

# Does Search Engine Visibility Help ETFs Attract Flows?

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#### Motivation

- Competition among exchange-traded funds (ETFs) led to a noticeable reduction in their fees (Investment Company Institute (2024)).
- When price and quality competitions are limited, other forms of competition may intensify (Scitovsky(1950)).
- Online space is important:
  - Consumers search for products online, for example, using Google.
  - Companies market and sell their products using online channels.

**My main question**: How online activities affect capital formation process in the asset management industry?



# Main steps

- 1. Propose a novel methodology to calculate a set of descriptive metrics of search engine visibility using the web analytics data.
- 2. Apply the methodology to the U.S. ETFs.
- 3. Design empirical tests to deal with various econometrics issues (endogeneity, unobservability of consumers' characteristics, etc)
- 4. Study whether better visibility on the search engine helps ETFs to attract more capital?



# Three datasets merged

I download and scrape data for the period of September 2019 through February 2021 from three sources:

- 1. ETFDB database.
  - ETFs' webpages URLs.
- 2. Bloomberg.
  - ETFs market data: performance, NAV, shares outstanding, contract.
- 3. SEMRush Web Analytics (main dataset).
  - Web analytics, 20B+ organic keywords, 1B+ ads, backlinks.



# SEMRush web analytics data

SEMRush collects historical data on Google's Search Engine Reporting Pages (SERP).

- Provides database of keywords that exceeds 20 billion keywords and covers 142 geographical regions.
- Scrapes top 100 URLs on the Google SERP for each keyword in its database on a monthly basis.
- Records information on paid and organic search results,  $\Omega_{i,t} = \{\Omega_{i,t}^{paid}, \Omega_{i,t}^{org}\}$ , for which the webpage i appears on the Google SERP in month t.



## Web analytics variables

For every keyword  $\omega \in \Omega_{i,t}$  of the webpage i in month t:

- Rank $_{i,t}(\omega)$  is the rank of the webpage i on Google's SERP for the keyword  $\omega$ ;
- PPC<sub>t</sub>(ω), is the Google ads auction-determined price-per-click (PPC) for the keyword ω;
- $SVol_t(\omega)$  is the estimated search volume for the keyword  $\omega$ ;
- #Clicks<sub>i,t</sub>( $\omega$ ) is the estimated number of clicks on the webpage i from the keyword search  $\omega$ .



## Illustrative example

ETF i has webpage URL "ETF URL".



### Organic keywords

$$\Omega_{i,t}^{\textit{org}} = \{\mathsf{Keyword}\ 1, \mathsf{Keyword}\ 2\}$$

$$Rank_{i,t}(Keyword 1) = 5$$

$$Rank_{i,t}(Keyword 2) = 2$$

#### Paid keywords

$$\Omega_{i,t}^{paid} = \{ \text{Keyword 3} \}$$

$$Rank_{i,t}(Keyword 3) = 1$$

## Wordcloud of keywords





#### Subsamples of keywords Summary Statistics

- No ad auctions (PPC = 0)
- Buy intentions  $(\Omega^1 = \{\text{buy, invest}\})$
- Sell intentions  $(\Omega^2 = \{\text{sell}\})$

- Fund types  $(\Omega^3 = \{\text{index funds, mutual funds,...}\})$
- Asset classes and popular indices  $(\Omega^4 = \{\text{stocks, bonds,...}\})$
- Names of ETF issuers  $(\Omega^5 = \{ Blackrock, ishares... \})$



# Search engine marketing

I construct the proxy for whether ETF i uses the search engine marketing (SEM) in month t:

$$\mathsf{SEM}_{i,t} = \begin{cases} 1, & \mathsf{if} \; \mathsf{ETF} \; \mathsf{engages} \; \mathsf{in} \; \mathsf{SEM} \\ 0, & \mathsf{otherwise}. \end{cases}$$



# Search engine marketing cost

I use the price-per-click (PPC) and the estimated number of clicks on the webpage across all paid keywords  $\Omega_{i,t}^{paid}$  of the ETF i in month t to calculate the fund's expenses on search engine marketing:

$$\mathsf{SEMCost}_{i,t} = \begin{cases} \sum_{\omega \in \Omega_{i,t}^{\textit{paid}}} \mathsf{PPC}_t(\omega) \cdot \#\mathsf{Clicks}_{i,t}(\omega), & \text{if ETF engages in SEM} \\ 0, & \text{otherwise}. \end{cases}$$



# **Effects of Search Engine Visibility**

The expected benefits for a fund from having its webpage on the search engine results page (SERP) depend on the two components:

$$\Big[ \mathsf{Number\ of\ Clicks} \Big] \times \Big[ \mathsf{Value\ of\ Click} \Big].$$

Since a fund appears at results pages for many queries, expected benefits have to be aggregated across all keywords.



# Search engine visibility: Average SERP rank

I construct a proxy for the number of clicks as the average SERP rank by aggregating the rank of the ETF i's webpage in month t across all keywords with weights proportional to keyword's overall search volume:

$$\overline{\mathsf{Rank}}_{i,t} = \frac{\displaystyle\sum_{\omega \in \Omega_{i,t}} \mathit{SVol}_t(\omega) \cdot \mathsf{Rank}_{i,t}(\omega)}{\displaystyle\sum_{\omega \in \Omega_{i,t}} \mathit{SVol}_t(\omega)}.$$

The webpages with lower average rank have better online visibility and higher chances to get clicks.



# Search engine visibility: Average page

Google (usually) displays 10 URLs on each page of SERP. To capture potential non-linearity in relationships, I construct the dummies:

$$\begin{aligned} &\mathsf{Page}_{i,t}^{1} = \mathbb{1}[1 \leq \overline{\mathsf{Rank}}_{i,t} \leq 10]; \\ &\mathsf{Page}_{i,t}^{2} = \mathbb{1}[10 < \overline{\mathsf{Rank}}_{i,t} \leq 20]; \\ &\mathsf{Page}_{i,t}^{3} = \mathbb{1}[20 < \overline{\mathsf{Rank}}_{i,t} \leq 30]; \\ &\mathsf{Page}_{i,t}^{4} = \mathbb{1}[30 < \overline{\mathsf{Rank}}_{i,t} \leq 40]. \\ &\mathsf{Page}_{i,t}^{5} = \mathbb{1}[40 < \overline{\mathsf{Rank}}_{i,t} \leq 50]. \end{aligned}$$



# Search engine visibility: Value of click

I construct a proxy for the value of a click as the average value of a click by aggregating  $PPC_{i,t}(\omega)$  of the ETF i's webpage in month t over all keywords with weights proportional to keyword's overall search volume:

$$\overline{\mathsf{PPC}}_{i,t} = \frac{\displaystyle\sum_{\omega \in \Omega_{i,t}} \mathsf{SVol}_t(\omega) \cdot \mathsf{PPC}_{i,t}(\omega)}{\displaystyle\sum_{\omega \in \Omega_{i,t}} \mathsf{SVol}_t(\omega)}.$$

A higher average PPC signals that advertisers especially value traffic from pages where a fund is shown among search engine results.



# Bloomberg data

Sample of 1,784 US ETFs from September 2019 to May 2021.

#### For ETF *i* in month *t*:

- Benchmark index:
- Asset class:
- Net asset value, P<sub>i,t</sub>;
- Shares outstanding, ShrOut<sub>i,t</sub>;
- Expense ratio, Fee<sub>i</sub>.

$$\%\mathsf{Flow}_{i,t} = \frac{\left(\mathsf{ShrOut}_{i,t} - \mathsf{ShrOut}_{i,t-1}\right) \cdot P_{i,t}}{\mathsf{ShrOut}_{i,t-1} \cdot P_{i,t-1}}.$$

Summary Statistics



# Main Fund Flows Regression

I estimate the relationship between ETF's fund flows and measures of online visibility using the following panel regressions with controls and fixed effects:

$$\begin{split} \mathsf{Flow}_{i,t+1} &= \alpha_0 + \alpha_{\mathit{rank}} \cdot \overline{\mathsf{Rank}}_{i,t} + \alpha_{\mathit{PPC}} \cdot \mathsf{In}(\overline{\mathsf{PPC}}_{it}) + \alpha_{\mathit{link}} \cdot \mathsf{In}(\#\mathsf{Links}_{it}) + \\ &+ \sum_{n=1}^4 \alpha_R^n \cdot R_{it}^n + \alpha_{\mathit{flow}} \cdot \mathsf{Flow}_{i,t} + \alpha_{\mathit{size}} \cdot \mathsf{In}(\mathsf{Size}_{i,t}) + \\ &+ \alpha_{\mathit{age}} \cdot \mathsf{In}(\mathsf{Age}_{i,t}) + \alpha_{\mathit{fee}} \cdot \mathsf{Fee}_i + \alpha_{\mathit{\%ba}} \cdot \mathsf{\%BASpread}_{it} + \\ &+ \lambda_{\mathit{asset}} + \lambda_{\mathit{issuer}} + \lambda_t + \epsilon_{\mathit{i},t+1}. \end{split}$$



# Problem: Ranking endogeneity

In regressions of fund flows on rankings, SERP rankings are endogenous:

- Google employs sophisticated algorithms and use information about users' choices for determining positions.
- Products with higher likelihood of being clicked are likely to be positioned at the top of SERP.

The previous literature suggested a number of solutions: Narayanan and Kalyanam (2015), Ghose et.al.(2009), Ghose et.al.(2014), Rutz et.al.(2012), Blake et.al(2015), and Ursu(2018).

# My approach



- Exclude sponsored listings and focus on organic search results.
  - Users search for various purposes, so the correlation should be weaker.
  - Janssen et al. (2023) provide theoretical arguments for why it might be optimal for Google to randomly assign organic search positions.
- Control for variables, such as the number of backlinks, that are known to affect both ranks and flows. Control for time, issuer, asset class fixed effects.
- Perform analysis on subsamples of keywords to better control for customers' characteristics.
- Check results for ETFs tracking the same index.



#### Fund Flows and SERP Positions: Results

I obtain the following results:

$$\begin{split} \text{\%Flow}_{i,t+1} = & 0.051^{****} \cdot \mathsf{Page}_{it}^1 + 0.045^{****} \cdot \mathsf{Page}_{it}^2 + 0.028^{****} \cdot \mathsf{Page}_{it}^3 + \\ & + 0.021^{***} \cdot \mathsf{Page}_{it}^4 + 0.007 \cdot \mathsf{Page}_{it}^5 + 0.013^{****} \cdot \mathsf{In}(\overline{\mathsf{PPC}}) + \\ & + \mathsf{Controls}_{it} + \mathsf{Fixed} \ \mathsf{Effects} + \epsilon_{i,t+1}. \end{split}$$

These results are robust to various specifications (only organic keywords, subsamples with ad auctions and w/o them, subsamples that exclude  $\Omega_1$ ,  $\Omega_2$ ,  $\Omega_3$ ,  $\Omega_4$ , and  $\Omega_5$ ).

# Results: Sample of ETFs with the Same Benchmark



	(1)	(2)	(3)	(4)	(5)
Rank	-0.001***	-0.001***	-0.001***	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ln(\overline{PPC})$	0.022***	0.014**	` — ´	0.016**	0.008***
, ,	(0.006)	(0.007)		(0.006)	(0.003)
In(#Links)	0.003	0.007**	0.008**	0.007**	0.007*
,	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes
Index FE	Yes	Yes	Yes	Yes	Yes
Sample	Ω	$\Omega^{org}$	$\Omega^{org}     PPC = 0$	$\Omega^{org} \setminus \Omega^3$	$\Omega^{org} \setminus \bigcup_{i=1}^{5} \Omega^{i}$
#Obs.	1,798	1,798	1,798	1,798	1,798
$Adj.R^2$	0.130	0.213	0.212	0.213	0.213

Results are similar even for the smaller sample of funds tracking the same indices with index FE.

## **SEM Results**



	(1)	(2)	(3)
SEM	0.020*	_	0.016
	(0.010)		(0.023)
In(SEM Expense)	_	0.002	
		(0.002)	
SEM * Top5%			0.005
			(0.024)
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes
Asset class FE	Yes	Yes	Yes
Sample	Ω	Ω	Ω
#Obs.	21,219	21,219	21,219
$Adj.R^2$	0.122	0.122	0.122



# ETF's fund flows: Variance decomposition

I do variance decomposition to analyze how important are measures of online activities for explaining fund flows:

Fixed Effects	Age	Past returns	Size	Google	BA spread	SEM	Fees	Past flows
45.6%	23.0%	16.3%	11.5%	1.9%	0.8%	0.5%	0.2%	0.2%

In additional to conventional factors, the fund's visibility on Google explains 1.9% of fund flows; this is more than funds' fees, past flows, and liquidity. SEM explains 0.5%.

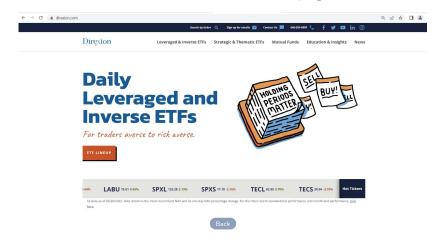


#### Conclusion

- Financial companies do use online marketing tools to gain advantage in attracting funds.
- 2. Search engine visibility is important for an ETF's capital formation:
  - ETFs that engage in search engine marketing(SEM) attract more flows in the next quarter.
  - ETFs with web pages that, on average, position higher on Google get higher future fund flows.
  - The quality of traffic proxied by the average pay-per-click is important.
- 3. The online visibility and SEM of an ETF explains an additional 2.5% of the variation in ETF fund flows (besides age, past performance, and size of the fund).

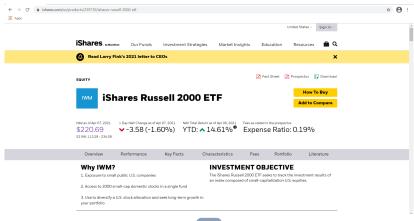


## Paid search: Direxion homepage





# Organic search: iShare IWM webpage



Back



# Summary stats: All keywords

	#Keywords	PPC=0	PPC(\$)	PPC > 0
	(millions)	(%)	avg	med
Set $\Omega$	1.674	64%	5.17	3.82
Set with auctions	0.609	0%	5.17	3.82
Set w/o auctions	1.065	100%	0.00	0.00





# **Bloomberg: Summary stats**

	AuM (\$) (billions)	Volume (\$) (billions)	Return	Fee (bps)	%BA spread (bps)	Age (years)
All	3.12	0.80	0.002	44	25	8.1
Page 1	11.62	1.49	-0.020	21	9	10.6
Page 2 Page 3	5.94 3.31	2.05 1.30	0.019 0.004	40 43	18 23	11.6 9.2
Page 4 Page 5	1.97 1.82	0.45 0.33	0.001 -0.006	43 46	27 29	7.4 6.5
Pages Below	0.86	0.16	0.005	58	32	6.4

