A Case of 'Wag the Dog'?

ETFs and Stock-Level Liquidity

Author
Daniel J. Sandberg, PhD, CFA
Quantamental Research
212.438.1407
Daniel.Sandberg@spglobal.com

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Exchange Traded Funds (ETFs) have become one of the most popular investment vehicles over the last two decades,[1,2] with some ETFs now having more than twice the assets of the largest hedge funds. The trading activity of any large fund is expected to impact the price of the securities traded, but to what extent do ETFs impact the prices of their underlying securities? This research presents a model for estimating the sensitivity of security prices to ETF flows. The analyses show the impact of ETF trading is transient and of only a modest magnitude under even extreme assumptions. Inclusion of ETF flow sensitivity in a risk model produces improved risk-adjusted performance.

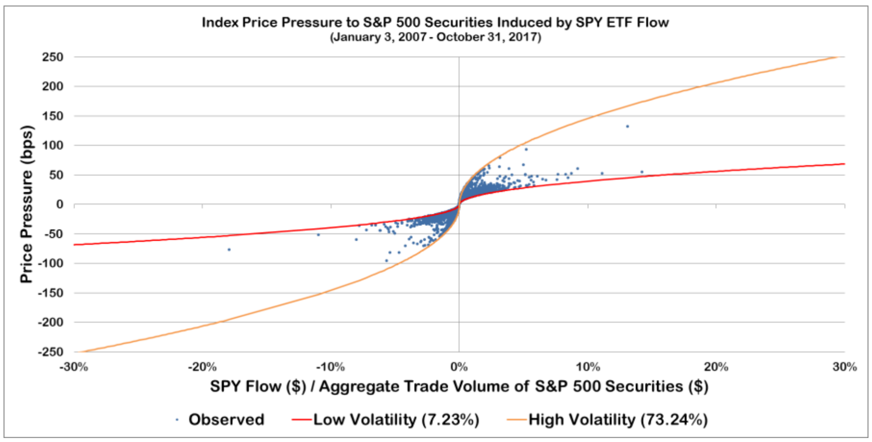

Figure 1. Index-level price pressure vs fraction of liquidity demanded and volatility. Index level price pressure was calculated as a weighted sum of security level price pressure values and plotted against total SPDR S&P 500 ETF (SPY) flow to total S&P 500 trading volume. Price pressure curves were plotted using fixed levels of volatility.
Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

- We present an ETF price impact model, which posits single-day impact of up to 370 bps / day on an individual security and up to 250 bps / day on the index itself. Analyses indicate the effect is transitory and reverses over a period of 3-5 trading days.

- The Feb 2018 market correction was accompanied by a $25B outflow of assets from ticker SPY, the SSGA S&P 500 Trust ETF.[3] Modeling suggests that as much as one-third of the pullback was due to price pressure from ETF trading and that securities more sensitive to ETF flow underperformed.

- Sensitivity to ETF flow is used to build a risk model, which generates improved performance in a historical optimization. We offer a method for estimating ETF sensitivity for funds, using the S&P Global Ownership dataset.

[1] Cheng, E. (2017, June 26). Goldman says there's one major force behind the market's gains this year: ETFs. Retrieved from http://www.cnbc.com.
[2] Vlastelica, R. (2018, Jan 3). ETFs shattered their growth records in 2017. Retrieved from https://www.marketwatch.com.
[3] Popina, E., Leinz, K. (2018, Feb 16) What Shaped the Stock Market's $3 Trillion Trauma. Retrieved from https://www.bloomberg.com.

1. Background

Exchange Traded Funds (ETFs) are investment vehicles with a unique primary market mechanism. Specifically, shares outstanding of an ETF product can change daily by means of an in-kind exchange between the fund sponsor and an authorized participant (AP). Creation (redemption) of shares of an ETF by the in-kind mechanism, involves the AP delivering (receiving) a basket of securities to (from) the Sponsor and the Sponsor delivering (receiving) shares of the ETF. This activity can be quantified as a time-series of ETF flow,

$$Flow_t = Price_{t-1} * (SHout_t - SHout_{t-1}) \quad \text{Equation 1}$$

where $SHout$ is the number of ETF shares outstanding, $Price$ is the price per share of the ETF, $Flow$ is the dollar-denominated flow, and subscripts index over time.

The impact of the primary market activity for ETFs on the underlying basket of securities has been widely debated in the literature. Because most ETFs passively trade a basket of securities, the flow of capital to or from the ETF can incentivize APs to trade larger volumes of securities than a discretionary trader might consider. That trading activity may consume liquidity from securities and cause prices to drift from levels supported by fundamentals when consumption is large relative to the liquidity available. The ability of trading activity to temporarily impact prices is termed price pressure.[4]

Another school of thought is that the availability of a low-cost, highly liquid product that is easily accessible to individual investors will lead to enhanced price discovery and that new information will be more efficiently reflected in prices. Ben-David and coworkers (2016) recently suggested that both mechanisms, enhanced price discovery and price pressure, may be occurring simultaneously.

The focus of this research is to better understand price pressure. Price pressure is caused by liquidity shocks to an ETF, which propagate to the underlying securities through the arbitrage channel (Fig 2). In the first stage of the mechanism, net buying (selling) of an ETF can cause the ETF to trade at a premium (discount) to the net asset value (NAV) of the underlying basket of assets, priming the price pressure mechanism. APs have an economic incentive to exchange the basket of assets for the ETF shares when ETF prices drift from NAV. This arbitrage trade, facilitated by the APs, should eliminate the price discrepancy between the ETF and its NAV, as well as propagate the aggregate demand for the ETF to the underlying basket. Finally, an efficient market will eventually see prices return to levels supported by fundamentals, in a reversal of the price pressure. (Ben-David 2017)

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[4] This research exploits the ability to track the daily change in shares outstanding for an ETF as a means of studying price pressure, but the impact of capital flows on prices can be generalized to any institutional fund or large trade. See Grinold and Kahn (1999) for a comprehensive discussion.

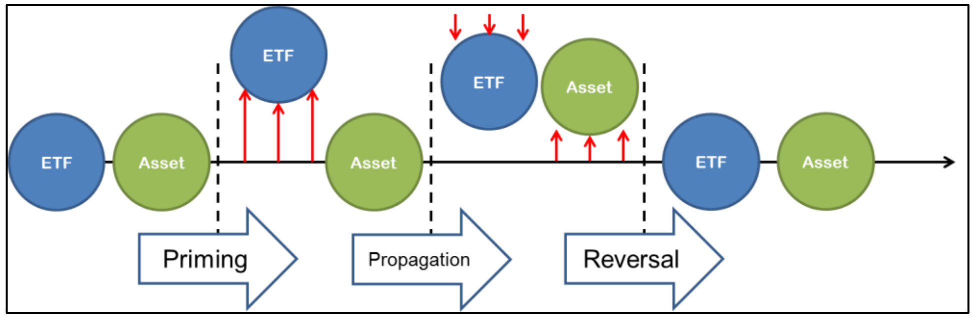

Figure 2. Price Pressure Mechanism. Depiction of the three stages of the price pressure mechanism following an inflow of capital to the ETF. Source: S&P Global Market Intelligence Quantamental Research.

2. Model of Price Pressure

The estimates presented in this work make the simplifying assumption that the change in shares in the primary market (i.e. share creation or redemption of the ETF) translates to trades executed by the authorized participants (APs) that equate to the basket of shares of the underlying that comprise the ETF. In practice, APs may hold shares of the underlying securities in inventory, or have the ability to settle delivery of the underlying at a date later than the flow was recorded. Further, ETFs that trade similar baskets of securities, and have opposing flows in the primary market, may generate offsetting trades in the secondary market. Despite the potential noise that these realities add to our analyses, the model presented provides a valuable quantitative framework to study ETF trading impact and results are supported by statistical analyses.

Estimates of price pressure are based on a modified form of a market impact model (equation 2), presented initially by Grinold and Kahn (1999) and used by Pope and Zhao (2015) to study ETF flows.

$$\text{PricePressure}_{k,t} = D_t\sqrt{F_t}\,S_{k,t} \qquad \text{Equation 2}$$

$$D_t = \begin{cases} +1 \mid SH_{out_t} > SH_{out_{t-1}} \\ -1 \mid SH_{out_t} < SH_{out_{t-1}} \end{cases} \qquad \text{Equation 2A}$$

$$F_t = \left|ETFPrice_{t-1} * \left(SH_{out_t} - SH_{out_{t-1}}\right)\right| \qquad \text{Equation 2B}$$

$$S_{k,t} = \left(liquidity\_premium * \sigma_{k,t}\right)\sqrt{\frac{w_{k,t}}{v_{k,t}}} \qquad \text{Equation 2C}$$

where t indexes over time and k indexes over securities; D_t is a directional indicator that keeps the expression positive for inflows and negative for outflows; SH_{out_t} is the number of shares outstanding of the ETF; F_t is the magnitude of the ETF flow; $S_{k,t}$ is a security-dependent sensitivity to ETF flow; $liquidity\_premium$ is a unitless risk-return ratio demanded by liquidity suppliers; $\sigma_{k,t}$ is the trailing 252-day standard deviation of daily returns; $w_{k,t}$ is the weight of the security in the basket underlying the ETF; and $v_{k,t}$ is the daily trading volume.

The $liquidity\_premium$ variable, carried over from Grinold and Kahn's presentation of market impact, represents a unitless risk-return ratio demanded by liquidity suppliers to facilitate the trade. This term is assumed to equal 1 for the remainder of section 2, but that assumption is challenged in Section 3.

2.1 Model Estimates

Price pressure estimates at the index level (Fig 1) and security level (Fig A1) were generated, where estimates based on observed volatility (data points) are bounded by estimates assuming high and low fixed volatility (volatility curves). The x-axis is the relative liquidity demanded, which is calculated by taking the dollar flow divided by the dollar trading volume. The range of the x-axis was intentionally expanded beyond the largest observed relative liquidity demand over the sample period, so that price pressure estimates could be extrapolated for larger flows, allowing for growth in the AUM of the fund relative to growth in the market. Allowing for SPY flow to account for about one-third of trading volume, which is more than double the largest liquidity demand observed to date, is a realistic upper bound for our considerations.[5] Extrapolated values were, at most, 370 bps at the security level (Apache Corp) and 250 bps at the index level. Given the modest magnitude of the price pressure under these extreme assumptions, coupled with the temporary nature of price pressure, the risks created by ETF flow underwhelm.

2.2 Model Robustness Checks

Results in this section support the model's ability to estimate the price pressure and subsequent reversal induced by ETF flows, and to discern which securities are most impacted by flow.

Securities were grouped into quantiles on the basis of price pressure, with daily rebalancing. The contemporaneous returns of each quantile were consistent with model estimates (Table 1) and were robust to Fama-French decomposition (Table A1).

Table 1: Business Daily Active Returns vs. Equal-Weighted S&P 500 to Portfolios by Sort on Contemporaneous ETF Price Pressure (S&P 500 Jan. 3, 2007 – Oct. 31, 2017)

	High	Q2	Q3	Q4	Low	Long-Short
Observation (bps)	4.65***	2.58***	0.51*	-0.84**	-6.90***	11.56***
Model Est (bps)	7.19	2.55	0.00	-2.56	-7.18	14.37

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

[5] Trades of larger relative volume are likely to require a different functional form (see Appendix II).

The proposed mechanism also posits a reversal of the observed price pressure in the forward period after the flow has occurred. Analysis on the daily time series produced noisy results, but thematically consistent conclusions were drawn from weekly data. Weekly results may be less noisy due to weekly rebalancing of ETF inventory by APs, as well as higher ETF trade volume around options and futures expiry, which occurs on Friday. Flow magnitudes on Fridays were statistically larger than flow magnitudes on Monday through Wednesday, at the 1% level, for the sample period.

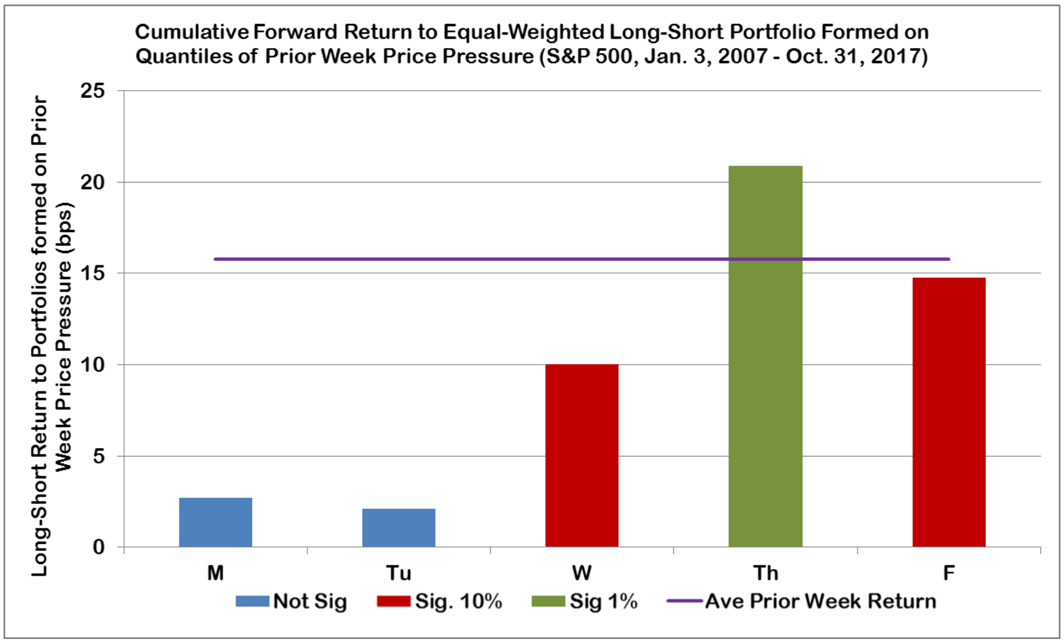

Figure 3. Price Pressure Reversal. Portfolios were formed from quantiles based on the calculated price pressure. Average weekly long Q1 – short Q5 returns contemporaneous to the period over which the price pressure was measured (purple line) are of a similar magnitude to the 5-day forward returns formed from long Q5 – short Q1. Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

Evidence of a price pressure reversal was observed 3-5 days after the prior week end (Fig 3). Because price pressure is correlated with contemporaneous returns, the reversal effect may be capturing a ‘buy losers and sell winners’ (return reversal) effect. To examine whether return reversal subsumes price pressure reversal, a two-way dependent sort was used. In this approach, the universe was first divided into quantiles based on the control variable (contemporaneous period return). Within each control variable bin, quantiles were formed on SPY-driven price pressure and the price pressure quantile assignments were used to combine securities across control variable bins. The controlled quantiles each contain an equal mix of securities with positive and negative active returns in the prior period and, consequently, should not have or benefit from any exposure to the control variable. With this active return control procedure in place, the price pressure reversal effect remained evident

(Table 2). As an additional robustness check, price pressure was included in both pooled and panel regressions of the type $r_{tj} = \beta x_{tj} + \varepsilon_{tj}$, along with control variables (Table A2), where coefficient estimates on price pressure remained around unity at the 1% significance level.

Table 2: Weekly Forward Returns without (row 1) and with (row 2) control for active return reversal to Portfolios by Sort on ETF Price Pressure (S&P 500, Jan. 3, 2007 – Oct. 31, 2017)

	High	Q2	Q3	Q4	Low	Low-High
Ave Ret (no control, bps)	-7.55*	-3.97*	0.47	2.19	8.75**	16.30**
Ave Ret (Control for Active Return Reversal, bps)	-6.62*	-2.98*	-0.14	2.96*	7.18**	13.80**

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

3. Model Assumptions under Extreme Conditions

In this section, the ETF flow is evaluated as a potential aggravating factor in market downturns, starting with an examination of the recent market correction in Feb 2018 in Section 3.1 and then examining select single-day declines in Section 3.2.

3.1 February 2018 Correction

On February 8, 2018, the S&P 500 Index declined by 3.74%. The pullback coincided with an exodus of capital from the S&P 500 SPDR Trust. As much as $25B, about 9% of AUM, in share redemptions occurred over the first full week in February.[6] The returns of securities in the S&P 500 for the Feb. 8 date cross-section were plotted against securities' sensitivity to flow (equation 2c), $S_{k,t} = flow\_sensitivity$, in regressions of the type,

$$R_{k,t} = ETF_{Prem} * S_{k,t} + Market\_Return_{no\_flow} + \varepsilon \qquad \text{Equation 3}$$

where ETF_{Prem} is the premium earned per unit sensitivity to flows; the regression intercept, $Market\_Return_{no\_flow}$, is used as a proxy for the index return adjusted to remove the impact of ETF flow; and ε is the regression error. Statistically significant regression coefficients were obtained (Fig 4) and several conclusions, outlined below, were drawn from this analysis.

- Securities with higher sensitivity to flow tended to underperform on February 8, consistent with the general trend shown in Section 2.2. This is consistent with our expectation, given the large outflow that occurred on this date.

[6] Popina, E., Leinz, K. (2018, Feb 16) What Shaped the Stock Market's $3 Trillion Trauma. Retrieved from https://www.bloomberg.com.

- The intercept provides an estimate of the return expected if there were no exposure to flow, -232 bps, from which we then infer that about 142 bps of the 374 bps daily decline (about 1/3) can be explained by price pressure.
- Securities demonstrated a statistically significant price pressure reversal, as well as an active return reversal (not shown), validating the final stage of the price pressure mechanism. Security level hit rate[7] for price pressure reversal was 59%.

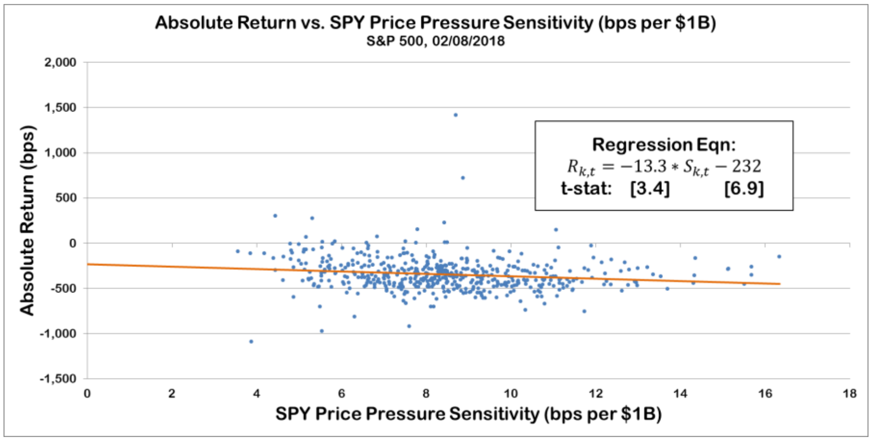

Figure 4. Dependence of Return on Price Pressure on February 8, 2018. Returns for securities in the S&P 500 showed a statistically significant dependence on model forecasted price pressure sensitivity.

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

These observations serve as evidence that the proposed price pressure and reversal mechanism was at play on February 8, 2018 and that ETF flow had a meaningful impact on this date.

3.2 Non-Unity Liquidity Premium

The regression approach used in Section 3.1 offers another method of determining the index level price pressure, albeit ex-post, in addition to the method used in Section 2.2. The value of interest in this approach is the intercept, which we interpret as a flow-adjusted return for the index.[8] The estimates obtained from this method are connected to observed security returns and, arguably, produce a more accurate estimate of price pressure for that reason.

Regression-based estimates for select date cross-sections (Fig 5) indicate that as much as two-thirds of the daily decline could be attributable to price pressure. Estimates from the theoretical model for these select date cross sections were much lower than those from the

[7] Hit rate defined as the average percentage of securities that outperformed the equally-weighted universe return (average return) for each portfolio across the backtest period.

[8] This method could also be used to calculate flow-adjusted individual security returns by including the error term for each security, $R^{adj}_{k,t} = R_{k,t} - ETF_{Prem} * S_{k,t} = Intercept + \varepsilon_{k,t}$ where $\varepsilon_{k,t}$ is the regression error term for security k.

regression based model. One explanation for this is that, on dates the index saw large declines, liquidity providers may have demanded more of a liquidity premium ($liquidity\_premium$ in equation 2) than the assumed value of one. This could be due to other institutional funds attempting to execute similar trades to those that satisfy the flow of SPY, perceived elevation in market risks, or fewer traders providing liquidity on a particular date. Values for the liquidity premium that rectify the discrepancy between the regression method and the model were calculated and found to have a median value of 4.5 and maximum value of 42. The ability of the liquidity premium to take values much larger than 1 suggests that a liquidity event could occur in the future that is more substantial than anything observed over the sample period.

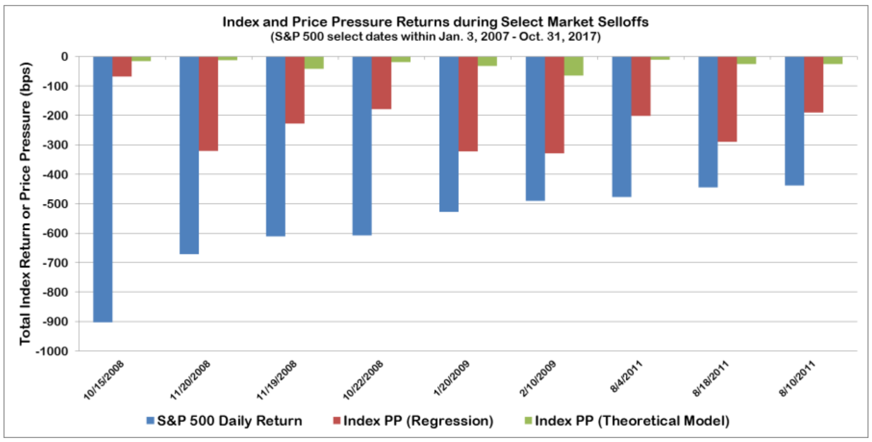

Figure 5. Observed S&P 500 Index Returns and Estimates of Index Price Pressure for select dates. Index price pressure was estimated by the model (equation 2, green bars) and a two-step regression method (red bars). Total Index return is also plotted (blue bars).

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

4. Optimization and Institutional Exposure

This section presents a risk model framework (Section 4.1) and provides flow sensitivity for institutional funds (Section 4.2), which investors can use to evaluate their ETF flow risk.

4.1 Mean-Variance Optimization

The ETF flow sensitivity term (equation 2c) was used as a risk factor in a Fama-French 3-Factor (FF3) cross-sectional risk model framework. The ETF flow risk factor exposure was limited to 80% of the S&P 500's exposure. Results of a mean-variance optimization with monthly rebalancing yielded lower standard deviation (annualized daily portfolio returns) and a higher Sharpe ratio compared to the same simulation parameters using a FF3 risk model. Performance over the Great Financial Crisis was separated from the post-crisis period (not shown) and similar results were obtained.

The optimization results are consistent with expectation. Securities with the highest sensitivity to ETF flow are expected to see a higher volatility in returns, owed to the price pressure, and subsequent reversal, created by AP trading. No significant change in the simulation result was observed when controlling for trailing volatility, supporting the improved performance is owed to limiting exposure to ETF flow sensitivity.

Table 3. Simulation Results using Fama-French 3 and Fama-French 3 plus ETF Sensitivity Risk Models (S&P 500, January 31, 2007 – February 28, 2018)

Simulation Risk Model	Sharpe Ratio[1]	Annual Return	Annual Stdev[2]	Median #Holdings	Turnover	Max Drawdown
FF3	0.507	9.85%	19.45%	185	210.46%	48.05%
FF3 + ETF Sensitivity	0.557	9.90%	17.76%	111	212.29%	46.82%

1. Probabilistic Sharpe Ratio (Bailey 2008) with limited ETF exposure is greater than simulation without ETF constraint to 95% confidence level.
2. Variance of simulation with limited ETF exposure is lower than simulation without ETF constraint to 99% confidence level.

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

In all simulations, acceptable solutions were constrained as follows: market beta of 0.95 to 1.05 relative to the S&P 500; no more than 0.5% of portfolio value in cash; monthly turnover constrained at 17%; and position sizes with a lower bound equal to $\max(0, B - 1\%)$ and upper bound equal to $B + 1\%$, where B is the security's weight in the benchmark.

4.2 Institutional Exposure

We calculated the exposure of select institutional funds by summing the products of position weights ($w_{k,t}$) and ETF flow sensitivity ($S_{k,t}$ defined in equation 2c), such that $S_t^{portfolio} = \sum w_{k,t} S_{k,t}$, where $S_t^{portfolio}$ is the ETF flow sensitivity of the institutional portfolio. Some institutional funds have comparable or greater exposure to ETF flow than the S&P 500 Index, itself. If these funds face redemptions in periods that SPY sees large outflows, the funds may have to trade against the APs and be forced to liquidate positions that have seen negative price pressure. All funds shown are benchmarked to the S&P 500 Index, as defined in the prospectus, except for the Fidelity Series 100 Index Fund, which benchmarks to the S&P 100 Index. Positions that are not in the S&P 500 were assumed to have zero sensitivity to SPY flow.

Table 4. Portfolio Level ETF Sensitivity ($S_t^{portfolio} = \sum w_{k,t} S_{k,t}$) for Select Funds based on February 28, 2018 holdings from S&P Global Ownership Database

Fund	ETF Sens. (bps / $B)	ETF Sens. (% of S&P 500)
BNY Mellon Funds Trust - BNY Mellon U.S. Core Equity 130/30 Fund	10.45	105.40%
Fidelity Congress Street Fund	10.02	101.09%
Fidelity Commonwealth Trust - Fidelity Series 100 Index Fund	10.02	101.09%
Columbia Funds Series Trust II - Columbia Large Core Quantitative Fund	9.99	100.80%
American Funds Insurance Series - Blue Chip Income and Growth Fund	9.99	100.75%
S&P 500	**9.91**	**100.00%**
Vanguard Index Funds - Vanguard S&P 500 ETF	9.90	99.91%
Vanguard Institutional Index Funds- Vanguard Institutional Index Fund	9.90	99.91%
T. Rowe Price Equity Series Inc. - T. Rowe Price Equity Index 500 Portfolio	9.90	99.90%
Vanguard Investment Series plc - Vanguard U.S. 500 Stock Index Fund	9.90	99.90%
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T. Rowe Price New America Growth Fund	7.92	79.88%
T. Rowe Price New America Growth Portfolio	7.92	79.86%
Fidelity Institutional Funds ICVC - America Earnings Growth Fund	7.79	78.57%
Fidelity Contrafund - Fidelity Advisor New Insights Fund	7.58	76.46%
Fidelity Capital Trust - Fidelity Capital Appreciation Fund	7.37	74.39%

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018.

5. Conclusions

ETFs have grown in size, with some ETFs rivaling other large institutional funds in assets under management. In this treatment, we aim to build a framework to analyze the impact of ETF flows on the prices of the underlying securities. Using the proposed framework, ETF flow was shown to have a modest, transient impact on the underlying securities (Section 2) and sensitivity to ETF flow was shown to exacerbate drawdowns for a subset of cross-sectional periods (Section 3). For investors seeking to limit their exposure to ETF flow risk, a risk model approach was provided and yielded improved risk-adjusted performance for a set of mean-variance optimizations. Investors can assess the ETF flow exposure for institutional funds using the quantitative framework presented and leveraging the ownership dataset from S&P Global (Section 4).

6. References

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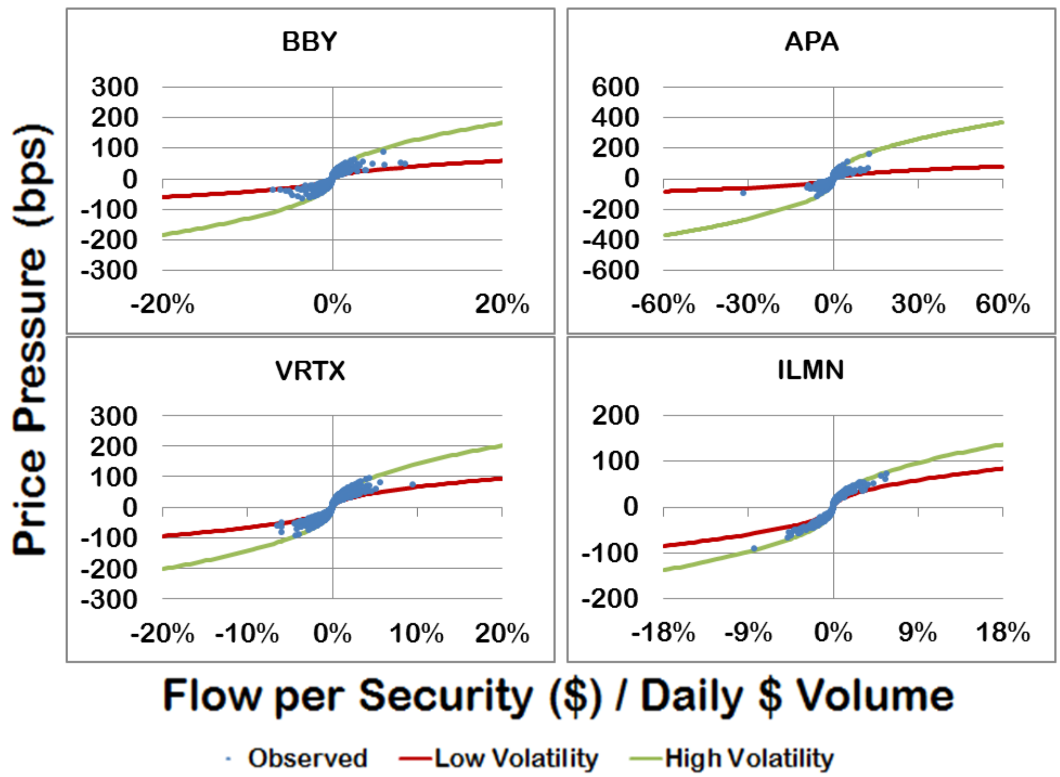
Appendix I. Additional Robustness Checks and Select Price Pressure Plots

In Section 2.1, model estimates were provided at the index and security level. Graphical depiction of the estimates, using observed volatility as well as fixed levels of volatility, were plotted at the index level (Fig 1). For the reader interested in the same representation at the security level, the four securities with the highest sensitivity to ETF flow (equation 2c) as of Oct. 31, 2017 were selected for the figure below. The securities selected have notably high volatilities, which is not surprising because the ETF sensitivity is a function of volatility.



Ticker	Low Volatility	High Volatility
BBY	20.99%	64.97%
APA	16.75%	75.95%
VRTX	33.44%	71.75%
ILMN	31.43%	51.39%

Figure A1. Price Pressure Estimates for the Top 4 Most Flow Sensitive Securities Based on Oct. 31, 2017 Date Cross Section

S&P 500 Index (Jan. 3, 2007 – Oct. 31, 2017)

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018.

In Section 2.2, we performed several robustness checks of the price pressure model and mechanism by showing that the model's forecasts for price pressure compared well with average active quantile returns (Table 1). To examine the source of returns, the daily absolute returns of each quantile, formed by the model-forecasted price pressure, less the

Federal Funds interest rate (i.e. the quantile return premiums) were regressed against Fama-French factor returns; where MKT represents the market risk premium calculated as the return spread between the S&P 500 return and the Federal Funds interest rate, SMB is the cap-weighted return spread between smallest market capitalization tertile and largest market capitalization tertile, and HML is the cap-weighted return spread between the highest book to price tertile and the lowest book to price tertile.

Table A1: Daily Absolute Return Premium Regressed on Factor Premiums for Equal Weight Portfolios formed by Sort on Contemporaneous ETF Price Pressure (S&P 500 Jan. 3, 2007 – Oct. 31, 2017)

	alpha	MKT	Value	Size
High PP	0.0005***	1.03***	0.05***	-0.02
Q2	0.0004***	1.03***	-0.01	0.02*
Q3	0.0000	1.02***	-0.03***	0.00
Q4	-0.0001	1.00***	0.02**	-0.04***
Low PP	-0.0007***	0.95***	0.02	-0.01
Spread	0.0012***	0.08***	0.03	-0.01

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

Regression coefficients showed little variation in FF3 exposures. The MKT coefficients were close to unity for all quantiles, with a very minor tilt toward higher MKT beta for high price pressure stocks. Some quantiles did have statistically significant non-zero coefficients on SMB or HML. However, coefficients were not monotonic across quantiles and were not significant for the long-short portfolio. The small coefficients to FF3 factors should not be surprising, based on the daily rebalancing of portfolios and the dependence of quantile membership on the direction of flow.

The unexplained returns (labeled alpha) showed a monotonic and statistically significant dependence on the price pressure quantile assignment. The average differentiation between high and low quantiles was 12 bps, which is similar to the value observed for the unadjusted returns. These results offer support for the propagation stage of the price pressure mechanism and indicate that we have not inadvertently captured a size, value, or market bias.

Following the examination of the propagation stage of the mechanism (Fig 2), we examined the reversal of price pressure in the forward week (Fig 3 and Table 2). Because price pressure is correlated to contemporaneous return, the reversal of price pressure is potentially a proxy for a reversal of active return. In the main paper, a double sort method was used to examine the price pressure reversal in an active return neutral scheme. Another approach would be to regress the cross-section of security returns against the forecasted price pressure, along with other control variables, and confirm that price pressure remained statistically significant. This procedure could be performed for all cross-sections (pooled), provided that standard errors are appropriately adjusted for serial autocorrelation, or coefficients could be averaged for n-many independent regressions over the n-many date cross-sections (panel). The results of both procedures are summarized in Table A2.

Table A2: Regressions of Forward Weekly Returns on Selected Independent Variables[9]
Slope coefficients for regressions of the form $r_{tj} = \beta x_{tj} + \varepsilon_{tj}$. Panel regressions show the average cross-sectional coefficient values over the period.
(S&P 500 January 1, 2007 – October 31, 2017)

Pooled[1]	1	2	3	4	5	6
Prior Week Price Pressure	-1.13***		-1.03***	-1.13***	-1.11***	-1.01***
Prior Week Return		-0.06***	-0.06***			-0.06***
Amihud (x10000)				1.28		-0.24
Volatility					0.05***	0.05***
Intercept	0.0015***	0.0017***	0.0016***	0.0015***	-0.0006**	-0.0007**

Panel	1	2	3	4	5	6
Prior Week Price Pressure	-1.07***		-1.06***	-1.11***	-0.63**	-0.84***
Prior Week Return		-0.02**	-0.01**			-0.01***
Amihud (x10000)				0.98		59.84
Volatility					-0.03	-0.03
Intercept	0.0013**	0.0010	0.0012*	0.0014**	0.0018***	0.0018**

1. Standard errors are Newey-West corrected to account for heteroscedasticity and serial autocorrelation
*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

Both pooled and panel regressions support the use of the prior week price pressure to forecast the forward week returns. Pooled regressions yielded a coefficient on the prior week price pressure slightly larger than unity, significant at the 1% level, for all specifications. In panel regressions, slightly smaller coefficients for price pressure were observed in specifications that included a control on volatility, but those coefficients remained economically and statistically significant, at a 5% level or greater.

[9] The 'Amihud' variable represents Kyle's Lambda from Amihud, Y., 2002. "Illiquidity and stock returns: cross-section and time-series effects". Journal of Financial Markets, 5, 31-56.

Appendix II. Alternative Functional Form

Rather than using a time-variant liquidity premium, as has been done in the model presented thus far, an alternative approach to account for extremely large demands on liquidity is to include a piecewise term to the model that adds a penalty for demands above some threshold. Models of this form have appeared elsewhere[10] and we would be remiss to fail to mention them. For example,

$$\text{PricePressure}_{k,t} = C_1\left(D_t\sqrt{F_t}S_{k,t}\right) + C_2 \max\left(0, w_{k,t}F_t - L\right)^2 \qquad \text{Equation A1}$$

where $S_{k,t}$, D_t and F_t are defined in the same way as equation 2; L specifies some level of liquidity above which routine liquidity is exhausted, and constants C_1 and C_2 control the relative contributions from the square root process and the second order term.

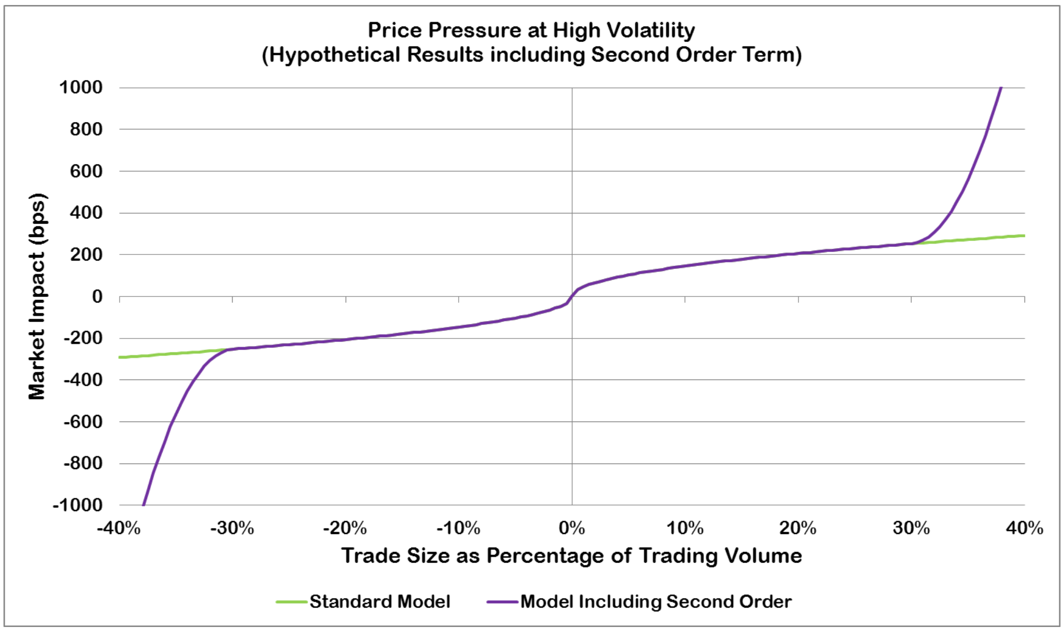


Figure A2. Hypothetical Market Impact given a square root process (standard model, green line) versus a second order process (purple line)

Source: S&P Global Market Intelligence Quantamental Research. Data as of February 28, 2018.

Implementing a functional form that takes a parabolic shape at extreme trade sizes implies that ETF flows (or any large trade) could have a market destabilizing effect, if they grow beyond a certain size or if a larger-than-normal flow were to occur.

We rejected the use of this functional form for this research for four reasons.

- First, functions with a positive concavity imply that traders could ameliorate their trading impact simply by splitting their orders between multiple agents who behave as

[10] diBartolomeo, D. (2018, March). The Liquidity Risk Time Bomb. Retrieved from http://northinfo.com.

independent, smaller agents. This behavior, diseconomies of scale, is in opposition to the empirical data presented elsewhere[11].

- Second, because trades above the liquidity threshold (L) are so expensive, they are rarely, if ever, observed. Consequently, there are insufficient data to appropriately estimate an empirical model of this form. Further, any attempt to approximate parameters would yield self-fulfilling results; that is, we would conclude that the model produces destabilizing price pressure above some flow, L, assuming the model adopts a quadratic term above some flow, L. The results would be tautological to the model assumptions.

- Third, models of this form can produce price pressure estimates in excess of 100%, which are particularly problematic on the downside. So, in addition to the variables mentioned above, a correct implementation would also have to estimate an upper bound for the price pressure of each security using some other model.

- Lastly, accounting for aberrant levels of market impact with a liquidity premium term, as has been done in equation 2, allows for more flexibility in the model. For example, if two ETFs trading similar mandates had flows in the same direction, the model in equation 2 could be used to understand market impact from one ETF flow where the other ETF flow would be impounded in the liquidity premium.

[11] Grinold, R.C., Kahn, R.N., 1999. "Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Controlling Risk." 2nd Edition, 451-2.

Our Recent Research

June 2018: The (Gross Profitability) Trend is Your Friend

Trend strategies based on changes in stock price or earnings are widely used by investors. In this report, we examine the performance of a trend strategy derived from gross profitability ("GP"). Gross profitability trend ("GPtrend"), was proposed by Akbas et al.[1] who argued that the trajectory of a firm's profitability is just as important as the level (GP). We define GPtrend as the year-on-year difference in either quarterly or trailing twelve month GP, where GP is calculated as revenue minus cost of goods sold, divided by total assets. Our back-tests confirm that GPtrend has historically been an effective stock selection signal globally, with the added benefit of low to moderate correlation with commonly used investment strategies. Our findings include:

- GPtrend generated statistically significant average annualized long-only and long-short excess returnsTable 1). Performance was strongest (long-short basis) in Asia ex-Japan (6.68%), Europe ex-U.K. (6.66%) and the U.S. (6.50%), and weakest in Japan (1.15%). [2] in five of the six regions we tested the signal (
- Gross profitability trend was effective across multiple investment style categories (Table 2), indicating that the factor can be beneficial to a value, growth or core and large/small cap investment process.
- GPtrend's performance is not subsumed by gross profitability, earnings revision or price momentum: GPtrend retains its ability to separate winner stocks from loser stocks, after controlling for GP (Table 3). The average annualized return of the most attractive GP/GPtrend interaction portfolio minus the least attractive interaction portfolio is 12.19%. The factor's excess return is also still significant after controlling for both earnings and price momentum (Table 4).
- Performance was robust to several methodologies of determining trend: We computed gross profitability trend using six different methods and all six trend metrics generated statistically significant average annualized long-short excess returns in the Russell 3000 universe (Table 5).

May 2018: Buying the Dip: Did Your Portfolio Holding Go on Sale?

Buy the Dip' ("BTD"), the concept of buying shares after a steep decline in stock price or market index, is both a Wall Street maxim, and a widely used investment strategy. Investors pursuing a BTD strategy are essentially buying shares at a "discounted" price, with the opportunity to reap a large pay-off if the price drop is temporary and the stock subsequently rebounds. In this report, we examine the stock performance of the 'Buy the Dip' (BTD) strategy within the Russell 1000 Index from January 2002 through October 2017. We find:

- A strategy of investing in securities that fell more than 10% relative to the broader market index, during a single day, significantly outperforms the index between 2002 and 2017 in the subsequent periods.
- Though many large sell-offs may result from earnings disappointments and guidance changes, these events do not seem to impact a BTD strategy.

- A group of stock selection signals including institutional ownership, price trend and valuation, help to improve the overall performance of the BTD strategy

March 2018: In the Money: What Really Motivates Executive Performance?

In this report, we explore what types of compensation motivate top executives to boost shareholder returns, and the fundamental characteristics of companies in which executives are motivated to boost stock performance. Our research findings include:

- We find no link between high levels of incentive compensation, alone, and higher-than-average shareholder returns.
- Companies where CEOs hold large (negligible) amounts of stock option holdings tend to outperform (underperform) peers.
- Companies where CEOs hold large amounts of options repurchase more shares and issue more debt than industry peers, and engage in less merger & acquisition activity. These companies also have higher long-term sales, earnings per share, and cash flow growth rates than industry peers.

February 2018: The Art of the (no) Deal: Identifying the Drivers of Canceled M&A Deals

Terminated deals impact capital market participants in various ways. Predicting deals that are likely to be canceled is of interest to both M&A advisers and equity investors. This report identifies several drivers of cancelled deals, including size, deal proportionality, perceived price discount, CEO age, and regulatory risk, and concludes with a model built from four of these drivers.

January 2018: U.S Stock Selection Model Performance Review

Starting with the U.S. Election in November 2016, the S&P 500 Index has registered 14 consecutive months of positive returns. Only once has the S&P 500 had a longer run of positive returns since 1959. Coincident with strong equity returns, U.S. stocks began to trade on the basis of their own idiosyncratic factors, as opposed to sector or common factor risk.

All 4 of our U.S strategy models returned positive long-only returns in 2017. This report reviews the performance of all 4 models during the year.

September 2017: Natural Language Processing - Part I: Primer

Given the growing interest in NLP among investors, we are publishing this primer to demystify many aspects of NLP and provide three illustrations, with accompanying Python code, of how NLP can be used to quantify the sentiment of earnings calls. The paper is laid out into four sections:

- **What is NLP:** We demystify common NLP terms and provide an overview of general steps in NLP.
- **Why is NLP Important:** Forty zettabytes (10^21 bytes) of data are projected to be on the internet by 2020, out of which more than eighty percent of the data are unstructured in nature, requiring NLP to process and understand
- **How can NLP help me:** We derive insights from earnings call transcripts measuring industry-level trends or language complexity.

- **Where do I start:** Code for each use is enclosed, enabling users to replicate the sentiment analysis

July 2017: Natural Language Processing Literature Survey

In client conversations, Natural Language Processing (NLP) and the analysis of unstructured data is a topic of regular conversation. S&P Global Market Intelligence offers several unstructured datasets garnering market attention. The first is earnings call transcripts, with unique speaker id's to identify who is speaking on the call. The second data set is the text content in the 10-K. In advance of a publication of Quantamental primer on NLP next month which will take readers through the process of handling unstructured data and generating sentiment scores, we offer this literature survey. What follows are ten papers that the team has identified as being of particular interest to investors on this topic.

June 2017: Research Brief: Four Important Things to Know About Banks in a Rising Rate Environment

With the Fed signaling further rate hikes ahead, bank investors may want to know which investment strategies have worked best in a rising rate environment historically. This paper leverages our empirical work on the SNL Bank fundamental data to aid investors in selecting bank stocks as rates rise.

April 2017: Banking on Alpha: Uncovering Investing Signals Using SNL Bank Data

This study leverages S&P Global Market Intelligence's SNL Financial data to answer three questions of importance to bank investors: 1. Which widely-used investment strategies have historically been profitable? 2. Which lesser-known strategies deserve wider attention? 3. How do these strategies perform across varying macro environments: rising vs. falling interest rates and above- vs. below-average financial stress?

March 2017: Capital Market Implications of Spinoffs

January 2017: U.S. Stock Selection Model Performance Review 2016

November 2016: Electrify Stock Returns in U.S. Utilities

October 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 2

September 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 1

August 2016: Mergers & Acquisitions: The Good, the Bad and the Ugly (and how to tell them apart)

July 2016: Preparing for a Slide in Oil Prices -- History May Be Your Guide

June 2016: Social Media and Stock Returns: Is There Value in Cyberspace?

April 2016: An IQ Test for the "Smart Money" – Is the Reputation of Institutional Investors Warranted?

March 2016: Stock-Level Liquidity – Alpha or Risk? - Stocks with Rising Liquidity Outperform Globally

February 2016: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2015

January 2016: What Does Earnings Guidance Tell Us? – Listen When Management Announces Good News

December 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 6

November 2015: Late to File - The Costs of Delayed 10-Q and 10-K Company Filings

October 2015: Global Country Allocation Strategies

September 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 5

September 2015: Research Brief: Building Smart Beta Portfolios

September 2015: Research Brief – Airline Industry Factors

August 2015: Point-In-Time vs. Lagged Fundamentals – This time i(t')s different?

August 2015: Introducing S&P Capital IQ Stock Selection Model for the Japanese Market

July 2015: Research Brief – Liquidity Fragility

June 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 4

May 2015: Investing in a World with Increasing Investor Activism

April 2015: Drilling for Alpha in the Oil and Gas Industry – Insights from Industry Specific Data & Company Financials

March 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 3

February 2015: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2014

January 2015: Research Brief: Global Pension Plans - Are Fully Funded Plans a Relic of the Past?

January 2015: **Profitability: Growth-Like Strategy, Value-Like Returns - Profiting from Companies with Large Economic Moats**

November 2014: **Equity Market Pulse – Quarterly Equity Market Insights Issue 2**

October 2014: **Lenders Lead, Owners Follow - The Relationship between Credit Indicators and Equity Returns**

August 2014: **Equity Market Pulse – Quarterly Equity Market Insights Issue 1**

July 2014: **Factor Insight: Reducing the Downside of a Trend Following Strategy**

May 2014: **Introducing S&P Capital IQ's Fundamental China A-Share Equity Risk Model**

April 2014: **Riding the Coattails of Activist Investors Yields Short and Long Term Outperformance**

March 2014: **Insights from Academic Literature: Corporate Character, Trading Insights, & New Data Sources**

February 2014: **Obtaining an Edge in Emerging Markets**

February 2014: **U.S Stock Selection Model Performance Review**

January 2014: **Buying Outperformance: Do share repurchase announcements lead to higher returns?**

October 2013: **Informative Insider Trading - The Hidden Profits in Corporate Insider Filings**

September 2013: **Beggar Thy Neighbor – Research Brief: Exploring Pension Plans**

August 2013: **Introducing S&P Capital IQ Global Stock Selection Models for Developed Markets: The Foundations of Outperformance**
July 2013: **Inspirational Papers on Innovative Topics: Asset Allocation, Insider Trading & Event Studies**

June 2013: **Supply Chain Interactions Part 2: Companies – Connected Company Returns Examined as Event Signals**

June 2013: **Behind the Asset Growth Anomaly – Over-promising but Under-delivering**

April 2013: **Complicated Firms Made Easy - Using Industry Pure-Plays to Forecast Conglomerate Returns**.

March 2013: Risk Models That Work When You Need Them - Short Term Risk Model Enhancements

March 2013: Follow the Smart Money - Riding the Coattails of Activist Investors

February 2013: Stock Selection Model Performance Review: Assessing the Drivers of Performance in 2012

January 2013: Research Brief: Exploiting the January Effect Examining Variations in Trend Following Strategies

December 2012: Do CEO and CFO Departures Matter? - The Signal Content of CEO and CFO Turnover

November 2012: 11 Industries, 70 Alpha Signals -The Value of Industry-Specific Metrics

October 2012: Introducing S&P Capital IQ's Fundamental Canada Equity Risk Models

September 2012: Factor Insight: Earnings Announcement Return – Is A Return Based Surprise Superior to an Earnings Based Surprise?

August 2012: Supply Chain Interactions Part 1: Industries Profiting from Lead-Lag Industry Relationships

July 2012: Releasing S&P Capital IQ’s Regional and Updated Global & US Equity Risk Models

June 2012: Riding Industry Momentum – Enhancing the Residual Reversal Factor

May 2012: The Oil & Gas Industry - Drilling for Alpha Using Global Point-in-Time Industry Data

May 2012: Case Study: S&P Capital IQ – The Platform for Investment Decisions

March 2012: Exploring Alpha from the Securities Lending Market – New Alpha Stemming from Improved Data

January 2012: S&P Capital IQ Stock Selection Model Review – Understanding the Drivers of Performance in 2011

January 2012: Intelligent Estimates – A Superior Model of Earnings Surprise

December 2011: Factor Insight – Residual Reversal

November 2011: Research Brief: Return Correlation and Dispersion – All or Nothing
October 2011: The Banking Industry

September 2011: Methods in Dynamic Weighting

September 2011: Research Brief: Return Correlation and Dispersion

July 2011: Research Brief - A Topical Digest of Investment Strategy Insights

June 2011: A Retail Industry Strategy: Does Industry Specific Data tell a different story?

May 2011: Introducing S&P Capital IQ's Global Fundamental Equity Risk Models

May 2011: Topical Papers That Caught Our Interest

April 2011: Can Dividend Policy Changes Yield Alpha?

April 2011: CQA Spring 2011 Conference Notes

March 2011: How Much Alpha is in Preliminary Data?

February 2011: Industry Insights – Biotechnology: FDA Approval Catalyst Strategy

January 2011: US Stock Selection Models Introduction

January 2011: Variations on Minimum Variance

January 2011: Interesting and Influential Papers We Read in 2010

November 2010: Is your Bank Under Stress? Introducing our Dynamic Bank Model

October 2010: Getting the Most from Point-in-Time Data

October 2010: Another Brick in the Wall: The Historic Failure of Price Momentum

July 2010: Introducing S&P Capital IQ's Fundamental US Equity Risk Model

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