

ETF Ownership and Seasoned Equity Offerings

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Abstract

This article investigates the impact of exchange-traded fund (ETF) ownership on seasoned equity offerings (SEOs). We find that increases to firms' ETF ownership is positively related to their propensity to conduct an SEO. ETF ownership is also associated with less negative SEO announcement returns, smaller discounts, and better long-run stock returns. Our evidence is consistent with equity issuance following investor demand for stocks driven by greater participation in ETFs, suggesting a possible alternative source of market timing opportunity.

I. Introduction

From 2000 to 2021, the U.S. exchange-traded fund (ETF) industry grew from 80 ETFs managing \$66 billion to 2,570 funds with \$7.2 trillion in assets under management (AUM) (Investment Company Institute (ICI) (2022)). Responding to this dramatic growth, a nascent literature has examined the impact of ETF ownership on securities, including volatility (Ben-David, Franzoni, and Moussawi (2018)), return co-movement (Da and Shive (2017)), pricing inefficiency (Israeli, Lee, and Sridharan (2017)), illiquidity (Hamm (2014)), price discovery in earnings (Glosten, Nallareddy, and Zou (2021)), and overvaluation (Zou (2019)). While prior studies focus on the capital market consequences, a new line of inquiry has begun to examine the implications of ETFs for corporate decisions, such as real investment (Antoniou, Li, Liu, Subrahmanyam, and Sun (2023)) and cash holdings

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(El Kalak and Tosun (2022)). Our study adds to this literature by investigating the role of ETF ownership on the likelihood of seasoned equity offerings (SEOs) and firm performance during three stages of these issues.

ETF ownership could influence a firm's propensity to conduct an SEO and its subsequent performance in several ways. First, as explained by Israeli et al. (2017), the benefits of ETFs can produce unintended consequences for liquidity and pricing efficiency. As firm ownership by ETFs grows, a smaller proportion of shares outstanding remains available for investors, meaning that informed investors have less opportunity to trade on their information. Compounding this problem, some uninformed investors migrate their trading from stocks to ETFs, removing their liquidity from individual securities and causing spreads to widen, thereby limiting the profitability of information collection. ETF ownership diminishes the incentives for agents to collect firm-specific information, worsening the information asymmetry problem, and making stock prices less informationally efficient.

Second, the high-frequency liquidity offered by ETFs attracts a new clientele of short-horizon traders. ETF trading sets off a specific arbitrage process, which, according to the liquidity-trading hypothesis of Ben-David et al. (2018), propagates non-fundamental demand shocks to stocks. Subject to the emergence of reversing liquidity, this trading can cause the temporary overvaluation of the equities in the ETF basket. Similarly, demand for ETFs for hedging and other strategies also imputes overvaluation onto stocks by the same arbitrage mechanism. An increase in the ETF ownership of a firm, therefore, constitutes a liquidity demand shock that transmits price impact and temporary mispricing to stocks.

Since both of these mechanisms rely on uninformed traders and operate in the same direction, we refer to them jointly as the noise trader hypothesis. Whether due to information inefficiency or liquidity trading, deviations of stock prices away from their fundamental values are positively associated with changes to ETF ownership. We posit that increases in ETF ownership of a firm may create opportunities for managers to time the market with their equity issuance decisions, thus increasing firms' propensities to conduct SEOs.

There may be other mechanisms that provide managers with opportunities to time the market. One plausible alternative is that favorable equity valuations follow ETF inflows due to higher equity market participation. The financial innovations of ETFs could attract retail flows into equities that may not otherwise have been allocated to financial markets. This corresponds with evidence of higher retail ownership of ETFs compared to stocks (Ben-David et al. (2018)) and the increased awareness and adoption of ETFs by retail investors and their advisors (Investment Company Institute (ICI) (2022)). To the extent that these retail flows can be regular or persistent, they may show different effects on SEOs compared to the liquidity trading of the noise trader hypothesis. Institutional demand for ETFs for hedging and other strategies due to their convenience may present another source of new ETF flows (Investment Company Institute (ICI) (2022)).

Demand for equity via ETFs may also stem from the substitution by investors. The shift from active to passive vehicles is well known, but this may not necessarily lead to incremental flows into equities. Perhaps more important is the allocation of investments into more risky equity ETFs, consistent with lower perceptions of risk or lower risk aversion. Since households that own ETFs are willing to take more risk

compared to those that own mutual funds, albeit according to survey data and its caveats (Investment Company Institute (ICI) (2022)), ETFs may attract flows from some investors who have greater appetite for risk.¹ Risk-taking by households is also conditional on low-interest rates. Recognizing the challenge of inferring investor behavior from capital markets, Lian, Ma, and Wang (2018) perform randomized experiments and show that when interest rates are low individual investors reach for yield, consistent with reference dependence and salience behavioral mechanisms. Market participation could channel relatively more of these risk-seeking investment flows into ETFs. These psychological mechanisms may also affect professional investors, and increased risk appetite by households may transmit to financial institutions (Lian et al. (2018)), with their subsequent riskier investment allocations flowing to ETFs as their popularity grows.

Therefore, ETF inflows motivated by market participation, or as an expression of risk-taking by both individual and professional investors, particularly in response to low-interest rates, may represent mechanisms that fuel demand for stocks. We combine these sources into the market participation hypothesis, which suggests an alternative channel by which increases in ETF ownership that lead to appreciation in stock prices may incentivize some managers to issue SEOs to take advantage of cheaper equity finance.²

Our first objective is to establish the relation between ETF flows and the propensity of firms to conduct an SEO. We construct a large sample of U.S. stocks between 2003 and 2020, identify ETFs from the CRSP stock and mutual fund databases, and calculate firm-level ETF ownership as the proportion of the firm's outstanding shares held by ETFs. Merging the ETF ownership data with SEO data from the Securities Data Company's (SDC) Global New Issues database, and with security and accounting data from the CRSP and Compustat databases, our final sample consists of 268,831 firm-quarter observations for 8,581 firms.

Estimations of linear probability models show that SEO likelihood increases with ETF flows, after controlling for firm characteristics known to determine SEO probability and industry and time-fixed effects (FEs). To examine whether the influence of ETF flows is distinct from active and index fund flows, we check the pairwise correlations, finding that ETF flows are only weakly correlated with the other two. We subject the three flow variables to the same regression, finding that the positive effect of ETF flows appears incremental to that of active and index fund flows.

Our next set of tests explores the heterogeneous effect of ETF flows on SEO probability. If an increase in ETF ownership leads to higher stock prices and creates opportunities for managers to time the market, we might expect this effect to be stronger for firms with more price inelastic demand for their stocks. Indeed, we find that smaller firms with lower stock prices, higher return volatilities, and narrower shareholder bases demonstrate stronger effects of ETF ownership on SEO likelihood.

¹See Table 4.14 of the ICI Fact Book (Investment Company Institute (ICI) (2022)). A total of 54% of households that own ETFs are willing to take above average or substantial risk. The same risk behavior was shown by 38% of households owning mutual funds and 26% of all U.S. households.

²We do not claim that this is the only alternative to the noise trader hypothesis for market timing, rather we suggest that it is pertinent in the context of the popularity of ETFs and their flows.

A positive and significant relation between ETF flows and SEO probability suggests market timing and is consistent with both the noise trader and market participation hypotheses. However, these mechanisms predict opposing effects for ETF ownership on post-SEO performance. Therefore, to investigate their relative influence, we investigate the SEO announcement effect, issue-day discount, and long-run performance.

Stock returns following SEO announcements are often negative.³ Such reactions are economically important since they represent part of the flotation cost to issuing seasoned equity (Lee and Masulis (2009)). The negative returns are interpreted by a range of interconnected explanations including information asymmetry around asset value, agency problems, anticipation of adverse selection at the issue, less than optimal capital structure, valuation uncertainty, price pressure, and inelastic demand. Under the noise trader hypothesis, ETF ownership increases information asymmetry or temporary overvaluation. If these are the sources of market timing opportunity, firms with higher ETF ownership should experience more negative reactions to SEO announcements. Alternatively, under the market participation hypothesis, ETF flows can signal higher demand for equity with associated price appreciation triggering market timing. As such, announcement returns should be less negative for firms with higher ETF ownership. Examining 3-day cumulative abnormal returns (CARs) around SEO announcements, we find that ETF ownership attenuates the negative SEO announcement effects, consistent with the market participation hypothesis.

On the SEO issue day, firms tend to offer a discount, defined as the offer price being lower than the previous day's closing price. The discount represents a compensation for adverse selection risk and is required to tempt investors to participate in seasoned offers. If ETF ownership is associated with less efficient stock prices (Israeli et al. (2017)) or transmits non-fundamental demand shocks (Ben-David et al. (2018)), the noise trader hypothesis predicts larger discounts for firms with higher ETF ownership. In contrast, to the extent that ETF ownership represents demand for equity under the market participation hypothesis, SEO issuers perceive a lower risk of the offer failing and investors require lower discounts to cover adverse selection risk. We find that ETF ownership reduces SEO discounts, again consistent with the market participation hypothesis.

Finally, we examine the impact of ETF ownership on post-issue stock returns. Long-run underperformance by seasoned equity issuers is well established and, in light of the difficulty in measuring information asymmetry and mispricing ex ante, is interpreted ex post as evidence of successful market timing (Loughran and Ritter (1995), (1997)). If increases to ETF ownership are associated with overvaluation of stock prices relative to the manager's superior information, according to the noise trader hypothesis, they are provided with opportunities to time the market, which would be followed by underperformance. In contrast, under the market participation hypothesis, the motivation for issuing equity arises from demand for equity, which does not imply relatively lower post-SEO underperformance. Using both

³See, for example, Asquith and Mullins (1986), Masulis and Korwar (1986), Loughran and Ritter (1995), Eckbo et al. (2007), Lee and Masulis (2009), Kim et al. (2013), and Gokkaya and Highfield (2014), among others.

event- and calendar-time approaches, we find that those issuers with higher ETF ownership show less negative long-run abnormal returns in the 3 and 5 years after the SEO, consistent with the market participation hypothesis.

Our analysis contributes to several strands of the literature. We add to the growing evidence on the effects of ETF ownership on securities. Recent work examines the role of ETF ownership in corporate decisions, including real investment (Antoniou et al. (2023)) and cash holdings (El Kalak and Tosun (2022)). Complementing this literature, we offer new evidence that ETF ownership has implications for corporate equity financing decisions. A closely related study is Zou (2019), which documents that ETF flows increase overvaluation, equity issuance, and insider trading activities. We extend Zou (2019) by examining the impact of ETF flows on firms' SEO decisions under alternate hypotheses that we then test by analyzing firm performance during three stages of the SEO process.

Second, our findings expand the literature on the motivations for the market timing of security issuance. Existing evidence reconciles SEO issuance with managerial market timing driven by information asymmetry (Loughran and Ritter (1995), (1997), Graham and Harvey (2001), Baker and Wurgler (2002), Lee and Masulis (2009), and DeAngelo, DeAngelo, and Stulz (2010)). We investigate the role of ETF ownership on this SEO issuance decision. Specifically, we consider the information asymmetry and liquidity mispricing motivations against a potential alternative, that market timing opportunities may also arise from increased investor demand for equity indicated by ETF ownership. Our results confirm that SEO likelihood increases with ETF flows. When investigating three important stages of SEOs, we find evidence consistent with seasoned equity issuance in response to investor demand for stocks. Building on the prior literature, our findings suggest that additional market timing opportunities may arise from increased market participation.

Third, we provide new findings on firm performance at the SEO announcement, on the issue day, and over the 5 years post-SEO. The popular view is that negative SEO announcement returns and the SEO discount both increase with information asymmetry (Dierkens (1991), Eckbo, Masulis and Norli (2007), Chemmanur, He, and Hu (2009), Lee and Masulis (2009), Chemmanur and Jiao (2011), and Chan and Chan (2014)). However, when adverse selection is alleviated by voluntary disclosure (Lang and Lundholm (2000)), accounting conservatism (Kim, Li, Pan, and Zuo (2013)), accounting quality (Lee and Masulis (2009)), or certain offer characteristics (Corwin (2003)), these effects are attenuated. Complementing these studies, we offer new evidence that ETF ownership also mitigates the negative SEO announcement effect and discount, but via the alternative mechanism of equity demand from market participation. For long-run performance, negative abnormal returns up to 5 years post-SEO are typically inferred as evidence of successful market timing by managers taking advantage of favorable prices and information asymmetry (Loughran and Ritter (1995), (1997)). We find that ETF ownership reduces this long-run underperformance for SEO issuers. This is consistent with successful market timing when those opportunities arise following the demand for equity via ETFs, driven by greater market participation.

Finally, our work relates to the literature that adopts mutual fund flows to measure stock price pressure on their constituents. Khan, Kogan, and Serafeim (2012) show that liquidity flows into mutual funds generate mispricing that increases the likelihood of firms timing the market and issuing an SEO. More recently, Berger (2023) raises important questions on the efficacy of this methodology relating to selection bias. For this and other reasons, we focus on ETF flows instead. First, the inflows into ETFs over recent years prompt us to consider demand for equity and market participation as an influence on SEO decisions, in addition to the liquidity price pressure mechanism asserted by Khan et al. (2012). Second, ETF flows may have different influence on securities compared to mutual fund flows due to their higher frequency of trading, turnover, unique arbitrage mechanism, and the lack of discretion when allocating capital to stocks in the ETF basket (Ben-David et al. (2018)). Third, the passive allocation of ETF flows to stocks is less likely to induce selection bias.

The remainder of this article is organized as follows: Section II describes the sample and the construction of the key variables. Section III reports the empirical results. Section IV concludes.

II. Data

A. Sample Selection

Our sample includes ETF holdings data from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database to construct an ETF ownership variable.⁴ We combine this with SEO data from the Refinitiv SDC Platinum database. Following Da and Shive (2017), we identify all ETFs from the CRSP stock database that have a share code of 73. To confirm that these are ETFs, we match them with funds in the CRSP mutual fund database that have the ETF indicator variable (“ETF_FLAG”) labeled as “F.” We include only ETFs investing in U.S. domestic equity.⁵ Following Ben-David et al. (2018), we select funds with a Lipper asset code of EQ and the following Lipper objective codes: CA, EI, G, GI, MC, MR, SG, and SP. We also include domestic Sector Funds by selecting Lipper objective codes: BM, CG, CS, FS, H, ID, NR, RE, TK, TL, S, and UT. We exclude leveraged funds by removing those with names containing the following keywords: 1.25x, 1.5x, 2x, 2.5x, 3x, and ultra. Our final sample contains 1,208 unique ETFs over the period 2003 to 2020, comparable to recent studies (see, e.g., Ben-David, Franzoni, Kim, and Moussawi (2021), Brown, Davies, and Ringgenberg (2021)).⁶ We then obtain

⁴Although empirical studies generally use the Thomson Reuters Mutual Fund Ownership Database for ETF holdings data, we follow Da and Shive (2017) in using the CRSP mutual fund holdings database due to data availability. Da and Shive (2017) note that the number of ETFs in the Thomson Reuters Holdings database is rather small.

⁵We screen out funds with non-US, international, or global coverage by removing those with Lipper class names that contain the following keywords: emerging, international, European, global, India, Latin, Japan, Pacific, and world. We also screen out funds whose names contain the following two keywords: international and global.

⁶ETF holding data are not available in the CRSP mutual fund holdings database prior to 2003 because few ETFs existed prior to this date (DeLisle, French, and Schutte (2017)).

holdings information for these ETFs from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database to build our quarterly ETF holdings data set.

To construct our SEO sample, we begin with all completed common share SEOs issued by U.S. firms listed on NYSE, AMEX, or NASDAQ. We exclude utility firms (with a SIC code of 4910–4939), rights issues, investment trusts, and American depositary receipts.⁷ We retain SEOs that are primary offerings or a combination of primary and secondary offerings. In total, we obtain 4,828 SEOs over our sample period.⁸ We merge the quarterly ETF holdings data, the SEO events, and a firm-quarter data set, which includes all firms from the CRSP/Compustat Merged Quarterly Fundamental Database that have a CRSP share code of 10 or 11, are listed on the NYSE, AMEX, or NASDAQ, and are not utilities. After excluding missing observations, we retain 268,831 firm-quarter observations (8,581 unique firms) and 4,568 SEO events for our main test of SEO probability.

B. Key Variable Construction

1. Firm-Level ETF Ownership

Following Israeli et al. (2017), ETF ownership of stock i in quarter t is defined as

$$(1) \quad \text{ETF}_{i,t} = \frac{\text{SHARES_HELD_BY_ALL_ETF}_{i,t}}{\text{TOTAL_SHARES_OUTSTANDING}_{i,t}},$$

where $\text{SHARES_HELD_BY_ALL_ETF}_{i,t}$ is the total number of stock i 's shares held by all ETFs at the end of quarter t and $\text{TOTAL_SHARES_OUTSTANDING}_{i,t}$ is the total number of shares outstanding of stock i at the end of quarter t . We calculate the quarterly change in ETF ownership and, following Glosten et al. (2021), transform it into a rank variable. Stocks are sorted into 10 groups according to their quarterly change in ETF ownership, and allocated the group number as their rank. Dividing this by 10 creates a variable ranging from 0.1 to 1, denoted ΔETF . For robustness, we also consider the change in ETF (continuous) variable, termed $\Delta\text{ETF_CONT}$. Applying the same procedures, we construct analogous variables for index funds (INDEX and ΔINDEX) and active mutual funds (ACTIVE and ΔACTIVE) to allow further analysis.⁹

2. SEO Issue Dates

Lease, Masulis, and Page (1991) demonstrate that publicized SEO issue dates are unsuitable for analyzing their effect on prices because firms issue equity when trading is closed. To remedy this, the offer dates should be corrected to the following

⁷We exclude utility firms because the approval process limits their ability of time the market (Khan et al. (2012)). Rights issues are excluded because they are different from common offerings being available to existing shareholders only. American depositary receipts are often issued by foreign companies, thus we exclude them.

⁸These procedures follow the existing literature (Corwin (2003), Chemmanur et al. (2009), and Li and Zhuang (2012)).

⁹These procedures yield 1,104 index funds and 7,656 active mutual funds. Full details available from the authors.

day. Following Corwin (2003), we use a volume-based method to correct the issue dates. If the trading volume on the day after the reported issue date is more than twice the trading volume on the issue date, and more than twice the average trading volume over the prior 250 days, we correct the issue date to the following day. In our original sample of 4,828 SEOs, we correct the issue dates for 2,294 of them (47.5%).¹⁰

C. Summary Statistics

Panel A of Table 1 reports the descriptive statistics for our ETF sample at the end of each year. The number of equity ETFs has increased steadily from 67 in 2003 to 633 in 2020 and their average AUM has increased from \$1,607.4 million to \$5,240.7 million, with obvious deviations from the trend from 2006 to 2009. ETF ownership of an average firm has also grown considerably over time, increasing from tiny proportions in the early 2000s to almost 9% in 2020. These trends show the growing role of ETFs over the sample period.

Panel B of Table 1 considers SEOs by year. SEOs have generally increased in number over our sample period, but not necessarily linearly. Although rising from 220 to nearly 500 per year in 2020, there has been considerable fluctuation along the way. On average, there are 268 SEOs in our sample in each year. The amount of shares offered is relatively stable around the average (median) of 9 (5) million, but we observe large variations in 2008–2011, 2016, and 2019–2020. The distribution of our sample SEOs resembles that reported in prior studies (Bowen, Chen, and Cheng (2008), Li and Zhuang (2012)).

Table 2 shows the summary statistics for our firm-quarter sample from 2003 to 2020. The average frequency of a firm conducting an SEO issue in quarter t is 1.7%, and from quarter t to $t + 3$ is 4.8%. ETF ownership has a mean (median) of 3.6% (1.4%), which is more than double the 1.2% (0.5%) for index funds (INDEX), whereas the mean (median) of active fund ownership is 8.6% (5.0%). The mean quarterly changes in ownership by ETF (Δ ETF_CONT), index funds (Δ INDEX_CONT), and active funds (Δ ACTIVE_CONT) are 14.5, 4.5, and 19.0 basis points, respectively. On average, our sample firms have negative return on assets of -1.3% , cash holdings ratio of 0.2, quarterly return of 2.9%, a BM equity ratio of 0.6, a leverage ratio of 0.21, a dividend yield of 0.2%, a daily return volatility of 3.2%, and an age of 17.9 years. The detailed definitions of the variables are included in the Appendix. The pairwise correlations can be found in Table OA.1 in the Supplementary Material.

III. Empirical Results

A. Changes to ETF Ownership and SEO Probability

Our first set of tests examines the impact of changes to ETF ownership on the probability of a firm conducting an SEO using the following linear probability model:

¹⁰This figure is comparable with that of Corwin (2003), who corrected 51.5% of the SEO offer dates between 1992 and 1998, and with that of Chan and Chan (2014), who corrected the offer dates for 49.0% of their SEOs between 1984 and 2007.

TABLE 1
Descriptive Statistics

Table 1 reports descriptive statistics. Panel A summarizes our ETF data at the fund level. To compute the average AUM (\$ million) of our sample ETFs, we calculate each fund's total net assets (TNAs) by aggregating the TNA across its share classes, average its TNA across the four quarters within each calendar year, and then average the TNA across funds for each calendar year. To compute the yearly average firm-level ETF ownership, we average a firm's percentage of shares held by ETFs across the four quarters within each calendar year and then compute the cross-sectional average of ETF ownership for each calendar year. Panel B presents our sample of SEO events by year from 2003 to 2020.

Panel A. Fund Level Descriptive Statistics by Year

Year	No. of ETFs	Average AUM (\$ Million) of ETFs	Average Firm-Level ETF Ownership (%)
2003	67	1,607.4	0.09%
2004	80	1,886.2	0.03%
2005	89	2,088.9	0.04%
2006	150	1,525.9	0.61%
2007	223	1,305.3	0.67%
2008	296	1,507.4	0.35%
2009	330	1,335.6	1.68%
2010	360	1,828.9	3.28%
2011	406	1,898.1	4.27%
2012	411	2,265.5	4.68%
2013	406	3,108.0	5.14%
2014	418	3,462.6	5.45%
2015	474	3,354.0	5.95%
2016	519	3,544.9	6.71%
2017	596	4,019.8	7.81%
2018	653	4,171.7	8.39%
2019	582	5,267.4	8.83%
2020	633	5,240.7	8.98%

Panel B. Descriptive Statistics of the SEO Events by Year

Year	No. of SEOs	Dollar Amount of Shares Offered (\$ Million)	
		Mean	Median
2003	220	8.6	5.2
2004	231	7.1	4.6
2005	175	6.3	5.0
2006	178	7.5	4.5
2007	143	9.1	5.4
2008	126	38.4	8.8
2009	479	31.9	6.7
2010	335	14.1	5.3
2011	220	13.4	6.1
2012	246	8.9	5.7
2013	281	9.5	5.2
2014	224	7.9	5.3
2015	266	9.5	5.3
2016	286	11.6	5.5
2017	352	8.4	5.2
2018	294	8.1	5.2
2019	274	12.5	5.9
2020	498	10.5	6.2

$$(2) \quad \text{SEO}_{i,t} = \alpha + \beta \Delta \text{ETF}_{i,t-1} + \gamma \text{CONTROL}_{i,t-1} + \text{INDUSTRY_FE} \\ + \text{YEAR} - \text{QUARTER_FE} + e_{i,t},$$

where $\text{SEO}_{i,t}$ is a dummy variable that equals 1 if firm i performed an SEO in quarter t , and 0 otherwise. $\Delta \text{ETF}_{i,t-1}$ is the rank variable for quarterly changes in ETF ownership; $\text{CONTROL}_{i,t-1}$ is a vector of firm controls including ROA, cash holdings, quarterly stock return, firm size, BM equity ratio, leverage, dividend yield, and stock volatility at the end of quarter $t - 1$, as well as the natural logarithm of firm age at the end of quarter t . Industry FEs based on the Fama–French 49-industry

TABLE 2
Firm-Level Summary Statistics

Table 2 reports the summary statistics at the firm level. $SEO_t(SEO_{t \rightarrow t+3})$ is a dummy variable that equals 1 if a firm performs an SEO in quarter t (from quarter t to $t+3$), and 0 otherwise. ETF is the total number of a firm's shares held by ETFs divided by the total number of shares outstanding. ΔETF_CONT is the quarterly change in ETF. ΔETF is the rank conversion of ΔETF_CONT , constructed by sorting firms into 10 groups according to quarterly ΔETF_CONT , allocating them the group number as their rank, and then dividing this by 10. ACTIVE and INDEX are the proportions of a firm's shares held by actively managed funds and index funds, respectively. The quarterly changes ($\Delta ACTIVE_CONT$ and $\Delta INDEX_CONT$) and their rank transformations ($\Delta ACTIVE$ and $\Delta INDEX$) are constructed analogously. ROA is the operating income before depreciation over total assets. CASH is cash and short-term investments divided by total assets. RETURN is a firm's stock return over the last quarter. $\ln(ASSET)$ is the natural logarithm of total assets. BTM is the book value of shareholders' equity over the market value of equity. LEVERAGE is long-term debt plus debt in current liabilities, divided by total assets. DIVIDEND is a dividend per share divided by stock price. VOLATILITY is the standard deviation of daily stock returns over the last quarter. AGE is a firm's age in years.

	No. of Obs.	Mean	Std. Dev.	25%	Median	75%
SEO_t	268,831	0.017	0.129	0.000	0.000	0.000
$SEO_{t \rightarrow t+3}$	263,527	0.048	0.213	0.000	0.000	0.000
ΔETF	268,831	0.501	0.304	0.200	0.500	0.800
ΔETF_CONT (%)	268,831	0.145	0.701	0.000	0.004	0.256
ETF	268,831	0.036	0.047	0.000	0.014	0.062
ROA	268,831	-0.013	0.071	-0.009	0.004	0.016
CASH	268,831	0.207	0.242	0.035	0.102	0.290
RETURN	268,831	0.029	0.259	-0.108	0.015	0.140
ASSET	268,831	5,236.940	17,680.810	127.670	588.801	2,373.345
$\ln(ASSET)$	268,831	6.373	2.129	4.849	6.378	7.772
BTM	268,831	0.637	0.633	0.264	0.497	0.827
LEVERAGE	268,831	0.208	0.217	0.023	0.148	0.320
DIVIDEND	268,831	0.002	0.004	0.000	0.000	0.003
VOLATILITY	268,831	0.032	0.021	0.018	0.026	0.039
AGE	268,831	17.919	13.122	7.000	15.000	25.000
$\ln(AGE)$	268,831	2.563	0.882	1.946	2.708	3.219
$\Delta ACTIVE$	268,831	0.532	0.293	0.300	0.500	0.800
$\Delta ACTIVE_CONT$ (%)	268,831	0.190	3.201	-0.552	0.000	0.856
ACTIVE	268,831	0.086	0.096	0.004	0.050	0.143
$\Delta INDEX$	268,831	0.531	0.293	0.300	0.500	0.800
$\Delta INDEX_CONT$ (%)	268,831	0.045	0.415	-0.034	0.000	0.112
INDEX	268,831	0.012	0.016	0.001	0.005	0.020

classification and year-quarter FE are included. Standard errors are clustered at the firm level.

The results are reported in column 1 of Table 3. The estimated coefficient on ΔETF is positive (0.0035) and significant at the 1% level, implying that firms with increased ETF ownership are more likely to conduct SEOs in the following quarter. Specifically, when ΔETF increases by 0.1, that is, moving the firm up to the next rank, the probability of the firm conducting an SEO increases by 3.5 basis points, or 2.1% ($= 0.00035/0.017$) relative to the sample mean.

Since a change in ETF ownership may influence equity issuance over a longer timeframe (Israeli et al. (2017)), and firm managers may need more than one quarter to issue an SEO due to the registration process with the SEC or the marketing effort required (Khan et al. (2012)), we extend the window of managerial response to four quarters. As such, we replace the dependent variable with $SEO_{t \rightarrow t+3}$, a dummy variable that equals 1 if the firm conducts an SEO in quarter t or the three subsequent quarters, and 0 otherwise. In column 2 of Table 3, the coefficient on ΔETF is positive (0.0072) and significant at the 1% level. An increase in ΔETF of 0.1 raises the probability of the firm conducting an SEO in quarter t or the three subsequent quarters by 7.2 basis points, or 1.5% ($= 0.00072/0.048$) relative to the sample mean.

Our evidence in Table 3 suggests a positive and significant relation between changes in ETF ownership and a firm's propensity to conduct an SEO, consistent

TABLE 3
Change in ETF Ownership and SEO Probability

Table 3 reports the estimation results of linear probability models examining the relationship between changes in ETF ownership and SEO probability. The dependent variables are SEO_t and SEO_{t-t+3} . The independent variable of interest is the rank variable of the quarterly change in ETF ownership (ΔETF). All other variables are defined in the Appendix. Industry and year-quarter fixed effects are included. Industry fixed effects are constructed based on the Fama–French 49-industry classification. *t*-statistics based on firm-clustered standard errors are reported in parentheses. The sample period is from 2003 to 2020. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SEO _{<i>t</i>}	SEO _{<i>t-t+3</i>}
	1	2
ΔETF	0.0035*** (3.758)	0.0072*** (4.780)
ROA	-0.1862*** (-19.540)	-0.3813*** (-19.198)
CASH	-0.0008 (-0.329)	0.0405*** (6.455)
RETURN	0.0240*** (14.258)	0.0294*** (12.511)
ln(ASSET)	0.0004** (2.071)	0.0018*** (3.264)
BTM	-0.0053*** (-9.807)	-0.0096*** (-6.856)
LEVERAGE	0.0109*** (5.118)	0.0285*** (5.441)
DIVIDEND	-0.2423** (-2.141)	-0.4097* (-1.810)
VOLATILITY	0.1239*** (4.900)	0.3753*** (7.343)
ln(AGE)	-0.0022*** (-5.247)	-0.0105*** (-9.103)
CONSTANT	0.0128*** (5.871)	0.0349*** (6.412)
Industry FE	Yes	Yes
Year-quarter FE	Yes	Yes
No. of obs.	268,831	263,527
R^2	0.033	0.075

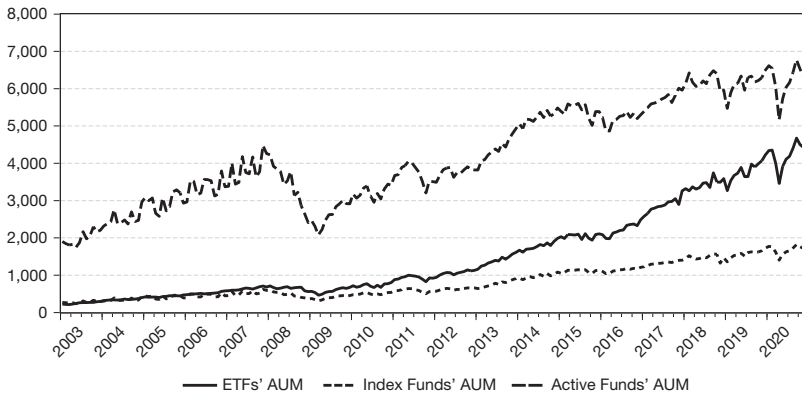
with ETF flows creating opportunities for managers to issue seasoned equity with lower cost. Table 3 also confirms the role of the other determinants of SEO probability that we control for. Consistent with prior studies, firms issue equity after their stock prices increase, revealed by positive coefficients on RETURN and negative coefficients on BTM, as predicted by market timing. Firms with higher ROA and lower LEVERAGE are less dependent on external and equity finance, respectively, and so are less likely to issue an SEO. Younger and larger firms, as well as those with more volatile stock returns, are more likely to issue equity for growth.

B. Robustness Tests

We perform a number of robustness tests. Since activities of other institutional investors, such as active mutual funds and index funds, may influence stock prices and thus corporate decisions (Khan et al. (2012), Ben-David et al. (2018)), we explore the extent to which the influence of ETF flows on SEO propensity is distinct. First, we gauge the similarity of the three types of funds by comparing their monthly total AUM, plotted in Figure 1. Of the three fund types, ETFs have experienced the largest and most persistent growth in AUM over the sample. From

FIGURE 1
Total AUM of ETFs, Index Funds, and Active Mutual Funds

Figure 1 reports the end-of-month total AUM (in \$ billion) of our sample ETFs, index mutual funds, and active mutual funds, calculated using data from the CRSP mutual fund database. The sample period is from Jan. 2003 to Dec. 2020.



late 2006 onward, the total AUM of ETFs surpasses that of the index funds and the gap widens over the remainder of the period.¹¹ Active mutual funds have the largest AUM, but this can also be more volatile. The gap between the AUM of active mutual funds and ETFs narrows noticeably later in our sample.

Graphs A–C of Figure 2 plot the aggregate monthly investor flows to ETFs, index funds, and active mutual funds, respectively. Compared to index funds, aggregate monthly flows for ETFs show larger magnitude and are slightly less likely to be negative, particularly later in the sample, which highlights the recent popularity of ETFs. Aggregate flows for active mutual funds seem to be smaller than for ETFs. They are generally inflows before 2008 and mostly outflows from 2014 onward documenting many investors' substitution from active to passive vehicles. Analyzing pairwise correlations between aggregate monthly flows (unreported), ETF flows are negatively, but only very weakly, correlated with both index fund (coefficient = -0.04) and active fund flows (coefficient = -0.08). Together, this evidence indicates that during our sample ETF flows have different properties compared to index and active funds, which helps to motivate their relevance in our sample and their potential influence on SEO decisions.

Second, we examine pairwise correlations between the changes to firm ownership for the three types of funds (reported in Table OA.1 in the Supplementary Material). The correlation between ΔETF and ΔACTIVE is quite small (coefficient = 0.138), between ΔETF and ΔINDEX is weak (0.202), and between ΔACTIVE and ΔINDEX is also weak (0.194), showing that the changes to firm ownership across the types of funds are not very similar.

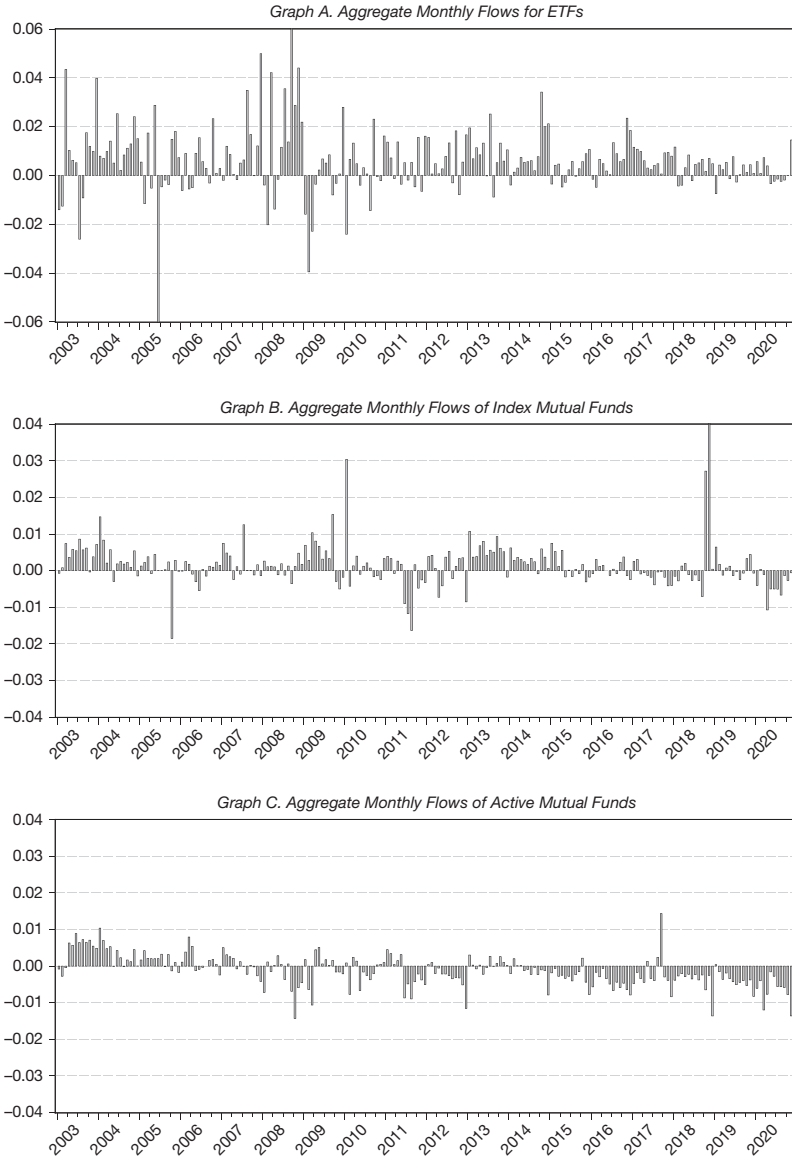
Third, we include ΔETF , ΔACTIVE , and ΔINDEX in the same regression. Panel A of Table 4 shows that the coefficients on all three variables are positive and significant. This is consistent with both the literature documenting a role for active fund flows in driving corporate decisions, and the similarities between index funds

¹¹A similar pattern is documented by Ben-David et al. ((2018), pp. 2477–2478).

FIGURE 2

Aggregate Monthly Flows for ETFs, Index Funds, and Active Mutual Funds

Graphs A–C of Figure 2 plot the aggregate monthly flows of ETFs, index mutual funds, and active mutual funds, respectively, all computed using data from the CRSP mutual fund database. The sample period is from Jan. 2003 to Dec. 2020.



and ETFs that attract passive investment flows. Importantly, the positive and significant effect of ΔETF on SEO propensity is maintained after controlling for the other fund types.

Next, Panel B of Table 4 presents a series of further checks based on alternative specifications. To save space, we only report the estimated coefficients on ΔETF ,

TABLE 4
Robustness Tests

Table 4 checks the robustness of our baseline result. Panel A presents linear probability models that control for the influences of active (Δ ACTIVE) and index (Δ INDEX) fund ownership. Panel B includes a range of specifications and robustness tests and reports only the estimates of the coefficient of interest. In Panel B, rows 1 and 2 employ probit and logit models, respectively. Row 3 uses the quarterly differences in ETF ownership (Δ ETF_CONT) as the main variable. Row 4 applies Δ ETF_CONT and controls for Δ ACTIVE_CONT and Δ INDEX_CONT. In rows 5 and 6, industry fixed effects are constructed using 2- and 3-digit SIC industry codes. In rows 7–10, we exclude firms with stock price less than \$3, financial firms (SIC code: 6000–6999), observations during the financial crisis period (2008:Q3 to 2009:Q4), and observations where ETF is 0, respectively. For row 11, the rank variable (Δ ETF) is based on quintiles rather than deciles. Row 12 includes the quarterly differences in control variables as well as their levels. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Controlling for the Changes to Active and Index Fund Ownership

	SEO _t	SEO _{t-1:t+3}
	1	2
Δ ETF	0.0027*** (2.880)	0.0074*** (4.908)
Δ ACTIVE	0.0037*** (4.314)	0.0074*** (5.476)
Δ INDEX	0.0034*** (4.041)	0.0033** (2.549)
Firm controls	Yes	Yes
Industry FE	Yes	Yes
Year-quarter FE	Yes	Yes
No. of obs.	268,831	263,527
R ²	0.033	0.100

Panel B. Other Robustness Tests

Row		SEO _t			SEO _{t-1:t+3}		
		Coef.	Pseudo R ² /R ²	No. of Obs.	Coef.	Pseudo R ² /R ²	No. of Obs.
1	Probit model	0.084*** (3.623)	0.131	268,564	0.078*** (4.607)	0.144	260,055
2	Logit model	0.204*** (3.649)	0.128	268,564	0.178*** (4.976)	0.142	260,055
3	Δ ETF_CONT	0.080* (1.753)	0.033	268,831	0.128* (1.801)	0.075	263,527
4	(3) + Δ ACTIVE_CONT and Δ INDEX_CONT	0.044 (0.925)	0.033	268,831	0.118* (1.661)	0.075	263,527
5	Industry FE: 2-digit SIC codes	0.0036*** (3.901)	0.031	268,831	0.0077*** (5.050)	0.073	263,527
6	Industry FE: 3-digit SIC codes	0.0034*** (3.700)	0.034	268,831	0.0071*** (4.712)	0.079	263,527
7	Remove stock prices <\$3	0.0022** (2.349)	0.034	230,425	0.0076*** (5.168)	0.075	226,861
8	Remove financials	0.0032*** (2.978)	0.038	212,935	0.0084*** (4.963)	0.088	208,627
9	Exclude the crisis period	0.0021** (2.175)	0.034	245,241	0.0068*** (4.642)	0.078	240,488
10	ETF > 0	0.0027** (2.180)	0.047	175,466	0.0052*** (2.681)	0.106	172,731
11	Quintile-ranked Δ ETF	0.0037*** (3.905)	0.033	268,831	0.0081*** (5.194)	0.075	263,527
12	Adding quarterly Δ (firm controls)	0.0030*** (3.193)	0.038	258,332	0.0082*** (5.355)	0.084	253,251

unless stated. In rows 1 and 2, we estimate probit and logit models, respectively. Row 3 considers an alternative measure of changes in ETF ownership, replacing the rank measure Δ ETF with its continuous version, Δ ETF_CONT. Row 4 retains the Δ ETF_CONT variable while controlling for the analogous Δ ACTIVE_CONT and Δ INDEX_CONT variables for other fund types. Rows 5 and 6 include industry FEs

constructed using 2- or 3-digit SIC industry classifications, respectively. Row 7 assesses the influence of small stocks by excluding firms with stock prices less than \$3 at the end of the previous quarter. Row 8 removes financial firms (SIC codes between 6000 and 6999) that are heavily regulated. Row 9 excludes firm-quarters during the 2008–2009 global financial crisis (specifically, from 2008:Q3 to 2009:Q4) when market conditions were extremely volatile. Since firms with some ETF ownership may differ substantially from those with none, row 10 re-estimates our baseline model on a sample containing only firms with nonzero ETF ownership to avoid potential concerns about selection. In row 11, the rank variable, ΔETF , is constructed using quintiles rather than deciles. Finally, row 12 includes the quarterly differences of control variables. Our results are qualitatively similar in all cases.

C. Changes to ETF Ownership and SEO Probability: Cross-Sectional Heterogeneity

Our next set of tests examines the cross-sectional heterogeneity in the effect of changes to ETF ownership on SEO probability. In a competitive equity market in which stocks are perfect substitutes, demand is infinitely elastic at a given price (Loderer, Cooney, and Van Drunen (1991), Zou (2019)). However, prior evidence suggests that the demand for stocks is inelastic (Corwin (2003)). An increase in ETF ownership may accentuate the propagation of non-fundamental demand to stocks (Ben-David et al. (2018), Zou (2019)), or indicate more demand for equity from market participation or potential lower risk aversion, both of which imply higher prices if demand is inelastic. Regardless of the mechanism, ETF ownership may give rise to opportunities for managers to time the market and make SEO issuance more likely. Therefore, the positive relation between changes to ETF ownership and SEO probability may be stronger among stocks with inelastic demand.

We consider four proxies for the price elasticity of demand for stocks. Following Corwin (2003), stocks in small firms with low price or high return volatility are predicted to have more inelastic demand. Our fourth proxy is the number of shareholders a firm has, from Armstrong, Core, Taylor, and Verrecchia (2011). Firms with a narrower shareholder base may have a less competitive market for their stocks, synonymous with less price elasticity of demand. For each of the four proxies, we divide firms into high and low groups according to the sample median, allocate them a dummy variable equal to 1 for the group with less elastic demand, and interact the dividing dummy variable with ΔETF in the baseline regressions. We estimate separate models for each proxy.

Table 5 reports the estimation results with $\text{SEO}_{t \rightarrow t+3}$ as the dependent variable.¹² Consistent with the predictions, in all four columns, the positive relation between ΔETF and SEO probability is significantly larger among firms believed to have more inelastic demand for their shares. It should also be noted that the significant effect of ETF flows is absent among big firms and those with a broad shareholder base. Furthermore, the proxies for inelastic demand are imperfect; firm

¹²In Table OA.2 in the Supplementary Material, we estimate the same linear probability models with interaction terms, but with SEO_t as the dependent variable. The results remain qualitatively similar, despite having weaker statistical significance.

TABLE 5
Change in ETF Ownership and SEO Probability: Cross-Sectional Heterogeneity

Table 5 reports the estimation results of linear probability models examining the cross-sectional heterogeneity in the effect of ETF ownership changes on SEO probability. The dependent variable is SEO_{t-t+3} . The main variable is ΔETF . SMALL is a dummy variable that equals 1 for firms with $\ln(\text{ASSET})$ below the sample median, and 0 otherwise. LOW_PRICE is a dummy variable that equals 1 for firms with below-median stock price measured at the end of the previous quarter, and 0 otherwise. HIGH_VOLATILITY is a dummy variable that equals 1 if a firm's volatility is above the sample median. LOW_#_SHAREHOLDER is a dummy variable that equals 1 for firms with the total number of shareholders below the sample median, and 0 otherwise. In each model, we include the same set of baseline firm controls as well as their interactions with the dividing variable. Detailed variable definitions can be found in the Appendix. Industry and year-quarter fixed effects as well as their interactions with the dividing variables are included. *t*-statistics based on firm-clustered standard errors are reported in parentheses. The sample period is from 2003 to 2020. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SEO _{t-t+3}			
	1	2	3	4
ΔETF	0.0009 (0.550)	0.0033** (2.115)	0.0029** (2.011)	0.0013 (0.644)
SMALL	0.0629*** (3.225)			
$\Delta ETF \times \text{SMALL}$	0.0124*** (3.853)			
LOW_PRICE		-0.0068 (-0.288)		
$\Delta ETF \times \text{LOW_PRICE}$		0.0097*** (3.054)		
HIGH_VOLATILITY			-0.0134 (-1.043)	
$\Delta ETF \times \text{HIGH_VOLATILITY}$			0.0073** (2.445)	
LOW_#_SHAREHOLDER				0.0677*** (3.605)
$\Delta ETF \times \text{LOW_#_SHAREHOLDER}$				0.0120*** (3.608)
Firm controls (including their interaction with the dividing variable)	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
No. of obs.	263,527	263,527	263,527	223,197
R ²	0.086	0.082	0.082	0.089

size and return volatility may imply firms with less robust prices related to information asymmetry.

D. Investigating the Mechanisms

A positive and significant relation between ETF flow and SEO probability is consistent with managers timing the market, but does not inform us about the likely mechanism. While both noise trader and market participation hypotheses predict higher SEO likelihood with ETF ownership, they imply opposing effects on SEO announcement effects, the issue-day discount, and long-run performance. In the following subsections, we investigate the role of ETF ownership on these important SEO stages.

1. ETF Ownership and Short-Term Abnormal Returns Around SEO Announcements

SEO issuers typically exhibit negative announcement returns in the range -2% to -3% (Eckbo et al. (2007)), which is consistent with an information

asymmetry explanation (Lee and Masulis (2009), Kim et al. (2013)). According to the adverse selection model of Myers and Majluf (1984), when managers have superior information about the true value of assets, they issue equity when they perceive the stock to be overvalued. At the issue, investors reduce their bid prices for the stock to compensate for adverse selection risk. Prior to the issue, the announcement of the SEO reveals the manager's information and motivation. In an efficient market, investors react negatively to the announcement, anticipating lower expected returns and adverse selection costs (Lee and Masulis (2009), Kim et al. (2013)).

There is ample evidence consistent with this information asymmetry explanation. Cross-sectional patterns show that firms with greater exposure to information asymmetry witness more negative SEO announcement returns. Therefore, if ETF ownership exacerbates information asymmetry (Israeli et al. (2017)), or propagates non-fundamental demand shocks from liquidity trading (Ben-David et al. (2018)), higher ETF ownership may offer SEO market timing opportunities. Given the motivations for market timing under this noise trader hypothesis, firms with higher ETF ownership should experience relatively worse SEO announcement returns.

Building on this prior literature, we consider market participation as an alternative hypothesis. If ETF ownership captures periods of increased demand for equity, from new investment flows, or possibly perceptions of lower risk or reduced risk aversion, managers may find market timing opportunities from a different source. Under these conditions, some investors may require less compensation for adverse selection risk, adjustments to lower expected returns may not be as severe, and equity may be issued with lower price impact. Therefore, the market participation hypothesis predicts less negative SEO announcement returns.

To explore these hypotheses, we first examine the univariate relation between ETF ownership (ETF) and SEO announcement returns. Following Kim et al. (2013), we use SEO filing dates from the Refinitiv SDC Platinum database as the SEO announcement dates. Short-term abnormal returns around SEO announcements are measured by the CARs over a 3-day window (-1 to $+1$) (3_DAY_CAR). Consistent with prior evidence, the mean 3_DAY_CAR for our sample of SEO announcement events is -2.7% (see Table OA.3 in the Supplementary Material), which is significant at the 1% level (unreported).¹³

For each year of the sample, we divide the SEO firms into 3 groups according to their ETF ownership (30th and 70th percentile breakpoints) prior to the announcement and calculate the mean 3_DAY_CAR for each group. Panel A of Table 6 reports these average CARs along with the difference in means between the high- and low-ETF groups (High – Low). For the low-, mid-, and high-ETF groups the average CARs are -3.5% , -2.8% , and -1.8% , respectively, which are all negative and significant as expected. More importantly, the mean CARs become less negative with ETF and the difference between high- and low-ETF groups is 1.8% , significant at the 1% level.

¹³A breakdown of the events and the average CAR by year can be found in Table OA.4 in the Supplementary Material.

Panel B of Table 6 reports results from multivariate tests (OLS regressions) estimating the relation between ETF ownership and 3_DAY_CAR. Following Kim et al. (2013), we control for firm characteristics known to determine SEO announcement returns, including the natural logarithm of total assets ($\ln(\text{ASSET})$), BM equity ratio (BTM), leverage (LEVERAGE), market run-up (MKT_RUNUP), individual stock run-up (RUNUP), relative offer size (REL_OFFER_SIZE), the

TABLE 6
ETF Ownership and Short-Term Abnormal Returns Around SEO Announcements

Table 6 examines the relationship between ETF ownership and short-term abnormal returns around SEO announcements. The dates of SEO announcements are based on their filing dates. In Panel A, in each year, we divide the SEO events into 3 groups according to the firm's most recent prior ETF ownership (30th and 70th percentile breakpoints) and report the mean 3-day CAR (3_DAY_CAR) for each group. We also report the difference in means between the high and low groups (High – Low). Panel B reports the results from multivariate analysis, where 3_DAY_CAR for each firm is regressed on ETF, firm controls, and fixed effects. Firm control variables include the natural logarithm of total assets ($\ln(\text{ASSET})$), BM equity ratio (BTM), financial leverage (LEVERAGE), market run-up (MKT_RUNUP), individual stock run-up (RUNUP), relative offer size (REL_OFFER_SIZE), the proportion of secondary shares offered (SECONDARY_SHARE), and a Nasdaq dummy (NASDAQ). Detailed variable definitions can be found in the Appendix. Industry and year-quarter fixed effects are included. *t*-statistics based on firm-clustered standard errors are reported in parentheses in both panels. The sample is from 2003 to 2020. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Univariate Analysis

ETF	3_DAY_CAR 1
Low (bottom 30%) ($N = 1,485$)	-0.035***
<i>t</i> -stat.	(-9.061)
Mid ($N = 1,532$)	-0.028***
<i>t</i> -stat.	(-6.715)
High (top 30%) ($N = 1,278$)	-0.018***
<i>t</i> -stat.	(-6.626)
High – Low	0.018***
<i>t</i> -stat.	(3.771)

Panel B. Multivariate Tests

	3_DAY_CAR	
	1	2
ETF	0.302*** (4.204)	0.140* (1.812)
$\ln(\text{ASSET})$		0.004** (2.259)
BTM		0.007 (1.341)
LEVERAGE		-0.009 (-0.937)
MKT_RUNUP		0.012 (0.402)
RUNUP		0.027*** (4.458)
REL_OFFER_SIZE		-0.077*** (-3.526)
SECONDARY_SHARE		0.076 (0.975)
NASDAQ		0.011** (2.197)
CONSTANT	-0.038*** (-9.670)	-0.057*** (-4.733)
Industry FE	Yes	Yes
Year-quarter FE	Yes	Yes
No. of obs.	4,295	4,295
R^2	0.051	0.076

proportion of secondary shares offered (SECONDARY_SHARE), and a Nasdaq dummy (NASDAQ).¹⁴

In column 1 of Table 6, where only industry and year-quarter FEs are controlled for, the coefficient on ETF is 0.302 and significant at the 1% level. In column 2, we add the firm controls to the model, and find that the positive estimate on ETF reduces to 0.140 and remains significant at the 10% level. The positive coefficient confirms the univariate evidence in Panel A that ETF ownership is associated with less negative SEO announcement returns. A standard deviation increase (0.040) in ETF ownership increases the 3_DAY_CAR by 56.0 basis points or 20.7% (= 0.0056/0.027) relative to the sample mean. The control variables show that firms with larger size, smaller relative offer size, a listing on Nasdaq, and higher price run-up prior to the announcement have less negative announcement returns, largely consistent with Kim et al. (2013).

The evidence in Table 6 is consistent with the market participation hypothesis, which predicts a less negative reaction to SEO announcements for firms with higher ETF ownership. Our findings suggest that some firms can take advantage of increased demand for equity to time the market when issuing seasoned equity. We interpret this to mean that opportunities for market timing can arise from different circumstances, one of which we highlight as episodes of equity demand driven by market participation.

2. ETF Ownership and SEO Discount

In the majority of SEOs, new shares are offered at a discount to the previous day's close (see, e.g., Loderer et al. (1991), Corwin (2003), Mola and Loughran (2004), Bowen et al. (2008), Chemmanur et al. (2009), Li and Zhuang (2012), and Chan and Chan (2014)). Uncertainty surrounding asset value and asymmetric information cause investors to demand a discount to compensate them for adverse selection risk. Empirical evidence has confirmed the positive relation finding that discounts are smaller for firms with lower uncertainty (Corwin (2003)) and when asymmetric information is reduced by analyst coverage and management guidance (Bowen et al. (2008), Li and Zhuang (2012), and Chan and Chan (2014)). Consistent with this theory, the noise trader hypothesis claims that ETF ownership contributes to worsening information asymmetry and increases valuation uncertainty and investors are only willing to purchase new shares at a discount. According to this view, the SEO discount increases with ETF ownership. Alternatively, under the market participation hypothesis, the discount and ETF ownership are negatively related. Higher ETF ownership of a firm is a proxy for an increase in aggregate demand for equity, which may prompt issuers to perceive less risk of SEO failure and investors to be less concerned about adverse selection risk, requiring a lower discount.

Following the extant literature, we measure the SEO discount (DISCOUNT) as the SEO's close-to-offer return. DISCOUNT is positive when the offer price is lower than the pre-offer closing price, reflecting a proportion of SEO underpricing and part of the flotation cost. The sample mean (median) of the DISCOUNT is 7.0%

¹⁴The detailed definitions of these control variables can be found in the Appendix. Their summary statistics can be found in Table OA.3 in the Supplementary Material.

(4.8%) (see Table OA.3 in the Supplementary Material).¹⁵ In univariate analysis, following the same procedure, we sort the SEO firms into 3 groups annually based on their ETF ownership prior to the issue day. Panel A of Table 7 shows that the mean DISCOUNT for the low-, mid-, and high-ETF groups are 8.5%, 7.4%, and 4.7%, respectively, all positive and statistically significant consistent with the literature. More pertinent to this study, average DISCOUNT declines with ETF ownership, especially for the high-ETF group, such that the High – Low difference in mean DISCOUNT is –3.8%, which is significant at the 1% level. A negative association between ETF ownership and SEO discounts is consistent with the market participation hypothesis.

Panel B of Table 7 reports the results of multivariate tests, where DISCOUNT is regressed on ETF ownership, firm controls, and industry and year-quarter FEs. Following Chan and Chan (2014), firm controls include daily stock return volatilities over the 20 trading days ending 11 days prior to the offer date (VOLATILITY_30_11) reflecting valuation uncertainty, the natural logarithm of the stock price (ln(PRICE)) to account for price clustering and rounding by underwriters, market capitalization (ln(ME)) at the end of the pre-offer day, relative offer size (REL_OFFER_SIZE) to capture price pressure effects, cumulative positive and negative market-adjusted returns over the 5 days prior to the offer date (CAR_POS and CAR_NEG) to control for pre-issue trading, and tick-size (TICK) and a Nasdaq dummy (NASDAQ) to detect underwriter price clustering and market structure effects.¹⁶

Column 1 of Table 7 shows the results when only FEs are included. The coefficient on ETF is –0.579, significant at the 1% level. In column 2, we add the firm controls, finding that the negative coefficient on ETF reduces to –0.185 and remains significant at the 1% level. A standard deviation increase in ETF (0.039) reduces DISCOUNT by 72.2 basis points or 10.3% (= 0.00722/0.070) relative to the sample mean. Confirming the evidence in Panel A and consistent with the market participation hypothesis, higher ETF ownership is associated with a smaller SEO discount, on average. The estimates on the control variables are mostly in line with the extant literature. Pre-issue return volatility, smaller stock price, a larger relative offer size, and pre-issue selling pressure all contribute to making the discount larger. The insignificant estimates for the tick size and Nasdaq dummies suggest that price clustering and market structures do not determine our SEO discounts. Surprisingly, CAR_POS has a significant positive coefficient, showing that pre-issue buying pressure increases discounts.

The traditional explanations of both SEO announcement reactions and discounts are couched in information asymmetry and adverse selection. Unsurprisingly, our findings for these events in Tables 6 and 7 are consistent.

¹⁵This is larger than prior studies because of a dramatic increase in average discount to around 7% from 2009 onward and to slightly above 11% in 2019 and 2020. The increases in SEO discounts over time is well documented in prior studies (see Corwin (2003), Mola and Loughran (2004), Chan and Chan (2014), and Gustafson (2018)). Although our average discount is higher than other studies, we confirm that our variable is consistent with Chan and Chan (2014) up to 2007 and Gustafson (2018) up to 2014, as shown in Table OA.4 in the Supplementary Material.

¹⁶The detailed definitions and summary statistics of the control variables can be found in the Appendix and Table OA.3 in the Supplementary Material, respectively.

TABLE 7
ETF Ownership and the SEO Discount

Table 7 examines the relationship between ETF ownership and the discount offered at SEO issuance. SEO discount (DISCOUNT) is the close-to-offer return of an SEO, computed as the percentage change from the pre-offer day closing price to the offer price. In Panel A, in each year, we divide the SEO events into 3 groups based on the firm's most recent prior ETF ownership (30th and 70th percentile breakpoints). We report the mean DISCOUNT for each of the three groups and the difference in means between the high and low groups (High – Low). Panel B reports results of multivariate tests in which DISCOUNT is regressed on ETF, firm control variables, and fixed effects. The firm control variables include return volatility from 30 to 10 days prior to the issue (VOLATILITY_30_11), the natural logarithm of stock price (ln(PRICE)), the natural logarithm of market capitalization (ln(ME)), relative offer size (REL_OFFER_SIZE), positive and negative 5-day CAR prior to the offer (CAR_POS and CAR_NEG), a dummy that equals 1 if the decimal portion of the pre-offer closing price is not an increment of 25 cents, and 0 otherwise (TICK), and a dummy that equals 1 if a firm is listed in the NASDAQ at the time of offer (NASDAQ), and 0 otherwise. Detailed variable definitions can be found in the Appendix. Industry and year-quarter fixed effects are included. *t*-statistics based on firm-clustered standard errors are reported in parentheses. The sample period is from 2003 to 2020. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Univariate Analysis

ETF	DISCOUNT 1
Low (bottom 30%) (<i>N</i> = 1,718)	0.085***
<i>t</i> -stat.	(26.011)
Mid (<i>N</i> = 1,631)	0.074***
<i>t</i> -stat.	(28.451)
High (top 30%) (<i>N</i> = 1,407)	0.047***
<i>t</i> -stat.	(29.375)
High – Low	–0.038***
<i>t</i> -stat.	(–10.516)

Panel B. Multivariate Analysis

	DISCOUNT	
	1	2
ETF	–0.579*** (–11.762)	–0.185*** (–3.820)
VOLATILITY_30_11		0.164** (2.218)
ln(PRICE)		–0.014*** (–6.648)
ln(ME)		0.001 (0.827)
REL_OFFER_SIZE		0.112*** (5.677)
CAR_POS		0.026*** (2.680)
CAR_NEG		0.101*** (3.508)
TICK		0.001 (0.111)
NASDAQ		–0.002 (–0.560)
CONSTANT	0.091*** (32.701)	0.079*** (6.070)
Industry FE	Yes	Yes
Year-quarter FE	Yes	Yes
No. of obs.	4,756	4,756
<i>F</i> ²	0.138	0.191

Our new evidence is the negative influence of ETF ownership on these effects, moderating negative SEO announcement returns and SEO discounts. Hence, ETF ownership can signal demand for equity, which may provide some firms with favorable conditions to time the market with the added benefit of relatively lower flotation costs.

3. ETF Ownership and Post-SEO Returns

Finally, we explore whether ETF ownership has a long-term effect on the stock returns of SEO issuers. This is important for at least two reasons. First, SEO announcement CARs and SEO discounts measure only short horizons, so longer periods give a different perspective on performance. Second, given the difficulty in estimating information asymmetry or mispricing prior to an SEO, post-SEO performance is often used to infer the ex ante motivation. SEO issuers tend to see price run-ups prior to the SEO and then perform poorly in the 5 years post-SEO, which is interpreted as successful market timing.

The established view of market timing is that managers exploit their informational advantages to raise equity capital when its cost is low (Loughran and Ritter (1995), (1997), Baker and Wurgler (2002)). This is captured by the noise trader hypothesis. If ETF ownership exacerbates information asymmetry (Israeli et al. (2017)) or propagates non-fundamental mispricing (Ben-David et al. (2018), Brown et al. (2021)), higher ETF ownership provides some managers with opportunities to time the market when they need to raise capital. After the SEO, the underlying reasons for raising capital and the market timing are revealed, which tend to magnify declines in stock returns according to information asymmetry arguments. Supplementing this traditional approach, we consider the market participation hypothesis, which may correspond to less severe reversals. Since SEOs are often conducted for cash needs (DeAngelo et al. (2010)), we expect SEO firms to underperform over longer horizons on average. The interesting test is whether ETF ownership moderates this poor performance.

We examine issuers' long-run abnormal stock returns in the 3- and 5-year periods after SEOs. We follow Healy and Palepu (1990) and include only the first SEO if there are multiple SEOs within a 5-year period, yielding a sample of 1,094 SEO events. To measure long-term post-SEO abnormal returns, we compute buy-and-hold abnormal return (BHAR) as the difference between the compounded return on the SEO firm and an appropriate benchmark over 3- and 5-year periods (BHAR_36M and BHAR_60M) after the SEO. Following Barber and Lyons (1997), the benchmark for each SEO firm is the size and BM matched portfolio (excluding the event firms), with annual rebalancing and an equal-weighting scheme. Consistent with long-run post-SEO underperformance, the means (medians) for BHAR_36M and BHAR_60M are negative and large, calculated as -13.4% (-28.5%) and -32.9% (-56.8%), respectively (reported in Table OA.3 in the Supplementary Material).

Panel A of Table 8 shows the results for univariate analysis, which sorts firms into portfolios each year based on their ETF ownership immediately before the SEO. We report the mean BHAR_36M and BHAR_60M for the three ETF groups along with the mean high-ETF minus and low-ETF difference. Across the low-, mid-, and high-ETF groups, the mean BHAR after SEOs are -18.1% , -18.2% , and -1.4% , respectively, over the 36-month window and -45.8% , -35.0% , and -11.6% for the 60-month horizon. Post-SEO underperformance is demonstrated by the negative BHAR, but these are statistically significant for the low- and mid-ETF groups only. For the high-ETF group, the BHARs are noticeably smaller and insignificant, such that the High – Low differences are positive and significant (16.8% for BHAR_36M and 34.2% for BHAR_60M). For the firms with the highest ETF

TABLE 8
ETF Ownership and Post-SEO Returns

Table 8 examines the relationship between ETF ownership and the post-issue long-term performance of SEOs. BHAR_36M (BHAR_60M) is the buy-and-hold abnormal return, measured against a benchmark portfolio of control firms matched by size and BM equity ratios, over the 36-month (60-month) period subsequent to SEO issuance. Following Healy and Palepu (1990), we include only the first SEO if there are multiple SEOs within a 5-year period. There are 1,094 SEO events included. In Panel A, in each year, we divide the SEO events into 3 groups according to the firm's most recent prior ETF ownership (30th and 70th percentile breakpoints) and calculate the mean BHAR for each group as well as the difference in mean BHAR between the high- and low-ETF groups. *t*-statistics based on firm-clustered standard errors are reported in parentheses. Panel B presents results of a calendar-time portfolio approach. In each year, we sort SEO firms into 3 groups according to their most recent prior ETF ownership (30th and 70th percentile breakpoints). For each of the three groups, we form equal-weighted (EW) and value-weighted (VW) portfolios including only stocks that conducted an SEO in the past 36 or 60 months and then compute the return to the High-minus-Low spread portfolio (High – Low). We regress the monthly returns on the Carhart (1997) and Fama and French (2015) factor models and report the estimated intercepts and their robust *t*-statistics in parentheses (based on Newey–West adjusted standard errors using 12 monthly lags). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Long-Term BHAR

ETF	BHAR_36M		BHAR_60M	
	1		2	
Low (bottom 30%) (N = 459)	-0.181***	-0.458***	-0.181***	-0.458***
<i>t</i> -stat.	(-3.723)	(-7.447)	(-3.723)	(-7.447)
Mid (N = 322)	-0.182***	-0.350***	-0.182***	-0.350***
<i>t</i> -stat.	(-3.835)	(-4.854)	(-3.835)	(-4.854)
High (top 30%) (N = 313)	-0.014	-0.116	-0.014	-0.116
<i>t</i> -stat.	(-0.285)	(-1.527)	(-0.285)	(-1.527)
High – Low	0.168**	0.342***	0.168**	0.342***
<i>t</i> -stat.	(2.434)	(3.475)	(2.434)	(3.475)

Panel B. Calendar-Time Portfolio Approach

ETF	4-Factor α				5-Factor α			
	36 Months		60 Months		36 Months		60 Months	
	EW	VW	EW	VW	EW	VW	EW	VW
	1	2	3	4	5	6	7	8
Low (bottom 30%)	-0.0040*	-0.0118***	-0.0068***	-0.0111***	-0.0027	-0.0086***	-0.0055***	-0.0092***
<i>t</i> -stat.	(-1.885)	(-3.771)	(-3.866)	(-3.473)	(-1.071)	(-3.536)	(-2.886)	(-3.023)
Mid	-0.0074*	-0.0057	-0.0030	-0.0022	-0.0061	-0.0035	-0.0018	-0.0015
<i>t</i> -stat.	(-1.822)	(-1.204)	(-1.392)	(-1.135)	(-1.318)	(-0.644)	(-0.731)	(-0.834)
High (top 30%)	0.0005	-0.0041*	-0.0031*	-0.0047**	0.0021	-0.0018	-0.0023	-0.0029
<i>t</i> -stat.	(0.269)	(-1.753)	(-1.750)	(-2.379)	(1.175)	(-0.906)	(-1.186)	(-1.605)
High – Low	0.0045*	0.0078***	0.0037*	0.0064**	0.0048*	0.0068***	0.0032	0.0063**
<i>t</i> -stat.	(1.889)	(2.953)	(1.784)	(2.253)	(1.845)	(2.859)	(1.519)	(2.110)

ownership, this evidence suggests that the long-run post-SEO underperformance is attenuated, which is consistent with the market participation hypothesis.

In light of the potential bias when measuring long-horizon abnormal returns using BHAR (Barber and Lyon (1997)), we also apply the calendar-time portfolio approach (Fama (1998)) and show the results in Panel B of Table 8. For each year in the sample, we sort SEO firms into portfolios according to their most recent ETF ownership and calculate monthly equal- (EW) and value-weighted (VW) average portfolio returns using only the firms in each portfolio that have conducted an SEO in the past 36 or 60 months. We then compute the High-minus-Low (High – Low) ETF spread portfolio return and regress all monthly returns series on the Carhart (1997) and Fama and French (2015) factors and report the estimated alphas in Panel B.

Consistent with the expectation of long-term SEO underperformance, almost all estimated alphas in Panel B of Table 8 are negative. For the low-ETF portfolio, most (all but two) of the alphas are negative and significant at the 1% level, which confirms the result in Panel A that there is general long-run underperformance for

the average low-ETF firm. Although exclusively negative, the alphas on the mid-ETF portfolios are all insignificant at conventional levels. Similarly, for the high-ETF portfolio, most estimates of alpha are not significant. Only one high-ETF portfolio intercept is significant at the 5% level (VW, 4-factor, 60 months). Although the estimated alphas do not show monotonic increases with ETF, the high-ETF portfolios appear to perform relatively better than the low-ETF portfolios in all our regressions. This is shown more clearly by the positive intercepts on the High – Low spread portfolios, which are significant at the 10%, 5%, or 1% level in 7 out of the 8 regressions, and are significant at the 5% or 1% levels for all portfolios under the value-weighting scheme. In the most extreme case (VW, 5-factor, 60 months), 63 basis points per month multiplies simply to an average 5-year horizon return differential of 37.8%.

Our evidence confirms the relatively poorer long-run stock return performance of the average SEO issuer. More important to this study is that this post-SEO performance can vary across firms according to ETF ownership. SEO issuing firms with the largest ETF ownership do not tend to significantly underperform their benchmarks on average, whereas low-ETF firms do. This contrast, emphasized by the High – Low analysis, shows that post-SEO underperformance can be diminished with ETF ownership. The direction of this relation is consistent with the market participation hypothesis suggesting that when firms wish to raise equity finance, they may be able to identify advantageous conditions to time the market, which can arise from alternative sources, such as episodes of higher demand for equity.

IV. Conclusion

In this study, we examine the impact of ETF ownership on firms' SEO decisions and subsequent firm performance. Under the noise trader hypothesis, increases in when ETF ownership exacerbate the information asymmetry between managers and investors (Israeli et al. (2017)) and non-fundamental demand shocks sometimes cause temporary overvaluation of equity (Ben-David et al. (2018)). These mechanisms suggest that increases in ETF ownership provide opportunities for managers to time the market with their SEO issuance. Due to greater valuation uncertainty and more adverse selection risk, SEO issuers with high ETF ownership are predicted to experience more negative SEO announcement effects, larger SEO discounts, and more severe long-run underperformance.

Building on this traditional approach, we consider an alternative market participation hypothesis. Increases in ETF ownership of firms may represent investors' demand for equity who are attracted to ETFs. Retail investors can participate in the equity market as ETFs become more widely adopted, whilst experienced and institutional investors can use them to construct more elaborate strategies. ETFs may also enable investors to substitute easily into equity funds at certain times to express their lower perceptions of risk or lower risk aversion. As ETF ownership increases, managers may spot opportunities to issue equity at favorable prices. The key difference is that SEO market timing is correlated with greater demand for equity. With relatively lower information asymmetry, valuation uncertainty, and adverse selection risk compared to the noise trader hypothesis, we predict less

negative SEO announcement returns, smaller SEO discounts, and less severe post-SEO underperformance for firms with higher ETF ownership.

Using a comprehensive sample of U.S. firms over the period 2003 to 2020, we find that increases to ETF ownership are associated with a higher propensity for firms to conduct an SEO, which is consistent with market timing. The positive relation is robust to controlling for flows to other fund types and suggests some cross sectional variation, being more pronounced among firms with characteristics indicating lower price elasticity of demand for their stocks. More important for exploring the alternative hypotheses, firms with higher ETF ownership exhibit less negative SEO announcement returns, smaller SEO discounts, and less severe long-run stock underperformance compared to firms with lower ETF ownership. These findings are all consistent with the market participation hypothesis. Our findings suggest additional circumstances, captured within investor demand for equity, under which managers that want to raise equity capital can time the market. Some firms that are able to take advantage of these favorable conditions may receive the added benefits of relatively lower flotation costs and less negative long-run stock returns.

We contribute to the literature in several ways. First, we add to the studies investigating the role of ETF ownership on corporate decisions, demonstrating that ETF ownership has a positive and significant influence on some firms' SEO decisions. Second, we offer new evidence on the conditions providing market timing opportunities. Our findings are consistent with an equity demand mechanism incorporating market participation, lower risk perception, and lower risk aversion, which is different from, but may operate alongside, the more traditional information asymmetry and mispricing channels. Future work may well investigate additional circumstances in which market timing opportunities may arise. Third, we add to the SEO literature that examines announcement effects, discounts, and post-SEO stock returns. These are important events for SEO firms and provide an ideal testing ground for our two hypotheses that predict opposing outcomes in all three stages. Our results are consistent with the market participation hypothesis. Fourth, the effect of ETF ownership on SEO likelihood is not subsumed by flows to index and mutual funds.

Appendix. Variable Definitions

ETF: The total number of shares owned by all ETFs divided by the total number of shares outstanding. Source: CRSP/Compustat.

Δ ETF_CONT: The quarterly differences in ETF. Source: CRSP/Compustat.

Δ ETF: A rank variable based on Δ ETF_CONT. In each quarter, we sort firms into 10 groups [1, 10] based on Δ ETF_CONT. Each firm is allocated the number of its group, which is then divided by 10. This variable ranges from 0.1 to 1. Source: CRSP/Compustat.

\ln (ASSET): The natural logarithm of total assets. Source: Compustat.

ROA: Income before extraordinary items divided by total assets. Source: Compustat.

CASH: Cash and short-term investments divided by total assets. Source: Compustat.

RETURN: The quarterly stock return. Source: CRSP.

BTM: Book value of shareholders' equity divided by market value of equity. Source: CRSP/Compustat.

LEVERAGE: Long-term debt plus debt in current liabilities, all divided by total assets. Source: Compustat.

DIVIDEND: Dividend per share divided by stock price. Source: Compustat.

VOLATILITY: The standard deviation of daily stock returns over a quarter. Source: CRSP.

ln(AGE): The natural logarithm of firm age in years. Source: Compustat.

ACTIVE: The total number of shares owned by all active mutual funds divided by the total number of shares outstanding. Source: CRSP/Compustat.

Δ ACTIVE_CONT: The quarterly differences in ACTIVE. Source: CRSP/Compustat.

Δ ACTIVE: A rank variable based on Δ ACTIVE_CONT. In each quarter, we sort firms into 10 groups [1, 10] based on Δ ACTIVE_CONT. Each firm is allocated the number of its group, which is then divided by 10. This variable ranges from 0.1 to 1. Source: CRSP/Compustat.

INDEX: The total number of shares owned by all index mutual funds divided by the total number of shares outstanding. Source: CRSP/Compustat.

Δ INDEX_CONT: The quarterly differences in INDEX. Source: CRSP/Compustat.

Δ INDEX: A rank variable based on Δ INDEX_CONT. In each quarter, we sort firms into 10 groups [1, 10] based on Δ INDEX_CONT. Each firm is allocated the number of its group, which is then divided by 10. This variable ranges from 0.1 to 1. Source: CRSP/Compustat.

SMALL: A dummy variable that equals 1 if a firm's ln(ASSET) is below the median, and 0 otherwise. Source: Compustat.

LOW_PRICE: A dummy variable that equals 1 if a firm's stock price as of the end of the previous quarter is below the sample median, and 0 otherwise. Source: Compustat.

HIGH_VOLATILITY: A dummy variable that equals 1 if a firm's VOLATILITY is above the median, and 0 otherwise. Source: CRSP.

LOW_#_SHAREHOLDER: A dummy variable that equals 1 if a firm's total number of shareholders as of the end of the previous quarter is below the sample median, and 0 otherwise. Source: Compustat.

DISCOUNT: Close-to-offer return of a SEO issue, computed as pre-offer closing price minus offer price, all divided by the pre-offer closing price. Source: Refinitiv SDC Platinum /CRSP.

MKT_RUNUP: Market return over 60 trading days prior to the SEO announcement. Source: CRSP.

RUNUP: Stock return over 60 trading days prior to the SEO announcement. Source: CRSP.

SECONDARY_SHARE: The number of SEO shares sold to existing shareholders divided by the total SEO shares offered. Source: Refinitiv SDC Platinum.

NASDAQ: A dummy variable that equals 1 if the firm was listed on the NASDAQ at the time of SEO, and 0 otherwise. Source: CRSP.

REL_OFFER_SIZE: The number of shares offered divided by the total number of shares outstanding prior to the issue date. Source: Refinitiv SDC Platinum/CRSP.

ln(ME): The natural logarithm of market capitalization, defined as the number of shares outstanding multiplied by the closing price on the day prior to the offer. Source: CRSP.

VOLATILITY_30_11: The standard deviation of daily returns from 30 trading days prior to the issue date to 11 days prior to the issue date. Source: CRSP.

CAR_POS (CAR_NEG): CAR_POS (CAR_NEG) is the CAR over the 5 trading days prior to the issue date if CAR is positive (negative), and 0 otherwise. Source: CRSP.

ln(PRICE): The natural logarithm of stock price on the day prior to the issue date. Source: CRSP.

BHAR_36M (BHAR_60M): Buy-and-hold abnormal return, measured against a benchmark portfolio of control firms matched by size and BM equity ratios, over the 36-month (60-month period) subsequent to a SEO issuance. Source: CRSP, Compustat.

Supplementary Material

To view supplementary material for this article, please visit <http://doi.org/10.1017/S002210902300042X>.

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