Man vs. Machine:

Quantitative and Discretionary Equity Management

Simona Abis

Columbia University

Quantitative Investment

- On the rise in recent decades
- The future of investment management?
- Potentially important implications for financial markets: Efficiency? Liquidity? Stability?
- Little academic research

FINANCIAL TIMES

APRIL 25, 2016 by: Robin Wigglesworth in New York

US Equities

Fund star Sudhir Nanda warns of threat to human role in finance

Technology set to erode industry's traditional backbone

FTfm

ThinkAdvisor

The Rise of the Machines in Investment Management

By Daniel S. Kern SEPTEMBER 30, 2016

THE WALL STREET JOURNAL.

MARKETS

How Computers Trawl a Sea of Data for Stock Picks

Funds managing billions hunt for investment clues in newswires, weather, Twitter

By BRADLEY HOPE

April 1, 2015 10:30 p.m. ET

theguardian

Rise of the billionaire robots: how algorithms have redefined hedge funds

The 25 best-paid hedge fund managers pocketed $13bn in 2015, and most of the big winners relied on programs, not contacts, for their big wins

Suzanne McGee

Sunday 15 May 2016 11.00 BST

Quantitative vs. Discretionary Mutual Funds

- Quantitative funds: Investment based on quantitative signals generated by computer-driven models using fixed rules to analyze large datasets

- Discretionary funds: Investment based on decisions by managers who use information and own judgment

- Do quantitative and discretionary funds differ in...

  1. ...the information they process?

  2. ...the assets they hold?

  3. ...performance?

- What does the rise of quants mean for this sector?
  Are new technologies changing the existing dynamics?

This Paper

- Documents the rise of quantitative mutual funds
  - No existing systematic classification
  - Machine learning to classify active US equity mutual funds
  - AuM: from \$100bn to \$420bn (8.8% to 14% of mkt) over 1999–2015
- Theory
  - Equilibrium model of rational inattention
  - Risky assets affected by idiosyncratic and aggregate shocks
  - Discretionary investors:
    - can learn about any shock
    - but have limited learning capacity
  - Quantitative investors:
    - unlimited learning capacity
    - but can only learn about idiosyncratic shocks
  - Predictions for learning, holdings and performance

This Paper: Empirics

1. Learning
   - Discretionary funds focus on stock picking (i.e. idiosyncratic shocks) in expansions and market timing (i.e. aggregate shocks) in recessions
   - As the share of quants rises, discretionary funds decrease their focus on idiosyncratic info and increase their focus on aggregate info
   - Quants focus on idiosyncratic shocks throughout the business cycle
2. Holdings
   - Quants hold a larger number of stocks
   - Discretionary funds invest in lesser known stocks
   - There is greater dispersion in the holdings of discretionary funds than of quants
3. Performance
   - Discretionary funds' performance is counter-cyclical
     - ⋆ As the share of quants rises, counter-cyclicality is accentuated
   - Quants' performance is pro-cyclical
     - ⋆ As the share of quants rises
       » profitability decreases in expansions
       » quants with the smallest holdings commonality outperform

Literature

- Technology and financial markets: HFT and Quant Investment (Harvey, et al. 2016, Khandani and Lo 2007, Fabozzi et al. 2007, 2008)
  - I provide a first systematic study of quantitative investment accounting for: learning, holdings and performance
- Rational inattention: Sims (2003); Mackowiak and Wiederholt (2009, 2015); Van Nieuwerburgh and Veldkamp (2010); Kacperczyk, Van Nieuwerburgh and Veldkamp (2016)
  - I use this framework to explain how quantitative and discretionary investors compete in equilibrium
- Mutual funds performance over the business cycle: Glode (2011); Kosowski (2011); Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014)
  - I further show that quant and discretionary funds display a different performance pattern over the business cycle
- Stocks connectivity and fragility: Greenwood and Thesmar (2011), Anton and Polk (2014)
  - Quants overcrowding might increase the fragility/connectivity of the stocks they hold

Roadmap

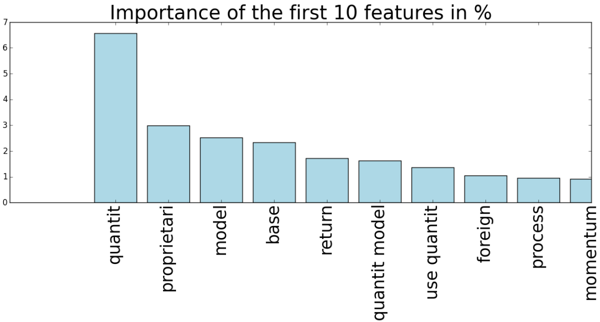
Roadmap

Procedure

- SEC $\rightarrow$ Prospectuses of 2,607 active US equity mutual funds over 1999–2015
- Training sample: 200 prospectuses classified manually
  - Fund name includes "quantitative" or "systematic"
  - Media mentions the fund as quantitative or traditional
- 170 are used to train 8 different machine learning algorithms
- 30 "hold-out"
- I use the most accurate algorithm to classify the rest of the sample
  - Random Forest with 1,000 trees and entropy impurity measure
  - 93.4% out-of-sample accuracy (tested on "hold-out" sample)
- NB: All results are robust to using other algorithms

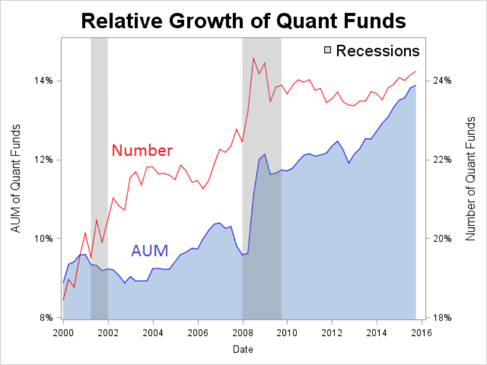
Outcome

- The algorithm chooses to employ 828 "features" (i.e. one- or two-word items)
- The top 10 features hold 21% informativeness
- Final sample:
  - 599 quantitative funds
  - 1,851 discretionary funds



The Rise of Quant Funds

- With this classification, I document the rise of quantitative mutual funds
- Over 1999-2015, quants' AuM increased
  - from \$100bn to \$420bn
  - from 8.8% to 14% of industry AuM
- Growth rate double that of discretionary funds



Roadmap

Model

- Equilibrium model of rational inattention.
  Extending Kacperczyk, Van Nieuwerburg and Veldkamp (KVV 2016)
  - $t = 1$: investors allocate learning capacity
  - $t = 2$: investors choose portfolio allocation
  - $t = 3$: assets pay off

- Assets: one riskless asset and n risky assets
  - One aggregate asset with payoff: $f_n = \mu_n + z_n$ with $z_n \sim N(0, \sigma_n)$
  - Assets $i = 1, \ldots, (n-1)$ with payoff: $f_i = \mu_i + b_i z_n + z_i$ with $z_i \sim N(0, \sigma_i)$
  - All assets are in random supply: $(\bar{x}_i + x_i)$ with $x_i \sim N(0, \sigma_x I)$

- Learning: investor j observes a private signal about each shock z_i
  - $s_{ij} = z_i + \epsilon_{ij}$ *with* $\epsilon_{ij} \sim N(0, \sigma_{ij})$
  - Learning determines $\sigma_{ij} \in [\ \underline{\sigma}_{ij}, \infty)$

Model (continued)

Investors: unit-mass of mean-variance investors with risk aversion ρ

- Unskilled investors (mass $(1-\chi)$): only learn from prices
- Skilled investors (mass χ): learn from prices and private signals
  - Discretionary investors (fraction $(1-\theta)$):
    - can learn about any and all shocks
    - but have limited learning capacity: $\sum_{i=1}^{n} {\sigma_{ij}}^{-1} \leq K$
  - Quantitative investors (fraction θ):
    - have unlimited learning capacity
    - but can learn only about idiosyncratic shocks
      $\rightarrow$ Technological assumption: industry survey evidence
      Survey
      $\rightarrow$ Plausible in the data: no skilled quantitative fund shifts from stock-picking to market-timing nor specializes in market-timing
      Table

Analysis

t = 1: investors allocate learning capacity

- Discretionary investors allocate all learning capacity to the shock(s) with the highest marginal benefit of learning, which is:
  - decreasing in average signal precision across investors
  - increasing in expected supply
  - increasing in prior volatility
- Quants learn all available information about idiosyncratic shocks only: $\sigma_{ij} = \underline{\sigma}_{ij}$ and $\sigma_{nj} = \infty$

t = 2: investors choose portfolio allocation

- Optimal portfolio allocation: $\tilde{q}_j{}^* = \frac{1}{\rho}\hat{\Sigma}_j{}^{-1}\left(E_j[\tilde{f}] - \tilde{p}r\right)$
  - Decreasing in risk aversion: ρ
  - Increasing in posterior expected payoffs: $E_j[\tilde{f}]$
  - Increasing in posterior precision of private signals: $\hat{\Sigma}_j{}^{-1}$
- More learning about an idiosyncratic shock translates into a larger position into the corresponding asset (long or short)

Roadmap

1. Introduction
2. The Rise of Quants
3. Model
4. Predictions and Empirics
   - Holdings
   - Performance
5. Conclusion
   - Summary of Findings
   - Other Differences
   - Future Research

Holdings

Proposition 2: Quants hold a larger number of assets

Intuition:

- Quantitative investors have a greater signal precision about more assets

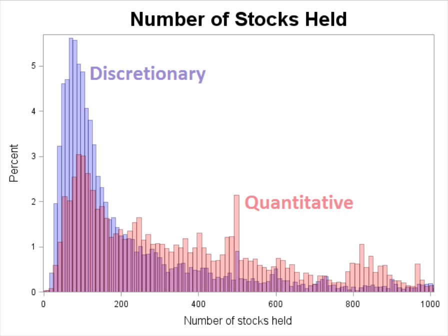
Holdings (Proposition 2)

- Quant funds hold a larger number of stocks than discretionary funds (significant also using quantile regressions and log(number of holdings))
- The distribution of the number of stocks held by quants is more right-skewed
- Quant funds have lower portfolio risk

	Number of stocks held	
intercept	117.6***	160.2***
	(0.000)	(0.000)
quant	108.4***	124.8***
	(0.000)	(0.000)
recession	-4.985	2.057
	(0.128)	(0.649)
quantXrecession	21.27***	12.87
	(0.005)	(0.127)
cash		-0.722
		(0.274)
AuM		26.47***
		(0.000)
controls	No	Yes
clustering	Yes	Yes

Holdings (Proposition 2)

- Quant funds hold a larger number of stocks than discretionary funds (significant also using quantile regressions and log(number of holdings))
- The distribution of the number of stocks held by quants is more right-skewed
- Quant funds have lower portfolio risk



Holdings (Proposition 2)

- Quant funds hold a larger number of stocks than discretionary funds (significant also using quantile regressions and log(number of holdings))
- The distribution of the number of stocks held by quants is more right-skewed
- Quant funds have lower portfolio risk

	Return Volatility	CAPM IdiosyncraticVol	3-factor IdiosyncraticVol	4-factor IdiosyncraticVol
intercept	4.316***	1.574***	1.187***	1.146***
	(0.000)	(0.000)	(0.000)	(0.000)
recession	1.690***	0.697***	0.733***	0.686***
	(0.000)	(0.000)	(0.000)	(0.000)
quant	-0.0794**	-0.149***	-0.180***	-0.177***
	(0.015)	(0.000)	(0.000)	(0.000)
quantXrecession	-0.146***	-0.0656**	-0.0451	-0.0388
	(0.003)	(0.039)	(0.121)	(0.156)
controls	Yes	Yes	Yes	Yes
clustering	Yes	Yes	Yes	Yes

Holdings

Proposition 3: As θ increases, discretionary funds shift their attention/holdings towards idiosyncratic shocks with smaller information gap: $G_i = \underline{\sigma}_{iq}^{-1} - \sigma_{id}^{-1}$

Intuition:

- Discretionary investors focus on shocks/assets for which they have less of an information disadvantage (or an information advantage) with respect to quants
- The information gap represents the difference between quants and discretionary investors in their signal precision about idiosyncratic shocks. The gap is heterogeneous across shocks and investor types.

Holdings (Proposition 3)

- Discretionary funds hold stocks that have a smaller information gap
- $InfoGap^{wd}_{jt} = \sum_{i=1}^{N^j} \left[w^{Active}_{it} Info_{it} \right]$ where:
  - $w^{Active}_{it} = \frac{|w^j_{i,t} - w^m_{i,t}|}{\sum_{i=1}^{N^j} |w^j_{i,t} - w^m_{i,t}|}$
  - $Info_{it}$ proxies: size, age, analysts coverage, media mentions

	Size	Age	Media Mentions	Analysts Coverage
intercept	34.06***	335.2***	293.7***	397.3***
	(0.000)	(0.000)	(0.000)	(0.000)
discretionary	-3.984**	-36.94***	-33.81**	-6.433
	(0.045)	(0.000)	(0.034)	(0.557)
recession	0.795	1.640	20.99	-135.6***
	(0.478)	(0.780)	(0.141)	(0.000)
discretionaryXrecession	-1.622**	-1.879	2.973	1.555
	(0.039)	(0.498)	(0.649)	(0.814)
controls	Yes	Yes	Yes	Yes
clustering	Yes	Yes	Yes	Yes

Holdings

Proposition 4: Dispersion of opinion is greater among discretionary investors than among quantitative investors

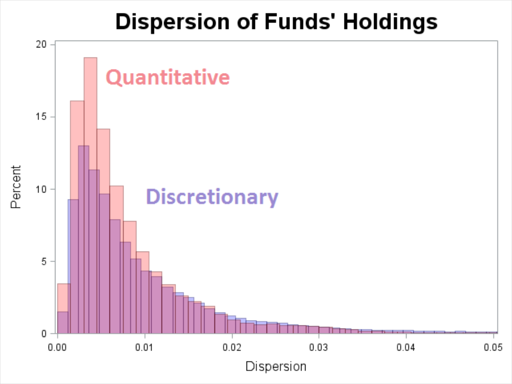
Intuition:

- Quantitative investors, thanks to their greater information processing capacity, learn all learnable information
  $\Rightarrow$ they receive similar signals
  $\Rightarrow$ low dispersion of opinions, and therefore in holdings

- Discretionary investors choose what to learn about
  $\Rightarrow$ might choose to learn about different shocks
  $\Rightarrow$ large dispersion of opinions and therefore in holdings

Holdings (Proposition 4)

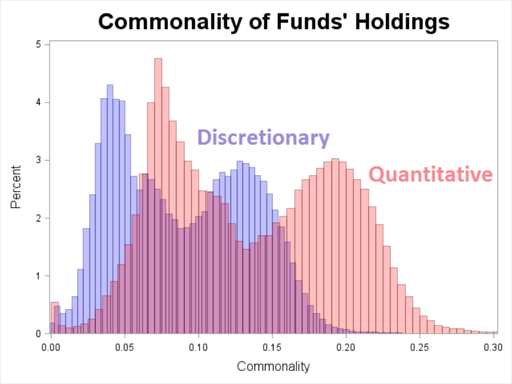
- Discretionary funds have a greater holdings dispersion
  $Dispersion_{jt}^{F} = \sum_{i=1}^{N_t^j} \left[\left(w_{it} - \overline{w}_{it}^{F} \right)^2 \right]$ for $\overline{w}_{it}^{F} = \frac{1}{N_F} \sum_{j=1}^{N_F} w_{it}$ and $F = Q, D$
- Discretionary funds have a smaller holdings commonality
  $Commonality_{jt}^{F} = \sum_{i=1}^{N_t^j} \left[w_{it}^{Active} \left(\frac{FundsNum_{it}}{FundsNum_t} \right) \right]$ for $F = Q, D$



Holdings (Proposition 4)

- Discretionary funds have a greater holdings dispersion
  $Dispersion_{jt}^{F} = \sum_{i=1}^{N_t^j} \left[\left(w_{it} - \overline{w}_{it}^{F} \right)^2 \right]$ for $\overline{w}_{it}^{F} = \frac{1}{N_F} \sum_{j=1}^{N_F} w_{it}$ and $F = Q, D$

- Discretionary funds have a smaller holdings commonality
  $Commonality_{jt}^{F} = \sum_{i=1}^{N_t^j} \left[w_{it}^{Active} \left(\frac{FundsNum_{it}}{FundsNum_t} \right) \right]$ for $F = Q, D$



Holdings (Proposition 4)

- Discretionary funds have a greater holdings dispersion
$Dispersion^F_{jt} = \sum_{i=1}^{N^j_t} \left[\left(w_{it} - \overline{w}^F_{it} \right)^2 \right]$ *for* $\overline{w}^F_{it} = \frac{1}{N_F} \sum_{j=1}^{N_F} w_{it}$ *and* $F = Q, D$

- Discretionary funds have a smaller holdings commonality
$Commonality^F_{jt} = \sum_{i=1}^{N^j_t} \left[w^{Active}_{it} \left(\frac{FundsNum_{it}}{FundsNum_t} \right) \right]$ *for* $F = Q, D$

	Dispersion	Commonality
intercept	0.00839***	14.79***
	(0.000)	(0.000)
discretionary	0.00257***	-5.782***
	(0.000)	(0.000)
recession	0.00173***	1.140***
	(0.005)	(0.000)
discretionaryXrecession	0.000135	-1.353***
	(0.783)	(0.000)
controls	Yes	Yes
clustering	Yes	Yes

Performance

Proposition 5:

- Discretionary investors' performance is counter-cyclical
- As the share θ of quants rises, discretionary investors' performance worsens in expansions and improves in recessions

Intuition:

- Performance is counter-cyclical thanks to discretionary investors' ability to learn about the aggregate shock when its volatility rises
- As θ increases, the effect is stronger due to a substitution effect

Performance (Proposition 5)

- Discretionary funds' performance is counter-cyclical

	CAPM Alpha		3-factor Alpha		4-factor Alpha	
intercept	-0.0328	-0.0286	-0.0775***	-0.0672***	-0.0567***	-0.0450***
	(0.131)	(0.209)	(0.000)	(0.000)	(0.000)	(0.003)
recession	0.282***	0.310***	0.0641***	0.0849***	0.0387***	0.0291***
	(0.000)	(0.000)	(0.112)	(0.035)	(0.465)	(0.594)
quant		-0.0269**		-0.0208*		-0.0204*
		(0.050)		(0.091)		(0.058)
quantXrecession		-0.153***		-0.0886***		-0.0604**
		(0.000)		(0.002)		(0.032)
controls	No	Yes	No	Yes	No	Yes
clustering	Yes	Yes	Yes	Yes	Yes	Yes

  - Similar results are obtained using value added instead of alphas ValueAdded

Performance

Proposition 6:

- Quant investors' performance is pro-cyclical
- As the share θ of quants rises or their information improves (signal noise $\underline{\sigma}_{ij}$ decreases), quants' performance worsens

Intuition:

- Quants have unlimited learning capacity for idiosyncratic shocks
- This is most valuable when these shocks matter the most i.e. in expansions
- Quants cannot learn about aggregate shocks
- This is most damaging when this shock matters the most i.e. in recessions
- As θ and $\underline{\sigma}_{ij}^{-1}$ increase, prices become more precise about idiosyncratic shocks s.t. each investor earns a smaller margin

Performance (Proposition 6)

- Quant funds' performance was greater in the two first expansions (Expansion1: Dec 1999–Mar 2001; Expansion2: Dec 2001–Nov 2007)
- Quant funds with lower holdings commonality perform better

	CAPM Alpha		
intercept	-0.106***	0.00906	-0.0530
	(0.000)	(0.891)	(0.194)
Expansion1	0.798***	0.758***	0.768***
	(0.000)	(0.000)	(0.000)
Expansion2	0.121***	0.106***	0.107***
	(0.000)	(0.006)	(0.006)
recession	0.207***	0.215***	0.209***
	(0.000)	(0.000)	(0.001)
commonality		-0.773**	
		(0.028)	
Dcommonality			-0.887**
			(0.040)
controls	Yes	Yes	Yes
clustering	Yes	Yes	Yes

- Similar results are obtained using value added instead of alphas ValueAddedQ

Roadmap

Summary of Findings

1. Document the rise of quantitative investment
    - Develop a classification methodology
    - 1999-2015: quants went form 8.8% to 14% of industry AuM
2. Identify differences between quantitative and discretionary funds in:
    1. Learning
        - Discretionary funds' incentive to learn about aggregate shocks increases with the share of quantitative funds
    2. Holdings
        - Quantitative funds have more diversified portfolios
        - Discretionary funds concentrate their holdings, focusing particularly on lesser known stocks
        - Dispersion of opinion is greater among discretionary funds than among quants
    3. Performance
        - Discretionary funds have counter-cyclical performance
        - Quantitative funds have pro-cyclical performance but are strongly affected by overcrowding

Other Differences Between Quant & Discretionary Funds

Size

- Quant funds are smaller than discretionary funds
- The size difference is more pronounced for smaller funds
- More

Fees

- Quant funds charge lower management fees
- More

Holdings:

- Quant funds hold more momentum and value stocks
- Quant funds have greater holdings turnover
- Quant funds hold less cash
- More

Flows:

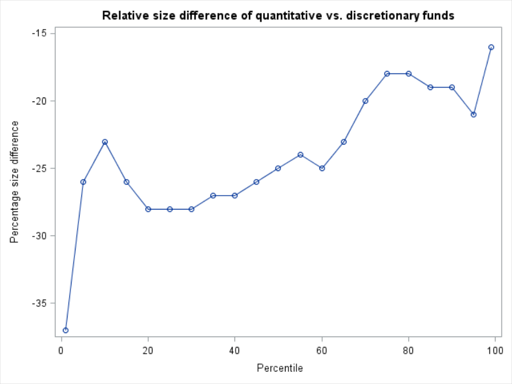
- Quant funds have more outflows in recessions
- Quant funds have been experiencing higher inflows since 2011
- More

Future Research

1. Implications of quants overcrowding
   1. Stocks fragility
   2. Excessive co-movement
2. Differences in economies/diseconomies of scale and implications for market concentration
3. Differences in factors exposure
   1. Factor timing
   2. Quant "closet-indexers" as Smart Beta
4. Implications of current technological trends
   1. Big Data
   2. Artificial Intelligence
   3. Innovative data sources (satellites, drones, social media, ...)

Size

- Quant funds are smaller than discretionary funds
- The size difference is more pronounced for smaller funds
  $TNA_{jt} = \alpha^p + \beta_1^p RECESS_t + \beta_2^p Quant_j + \gamma^p X_{jt} + \varepsilon_t$
- Displayed below is the percentage size difference: β_2^p / α^p



Back

Holdings

Quant funds:

- Hold more momentum and value stocks
- Have greater holdings turnover
- Hold less cash

	Momentum	Size	Value	TurnoverRatio	Cash
intercept	0.00461	0.272***	-0.0594***	0.757***	3.174***
	(0.659)	(0.000)	(0.000)	(0.000)	(0.000)
recession	-0.0107	-0.0624**	0.0753*	0.0979***	0.504***
	(0.580)	(0.023)	(0.074)	(0.000)	(0.000)
quant	0.00822*	-0.0275	0.0769***	0.147***	-0.729***
	(0.051)	(0.211)	(0.000)	(0.000)	(0.000)
quantXrecession	-0.00974*	0.0315**	-0.00497	0.00658	-0.668**
	(0.100)	(0.016)	(0.778)	(0.816)	(0.021)
controls	Yes	Yes	Yes	Yes	Yes
clustering	Yes	Yes	Yes	Yes	Yes

Back

Fees

Quant funds:

- Charge lower management fees

	ExpenseRatio	MgmtFee	12b1Fee	Loads
intercept	0.0121***	0.00687***	0.00365***	0.000233***
	(0.000)	(0.000)	(0.000)	(0.000)
recession	0.0000578	0.000548***	0.0000662	-0.0000446*
	(0.594)	(0.000)	(0.299)	(0.067)
quant	-0.00135***	-0.000590***	0.0000556	-0.00000609
	(0.000)	(0.001)	(0.706)	(0.922)
quantXrecession	-0.000152	-0.000231	-0.000155**	0.0000492
	(0.137)	(0.173)	(0.043)	(0.325)
ExpenseRatio				0.0447***
				(0.001)
controls	Yes	Yes	Yes	Yes
clustering	Yes	Yes	Yes	Yes

Back

Flows

Quant funds:

- Have more outflows in recessions
- Have been experiencing higher inflows since 2011

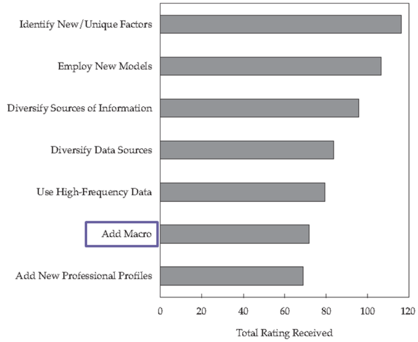
	NetFlows	FlowVol	NetFlows2011
intercept	0.00175***	0.0337***	-0.00183**
	(0.001)	(0.000)	(0.012)
recession	-0.000606	-0.000691	
	(0.704)	(0.313)	
quant	-0.00104	0.00135	0.00449***
	(0.191)	(0.252)	(0.000)
quantXrecession	-0.00520***	0.00269	
	(0.005)	(0.101)	
netFlows		0.132***	
		(0.000)	
controls	Yes	Yes	Yes
clustering	Yes	Yes	Yes

Back

Macro

Quants don't model macroeconomic info directly into their systems

Figure 5.9. Strategies to Which Quantitative Managers Will Turn in an Effort to Improve Performance as Rated by Survey Participants



Fabozzi, Focardi and Jonas (2008)

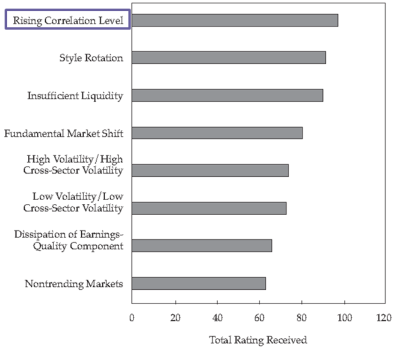
"Adding macroeconomic data was rated next to last on the list of seven possible strategies to improve performance. Many sources mentioned that macro data are already in the price of the stock"

Fabozzi, Focardi and Jonas (2008, page 83)

Back

Technological Constraints

Figure 5.5. Recent Market Conditions Rated by Survey Participants in Terms of the Challenge They Pose to a Quantitative Approach



Fabozzi, Focardi and Jonas (2008)

- "Correlations are not a problem most of the time, but in times of stress, correlations converge"

  Fabozzi, Focardi and Jonas (2008, page 74)

- "The ability to identify regime shifts sufficiently early requires a rich data structure, but estimating a rich regime-shifting model requires a very large data sample, something we rarely have in finance"

  Fabozzi, Focardi and Jonas (2008, page 57)

Back

Switching Type

Figure 3.3. Barriers to New Entrants into the Quantitative Equity Investment Space as Rated by Survey Participants

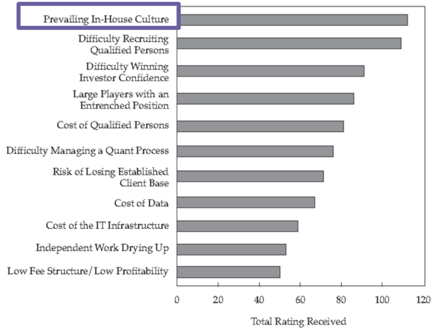
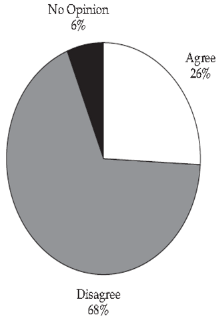


Figure 2.1. Response to: The Most Effective Equity Portfolio Management Process Combines Quantitative Tools and a Fundamental Overlay



Fabozzi, Focardi and Jonas (2008)

Back

Data and Variables

Data

- CRSP Mutual Fund Dataset–US diversified active equity funds
- CRSP/Compustat stocks information, IBES forecasts, Federal Reserve Industrial Production, Dow Jones news

Variables

$j = fund$, $i = stock$

- As in KVV, market timing and stock picking are measured as the covariance of the fund j's holdings with future idiosyncratic or aggregate shocks
- Higher covariances are indicative of learning
  - $Picking_{jt} = \frac{1}{N^j}\sum_{i=1}^{N^j}(w^j_{i,t} - w^m_{i,t})(SUE_{i,(t+1)})$
  - $Timing_{jt} = \frac{1}{TN^j}\sum_{i=1}^{N^j}\sum_{\tau=0}^{T-1}(w^j_{i,t+\tau} - w^m_{i,t+\tau})(b_i IndProd_{n,(t+\tau+1)})$

Back

Motivation of Quant Learning Technology Assumption

Define top funds as those who persistently show high levels of skill:

- Discretionary funds: top stock pickers in expansions are top market timers in recessions
- Quants: top stock pickers in expansions are top stock pickers in recessions
- No top market timer in recessions is also top market timer in expansions

	TimingRecessions	PickingRecessions	TimingExpansions
intercept	0.664***	-1.072***	-0.203***
	(0.000)	(0.000)	(0.000)
quant	-0.196***	0.356***	0.0405***
	(0.000)	(0.000)	(0.001)
topPickersExpansions	0.454***	-0.864***	
	(0.000)	(0.000)	
quantXtopPickersExpansions	-0.621***	0.248***	
	(0.000)	(0.004)	
topTimersRecessions			0.0323
			(0.494)
quantXtopTimersRecessions			-0.0412
			(0.352)
controls	Yes	Yes	Yes
clustering	Yes	Yes	Yes

Back

Measuring Performance as Value Added (Proposition 5)

- Discretionary funds' performance is counter-cyclical

	CAPM Alpha		3-factor Alpha		4-factor Alpha	
intercept	-0.200*	-0.157	-0.416***	-0.363***	-0.309***	-0.246***
	(0.060)	(0.170)	(0.000)	(0.000)	(0.000)	(0.000)
recession	1.371***	1.541***	0.422**	0.515**	-0.0793	-0.0483
	(0.000)	(0.000)	(0.026)	(0.011)	(0.166)	(0.484)
quant		-0.202***		-0.110*		-0.117***
		(0.005)		(0.094)		(0.007)
quant_recess		-0.847***		-0.406***		-0.232**
		(0.000)		(0.004)		(0.046)
controls	No	Yes	No	Yes	No	Yes
clustering	Yes	Yes	Yes	Yes	Yes	Yes

Back

Measuring Performance as Value Added (Proposition 6)

- Quant funds' performance was greater in the two first expansions (Expansion1: Dec 1999–Mar 2001; Expansion2: Dec 2001–Nov 2007)
- Quant funds with lower holdings commonality perform better

	CAPM Value Added		
intercept	-0.464***	0.367	-0.514***
	(-4.95)	(1.32)	(-4.82)
E1	3.074***	2.904***	3.036***
	(7.28)	(6.99)	(7.15)
E2	0.306*	0.327*	0.312*
	(1.74)	(1.87)	(1.77)
recession	0.868***	0.927***	0.860***
	(3.56)	(3.82)	(3.55)
comonality		-5.774***	
		(-3.57)	
dispersion			5.895
			(1.11)
controls	Yes	Yes	Yes
clustering	Yes	Yes	Yes

Back