How Can Quantitative Behavioral Finance Uncover Trader Motivations?

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REFERENCES.

"Are flash crashes caused by instabilities arising from rapid trading?" Wilmott (2011) (with Mark DeSantis and David Swigon).


“The Price Dynamics of Large Market Capitalization Equity ETFs” (with Mark DeSantis and Akin Sayrak) Preprint (18 pages).


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Hence, the actions of the "uninformed" investors contribute only small fluctuations.
Introduction

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- While some market participants may make cognitive errors, or be subject to behavioral bias, the large amount of money managed by savvy investors quickly capitalizes on these errors and restores efficiency.
- Hence, the actions of the "uninformed" investors contribute only small fluctuations.
- Any info available to public (e.g., graphs) is immediately incorporated into the asset price.
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- under-reaction
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- Kahneman psychological experiments indicating that subjects are influenced by "framing" and "anchoring."
- Vernon Smith et. al. asset market experiments indicating that bubbles arise endogenously.
- EMH theorists are not convinced by either approach.
Evidence for Classical Finance: Raw data seems to be noise...
But data also yields...

The Deviation Model: Mean vs Threshold

- Positive: 2.5 < thr <= 5
- Negative: -5 <= thr < -2.5
- Positive: 5 < thr <= 9
- Negative: -9 <= thr < -5
- Positive: 9 < thr <= 50
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And also...
How can we decide which is a suitable model?

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- Even then, who makes the decision in a mutual fund? Manager or "uninformed investor" who can redeem shares.
- Stochastic changes in valuation make testing of hypotheses difficult.
Classical or Behavioral?

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- By rapid algorithms? By value-based managers?
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The issue is quantitative.

- What fraction of the assets are controlled by trend-based traders?
- By rapid algorithms? By value-based managers?
- How do we deduce the motivations of traders/investors from data with so much noise?
Our Approach

- Quantitative study of over 100,000 data points (daily closing prices) for 119 closed-end funds (1998-2008).

Why closed-end funds?
- Clear valuation (NAV); trade like any other stock.

Why daily data?
- Few changes in corporate structure on this time scale.

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Mixed Effects Regression (with DeSantis)

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Variables can be standardized, so it is possible to compare the impact of trend versus valuation, etc.
Regression variables

\[ R(t) = \frac{P(t) - P(t-1)}{P(t-1)} \]

\[ V(t) = \frac{NAV(t) - P(t)}{NAV(t)} - \text{(weighted avg ten days)} \]

\[ T(t) = \text{weighted trend variable (10 days)} \]

\[ R(t + 1) = \beta_0 + \beta_1 T(t) + \beta_2 T^2(t) + \beta_3 T^3(t) + \beta_4 V(t) + \ldots \]
<table>
<thead>
<tr>
<th>Term</th>
<th>Value (x100)</th>
<th>Std. Error (x100)</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.0265656</td>
<td>0.00543</td>
<td>4.88</td>
<td>&lt;.0001</td>
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<tr>
<td>Price Trend</td>
<td>0.1668129</td>
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<td>Valuation</td>
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<td>Trend&lt;sup&gt;2&lt;/sup&gt;</td>
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<td>0.00388</td>
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<td>Trend&lt;sup&gt;3&lt;/sup&gt;</td>
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<tr>
<td>Valuation&lt;sup&gt;2&lt;/sup&gt;</td>
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<tr>
<td>Valuation&lt;sup&gt;3&lt;/sup&gt;</td>
<td>-0.0007622</td>
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<tr>
<td>Trend * Val</td>
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<td>Trend&lt;sup&gt;2&lt;/sup&gt; * Val</td>
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<tr>
<td>Trend * Val&lt;sup&gt;2&lt;/sup&gt;</td>
<td>-0.0008461</td>
<td>0.00098</td>
<td>-0.87</td>
<td>0.3865</td>
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</tbody>
</table>
Return Versus Trend (Normalized)

Nonlinear Influence of Trend (CEF)

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Return as a Function of Nonlinear Trend and Valuation
Nonlinear Effect of Trend for Large Capitalization ETFs
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- When the downtrend is something we see 2.5% of the time, the "buyin on dips" and trend following cancel out.
- We have similar regressions with direct changes (instead of "standard deviations") as well.
Other variables.

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- Resistance
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- Resistance
- Money supply (M2)
How do we compare apples and spa treatments?

- With each variable standardized, we compare the effects one st. dev. events.
- E.g., If Trend has coef 0.10, while M2 has coef 0.05, then an uptrend that is observed 15% of the time (i.e., 1 st. dev.) cancels an M2 decrease that we see 2.5% of the time (2 st. dev).
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</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
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<td>Price Trend</td>
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<td>M2 Money</td>
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<td>Sh. Term Volatility</td>
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<td>L. Term Volatility</td>
<td>-0.0138966</td>
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<tr>
<td>L. Term Trend</td>
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<td>Volume Trend</td>
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<td>6.438</td>
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<td>Resistance</td>
<td>-0.0708118</td>
<td>0.0602</td>
<td>-1.176</td>
<td>0.2398</td>
</tr>
</tbody>
</table>
The complex role of volatility

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For short term volatility the result is opposite; it increases the return.
Measuring the impact of news
Two issues: True change in valuation; Over-reaction

Example: Nonfarm payroll is released in US. There is some change to economic and profit forecast.
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How much should the S&P change? How much can we expect it to over-react?
List of news announcements

About 60 announcements each (during 2005-2010):
Business Inventories
Capacity Utilization
Consumer Sentiment
Consumer Spending
Durable Goods
Housing Starts
New Home Sales
Non Farm Payrolls
Personal Income
Philadelphia Federal Survey
Retail Sales
Unemployment Rate
\[ x = \frac{E_a - E_f}{|E|}; \quad E = \text{average}\{E_a\} \]

so \( x \) is the fractional deviation from expected value

\[ y = \frac{x - m}{s}; \quad m = \text{mean of}\{x\} \]

so \( y \) is the measure (in st. dev.) from the norm.

- Use indicator functions for day \( k \) after the announcement.
Daily Coefficients for
Business Inventories, Phil. Fed. Survey, Retail Sales,
Durable Goods, New Home Sales
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- Coefficients can be calibrated for a single stock for trading.
- Ongoing research suggests that one can use a simple valuation model in place of NAV.
- Similar methods for going long on one stock while hedging with SPY.
Dynamics of over-reaction

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On a longer time scale, similar issue

- Large part of population underinvested (e.g., 1982, now).
- Stocks suppressed, values compelling, public disenchanted.
- Catalyst starts an uptrend (e.g., dissatisfaction with interest rates).
- Uptrend fuels more buying.
- Excess cash moves into the market pushing the market much higher.
- Eventually, connection between stock price and value disappears.
In 1982 interest rates were high while stocks had been underperforming for 15 years.

Now fear is high enough that people are willing to lend to governments at near zero rates.

In both cases there is ample cash on sidelines. Improving economics leads to uptrend which leads to greater confidence. Further feedback as confidence leads to improving economics.
Key ingredients of a behavioral model

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- Distinct groups with differing motivations and assessments of value.
- Different time scales for different groups (e.g., high frequency trading).
- **Finite cash**; absence of infinite arbitrage
Ingredients above can be incorporated into a DE model
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Most difficult part: estimating the cash position of each group
Effect of shorter time scales in trend investing
Papers at ssrn.com
Thank you!