# A Appendix

## A.1 Estimation of the price impact using high frequency data

To estimate price impact, we use high frequency data. For each day $d$ in our sample, we first identify all 1-sec intervals with non-zero trading and we number these intervals with $\tau$. We then estimate the following regression of absolute returns on the square root of trading volume in dollars:

$$|r_\tau| = \alpha_d + \beta_d \sqrt{V_\tau} + \varepsilon_\tau$$

This gives us an estimate of $\beta_d$, which we use as a measure of the price impact over day $d$. Our approach is similar to Hasbrouck (2009), Shim (2018), and many other papers that document a square root relationship between returns and volumes. To create annual measures, we take a simple average of price impacts over the year. [30]Our measure of price impact is conceptually similar to the Amihud ratio, except that we use high frequency data and specify a square root relationship, whereas the Amihud ratio takes the average of the daily ratios of absolute returns over trading volume (also in dollars).

In our regressions, we use logarithms of three liquidity measures: bid-ask spread, the Amihud ratio, and our measure of price impact. Table 10 shows correlations of three different measures for our sample of non energy S&P 500 firms and for the period from 2010 to 2016. We can see that our measure is highly correlated with the Amihud ratio; the correlation is 0.81, and has 0.63 correlation with the bid-ask spread. However, for robustness we use all three measures in our analysis.

Table 10: Correlation of different measures of liquidity and price impact.

| | Bid ask spread | Price impact | Amihud ratio |
|---|---|---|---|
| Bid ask spread | 1 | | |
| Price impact | 0.63 | 1 | |
| Amihud ratio | 0.38 | 0.81 | 1 |

[30]It should be noted that an estimate of the beta coefficient in a linear model: $|r_\tau| = \alpha_d + \beta_d V_\tau + \varepsilon_\tau$, as well as the price impact calculated as the total sum of absolute values of 1-sec returns over the total volume($\sum_\tau |r_\tau| / \sum_\tau V_\tau$) produce very similar time series of the price impact which highly correlated with each other. Our main results also remain unchanged.

## A.2 Descriptive statistics

Table 11: Estimated oil betas for the firms in the S&P 500 index.

Panel A: Average oil beta by sector.
The table displays average oil betas calculated using 1 minute returns.

| | 2005-2006 | 2007-2008 | 2009-2013 | 2014-2016 |
|---|---|---|---|---|
| Basic Materials | -0.05 | 0.01 | 0.11 | 0.11 |
| Consumer | -0.07 | -0.08 | 0.06 | 0.05 |
| Financial | -0.06 | -0.12 | 0.07 | 0.05 |
| Health Care | -0.07 | -0.04 | 0.04 | 0.04 |
| Industrials | -0.07 | -0.05 | 0.07 | 0.06 |
| Information Technology | -0.09 | -0.05 | 0.07 | 0.06 |
| Real Estate | -0.04 | -0.08 | 0.07 | 0.02 |
| Telecommunications | -0.07 | -0.05 | 0.07 | 0.05 |
| Utilities | -0.05 | -0.01 | 0.04 | 0.04 |
| Energy | 0.42 | 0.45 | 0.31 | 0.40 |

Panel B: Average probability of simultaneous trading with SPY by sector

| | 2005-2006 | 2007-2008 | 2009-2013 | 2014-2016 |
|---|---|---|---|---|
| Basic Materials | 0.04 | 0.12 | 0.10 | 0.09 |
| Consumer | 0.05 | 0.13 | 0.11 | 0.11 |
| Financial | 0.04 | 0.15 | 0.13 | 0.11 |
| Health Care | 0.05 | 0.11 | 0.10 | 0.11 |
| Industrials | 0.04 | 0.12 | 0.10 | 0.10 |
| Information Technology | 0.07 | 0.14 | 0.12 | 0.12 |
| Real Estate | 0.02 | 0.09 | 0.08 | 0.07 |
| Telecommunications | 0.05 | 0.12 | 0.13 | 0.15 |
| Utilities | 0.04 | 0.10 | 0.08 | 0.10 |
| Energy | 0.08 | 0.17 | 0.14 | 0.16 |

Table 12: Descriptive statistics of U.S. equity ETFs.

Panel A: Sector composition of the U.S. equity ETFs.

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Broad-based | 52 | 63 | 74 | 84 | 86 | 101 | 114 | 121 | 139 | 153 | 167 | 175 |
| Basic Materials | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| Consumer | 6 | 6 | 7 | 9 | 9 | 8 | 8 | 8 | 11 | 11 | 11 | 11 |
| Financial | 3 | 7 | 7 | 8 | 10 | 10 | 10 | 11 | 13 | 13 | 13 | 13 |
| Health Care | 3 | 5 | 6 | 7 | 7 | 8 | 10 | 8 | 10 | 11 | 11 | 11 |
| Industrials | 3 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 5 | 5 | 5 | 5 |
| Internet & Softw | 1 | 2 | 3 | 3 | 4 | 4 | 4 | 4 | 3 | 3 | 4 | 4 |
| Real Estate | 4 | 4 | 5 | 5 | 5 | 5 | 7 | 7 | 7 | 7 | 9 | 10 |
| Telecomm | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| Utilities | 3 | 3 | 3 | 5 | 5 | 4 | 5 | 5 | 5 | 6 | 6 | 6 |
| Energy | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 5 |
| Oil & Gas Eq&Serv | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Oil & Gas E&P | 0 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| Other Sectors | 11 | 22 | 22 | 22 | 24 | 27 | 28 | 30 | 33 | 35 | 36 | 36 |
| Total | 93 | 126 | 142 | 158 | 165 | 183 | 202 | 210 | 239 | 257 | 275 | 284 |

Panel B: Average oil betas
The table displays average oil betas calculated using 1 minute returns.

| | 2007-2008 | 2009-2013 | 2014-2016 |
|---|---|---|---|
| Broad-based ETFs | -0.006 | 0.032 | 0.027 |
| Basic Materials | 0.024 | 0.085 | 0.066 |
| Consumer | -0.023 | 0.015 | 0.016 |
| Financial | -0.081 | 0.039 | 0.024 |
| Health Care | -0.012 | 0.007 | 0.018 |
| Industrials | -0.010 | 0.028 | 0.023 |
| Internet and Software | 0.003 | 0.005 | 0.029 |
| Real Estate | -0.062 | 0.047 | 0.011 |
| Telecommunications | -0.012 | 0.014 | 0.024 |
| Utilities | 0.018 | 0.015 | 0.018 |
| Energy | 0.253 | 0.144 | 0.271 |
| Oil & Gas Equipment & Services | 0.059 | 0.119 | 0.189 |
| Oil & Gas Exploration & Production | 0.147 | 0.263 | 0.381 |
| Other Sectors | -0.017 | 0.034 | 0.048 |

## A.3 Subsamples

Although the development of unconventional oil had already gained momentum by 2010, U.S. oil production dramatically increased afterwards. It is likely that the U.S. economy has continued adjusting to new sources of domestic oil, new financing of the oil industry, and thus the sensitivities of firms to oil has continued to evolve. Hence, our assumption of time invariant individual effects may be too strong. To show that our results are not driven by changes in the fundamental sensitivites to oil, we break the sample into two subperiods. As 2014 is characterized by a significant collapse of oil prices that triggered a series of defaults in the oil producing industry, we break the sample at the end of 2013.

Table 13 breaks the sample period into 2010/13 and 2014/16. The point estimates are large and positive for all years in both subsamples and for both frequencies of returns. As before, we observe significant results for the second subsample and, in addition, for some years in the first subsample. Again, the results are stronger for 5 minute returns. Overall the results are similar.

Table 13: Impact of the probability of joint trading on oil betas in the cross section of S&P 500 firms by subperiod 2010-2013 and 2014-2016..

| | 1 min returns | | 5 min returns | |
|---|---|---|---|---|
| | 2010-13 | 2014-16 | 2010-13 | 2014-16 |
| Prob - | | | | |
| 2010 | 1.03 | | 1.83 | |
| | (1.32) | | (1.60) | |
| 2011 | 0.69 | | 1.39 | |
| | (1.36) | | (1.88) | |
| 2012 | 0.77 | | 1.28 | |
| | (1.28) | | (1.47) | |
| 2013 | 0.83 | | 1.94 | |
| | (1.62) | | (2.56) | |
| 2014 | | 0.29 | | 0.74 |
| | | (1.61) | | (2.68) |
| 2015 | | 0.30 | | 0.68 |
| | | (1.80) | | (2.64) |
| 2016 | | 0.46 | | 0.76 |
| | | (2.45) | | (3.09) |
| Controls(mcap, book-to-market, turnover, dollar volume, price impact) | Yes | Yes | Yes | Yes |
| Year sector effects | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | Yes | Yes | Yes | Yes |
| R-sq within | | 0.48 | 0.50 | 0.59 |
| R-sq between | | 0.01 | 0.01 | 0.02 |
| N | 1,606 | 1,271 | 1,606 | 1,271 |
| N groups | 418 | 440 | 418 | 440 |

## A.4 Conditional probability

For robustness, we also use an estimate of conditional probability calculated as

$$\pi^c_{j,t} = \frac{\sum\limits_{\tau=1}^{T} \mathbb{I}_{V_{ETF,\tau}>0} \mathbb{I}_{V_{j,\tau}>0}}{\sum\limits_{\tau=1}^{T} \mathbb{I}_{V_{j,\tau}>0}}.$$

By conditioning on firm j's trading, we can further filter our intensity of overall trading from our measure of the intensity of arbitrage transactions. In our sample, $\pi^c_{j,t}$ lies in the range from 0.70 to 0.91, and the first, second, and third quantiles are 0.83, 0.85,0.87, respectively. Thus, surprisingly, we have very little variation in conditional probability. Table 14 repeats our main estimation and shows the results. The results are now even stronger. We see significant coefficients in all specifications, for all years and both frequencies of returns. To compare the magnitude of the effect, again consider an increase in conditional probability associated with a move from the first to the third quantile. This increase is associated with an increase in beta by 0.1 (using an estimate for 1 minute returns). Thus, the effect is even larger when we use conditional probabilities.

Table 14: Impact of conditional probability of simultaneous trading with SPY on oil betas in the panel of S&P 500 firms.

The table displays the estimates of the following panel fixed effect regression: $\beta_{j,t} = c_j + \alpha_{J,t} + \gamma_t \pi^c_{j,t} + \delta_t X_{j,t} + \varepsilon_{j,t}$, where $\beta_{j,t}$ is the estimated oil beta of stock $j$ in year $t$, $\pi^c_{j,t}$ is the estimated probability of simultaneous trading of stock $j$ and SPY conditional on trading of stock $j$ over the same period, $\alpha_{J,t}$ are year by sector dummies, and $X_{j,t}$ is a vector of control variables. Controls include logarithms of market capitalization, book-to-market ratio, dollar volume, turnover, volatility, and three measures of liquidity and price impact: bid-ask spread, the price impact coefficient estimated using high frequency data, and the Amihud ratio. St.err are clustered at the firm level, t-statistics in parenthesis. The sample period covers 2010-2016.

| | 1 min returns | | | | | 5 min returns | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (4) | (5) | (6) | (7) | (8) | (4) | (5) | (6) | (7) | (8) |
| ProbTrad | 2.58 | 3.14 | 2.55 | 2.45 | | 3.60 | 4.34 | 3.46 | 3.39 | |
| | (2.19) | (2.41) | (2.26) | (2.10) | | (2.05) | (2.22) | (2.07) | (1.93) | |
| Prob - | | | | | | | | | | |
| 2010 | | | | | 3.75 (2.03) | | | | | 5.39 (1.94) |
| 2011 | | | | | 2.06 (4.01) | | | | | 3.08 (5.66) |
| 2012 | | | | | 1.51 (3.29) | | | | | 2.31 (3.63) |
| 2013 | | | | | 1.18 (2.61) | | | | | 1.51 (2.28) |
| 2014 | | | | | 1.68 (2.97) | | | | | 1.40 (1.62) |
| 2015 | | | | | 1.46 (2.79) | | | | | 2.16 (2.82) |
| 2016 | | | | | 1.40 (2.52) | | | | | 2.54 (3.16) |
| Controls(mcap, book-to-market, turnover, dollar volume) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bid-ask spread | Yes | | | | | Yes | | | | |
| Price impact | | Yes | | | | | Yes | | | |
| Amihud | | | Yes | | | | | Yes | | |
| Volatility | | | | Yes | | | | | Yes | |
| Year sector effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | | | | | Yes | | | | | Yes |
| R-sq within | 0.34 | 0.37 | 0.34 | 0.36 | 0.40 | 0.54 | 0.55 | 0.54 | 0.55 | 0.58 |
| R-sq between | 0.08 | 0.12 | 0.09 | 0.12 | 0.00 | 0.12 | 0.14 | 0.10 | 0.14 | 0.001 |
| N | 2,876 | 2,884 | 2,884 | 2,884 | 2,884 | 2,876 | 2,884 | 2,884 | 2,884 | 2,884 |
| N groups | 444 | 445 | 445 | 445 | 445 | 444 | 445 | 445 | 445 | 445 |

## A.5 Oil betas vs. market betas

The cash flow sensitivities to the oil price are largely driven by the nature of business and reflect a lot of idiosyncratic variation. As a result, our oil betas are quite different from the market betas. To show that, we calculate the cross-sectional correlations of the market betas with our oil betas. To calculate market betas, we use daily returns on the stocks in the S&P 500 index and the SPY returns. As in the main exercise, we use 1 minute and 5 minute announcement returns to estimate oil betas. The correlations are calculated separately for each calendar year.

Figure 3 displays the results. Before 2008 the correlations were extremely low suggesting absolutely no connection between oil and market betas. The oil betas of most non-oil related companies were *negative* (see Figure2) in line with conventional wisdom. Intuitively, an increase in oil prices raises input costs for most business, as well as forces consumers to spend more money on gasoline and less on everything else. Thus, although oil risk could represent a market source of risk, the idiosyncratic component outweighed the systematic one.

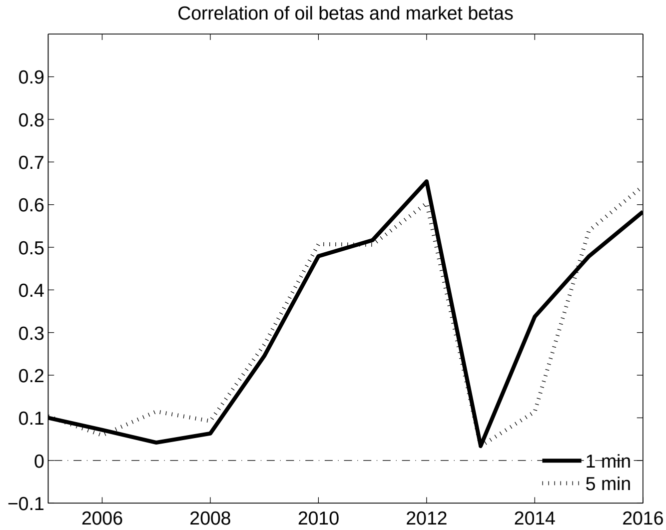
By 2012 the oil betas became positive and the correlation increased dramatically. One potential reason behind these changes is the shale boom. The development of unconventional oil through various channels, including the high indebtedness of the energy sector, could have amplified the importance of the systematic component of the oil price fluctuations (seeAnatolyev et al. (2019)). However, the correlation fell below 0.1 in 2013 right in the midst of the shale boom. As the unconventional oil production continued to gain momentum in 2013, it is highly unlikely that the shale boom permanently transformed oil price risk into a market wide risk.

In sum, oil betas reflect mostly idiosyncratic variation. Hence, our approach of focusing on oil betas rather than on market betas allows to mitigate a concern that joint exposure to a market wide risk triggers simultaneous trading at the stock and ETF markets in response to oil news and thus drives a spurious relationship between our measure of arbitrage intensity and betas.

## A.6 ETF arbitrage and stock volatility

Ben-David et al. (2018) find the effect of ETF ownership on the volatility of underlying stocks. As an additional test of our measure, we estimate the relationship between the probability of simultaneous trading with SPY and the volatility of individual stocks estimated as the variance of daily returns. Table 15 shows our results: The firms more actively traded with SPY indeed have higher volatility, consistent with the original hypothesis. The lower panel in Table 15 shows the estimates of the interaction coefficients added to specifications (4)-(6) and estimated over the 2014-2016 period. All interaction

Figure 3: Correlation of oil betas and market betas.




terms are positive. If the intraday measure of price impact is used, the interaction coefficient is also significant. Hence, similarly to our main results, the distortive effects are stronger for stocks with lower liquidity and stronger price impact, consistent with the ETF arbitrage mechanism. We repeat the estimation using realized variance, and obtain similar results (available upon request).

Table 15: Impact of the probability of simultaneous trading with SPY on volatility in the panel of S&P 500 firms.

The table displays the estimates of the following panel fixed effect regression: $\ln\sigma^2_{j,t} = c_j + \alpha_{J,t} + \gamma_t \pi_{j,t} + \delta_t X_{j,t} + \varepsilon_{j,t},$, where $\sigma^2_{j,t}$ is the estimated volatility of stock $j$ in year $t$, $\pi_{j,t}$ is the average probability of simultaneous trading of stock $j$ and SPY over the same period, $\alpha_{J,t}$ are year by sector dummies, and $X_{j,t}$ is a vector of control variables. Controls include logarithms of market capitalization, book-to-market ratio, dollar volume, turnover, and three measures of liquidity and price impact: bid-ask spread, the price impact coefficient estimated using high frequency data, and the Amihud ratio. St.err are clustered at the firm level, t-statistics in parenthesis. The sample period covers 2010-2016.

| | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|
| ProbTrad | 3.22 | 2.93 | 2.70 | 1.32 | | | |
| | (5.77) | (4.93) | (3.73) | (2.53) | | | |
| Prob - | | | | | | | |
| 2010 | | | | | 3.61 (3.59) | 0.80 (0.6) | 1.86 (2.16) |
| 2011 | | | | | 2.85 (3.47) | 1.15 (1.34) | 0.79 (1.4) |
| 2012 | | | | | 2.91 (3.31) | 0.40 (0.45) | 0.74 (1.2) |
| 2013 | | | | | 2.50 (2.72) | 1.58 (1.56) | 0.54 (0.78) |
| 2014 | | | | | 2.52 (3.18) | 2.88 (3.21) | 0.87 (1.57) |
| 2015 | | | | | 3.22 (4.03) | 4.40 (4.68) | 1.12 (1.64) |
| 2016 | | | | | 4.01 (5.37) | 5.03 (5.88) | 1.08 (2.01) |
| Controls(mcap, book-to-market, turnover, dollar volume) | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bid-ask spread | | Yes | | | Yes | | |
| Price impact | | | Yes | | | Yes | |
| Amihud | | | | Yes | | | Yes |
| Year sector effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | | | | | Yes | Yes | Yes |
| R-sq within | 0.70 | 0.71 | 0.73 | 0.82 | 0.73 | 0.77 | 0.84 |
| R-sq between | 0.54 | 0.55 | 0.64 | 0.84 | 0.43 | 0.16 | 0.85 |
| N | 2,877 | 2,876 | 2,877 | 2,877 | 2,876 | 2,877 | 2,877 |
| N groups | 444 | 444 | 444 | 444 | 444 | 444 | 444 |

| | 2014-2016 | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| ProbTrad | 14.11 (2.55) | 30.03 (2.89) | 33.02 (1.73) |
| ProbTrad × Bid ask | 1.14 (1.83) | | |
| ProbTrad × Price impact | | 1.71 (2.36) | |
| ProbTrad × Amihud | | | 1.19 (1.60) |

## A.7 Long-term effects

Table 16: Impact of the probability of simultaneous trading with SPY on oil betas in the panel of S&P 500 firms.
The table displays the estimates of the following panel fixed effect regression: $\beta_{j,t} = c_j + \alpha_{J,t} + \gamma_t \pi_{j,t} + \delta_t X_{j,t} + \varepsilon_{j,t}$, where $\beta_{j,t}$ is the estimated oil beta of stock $j$ in year $t$, $\pi_{j,t}$ is the average probability of simultaneous trading of stock $j$ and SPY over the same period, $\alpha_{J,t}$ are year by sector dummies, and $X_{j,t}$ is a vector of control variables. Controls include logarithms of market capitalization, book-to-market ratio, dollar volume, turnover, volatility, and three measures of liquidity and price impact: bid-ask spread, the price impact coefficient estimated using high frequency data, and the Amihud ratio. St.err are clustered at the firm level, t-statistics in parenthesis. The sample period covers 2010-2016.

| | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| ProbTrad | 1.34 | 1.45 | 1.45 | 1.49 | 1.41 | |
| | (2.36) | (2.51) | (2.49) | (2.54) | (2.40) | |
| Prob - | | | | | | |
| 2010 | | | | | | 1.34 (1.78) |
| 2011 | | | | | | 0.03 (0.03) |
| 2012 | | | | | | 0.16 (0.15) |
| 2013 | | | | | | 0.36 (0.27) |
| 2014 | | | | | | 3.37 (3.04) |
| 2015 | | | | | | 1.01 (1.5) |
| 2016 | | | | | | 1.23 (1.88) |
| Controls(mcap, book-to-market, turnover, dollar volume) | Yes | Yes | Yes | Yes | Yes | Yes |
| Bid-ask spread | | Yes | | | | |
| Price impact | | | Yes | | | |
| Amihud | | | | Yes | | |
| Volatility | | | | | Yes | |
| Year sector effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | | | | | | Yes |
| R-sq within | 0.45 | 0.45 | 0.45 | 0.45 | 0.45 | 0.48 |
| R-sq between | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.007 |
| N | 2,852 | 2,851 | 2,852 | 2,852 | 2,852 | 2,852 |
| N groups | 440 | 440 | 440 | 440 | 440 | 440 |

## A.8 Mutual fund fire sales

Mutual fund fire sales are widely used in the literature to identify exogenous variations in the prices of securities. Ideally, fire sales of mutual funds should represent a series of sell orders unrelated to any news about the value of stocks. To ensure that selling pressure does not reflect fundamental news, it is common to restrict the choice only to funds that invest in a broad set of stocks rather than cover a narrow sector. Another issue is that managers of the funds have a choice over which securities to keep and which to sell. To dampen any strategic consideration, Edmans et al. (2012) suggest using hypothetical sales and not actual changes in positions. The two will coincide only if the fund proportionally sells all of its securities in the portfolio. Coval and Stafford (2007) have shown that the identified price pressure is significant and large, but temporary, which confirms the liquidity pressure story.

The SEC requires all mutual funds to report their asset holdings at the end of each quarter. We use Thomson Returns data on mutual fund holdings and the CRSP mutual funds database to identify exposed mutual funds and calculate the overall selling pressure on each stock in each quarter. Flows to fund $k$ in quarter $t$ are given by the growth rate of the total net assets under management after adjusting for the change in the market value of the mutual fund's assets

$$Flow_{k,t} = \frac{TNA_{k,t} - TNA_{k,t-1}(1 + R_{k,t})}{TNA_{k,t-1}}$$

We identify exposed funds as funds losing at least 5% of their assets. For each individual stock $j$ we then calculate total *hypothetical* sales as $MFHS_{j,t} = \sum_k \mathbb{I}_{Flow_{k,t}<-5\%} Flow_{k,t} S_{j,k,t-1}$, where $S_{j,k,t-1}$ denotes the number of shares of firm $j$ held by fund $k$ in quarter $t$. It is standard in the literature to normalize MFHS by trading volume. In our case, that would complicate the interpretation because periods of high trading volume can be associated with more active trading and thus higher probability of simultaneous trading.

## A.9 Intraday Evidence of Price Discovery and ETF Arbitrage

Our mechanism relies on the assumption that the ETF market plays at least a partial role in the price discovery process. When new information arrives it can be incorporated into the ETF price first, and only afterwards be transmitted to the underlying market by arbitrage. In this section, we investigate the behavior of quotes and volumes around our announcements.

We pick sixteen oil inventory announcements that induced the largest movements in the price of oil, eight negative and eight positive. Our goal is to examine how new information is incorporated into the prices following each announcement. In the first exercise, we investigate the behavior of quotes. We use the data on best bids and offers at each second prepared by WRDS to calculate the midpoints. When calculating the quotes for the underlying portfolio, we use the quotes of the underlying constituents and weight them with the index weights. [31] We plot the cumulative midpoint returns over a two minute period following each announcement on Figures 4 and A.9. Each picture corresponds to a particular announcement day; the red line corresponds to the SPY, and the blue line reflects the underlying portfolio.

A number of interesting observations emerge. First, many days are characterized by a distinct jump which occurs simultaneously on the ETF and the underlying markets. It implies that the ETF and the underlying portfolio react simultaneously to news. Hence, our results contradict the findings of Box et al. (2019) who argue that the underlying portfolio tends to incorporate new information faster. It should be noted that we use higher frequency data than Box et al. (2019), and still we find no difference in the timing of responses.

Moreover, we find that in most cases SPY overreacts to news relative to the underlying portfolio. Indeed, the red line lies above the blue line when the announcement return is positive, and lies below when the return is negative. This effect is especially pronounced when the announcement return is large. Hence, SPY plays at least a partial role in the price discovery process. Importantly, if a price deviation or a mispricing caused by SPY overreaction is large enough for an arbitrage opportunity to open up, its direction is such that arbitrageurs would push the price of the underlying securities in the direction of the initial shock. For example, when the announcement return is positive and SPY overreacts, arbitrageurs should purchase the underlying stocks, pushing prices upwards, consistent with our story.

We also document a widening of the bid-ask spread at the underlying market following each announcement. Figure 5 depicts the difference in cumulative changes in the best bids and offers. To save the space, we only show the results for the four largest announcements (other days show similar pattern). We see a clear increase in the spread immediately after an announcement and a slow convergence afterwards, which is consistent with an increased buying or selling pressure in response to news arrivals. This result again contradicts the findings of Box et al. (2019) that bid and ask adjust smoothly and symmetrically to the arrival of new information to the underlying market.

To provide additional evidence, we investigate the behavior of trading volumes. We consider the directional volume of the ETF and underlying portfolio for the two minute period following each announcement. The directional volume is calculated as the normalized difference between buy and sell volume over the two minute period following an announcement: $dVol_t = \dfrac{BuyVol_t - SellVol_t}{BuyVol_t + SellVol_t}$. Buy (sell) volume is the trading volume occurring at prices above (below) the prevailing midpoint[32]. For the underlying portfo-

[31] We use the weights provided by ETF Global.

[32] We use the data files prepared by WRDS, where each transaction is matched with the corresponding

Figure 4: Cumulative midpoint returns following oil inventory announcements.

Each picture corresponds to one of the 16 announcement days characterized by the largest oil price announcement returns. We consider a two minute period following each announcement; the x-axis runs from 5 seconds before the announcement to 2 minutes after. The red line reflects the cumulative midpoint SPY returns, the blue line corresponds to the underlying portfolio cumulative midpoint returns.

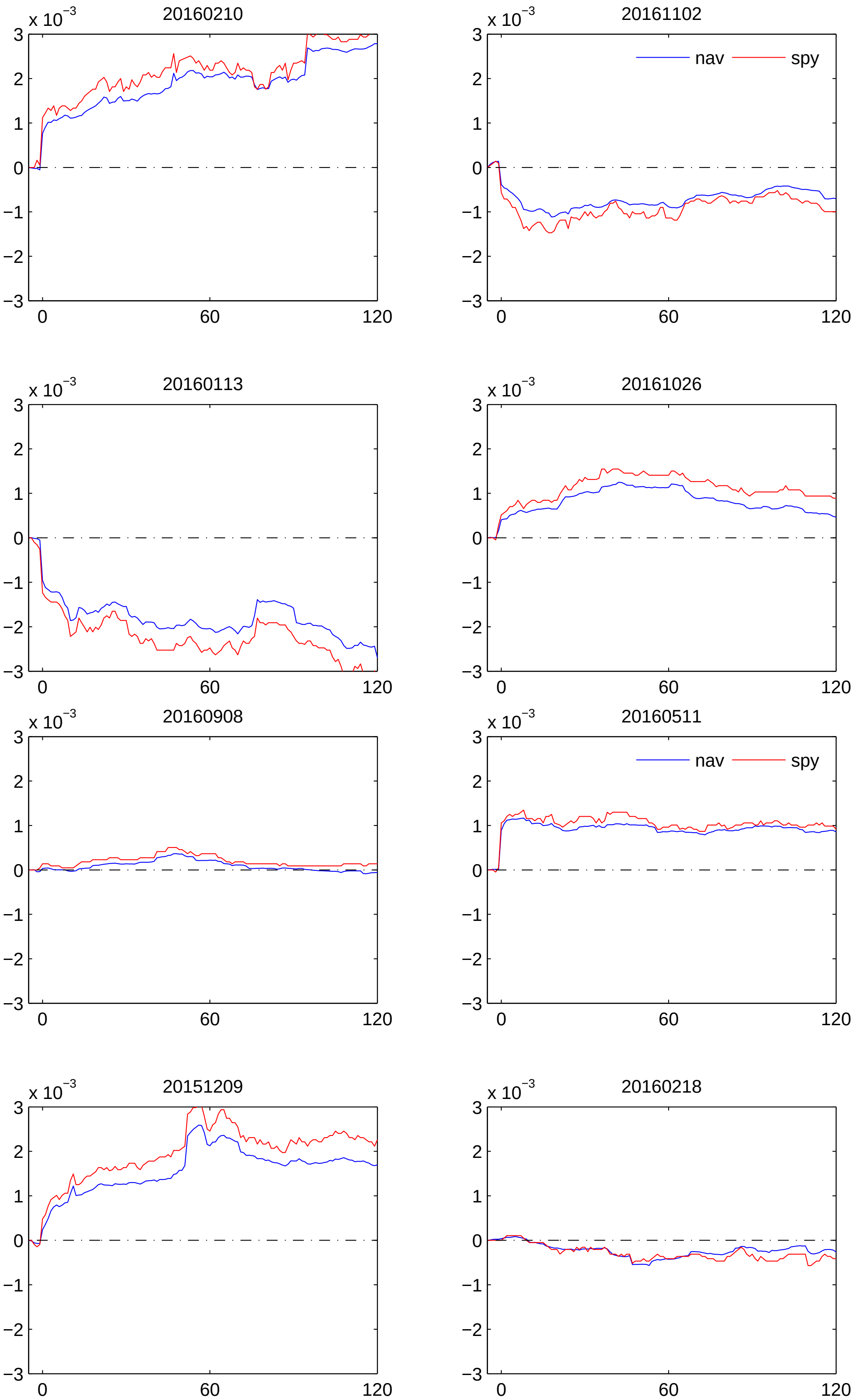


Figure 3 (continue)

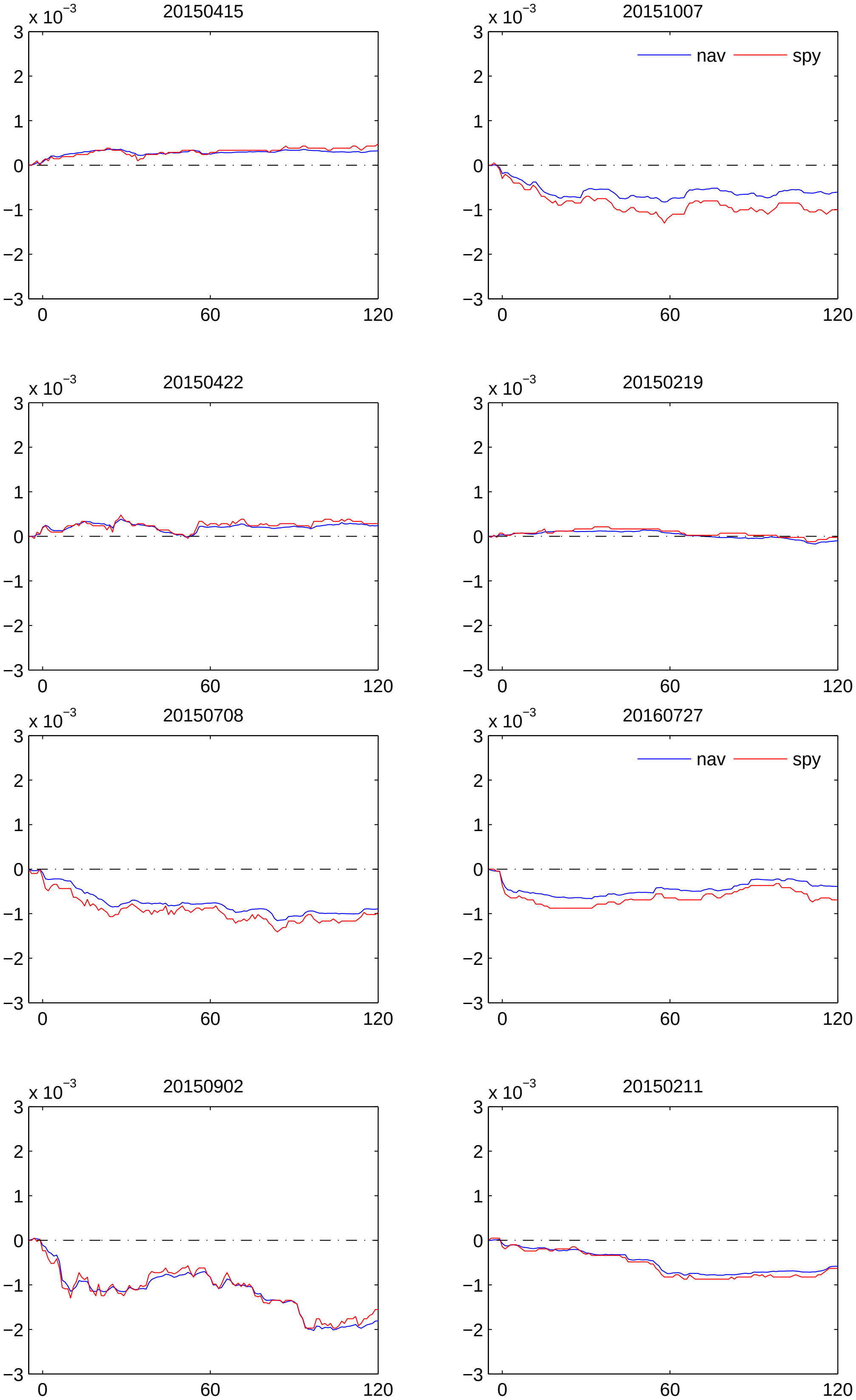


Figure 5: Difference in cumulative returns on best bid and best ask for the underlying portfolio following oil inventory announcements.

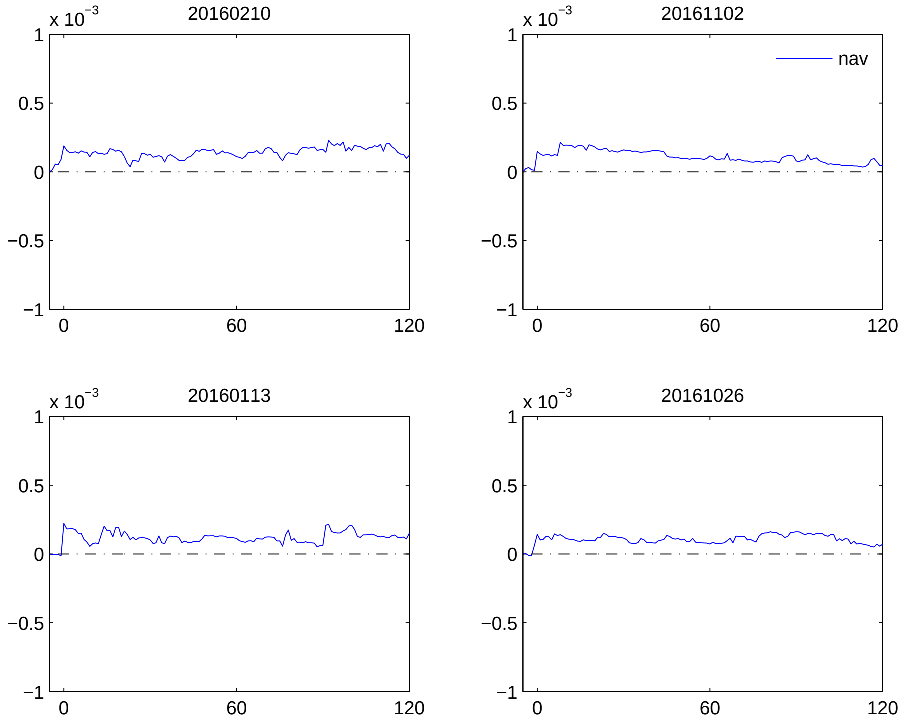
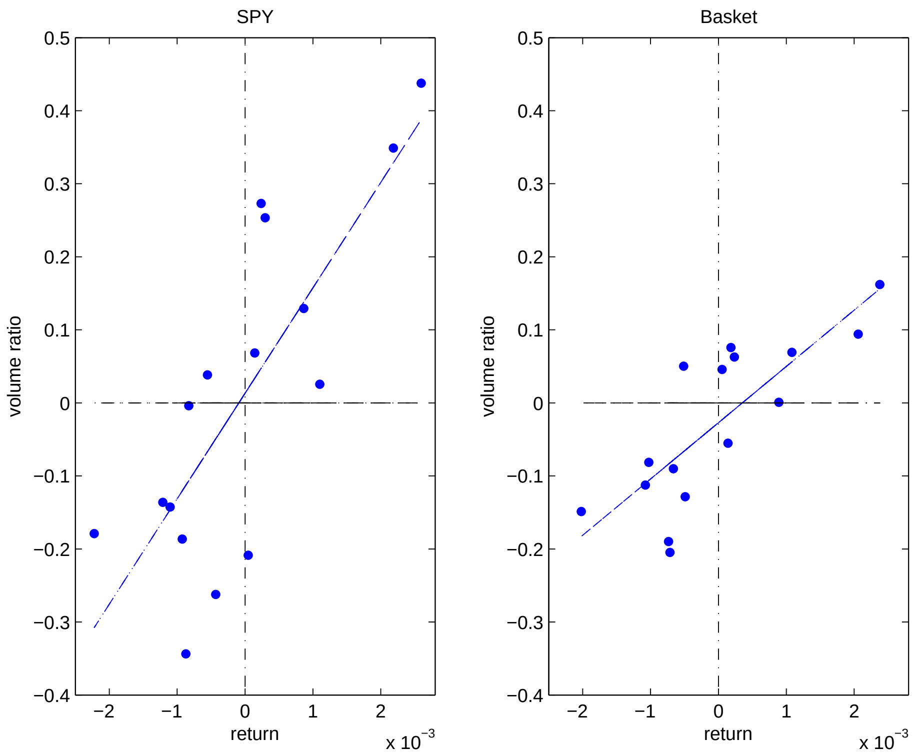



Figure 6: Directional volume and returns.
Each dot represents one of the 16 announcement days with the largest oil price movements.



lio, we take the portfolio-weighted average of the directional volumes of the individual constituents.

Figure 6 shows the results. Both the ETF and the underlying portfolio display a positive link between returns and order flow. Marketable buy orders arrive more frequently when the return is positive. Our results again contradict Box et al. (2019) who show that overvalued ETFs are typically purchased following the mispricing despite a generally negative trend in ETF returns that corrects the initial mispricing. More generally, Box et al. (2019) do not find any evidence that directional trading in the ETF market has any relation to midpoint ETF returns, and thus argue that ETF order flow appears to be devoid of information. In contrast, we find a strong positive link even when we use one minute intervals outside the announcement window. The median correlation of one minute SPY returns and directional volumes is 0.44, where the median is taken over our chosen announcement days[33].

We would like to emphasize that directional volume results can neither confirm, no reject the presence of arbitrage transactions. We see that marketable orders tend to follow the returns, and thus can mask the arbitrage transactions. Indeed, when the market receives positive news, we cannot say whether the buy orders for the underlying stocks reflect arbitrage transactions or informed buy orders following positive news. Similarly, even though arbitrageurs are expected to sell overvalued SPY shares, these transactions can be dominated by the bulk of buy orders again following positive news.

It also should be noted, that our mechanism may work indirectly, if the market makers change their behavior in the presence of ETF arbitrage. If the market makers on the markets for individual stocks rationally expect arbitrage transactions to occur in response to news, they may be inclined to adjust the quotes accordingly in anticipation of the trading pressure. Hence, we can observe a change in quotes without actual trading volumes, however this effect still represents a direct consequence of the presence of ETF arbitrage, and thus should be considered as a part of our story.

Box et al. (2019) question the results of all empirical papers that try to identify the effects of ETF arbitrage on the underlying market. They find that mispricing is typically originated from a permanent shock in the underlying portfolio, and that it is corrected by quote adjustment and not by arbitrage transactions. However, our results contradict all major findings of Box et al. (2019). One reason for the discrepancy of results, could be our exclusive focus on SPY. Perhaps smaller ETFs induce much smaller effects on the underlying markets that are harder to detect. However, SPY is the world's largest ETF, it accounts for more than 10% of the overall investment in the ETFs, thus, it deserves special attention. Another potential reason is our improved identification of the shocks that cause mispricings. We focus on clearly identified fundamental shocks that come at

best bid and best offers.

[33]For each day we consider the period from 9:30 to 11 am.

a prespecified time and are known to significantly move the market. Finally, it might also be that the 1-minute frequency utilized by Box et al. (2019) is too low to capture arbitrage behavior.

## A.10 Absolute value of betas

Table 17: Impact of probability of simultaneous trading with SPY on *absolute* oil betas in the panel of S&P 500 firms.

The table repeats the estimation in Table 1, but using the *absolute* value of the estimated oil beta of stock $j$ in year $t$, $|\beta_{j,t}|$, as the dependent variable. See Table 1 for details. St.err are clustered at the firm level, t-statistics in parenthesis. The sample period covers 2010-2016.

| | 1 min returns | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ProbTrad | 0.28 | 0.20 | 0.13 | 0.07 | 0.09 | -0.01 | 0.06 | |
| | (5.03) | (2.49) | (1.34) | (0.55) | (0.80) | (-0.05) | (0.67) | |
| Prob - | | | | | | | | |
| 2010 | | | | | | | | -0.08 (-0.37) |
| 2011 | | | | | | | | -0.01 (-0.09) |
| 2012 | | | | | | | | 0.10 (0.67) |
| 2013 | | | | | | | | -0.02 (-0.15) |
| 2014 | | | | | | | | -0.03 (-0.31) |
| 2015 | | | | | | | | 0.10 (1.07) |
| 2016 | | | | | | | | 0.21 (2.00) |
| Controls(mcap, book-to-market, turnover, dollar volume) | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bid-ask spread | | | | Yes | | | | |
| Price impact | | | | | Yes | | | |
| Amihud | | | | | | Yes | | |
| Volatility | | | | | | | Yes | |
| Year sector effects | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | | | | | | | | Yes |
| R-sq within | 0.016 | 0.191 | 0.325 | 0.338 | 0.345 | 0.377 | 0.338 | 0.355 |
| R-sq between | 0.003 | 0.238 | 0.147 | 0.163 | 0.184 | 0.224 | 0.199 | 0.050 |
| N | 3,058 | 2,877 | 2,877 | 2,876 | 2,877 | 2,877 | 2,877 | 2,877 |
| N groups | 461 | 444 | 444 | 444 | 444 | 444 | 444 | 444 |

Table 1(continue)

| | 5 min returns | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ProbTrad | 0.92 | 0.91 | 0.41 | 0.32 | 0.35 | 0.20 | 0.29 | |
| | (8.33) | (6.92) | (2.72) | (1.64) | (1.92) | (0.97) | (2.09) | |
| Prob - | | | | | | | | |
| 2010 | | | | | | | | 0.10 (0.30) |
| 2011 | | | | | | | | 0.28 (1.12) |
| 2012 | | | | | | | | 0.18 (0.75) |
| 2013 | | | | | | | | 0.43 (1.93) |
| 2014 | | | | | | | | 0.18 (0.92) |
| 2015 | | | | | | | | 0.50 (3.15) |
| 2016 | | | | | | | | 0.56 (3.69) |
| Controls(mcap, book-to-market, turnover, dollar volume) | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bid-ask spread | | | | Yes | | | | |
| Price impact | | | | | Yes | | | |
| Amihud | | | | | | Yes | | |
| Volatility | | | | | | | Yes | |
| Year sector effects | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | | | | | | | | Yes |
| R-sq within | 0.051 | 0.317 | 0.507 | 0.516 | 0.522 | 0.549 | 0.520 | 0.528 |
| R-sq between | 0.016 | 0.216 | 0.162 | 0.175 | 0.197 | 0.269 | 0.247 | 0.013 |
| N | 3,058 | 2,877 | 2,877 | 2,876 | 2,877 | 2,877 | 2,877 | 2,877 |
| N groups | 461 | 444 | 444 | 444 | 444 | 444 | 444 | 444 |

## A.11 Measures of algorithmic trading

Table 18: Impact of probability of simultaneous trading with SPY on oil betas in the panel of S&P 500 firms.

The table repeats the estimation in Table 1, but the controls also include the two measures of algorithmic trading, cancels-to-trades ratio and trades-to-orders volume ratio developed inWeller (2018) and calculated using MIDAS data. The sample period covers 2012-2016, as MIDAS data on AT starts only in 2012. St.err are clustered at the firm level, t-statistics in parenthesis.

| | 1 min returns | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ProbTrad | 0.39 | 0.62 | 0.28 | 0.27 | 0.30 | 0.21 | 0.20 | |
| | (5.08) | (5.70) | (2.45) | (2.34) | (2.57) | (1.79) | (1.75) | |
| Prob - | | | | | | | | |
| 2012 | | | | | | | | 0.38 (2.25) |
| 2013 | | | | | | | | 0.01 (0.06) |
| 2014 | | | | | | | | 0.30 (1.91) |
| 2015 | | | | | | | | 0.21 (1.48) |
| 2016 | | | | | | | | 0.41 (2.65) |
| Controls(mcap, book-to-market, turnover, dollar volume, cancel-to-trade, trade-to-orders) | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bid-ask spread | | | | Yes | | | | |
| Price impact | | | | | Yes | | | |
| Amihud | | | | | | Yes | | |
| Volatility | | | | | | | Yes | |
| Year sector effects | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | | | | | | | | Yes |
| R-sq within | 0.0292 | 0.1912 | 0.3846 | 0.3873 | 0.3898 | 0.4024 | 0.3970 | 0.4365 |
| R-sq between | 0.0024 | 0.2238 | 0.1260 | 0.1302 | 0.1459 | 0.1616 | 0.1701 | 0.0217 |
| N | 2,223 | 1,861 | 1,861 | 1,861 | 1,861 | 1,861 | 1,861 | 1,861 |
| N groups | 461 | 399 | 399 | 399 | 399 | 399 | 399 | 399 |

Table 1(continue)

| | 5 min returns | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ProbTrad | 0.45 | 0.97 | 0.58 | 0.56 | 0.60 | 0.53 | 0.51 | |
| | (4.14) | (5.60) | (3.55) | (3.39) | (3.61) | (3.39) | (3.10) | |
| Prob - | | | | | | | | |
| 2012 | | | | | | | | 0.22 (0.76) |
| 2013 | | | | | | | | 0.14 (0.35) |
| 2014 | | | | | | | | 0.60 (2.30) |
| 2015 | | | | | | | | 0.46 (1.98) |
| 2016 | | | | | | | | 0.47 (2.08) |
| Controls(mcap, book-to-market, turnover, dollar volume, cancel-to-trade, trade-to-orders) | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bid-ask spread | | | | Yes | | | | |
| Price impact | | | | | Yes | | | |
| Amihud | | | | | | Yes | | |
| Volatility | | | | | | | Yes | |
| Year sector effects | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Time varying $\gamma_t, \delta_t$ | | | | | | | | Yes |
| R-sq within | 0.0124 | 0.2092 | 0.4263 | 0.4281 | 0.4286 | 0.4299 | 0.4302 | 0.4742 |
| R-sq between | 0.0141 | 0.1369 | 0.0954 | 0.1002 | 0.1095 | 0.1088 | 0.1128 | 0.0610 |
| N | 2,223 | 1,861 | 1,861 | 1,861 | 1,861 | 1,861 | 1,861 | 1,861 |
| N groups | 461 | 399 | 399 | 399 | 399 | 399 | 399 | 399 |