 PM expiry options and a decay rate d of 2 (with τ expressed in hours). The results that follow are qualitatively similar for other choices, including N = 1, although using very small N does produce a slightly noisier index.

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[19] Results that follow are qualitatively similar if I follow the alternative approach of weighting the options with z-scores between 0.5 and 2 by their vegas.

Table 11 presents means of the IVT measure for different expiry times and time of day and compares them to measures of future realized volatility. The figures are standard deviations of future returns to expiry, expressed in basis points. Consistent with what would have expected from the results in the last section, IVT appears to slightly overestimate future volatility, especially in the 10 AM and 1 PM expiry markets and within an hour of expiry. The sample period of June 2003 to August 2005 was a period of declining volatility (the monthly average of the VXD index fell from 22.5 to 12.1 during this period), which could have contributed to some of the Tradesports markets' overestimation of volatility. But given the daily frequency of the markets, this effect is likely small, and, indeed, an (unreported) version of Table 11 that restricts the sample period to January to August 2004 (a period in which the VXD was roughly stable at 16) yields very similar results.[20]

Table 12 presents regressions that predict future realized volatility using the IVT index and more conventional predictors. Each observation consists of the most recent value of each predictor at the end of a 15 minute period and the future realized volatility (sum of squared minute-by-minute log futures changes) between that time and expiry. The results suggest that IVTs from the 4 PM expiry markets have significantly more predictive power than those from the 10 AM and 1 PM markets. IVT also has significant incremental predictive power in regressions that include only predictions from a particular time of day forward, especially in the afternoon.

[20] To assist readers interested in replicating the results in Tables 11 to 15, a file containing 15-minute values of the 4-PM-expiry IVT index is available at http://faculty-gsb.stanford.edu/zitzewitz. The underlying Tradesports prices used to calculate the index are unfortunately proprietary, but may be available directly from Tradesports.

Table 13 presents robustness tests of the results for the 4-PM-expiry IVT. The first set of specifications add additional predictors of volatility. Andersen, et. al. (2003) find that predictions of GARCH and other models have little additional predictive power after multiple lags of high-frequency realized volatility are controlled for. Given this finding, I begin by adding additional controls for lagged hourly and daily realized volatility. Doing so reduces the incremental predictive power of the IVT index, but not to the point where it is statistically insignificant. Adding additional lags of the VXD index or fixed effects for the exact minute of the day (which would control for issues arising from the construction of $\sigma(\tau)$) does not materially affect the results. I also examine the effect of making different choices in the construction of the IVT index. Using only the most recent observation of IVT does reduce the indexes predictive power, which is unsurprising given the microstructural noise that was apparent in Table 8. Switching from equal to vega-weighting the options has essentially no effect. Replacing $\sigma(\tau)$ with the more standard $\tau = 0.5$ increases the incremental predictive power of IVT. Intuitively, this is because doing so gives IVT credit for predicting the fact that volatility varies by time of day, which is arguably inappropriate.

Table 14 uses the same three measures (IVT, VXD, and lagged 24-hour realized volatility) at 2 PM to predict future realized volatility over the longer horizons. Interestingly, for the next day, week, or month, the 2 PM value of the IVT index has statistically significant incremental predictive power.[21]

Finally, Table 15 examines whether IVT can be useful as a predictor of DJIA futures changes. Persistence coefficients are estimated by regressing log DJIA returns

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[21] Similar results were obtained for the 1 or 3 PM values. Values from the morning, when the 4 PM expiry markets are less liquid, had less incremental predictive power for longer term volatility, however.

from minute t + 1 to minute t + k + 1 using returns from minute t – k to minute t for different time horizons k. Each minute is divided into quintiles based on the within minute-of-the-day ranking of the three measures of volatility (IVT, VXD, and lagged 24-hour realized volatility). The persistence coefficients for that minute are then compared for high and low volatility time periods.[22]

As has been found elsewhere (CITE) for longer frequencies, futures movements are more persistent when (expected future or past) volatility is low. For time horizons of 30 or 60 minutes, IVT is the best of the three measures at predicting high or low persistence. Given the low trading costs for the DJIA futures (typical bid-ask spreads during regular trading hours are about a basis point), the return predictabilities shown in Table 15 are large enough to allow for (modest) trading profits, even after transaction costs.

Discussion

Despite volumes that are beginning to approach those on regulated exchanges, financial prediction markets have received much less academic attention than their political counterparts. This is despite the fact that most financial prediction market trading is in securities that are not redundant. This paper's results suggest that the prices of these securities are roughly efficient and that they contain information about future volatility that is not available in more conventional predictors.

The utility of these markets is perhaps surprising given that at many participants can probably be best thought of as noise traders. The presence of these noise traders has

[22] Newey-West (1987) standard errors are calculated allowing for k lags to adjust for the use of overlapping return time periods.

encouraged the entry of many sophisticated traders who use proprietary models for predicting future intraday volatility. The aggregation of these models, together with the information content of the other participants' trading, yields prices that contain significant incremental predictive power. This incremental predictive power is present despite the fact that the markets do not appear to be perfectly efficient. In particular, like prediction markets in other domains, they appear to suffer from overestimation of future volatility that gives rise to a favorite-longshot bias.

The utility of financial prediction markets in predicting intraday volatility is arguably suggestive of their wider utility in quantifying factors affecting the value of traditional financial market assets. Slemrod and Griemel (1999), Wolfers and Zitzewitz (2005), Knight (2006), and Snowberg, Wolfers, and Zitzewitz (2007) provide other examples, finding that measuring the probabilities of political events can help investors interpret movements in traditional financial market prices. As argued by Wolfers and Zitzewitz (2005), using prediction markets to aggregate information about factors such as political risk or near-term volatility could improve the efficiency of asset pricing, potentially lowering required rates of return on capital. If so, this could be one of the highest value applications of prediction markets yet envisaged.

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Table 1. Contracts offered, trades, and volume on Tradesports by type of contract, June 2003 to August 2005

	Unique contracts offered	Trades	Contracts traded	Percent of total
Finance -- daily and intraday frequency	35,669	1,192,326	21,023,908	34.3%
DJIA	9,793	775,893	15,274,036	24.9%
S&P 500	4,984	101,961	2,566,187	4.2%
Nasdaq 100	4,006	106,684	1,365,248	2.2%
FTSE	4,084	63,348	1,065,192	1.7%
Commodities (oil and gold)	1,997	13,326	239,657	0.4%
DAX	2,740	19,116	218,749	0.4%
Forex	3,227	34,391	115,098	0.2%
Nikkei	2,727	7,694	91,985	0.2%
Single stocks	2,111	69,913	87,756	0.1%
Finance -- weekly, monthly, yearly frequency	2,373	30,849	754,805	1.2%
DJIA	734	18,797	473,527	0.8%
Commodities (oil and gold)	92	5,969	108,953	0.2%
Forex	922	4,165	99,177	0.2%
Nasdaq 100	302	1,033	39,032	0.1%
S&P 500	323	885	34,116	0.1%
Politics and current events	2,697	183,207	4,167,900	6.8%
Elections	481	121,436	3,242,951	5.3%
Sports and entertainment	232,439	2,045,130	35,333,176	57.7%
NFL	5,151	407,790	8,440,342	13.8%
MLB	21,220	534,133	8,331,943	13.6%
NCAA sports	23,728	438,470	8,001,669	13.1%
NBA	12,841	319,490	5,098,796	8.3%
Golf	7,949	70,789	2,364,844	3.9%
Horse racing	127,405	40,018	512,960	0.8%
Other sports/entertainment	34,145	234,440	2,582,622	4.2%
Total	273,178	3,451,512	61,279,789	100.0%

Table 2. Average monthly volumes of Tradesports Dow binary options and CBOT and CBOE Dow futures and options
Thousands of contracts traded

3-Month Period	Tradespots binary options	CBOT futures	CBOT options on futures	CBOE options
Jun to Aug 2003	118	889	18	779
Sep to Nov 2003	132	792	33	685
Dec 2003 to Feb 2004	192	838	38	584
Mar to May 2004	252	1,219	33	724
Jun to Aug 2004	375	1,065	20	568
Sep to Nov 2004	666	1,078	71	575
Dec 2004 to Feb 2005	1,536	1,031	43	601
Mar to May 2005	1,043	1,293	48	606
Jun to Aug 2005	667	1,134	26	656
Monthly volume				
June 2003 to Aug 2004	214	961	28	668
Sep 2004 to Aug 2005	978	1,134	47	600
Contract size	$10 or $0	$10 x index	$10 x (index - strike)	$1 x (index - strike)
Daily standdard deviation of contract value change in $	4.8	690	414	41.4
Average holding period (trading days)	1	1.3	11.7	24.2
Economic size of contract trade (Daily SD * sqrt(trading days held))	4.8	791	1416	204
CBOT future-equivalent volume				
June 2003 to Aug 2004	1.3	961	51	172
Sep 2004 to Aug 2005	5.9	1,134	84	155
Index (Tradesports = 1)	1.0	191	14	26

Notes: Monthly volume figures for CBOT futures and options are the sum of the volume of regular ($10) contracts and one half the volume of "mini" ($5) contracts. Average holding period in trading days is calculated as the ratio of open interest and average daily volume. Data for CBOT is from www.cbot.com; data for CBOE is calculated from Optionmetrics' Ivy DB.

Table 3. DJIA Binary Options Volume by Hour and Moneyness
Thousands of contracts traded

	Moneyness at time of binary options trade (spot less strike price, in basis points)						
Trade time	-50 or less	-50 to -25	-25 to 0	0 to 25	25 to 50	50 or more	Total
Contracts expiring at 10 AM ET (Contracts traded from 11/24/04 - 8/31/05; 195 unique trading days)							
Before 7 AM	1	3	5	5	3	1	18
7 to 8 AM	1	3	12	10	2	1	28
8 to 9 AM	2	19	51	46	14	1	134
9 to 10 AM	3	41	411	308	24	3	790
Total	7	66	479	369	44	5	970
Contracts expiring at 1 PM ET (Contracts traded from 3/8/04 - 8/31/05; 375 unique trading days)							
Before 9 AM	12	24	37	38	25	10	146
9 to 10 AM	11	35	63	69	31	9	218
10 to 11 AM	23	113	374	316	88	15	930
11 AM to Noon	8	92	388	330	66	7	891
Noon to 1 PM	8	46	808	562	42	8	1,475
Total	63	309	1,670	1,315	252	50	3,659
Contracts expiring at 4 PM ET (Contracts traded from 6/1/03 - 8/31/05; 570 unique trading days)							
Before 8 AM	47	44	84	75	42	40	332
8 to 9 AM	21	24	36	39	22	18	159
9 to 10 AM	80	111	133	111	79	68	582
10 to 11 AM	109	162	192	193	116	97	869
11 AM to Noon	81	124	157	148	97	78	685
Noon to 1 PM	63	114	185	168	106	59	694
1 to 2 PM	81	242	419	394	208	73	1,416
2 to 3 PM	81	302	716	660	242	71	2,071
3 to 4 PM	71	231	1520	1299	205	63	3,388
Total	634	1,353	3,441	3,088	1,116	566	10,198

Notes: Volumes are the total number of contracts traded, in thousands. Contracts with 10 AM and 1 PM expiry times were only traded during the dates reported above. Trading in contracts of all expiry times usually begins slightly after the opening of the CBOT futures market at 8 PM ET on the prior day. Moneyness is defined as the log difference between the strike price of the option and the most recent trade price in the near-month CBOT DJIA future (adjusted for the future-spot difference using the method described in footnote 7).

Table 4. DJIA Binary Option Prices by Hour and Moneyness

	Moneyness at time of binary options trade (spot less strike price, in basis points)						
Trade time	-50 or less	-50 to -25	-25 to 0	0 to 25	25 to 50	50 or more	Total
Contracts expiring at 10 AM ET							
Before 7 AM	9.2	21.3	41.2	62.5	80.6	91.9	50.9
7 to 8 AM	6.5	16.7	38.1	66.4	85.7	93.9	51.8
8 to 9 AM	6.4	14.6	37.5	67.5	85.1	94.2	49.7
9 to 10 AM	3.1	7.7	33.8	71.7	92.7	97.0	49.4
Contracts expiring at 1 PM ET							
Before 9 AM	12.5	25.4	42.3	59.4	75.7	87.5	50.1
9 to 10 AM	10.6	22.8	40.9	60.7	78.5	90.0	49.3
10 to 11 AM	7.6	18.2	39.8	63.1	82.8	93.2	49.5
11 AM to Noon	5.2	12.7	35.9	67.3	87.9	95.7	49.2
Noon to 1 PM	2.2	5.6	31.7	74.1	94.4	98.0	49.5
Contracts expiring at 4 PM ET							
Before 8 AM	16.0	33.1	45.6	55.9	67.8	84.0	49.3
8 to 9 AM	16.0	31.3	44.8	57.4	68.1	83.6	49.8
9 to 10 AM	15.4	29.9	44.0	57.5	70.0	83.8	49.7
10 to 11 AM	14.2	27.9	43.0	58.6	72.3	85.5	49.4
11 AM to Noon	11.7	25.4	42.1	59.1	74.1	87.2	49.1
Noon to 1 PM	9.7	23.0	41.2	60.7	77.0	88.6	49.9
1 to 2 PM	7.6	18.1	39.3	62.0	81.1	91.2	49.0
2 to 3 PM	6.6	15.4	37.6	64.5	84.6	93.3	49.4
3 to 4 PM	6.0	8.1	31.2	71.5	90.1	96.8	50.1

Notes: Prices are reported in percentage points (these contracts expire at either $0 or $10, so one percentage point represents 10 cents). Moneyness is defined as the log difference between the strike price of the option and the most recent trade price in the near-month CBOT DJIA future (adjusted for the future-spot difference using the method described in footnote 7). For consistency, options are redefined to have a "bullish" frame, so if an option that pays if the DJIA closes below X trades at 40, this is considered to be a trade at 60 of an option that pays if the DJIA closes above X.

Table 5. DJIA Binary Option Returns by Hour and Moneyness

	Moneyness at time of binary options trade (most recent DJIA spot less strike price, in basis points)						
Trade time	-50 or less	-50 to -25	-25 to 0	0 to 25	25 to 50	50 or more	Total
Contracts expiring at 10 AM ET							
Before 7 AM	-8.4***	-15.0***	-1.7	2.7	13.9***	6.6***	-0.3
7 to 8 AM	-5.6***	-9.3***	-11.4***	6.2*	7.8***	-0.5	-1.9
8 to 9 AM	-6.4***	-8.1***	-5.0	2.0	10.8***	5.8***	-1.1
9 to 10 AM	-1.0	0.8	0.5	-1.6	4.9***	1.6	-0.1
Total	-5.0***	-3.3	-0.4	-0.7	7.5***	4.0***	-0.3
Contracts expiring at 1 PM ET							
Before 9 AM	-3.4	-4.0	-3.4	4.8	6.2*	2.8	0.5
9 to 10 AM	-2.6	-4.9*	-1.9	4.4	-1.3	4.1**	-0.2
10 to 11 AM	-0.8	-2.7	-5.9**	1.2	1.8	3.3***	-1.8
11 AM to Noon	-2.8*	-4.7***	-3.9	5.1*	1.8	1.1	-0.2
Noon to 1 PM	-1.7***	-3.0***	-5.1**	2.8	3.0**	2.0***	-1.5
Total	-2.2*	-3.7**	-4.8**	3.2	2.4	2.8**	-1.1
Contracts expiring at 4 PM ET							
Before 8 AM	-2.3	-3.1	-0.1	3.6	3.4	0.5	0.4
8 to 9 AM	-1.4	-1.7	-3.7	0.0	2.8	4.3**	-0.2
9 to 10 AM	-2.1	-0.3	-0.7	-1.9	4.9**	3.1	0.2
10 to 11 AM	0.0	-0.1	-1.6	1.6	-0.3	4.6***	0.5
11 AM to Noon	0.7	-0.4	-0.2	1.1	1.0	2.9	0.7
Noon to 1 PM	-1.4	-1.2	-0.1	1.6	4.7**	5.8***	1.3
1 to 2 PM	-1.6	-1.4	0.7	0.8	-2.5	-0.5	-0.3
2 to 3 PM	-0.3	-2.5*	-2.3	2.6	1.4	0.6	-0.1
3 to 4 PM	0.6	-0.6	-4.6***	0.2	3.4**	2.0***	-1.6
Total	-0.8	-1.3	-2.6	1.0	1.8	2.5**	-0.4

Notes: Returns are defined as the percentage point difference between transaction and expiry prices. Moneyness is defined as the log difference between the strike price of the option and the most recent trade price in the near-month CBOT DJIA future (adjusted for the future-spot difference using the method described in footnote 6). All options are redefined to have a "bullish" frame as in Table 4. Returns that are statistically significantly different from zero at the (two-tailed) 10, 5, and 1 percent level are indicated by *, **, and ***, respectively. Significance is calculated using standard errors that adjust for clustering within contract and trading day (see footnote 8 in the text for details).

Table 6. Time unadjusted implied and realized volatility of DJIA binary options

	Implied volatility: Moneyness at time of binary options trade (spot less strike price, in basis points)							Future market movements: Change in log DJIA to expiry time (basis points)			
Trade time	-100 or less	-100 to -50	-50 to -25	25 to 50	50 to 100	100 or more	Total	Mean	SD	Skew	Kurtosis
Contracts expiring at 10 AM ET											
Before 7 AM	64	45	43	43	45	55	44	1.8	24	0.74	3.73
7 to 8 AM	.	39	35	33	39	.	35	-2.1	22	-0.25	3.43
8 to 9 AM	70	41	33	33	38	68	34	-0.1	20	0.10	3.15
9 to 10 AM	56	31	23	22	31	54	23	0.4	13	0.15	4.93
Total	64	38	28	28	39	57	30				
Contracts expiring at 1 PM ET											
Before 9 AM	72	56	55	52	54	72	54	2.0	45	-0.21	3.21
9 to 10 AM	68	50	48	45	51	68	48	0.7	40	-0.17	3.56
10 to 11 AM	61	43	40	37	42	58	39	-0.5	32	-0.08	3.87
11 AM to Noon	54	38	30	28	36	52	31	0.0	22	-0.30	4.39
Noon to 1 PM	50	28	20	20	28	49	21	-0.1	11	-0.54	8.83
Total	58	46	35	34	45	57	37				
Contracts expiring at 4 PM ET											
Before 8 AM	80	73	71	67	70	79	72	-0.1	64	-0.09	3.14
8 to 9 AM	77	71	69	69	71	80	71	-1.7	66	0.02	2.95
9 to 10 AM	79	69	67	64	68	80	68	-0.9	62	-0.07	3.07
10 to 11 AM	76	65	62	59	64	77	63	0.8	58	-0.06	3.47
11 AM to Noon	71	59	55	54	60	76	57	0.6	53	-0.26	3.58
Noon to 1 PM	67	53	49	48	55	71	52	-0.5	47	-0.32	4.06
1 to 2 PM	62	46	40	40	47	65	42	-2.4	40	-0.31	4.06
2 to 3 PM	61	40	35	35	42	64	37	-0.5	32	-0.21	4.74
3 to 4 PM	53	32	24	25	32	53	27	-0.6	17	-0.08	6.28
Total	71	55	43	42	55	72	48				

Notes: Time-unadjusted implied volatility is defined as m/Φ^-1(p), where m is the moneyness of the binary option, p is its price (scaled 0 to 1) and Φ^-1 is the inverse of the standard normal cumulative distribution function. Moneyness is defined as the log difference between the strike price of the option and the most recent trade price in the near-month CBOT DJIA future (adjusted for the future-spot difference using the method described in footnote 7). All options are redefined to have a "bullish" frame as in Tables 3-5. Moneyness and implied volatility are expressed in basis points; the average level of the DJIA during the sample period was 10,350, so one basis point equals roughly one DJIA point.

Table 7. Regressions predicting returns to expiry using price alone

Contract type	All Tradesports binary options	Intraday DJIA binary options			Other daily/intraday financial	Politics	Sports	CBOE DJIA spreads
		10 AM or 1 PM expiry	4 PM expiry	All				
Trades	3,079,762	225,808	513,630	739,438	247,439	130,573	1,921,610	65,155
Unique contracts	90,547	2,880	4,592	7,472	12,232	1,788	68,145	4,747
Unique expiry days	825	375	564	570	585	360	825	92
Panel A. Linear regression (dependent variable = returns to expiry (in percentage points))								
Price = 0 to 9.9	-0.7***	-1.5**	-1.1**	-1.2***	-0.2	-1.3	-1.0***	-0.4
	(0.2)	(0.6)	(0.6)	(0.4)	(0.5)	(1.5)	(0.3)	(1.2)
Price = 10 to 19.9	-1.1**	-3.6***	-0.6	-1.6	0.3	-8.8***	-2.1**	0.6
	(0.6)	(1.2)	(1.3)	(1.0)	(0.9)	(2.5)	(0.9)	(2.6)
Price = 20 to 29.9	-0.7	-5.1***	-0.4	-1.8	0.3	-3.4	-2.0	1.5
	(0.9)	(1.7)	(1.6)	(1.3)	(1.1)	(4.5)	(1.5)	(3.3)
Price = 30 to 39.9	-0.2	-4.7**	-1.4	-2.4*	-0.2	3.0	-1.2	3.2
	(1.0)	(2.2)	(1.8)	(1.5)	(1.3)	(3.2)	(1.4)	(3.9)
Price = 40 to 49.9	-1.1	-3.8	-0.6	-1.5	1.9	-8.9**	-2.4***	3.6
	(0.8)	(2.3)	(2.0)	(1.7)	(1.5)	(3.5)	(0.9)	(4.1)
Price = 50 to 59.9	0.8	1.4	0.5	0.7	4.3***	29.2***	-1.7**	4.3
	(1.3)	(2.5)	(2.0)	(1.7)	(1.6)	(7.4)	(0.7)	(4.1)
Price = 60 to 69.9	1.6	6.3***	0.7	2.3	5.0***	16.0*	-0.9	4.2
	(1.0)	(2.3)	(1.9)	(1.6)	(1.6)	(9.3)	(0.9)	(3.7)
Price = 70 to 79.9	2.5***	3.6*	0.2	1.3	4.2***	2.0	1.3	4.4
	(0.8)	(2.1)	(1.7)	(1.4)	(1.4)	(9.7)	(1.0)	(3.3)
Price = 80 to 89.9	1.2*	0.8	-0.2	0.2	2.5**	2.5	0.2	5.2***
	(0.7)	(1.9)	(1.4)	(1.2)	(1.2)	(8.2)	(0.9)	(1.9)
Price = 90 to 99.9	0.4	0.3	-0.4	-0.2	0.8	1.9	-0.1	2.5**
	(0.3)	(0.9)	(0.8)	(0.6)	(0.6)	(2.3)	(0.5)	(1.2)
Panel B. Linear regression (dependent variable = returns to expiry (in percentage points))								
Price = 50 to 99.9	2.0**	6.2***	1.0	2.6***	1.3*	19.0**	1.0	1.5
	(0.8)	(1.5)	(1.0)	(0.8)	(0.8)	(8.1)	(0.6)	(1.9)
Constant	-0.8*	-3.7***	-0.8	-1.7	2.2***	-4.0***	-1.8***	1.4
	(0.4)	(1.4)	(1.3)	(1.1)	(0.8)	(1.2)	(0.6)	(2.4)
Panel C. Probit regression (dependent variable = contract expires at 100)								
Φ^-1(Price)	1.052***	1.131***	1.020	1.053**	1.019	1.303	1.047**	1.101*
	(0.019)	(0.044)	(0.030)	(0.024)	(0.022)	(0.275)	(0.019)	(0.064)
Constant	0.009	-0.026	-0.012	-0.016	0.093***	0.233	-0.041**	0.117
	(0.019)	(0.051)	(0.044)	(0.037)	(0.027)	(0.211)	(0.018)	(0.091)

Notes: the table analyzes two types of contracts -- binary options traded on Tradesports, and spreads constructed using CBOE DJIA options with consecutive strike prices that approximate binary-options (see footnote 11 for details on how these spreads were constructed). The first two panels present regressions of returns-to-expiry on indicator variables for whether price falls into certain ranges. The third panel presents probit regressions of an indicator for whether a contract expires at 100 on the z-score implied by price (i.e., Φ^-1(Price), where Φ is the standard normal cumulative distribution function). In the second regression, market efficiency would imply a slope of one and a constant of zero. *, **, and *** indicate statistically significant differences from zero at the 10, 5, and 1 percent level, respectively. Standard errors are in parenthesis and are adjusted for heteroskedasticity and clustering within contract and expiry day.

Table 8. Predicting binary option returns
Return from holding bullish binary option to expiry

Specification	OLS						Probit
Dependent variable	Returns-to-expiry						= (Expires at 100)
Observations	731,912	731,912	731,912	731,912	731,912	731,912	731,912
Unique contracts	7,472	7,472	7,472	7,472	7,472	7,472	7,472
Trading days	570	570	570	570	570	570	570
Price (tick - 1)	0.034***	0.034***	0.051***	0.005	0.009	-0.002	1.016
	(0.013)	(0.014)	(0.014)	(0.022)	(0.022)	(0.023)	(0.038)
Price - Price(tick - 1)		-0.061***	-0.060***	-0.131***	-0.089***	-0.097***	0.904***
		(0.013)	(0.012)	(0.022)	(0.016)	(0.017)	(0.025)
Contract framing = (Buy => Bearish position)			-0.053***	-0.057***	-0.024	-0.026	-0.112
			(0.019)	(0.020)	(0.028)	(0.028)	(0.098)
Moneyness				4.9**	1.7	10.7*	28.4
[ln(Dow spot) - ln(Strike price)]				(2.1)	(2.7)	(6.2)	(28.8)
Spot-future difference					13.9*	8.1	61.3*
ln(Dow spot) - Ln(Dow future)					(7.6)	(8.2)	(32.4)
DJIA change in last minute					4.6	4.4	12.8
					(4.7)	(4.7)	(16.5)
DJIA change t-5 to t-1 minutes					1.4	1.4	4.6
					(3.7)	(3.7)	(12.9)
Moneyness*(Realized volatility last 24 trading hrs)						-10.6*	-59.3*
						(6.4)	(34.4)
Realized volatility last 24 trading hours						0.089	0.312
						(0.583)	(0.202)
Constant	-0.021*	-0.021*	-0.014	0.009	-0.002	-0.058	-0.210
	(0.012)	(0.012)	(0.012)	(0.016)	(0.017)	(0.045)	(0.152)

This table contains two types of regressions: OLS regressions predicting returns-to-expiry and Probit regressions predicting expiry at 100. The price, expiry price, and return variables are scaled 0 to 1 for the OLS models; for the probit model, the price variable is Φ^-1(Price) as in Table 7, Panel C. Price and expiry data for contracts with a bearish framing (e.g., "DJIA to close down 50 points or more") are converted to those for the reciprocal bullishly framed contract. These contracts are indicated by the "contract framing = (Buy => Bearish position)" dummy variable. Realized volatility in the last 24 trading hours is the square root of the sum of squared minute-by-minute changes in the most recent trade of the DJIA future since the same calendar time on the most recent prior day when the market was open. The spot-future difference is estimated as described in footnote 7. *, **, and *** indicate statistically significant differences from zero at the 10, 5, and 1 percent level, respectively. Standard errors are in parenthesis and are adjusted for heteroskedasticity and clustering within contract and expiry day.

Table 9. Predicting future realized volatility using binary option implied volatility
Dependent variable: future minute-by-minute realized volatility

Time window	Before 9 AM	9 to 10 AM	10 to 11 AM	11 AM to Noon	Noon to 1 PM	1 to 2 PM	2 to 3 PM	3 to 3:15 PM	3:15 to 3:30 PM	3:30 to 3:45 PM
Binary option implied volatility, by absolute value of z-score										
IVT*(z-score = 0 to 0.25)	0.132***	0.165***	0.121***	0.104***	0.060***	0.050***	0.039***	0.015*	0.009	0.010
	(0.012)	(0.015)	(0.013)	(0.011)	(0.009)	(0.007)	(0.007)	(0.009)	(0.007)	(0.013)
IVT*(z-score = 0.25 to 0.5)	0.144***	0.174***	0.149***	0.128***	0.087***	0.078***	0.065***	0.019***	0.001	0.005
	(0.013)	(0.015)	(0.014)	(0.014)	(0.011)	(0.009)	(0.009)	(0.008)	(0.007)	(0.006)
IVT*(z-score = 0.5 to 0.75)	0.161***	0.206***	0.179***	0.158***	0.127***	0.114***	0.093***	0.039***	0.024**	0.003
	(0.015)	(0.017)	(0.016)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)	(0.010)	(0.006)
IVT*(z-score = 0.75 to 1)	0.159***	0.221***	0.198***	0.179***	0.156***	0.145***	0.120***	0.098***	0.028***	0.023**
	(0.016)	(0.018)	(0.021)	(0.018)	(0.018)	(0.017)	(0.018)	(0.015)	(0.010)	(0.010)
IVT*(z-score = 1 to 1.25)	0.187***	0.228***	0.216***	0.160***	0.166***	0.174***	0.158***	0.101***	0.071***	0.025**
	(0.016)	(0.020)	(0.020)	(0.017)	(0.022)	(0.018)	(0.023)	(0.015)	(0.013)	(0.012)
IVT*(z-score = 1.25 to 1.5)	0.202***	0.241***	0.223***	0.192***	0.207***	0.207***	0.168***	0.102***	0.111***	0.040***
	(0.017)	(0.018)	(0.018)	(0.018)	(0.029)	(0.022)	(0.024)	(0.022)	(0.015)	(0.013)
IVT*(z-score = 1.5 to 1.75)	0.231***	0.277***	0.240***	0.234***	0.183***	0.214***	0.192***	0.155***	0.102***	0.052***
	(0.020)	(0.025)	(0.022)	(0.020)	(0.018)	(0.021)	(0.020)	(0.025)	(0.019)	(0.018)
IVT*(z-score = 1.75 to 2)	0.226***	0.289***	0.255***	0.223***	0.211***	0.228***	0.240***	0.202***	0.168***	0.039*
	(0.022)	(0.030)	(0.042)	(0.026)	(0.024)	(0.025)	(0.025)	(0.027)	(0.020)	(0.021)
IVT*(z-score = 2 to 2.25)	0.238***	0.316***	0.290***	0.240***	0.198***	0.203***	0.215***	0.166***	0.136***	0.064**
	(0.029)	(0.034)	(0.026)	(0.039)	(0.025)	(0.020)	(0.026)	(0.029)	(0.027)	(0.029)
IVT*(z-score = 2.5 to 2.5)	0.274***	0.271***	0.313***	0.284***	0.189***	0.204***	0.199***	0.169***	0.114***	0.147***
	(0.034)	(0.024)	(0.034)	(0.045)	(0.027)	(0.025)	(0.025)	(0.030)	(0.024)	(0.028)
Trades	33,307	28,011	37,184	30,874	30,397	56,218	82,042	26,055	29,865	39,753
Unique expiry days	559	559	559	559	559	559	559	559	559	559

Notes: Time-unadjusted implied volatility (IVT) is used to predict future minute-by-minute realized volatility. For each binary option trade, a z score is calculated as mσ(t), where m is moneyness (the log difference between the log of the most recent DJIA future transaction price and the strike price of the option) and σ(t) is the estimated future volatility from minute t to 4 pm. IVT is calculated as mΦ^-1(p), where p is the option's price (scaled 0 to 1) and Φ^-1 is the inverse of the standard normal cumulative distribution function. Observations for options with z scores greater than 2.5 in absolute value are excluded. Regressions include a constant term that is also allowed to vary with the option's z-score. *, **, and *** indicate statistically significant differences from zero at the 10, 5, and 1 percent level, respectively. Standard errors are in parenthesis and are adjusted for heteroskedasticity and clustering within contract and expiry day.

Table 10. Predicting future realized volatility using binary option implied volatility and other measures

	Future minute-by-minute realized volatility				Absolute now-to-4PM change	
Dependent variable	No autocorrelation adjustment		Hanson-Lunde correction			
Binary option implied volatility, by absolute value of z-score						
IVT*(z-score = 0 to 0.25)	0.418***	0.067***	0.392***	0.057***	0.281***	0.056***
	(0.008)	(0.005)	(0.007)	(0.010)	(0.014)	(0.005)
IVT*(z-score = 0.25 to 0.5)	0.422***	0.078***	0.395***	0.066***	0.286***	0.066***
	(0.009)	(0.006)	(0.009)	(0.009)	(0.014)	(0.006)
IVT*(z-score = 0.5 to 0.75)	0.479***	0.094***	0.448***	0.089***	0.334***	0.079***
	(0.011)	(0.007)	(0.011)	(0.013)	(0.018)	(0.007)
IVT*(z-score = 0.75 to 1)	0.509***	0.099***	0.475***	0.093***	0.354***	0.082***
	(0.014)	(0.008)	(0.013)	(0.014)	(0.021)	(0.009)
IVT*(z-score = 1 to 1.25)	0.506***	0.098***	0.473***	0.090***	0.351***	0.081***
	(0.015)	(0.009)	(0.014)	(0.017)	(0.023)	(0.010)
IVT*(z-score = 1.25 to 1.5)	0.526***	0.104***	0.491***	0.079***	0.350***	0.085***
	(0.015)	(0.009)	(0.015)	(0.018)	(0.024)	(0.010)
IVT*(z-score = 1.5 to 1.75)	0.500***	0.107***	0.468***	0.074***	0.326***	0.090***
	(0.016)	(0.010)	(0.015)	(0.020)	(0.024)	(0.011)
IVT*(z-score = 1.75 to 2)	0.438***	0.098***	0.410***	0.065***	0.283***	0.082***
	(0.022)	(0.010)	(0.021)	(0.023)	(0.024)	(0.012)
IVT*(z-score = 2 to 2.25)	0.411***	0.100***	0.384***	0.071***	0.272***	0.085***
	(0.025)	(0.012)	(0.024)	(0.026)	(0.031)	(0.013)
IVT*(z-score = 2.5 to 2.5)	0.352***	0.083***	0.324***	0.029	0.203***	0.064***
	(0.024)	(0.014)	(0.023)	(0.029)	(0.032)	(0.016)
VXD index * σ(t)		2.921***		1.367*		2.734***
		(0.210)		(0.727)		(0.234)
Lagged 24-hour realized volatility * σ(t)		0.505***		0.429***		0.493***
		(0.044)		(0.153)		(0.049)
Trades	445,465	445,465	445,465	445,465	445,465	445,465
Unique expiry days	559	559	559	559	559	559

Notes: The time-unadjusted implied volatility (IVT) is used to predict future realized volatility. Three measures of future realized volatility are used: 1) the square root of the sum of squared minute-by-minute changes in the DJIA future from the time of the trade to 4 PM ET, 2) this measure with the Hanson and Lunde correction for autocorrelation, and 3) the absolute value of the log change in the DJIA future from the time of the trade to 4 PM. For each binary option trade, a z score is calculated as m/σ(t), where m is moneyness (the log difference between the log of the most recent DJIA future transaction price and the strike price of the option) and σ(t) is the estimated future volatility from minute t to 4 pm. IVT is calculated as m/Φ^-1(p), where p is the option's price (scaled 0 to 1) and Φ^-1 is the inverse of the standard normal cumulative distribution function. Observations for options with z scores greater than 2.5 in absolute value are excluded. *, **, and *** indicate statistically significant differences from zero at the 10, 5, and 1 percent level, respectively. Standard errors are in parenthesis and are adjusted for heteroskedasticity and clustering within contract and expiry day.

Table 11. Summary statistics for time-unadjusted volatility

		Future realized volatility			Time-unadjusted implied volatility (IVT)	
Expiry time	Time	Future minute-by-minute realized volatility	Hanson-Lunde (2005b) corrected (1 lag)	SD (future price change)	Mean	SD
10:00 AM	8:00 AM	35.1	33.0	28.7	36.7	10.8
	9:00 AM	28.4	27.0	24.7	32.8	9.3
	9:30 AM	25.2	24.5	22.4	28.6	5.8
1:00 PM	10:00 AM	47.6	45.1	36.7	47.1	14.1
	11:00 AM	34.1	32.1	28.0	39.1	14.4
	12:00 PM	22.8	21.6	18.3	30.9	14.4
	12:30 PM	15.6	14.8	12.8	26.8	14.9
4:00 PM	8:00 AM	74.8	70.6	64.3	77.3	21.4
	9:00 AM	71.8	68.0	63.7	77.1	19.9
	10:00 AM	66.3	62.8	59.7	71.4	18.0
	11:00 AM	57.4	54.1	55.7	65.4	17.3
	12:00 PM	51.4	48.7	50.1	57.9	15.4
	1:00 PM	46.2	43.9	45.9	51.1	14.5
	2:00 PM	40.1	38.5	40.7	43.5	14.3
	3:00 PM	28.5	27.4	27.6	34.7	13.6
	3:30 PM	20.0	19.3	19.0	29.0	15.3

Notes: Future realized volatility is calculated from the time given to expiry time using the three methods used in Table 10. Volatility is expressed as the standard deviation of expected future price changes in basis points. Each trading day is one observation: sample sizes are 191, 350, and 571 trading days for the 10 AM, 1 PM, and 4 PM expiry times, respectively.

Table 12. Regressions predicting future intraday volatility
Dependent variable: Minute-by-minute realized volatility from now to expiry

Expiration time	10 AM	1 PM	4 PM	4 PM	4 PM	4 PM	4 PM	4 PM	4 PM	4 PM
First time included	8:30 PM (t-1)	8:30 PM (t-1)	8:30 PM (t-1)	8:30 PM (t-1)	9:30 AM	9:30 AM	10:00 AM	12:00 PM	2:00 PM	3:00 PM
Last time included	9:30 AM	12:30 PM	3:30 PM	3:30 PM	3:30 PM	3:30 PM				
IVT index	0.099*	0.414***	0.627***	0.170***	0.166***	0.154***	0.054*	0.116**	0.084***	0.065***
	(0.041)	(0.073)	(0.026)	(0.021)	(0.030)	(0.030)	(0.039)	(0.045)	(0.029)	(0.020)
(Lagged 24-hour realized volatility)*σ(t)				0.920***	1.300***	1.120***	1.078***	1.302***	1.329***	3.002***
				(0.031)	(0.050)	(0.107)	(0.087)	(0.154)	(0.205)	(0.293)
(VXD index)*σ(t)						0.949**	3.369***	3.357***	4.327***	3.888**
						(0.473)	(0.459)	(0.890)	(1.104)	(1.570)
Other controls included										
20 lags of hourly realized volatility										
Ten daily lags of same-time VXD index										
Minute fixed effects										
Observations	4,028	11,444	36,275	36,275	12,820	12,820	559	558	558	558
Unique days	188	350	559	559	559	559	559	558	558	558
R-squared	0.2821	0.3009	0.4702	0.7257	0.7279	0.7292	0.6312	0.4793	0.424	0.5103

Notes: The sum of future minute-by-minute squared log DJIA changes are between the current time and expiry are predicted using IVT, realized volatility over the last 24 trading hours, and the current VXD index. The last two variables are multiplied by the square of σ(τ) to adjust for differences in expected volatility between now and expiry. An observation is constructed every 15 minutes, except for the last four columns, which include only daily observations from a particular time. *, **, and *** indicate statistically significant differences from zero at the 10, 5, and 1 percent level, respectively. Standard errors are in parenthesis and are adjusted for heteroskedasticity and clustering within contract and expiry day.

Table 13. Robustness checks

Dependent variable: Minute-by-minute realized volatility from now to expiry

Expiration time	4 PM	4 PM	4 PM	4 PM	4 PM	4 PM	4 PM	4 PM
First time included	9:30 AM	9:30 AM	9:30 AM	9:30 AM	9:30 AM	9:30 AM	9:30 AM	9:30 AM
Last time included	3:30 PM	3:30 PM	3:30 PM	3:30 PM	3:30 PM	3:30 PM	3:30 PM	3:30 PM
IVT index	0.154***	0.088***	0.074***	0.069***	0.055***	0.073***	0.154***	0.183***
	(0.030)	(0.024)	(0.023)	(0.021)	(0.020)	(0.015)	(0.030)	(0.027)
(Lagged 24-hour realized volatility)*σ(t)	1.120***	1.043***	1.258***	1.321***	1.020***	1.201***	1.132***	2.079***
	(0.107)	(0.135)	(0.146)	(0.203)	(0.184)	(0.105)	(0.107)	(0.183)
(VXD index)*σ(t)	0.949**	2.570***	1.668***	3.045***	2.432***	1.300***	0.944**	6.820***
	(0.473)	(0.495)	(0.512)	(0.736)	(0.832)	(0.480)	(0.472)	(0.864)
Other controls included								
20 lags of hourly realized volatility		X	X	X	X			
5 lags of daily realized volatility			X	X	X			
10 daily lags of same-time VXD index				X	X			
Time of day fixed effects					X			
IVT index construction choices	As described in the text							
Number of IVT observations used	50					1	50	50
Weighting of IVT observations based on moneyness	Equal					Equal	Vega-weighted	Equal
Functional form for σ(t)	Estimated, based on average future realized volatility					Estimated	Estimated	σ(t) = t^0.5
Observations	12,820	12,820	12,820	12,820	12,820	12,820	12,820	12,820
Unique days	559	559	559	559	559	559	559	559
R-squared	0.7292	0.8088	0.8081	0.7901	0.8081	0.7234	0.7292	0.7476

Notes: This table repeats one of the specifications from Table 12 with additional controls or alternative choices in the design of the IVT index. *, **, and *** indicate statistically significant differences from zero at the 10, 5, and 1 percent level, respectively. Standard errors are in parenthesis and are adjusted for heteroskedasticity and clustering within contract and expiry day.

Table 14. Predicting realized volatility over longer horizons
Dependent variable: Minute-by-minute realized volatility over the given time period

Time horizon	Next trading day	Next 5 trading days	Next 20 trading days
Sample includes	Every day	Wednesdays	First trading day of month
Observations	553	115	25
R-squared	0.5627	0.7763	0.8084
IVT index at 2 pm	0.193***	1.419***	7.462**
	(0.060)	(0.392)	(3.375)
Lagged 24-hour realized volatility at 2 pm	0.386***	2.632***	3.887***
	(0.042)	(0.318)	(0.939)
VXD index at 2 pm	0.036***	0.087***	0.106
	(0.004)	(0.032)	(0.125)

Notes: Future realized volatility is predicted at 2pm each day using the current values of the IVT index and VXD index, and realized volatility over the prior 24 trading hours. *, **, and *** indicate statistically significant differences from zero at the 10, 5, and 1 percent level, respectively. Standard errors are in parenthesis and are adjusted for heteroskedasticity.

Table 15. DJIA future return persistence coefficients and intraday implied volatility
Dependent variable: log futures returns over next k minutes [Ln(DJIA(t + 1 + k) - Ln(DJIA(t + 1)]
Independent variable: [Ln(DJIA(t) - Ln(DJIA(t-k)]

Time horizon (k minutes)	5	10	30	60	24 trading hours
Regression coefficients by IVT quintile					
1 (lowest)	-0.013**	0.021***	0.046***	0.045**	0.017***
	(0.005)	(0.007)	(0.013)	(0.020)	(0.049)
2	-0.035***	-0.012*	-0.019	-0.019	-0.072*
	(0.005)	(0.007)	(0.012)	(0.018)	(0.044)
3	-0.030***	-0.025***	-0.009	-0.002	0.028
	(0.005)	(0.007)	(0.013)	(0.019)	(0.043)
4	-0.024***	-0.017**	0.001	-0.005	-0.065***
	(0.005)	(0.007)	(0.012)	(0.017)	(0.038)
5 (highest)	-0.041***	-0.036***	-0.047***	-0.035**	-0.103**
	(0.005)	(0.007)	(0.012)	(0.017)	(0.041)
5 less 1	-0.028***	-0.057***	-0.093***	-0.081***	-0.120*
	(0.007)	(0.010)	(0.018)	(0.026)	(0.064)
Regression coefficients by VXD quintile					
1 (lowest)	-0.031***	-0.002	0.008	0.015	0.005
	(0.006)	(0.008)	(0.013)	(0.021)	(0.048)
2	-0.019***	-0.020**	-0.033**	0.051***	-0.001
	(0.006)	(0.008)	(0.014)	(0.019)	(0.046)
3	-0.021***	-0.003	0.021	-0.012	-0.037
	(0.006)	(0.008)	(0.014)	(0.018)	(0.053)
4	-0.032***	-0.028***	-0.012***	-0.038***	0.057
	(0.006)	(0.008)	(0.014)	(0.017)	(0.049)
5 (highest)	-0.027***	-0.030***	-0.026**	-0.030*	-0.161***
	(0.006)	(0.008)	(0.013)	(0.017)	(0.042)
5 less 1	0.005	-0.027**	-0.034*	-0.045*	-0.166***
	(0.008)	(0.011)	(0.019)	(0.027)	(0.064)
Regression coefficients by lagged 24-hour realized volatility quintile					
1 (lowest)	-0.016***	0.028***	0.014	0.025	-0.009
	(0.005)	(0.008)	(0.014)	(0.019)	(0.052)
2	-0.030***	0.008	0.025***	-0.032	0.075
	(0.005)	(0.007)	(0.013)	(0.020)	(0.048)
3	-0.027***	-0.009***	0.001	0.053***	0.029
	(0.005)	(0.007)	(0.012)	(0.020)	(0.042)
4	-0.021***	-0.041***	-0.038***	-0.024	-0.032
	(0.005)	(0.007)	(0.012)	(0.020)	(0.039)
5 (highest)	-0.045***	-0.035***	-0.033***	-0.028	-0.145***
	(0.005)	(0.007)	(0.012)	(0.019)	(0.039)
5 less 1	-0.029***	-0.063***	-0.047**	-0.053**	-0.136**
	(0.007)	(0.010)	(0.018)	(0.027)	(0.065)

Notes: Each cell is the coefficient from a regression of log DJIA futures returns from t + 1 to t + k + 1 on returns from t - k to k, where k is expressed in minutes. IVT, VXD, and lagged 24-trading-hour realized volatility are ranked within minute-of-day, and the sample is split based on this rank in each of the panels. Newey-West (1987) standard errors, allowing for k lags, are in parenthesis. Standard errors for the differences between coefficients for quintiles 5 and 1 assume independence of the errors for the individual coefficient estimates.

Figure 1. Average future realized volatility and time to expiry -- 4 PM expiry options