Financial Economics Letters 2024 3(2) 26-39

Financial Economics Letters

Homepage: https://www.anserpress.org/journal/fel

Funds Flows and Returns: The Case of the Australian Equity ETFs

Gerasimos G. Rompotis [a, *]

[a] *Department of Economics, National and Kapodistrian University of Athens, Athens, Greece*

ABSTRACT

The relation between fund flows and returns in the Australian ETF industry is assessed in this study. Daily data from 43 equity ETFs over the period 2019-2023 are used. The main research objective is to accentuate whether past returns can predict future fund flows and in what way and vice versa. According to the results of the applied regression analysis, past flows and past returns can predict to some extent concurrent flows. This is also the case about concurrent returns. However, in both cases, the results are not unanimous and depend on the specification of the applied regression model.

KEYWORDS

ETFs; Performance; Fund Flows; Australian Stock Market

---

* Corresponding author: Gerasimos G. Rompotis
E-mail address: geras3238@yahoo.gr

ISSN 2972-3426
doi: 10.58567/fel03020003

Received 29 March 2024; Accepted 15 April 2024; Available online 5 July 2024; Version of Record 15 June 2024.

1. Introduction

The relationship between fund flows and performance is the subject of the current paper. As evidenced by several early studies using data from the mutual fund and pension fund industries, this relation tends to be significantly positive (Smith, 1978; Patel et al., 1991; Del Guercio and Tkac, 2002). However, other studies, including those by Ippolito (1992), Capon et al. (1996), and Sirri and Tufano (1992 & 1998), suggest that there is an asymmetric relationship between fund flows and performance given that, even though funds with high performance over a specific period attract the largest money injections, as a reward to their goof performance records, poor performing funds do not experience proportional outflows as a response to their bad performance records.

The studies above are mainly focused on the United States. A study with a more international focus is that by Ferreira et al. (2012), which examines the dependence of mutual fund flows on past performance with data from 28 countries around the world. The results show that there are notable differences in the flow-performance relationship across the countries considered. They also find that mutual fund investors sell losers more and buy winners less in more developed countries. Ciccone et al. (2022) study how globalization affects the relationship between mutual fund flows and past performance using data on bond funds from the fund industry in Luxembourg. The results show that inflows to global funds, which issue shares in several currencies, are more sensitive to past performance than flows to domestic funds, whose shares are issued only in one currency. Moreover, the flows of global funds are more sensitive to low and high performance, while domestic funds are more reactive to medium performance.

The relationship of fund flows and performance is examined in the current study with data from the Australian Exchange Traded Funds (ETFs) industry. The choice of the Australian ETF market is justified by its increasing growth over the recent years. More specifically, the Australian ETF industry grew by 33% in 2023 reaching A$177 billion in assets under management. The net inflows of 2023 amounted to A$15 billion. The market is expected to grow even more in 2024 and assets under management are projected to reach A$200 billion by the end of the year.[1] Along with the spectacular growth records, the choice of the Australian ETF market is justified by the lack of a study dealing with the relationship of ETFs' flows and performance.

In fact, there are two known studies on the performance of Australian ETFs, which, however, do not touch the fund flows issue. In particular, Gallagher and Segara (2002) assess the ability of four passively managed ETFs to replicate the return of their benchmarks revealing a close proximity in returns between ETFs and the underlying indexes. Sun and Small (2022) assess the impact of sustainability on the performance of 244 ETFs in Australia during the period of Covid-19. The results indicate that ETFs with lower carbon risk and fossil fuel exposure tend to outperform, while ETFs with higher social risk deliver higher returns. It is also shown that ETFs with high environmental, governance and carbon risk, as well as high fossil fuel exposure are more volatile.

In our study, we evaluate the relation between fund flows and return using data from 43 equity ETFs traded on the Australian Stock Exchange. Two hypotheses are tested, namely whether past returns can predict future fund flows and whether past flows can predict future returns and in what way. Daily data frequencies are used over the period 2019-2023. According to our calculations, the average daily and total return of the sample has been positive over the study period, while the average daily flow has been negative. Based on regression analysis, to some degree, concurrent flows can be explained by past flows and past returns. Concurrent returns can also be explained by past flows and past returns. However, in both cases, the results are not unanimous and depend on the specification of the applied regression model.

The remainder of this paper is structured as follows: Section 2 provides a review of the main studies on the relation between flows and performance in the case of ETFs. Section 3 describes the ETF landscape in Australia. The

[1] Source: www.afr.com/markets/equity-markets/etf-industry-hits-record-as-rba-boosts-bonds-appeal-20240114-p5ex2p.

sample of the study and research methodology are presented in Section 4. Empirical findings are discussed in Section 5 and conclusions are provided in Section 6.

2. Literature Review

The literature on the relationship between flows and returns of ETFs is not that voluminous. The first study on the flows of ETFs was that by Kalaycıoğlu (2004). The author investigates the relationship between flows and return with a sample of four ETFs from the United States. Fund flow is calculated by considering the changes in the outstanding shares of ETFs. Correlation and causality between fund flows and returns is assessed at individual and aggregate levels. The results reveal significant negative correlation between flows and returns at the monthly level. Furthermore, it is found that the ETF flows put pressure on market returns. Finally, when a higher data frequency is considered, flows to ETFs seem to be the result of a return chasing behavior on behalf of some ETFs.

One newer study on the fund flows of ETFs is that by Clifford et al. (2014). The authors use monthly implied flows for over 500 ETFs and actual inflows and outflows for more than 300 ETFs in the US over the period 2001-2010. The empirical findings show that, similar to mutual funds, flows to ETFs decrease when the size, expenses and turnover of the funds increase. The results also indicate that like mutual funds, ETF flows respond to past performance. This means that significant positive returns are often followed by significant fund inflows. A positive relationship between ETFs' fund flows and returns is reported by Yousefi (2021) too.

Ivanov (2016) also tries to identify the factors that can affect the money stream to ETFs in the US using daily data of a sample of 1,212 ETFs. The study period spans from December 22, 2005 to July 28, 2010. The results show that autocorrelation is not universally present over the sample. Moreover, the results provide limited support for the contrarian investor hypothesis on the daily basis. Finally, the results do not verify that tracking error can be a factor that prompts changes in net fund flows.

Focusing on the same subject, Narend and Thenmozhi (2016) try to identify the factors that drive fund flows to passively managed ETFs and index funds using a data set from the stock market in India. The authors find that ETFs with lower expense ratio and large asset base attract more funds. On the other hand, age is not a factor that can explain flows to ETFs. This is also the case about ETFs' past performance, as well as the past return of the underlying benchmarks.

Boney et al. (2007) investigate the demand for SPDRs, an ETF that is written on the S&P 500 Index, relative to the demand for corresponding index funds by considering the intraday trading advantage of the ETF over its index funds competitors. According to the authors, this advantage can lead to a shift in demand from index funds to the ETF. Whether such a shift exists is assessed by examining the flow into and out of index funds and the net creation and redemption levels of the ETF. The results show that the SPDRs has a significantly negative effect on the fund flows to index funds.

Staer (2017) examines the relationship between ETF flow and the returns of the underlying securities using an extensive sample of ETFs from the US. The results reveal price pressure along with price reversal patterns in the relation of flows and returns. At the aggregate level, the applied tests show that 38% of the price change associated with the flow shock corresponds to price pressure and is reversed after five days.

Finally, Hu et al. (2022) assess the relation between ETFs' fund flows and returns from an information asymmetry perspective using data from the US over the period 2001-2016. By decomposing daily ETF flows, the authors find that the unexpected flow component, orthogonal to the components driven by the activity of market makers and arbitragers, can contribute to predicting next day's ETF returns. In fact, informed traders do exploit this information advantage and realize an annualized open-to-close return of 19.16% or close-to-close return of 22.42% during the study period.

3. The Australian ETF Landscape

Currently, there are 230 ETFs that trade on the Australian stock market. These products are classified in seven broad categories, namely, equity (156 funds), property (6 funds), currency (3 funds), fixed income (45 funds), cash (4 funds), commodity (7 funds), and mixed assets (10 funds). Similar to other developed ETF markets, such as that in the United States, the majority of the Australian ETFs (98%) apply passive management and track specific indexes, currencies, commodities and blends of index tracking ETFs. 98 of these ETFs have been launched in 2019 or later.

Just 3 ETFs in Australia try to outperform specific market indexes by applying active management techniques.[2] The low number of actively managed ETFs shows that the Australian ETF market is yet to follow the growth that has been observed in the active niche of the ETF industry in the US and other developed markets over the last years.[3] Moreover, there are only one long (leveraged) and one short (inverse leveraged) ETFs in Australia.

The rather anemic growth in actively managed and leveraged ETFs might reflect a conservativeness on behalf of the Australian investors, who frequently consider ETFs as alternative sources of income with controlled risk (as evidenced by the fact that 45 or 20% of the available ETFs on the Australian Stock Exchange are fixed income funds). The relative conservative behavior of the Australian investors might have an impact on the flows inwards and outwards ETFs and, possibly, on the performance of these investment products.

Another element that might affect the flows to ETFs concerns the strict regulation from the Australian Securities and Investments Commission when it comes to launching an exchange traded product (ETP). In particular, there are only three types of ETPs available to investors in Australia including ETFs, exchange traded managed funds (ETMFs), and structured products.[4] Moreover, the process relating to launching an ETF is quite onerous as the level of regulator's scrutiny is high, while there are lots of factors to consider, such as transparency, liquidity, the impact of different time zones, client demand and cost effectiveness. In addition, regulation requires that the name of a fund accurately reflect the product and say whether it is active or passive to make sure that products are appropriate and transparent.[5]

Based on the barriers to entry above, speculative ETFs that are offered in the US cannot be available in Australia. Overall, strict regulation poses burdens to the range of the exchange traded products that can be launched in the Australian market compared to the range of products in the US and other developed markets.[6] Such burdens might have an impact on the flow-return relationship in the case of ETFs.

Another factor that might affect the flows (and possibly returns) in the Australian ETF market is the availability of fewer free trading platforms in comparison to the US and other developed markets. In this respect, investors in Australia have to pay an amount per each trade they wish to execute (typically $5 to $8) or invest via a financial adviser. On the other hand, various commission-free platforms for ETFs are available in the US. In addition, the activity of institutional investors in Australia is weaker than the corresponding activity in the United States as institutional investors prefer to invest a small sum and watch performance before investing larger amounts of assets.

---

[2] The numbers and categories of ETFs in Australia have been found on the website of the Australian Stock Exchange (www.asx.com.au/markets/trade-our-cash-market/asx-investment-products-directory/etps).

[3] In fact, the actively managed ETFs in US outpaced their passive counterparts in 2023. Assets in actively managed ETFs grew by 37% in 2023, while passive ETFs only grew 8%. In the equity section of active ETFs, the growth rate was even stronger at 48% (https://www.etf.com/sections/news/actively-managed-etf-assets-soared-37-2023).

[4] ETFs and ETMFs are types of managed investment schemes under which an investor holds the units in the managed investment scheme that operates the fund, with each unit representing a proportionate interest in a portfolio of assets held by the fund. On the other hand, the structured products typically aim to replicate the performance of the underlying asset synthetically by holding financial instruments such as a futures contract.

[5] For a more detailed discussion on the regulatory burdens in the Australian ETF market, refer to: https://www.moneymanagement.com.au/features/how-does-aussie-etf-landscape-compare-us

[6] For instance, Exchange Traded Notes (ETNs) are not available in Australia.

A last element to consider is the tax implications of investing in Australia-listed ETFs. Generally speaking, for any income and capital gain earned, either within the country, in the case of locally oriented ETFs, or abroad, in the case of the Australian ETFs with an international focus, a tax must be paid. The latter are also affected by the fact that quite often the countries of underling assets' origin require the investments to be taxed. Such double taxation can affect the investment decisions (and consequently flows) of the Australian ETF investors. To alleviate the impact of double taxation, individual investors in Australia are offered a foreign tax offset when there's withholding tax from the investment's country of origin. This tax relief also applies when investing though a trust but not when investing through a company account as the income that is distributed to individuals from a company account does not receive any withholding tax credit. Overall, the scheme of an investment in Australian ETFs is crucial for the maximization of returns, especially given the Stage 3 tax cuts that are to come into effect on the 1st of July 2024, which are expected to make domestic investments even more appealing than the foreign ones.[7]

4. Data and Methodology

4.1. Data and Statistics

In our study, we decide to delve into the equity niche of the Australian ETF market. As mentioned above, 156 equity ETFs are currently available in Australia. In order to have a sufficiently lengthy investigation period, we chose to examine a period spanning from December 1, 2019, to December 31, 2023. 62 out of the available equity ETFs have been launched before the 1st of December 2019. However, 19 of them present a significant number of days with nil trading activity. Based on this observation, we decide to include only 43 ETFs in our sample. Assets-wise, the selected funds are some of the largest ETFs that trade on the Australian Stock Exchange. Overall, we deem that our sample is quite representative of the market as it covers 28% of the total number of the Australia-listed equity ETFs.

The sample is presented in Table 1, which provides the ticker and name of each ETF, its inception date, along with its age at the end of the study period, average daily assets under management and trading volume over the examined period, the published expense ratio, and the average intraday volatility, which is calculated as the fraction of the daily highest minus the daily lowest trade price to the daily close trade price. Trade data for this calculation, as well as daily volumes, have been found on yahoo.finance. The examined ETFs are managed by three companies, namely Global X Management Co (7 ETFs), BlackRock (25 iShares), and State Street Global Advisors (11 ETFs).

Table 1. Sample.

Ticker	Name	Inception Date	Age	Average Assets (AUD)	Volume	Expens e Ratio	Intraday Volatility
ACDC	Global X Battery Tech & Lithium ETF	3/9/2018	5.33	285,391,815	9,287	0.69%	1,08
ESTX	Global X EURO STOXX 50 ETF	21/7/2016	7.45	64,427,816	3,644	0.35%	0,56
TECH	Global X Morningstar Global Technology ETF	11/4/2017	6.73	237,913,726	5,854	0.45%	1,09
ROBO	Global X ROBO Global Robotics & Automation ETF	14/9/2017	6.30	191,395,165	4,798	0.69%	1,11
ZYUS	Global X S&P 500 High Yield Low Volatility ETF	12/6/2015	8.56	72,323,157	15,664	0.35%	0,70
CURE	Global X S&P Biotech ETF	12/11/2018	5.14	31,288,791	2,081	0.45%	1,09
ZYAU	Global X S&P/ASX 200 High Dividend ETF	12/6/2015	8.56	94,206,926	19,283	0.24%	0,87
IJR	iShares S&P Small-Cap ETF	10/10/2007	16.24	316,495,871	13,120	0.09%	1,03
IHOO	iShares Global 100 AUD Hedged ETF	18/12/2014	9.04	145,861,911	1,650	0.43%	0,18
IXJ	iShares S&P Global Healthcare ETF	11/3/2009	14.82	927,460,300	491	0.40%	0,64

[7] For a more detailed discussion on the tax implications of investing in Australian ETFs refer to: https://www.morningstar.com.au/insights/personal-finance/232029/tax-implications-when-investing-in-overseas-shares-and-etfs.

IOO	iShares S&P Global 100 ETF	10/10/2007	16.24	2,204,585,24	2,412	0.40%	0,47
IVE	iShares MSCI EAFE ETF	10/10/2007	16.24	388,076,921	23,534	0.31%	0,79
IJP	iShares MSCI Japan ETF	10/10/2007	16.24	373,242,649	2,767	0.50%	0,43
IKO	iShares MSCI South Korea Capped Index ETF	15/11/2007	16.14	85,289,608	13,956	0.57%	0,71
IXI	iShares Global Consumer Staples ETF	12/9/2006	17.31	166,452,594	29,885	0.41%	1,09
IAA	iShares S&P Asia 50 ETF	10/9/2008	15.32	665,449,475	157,014	0.51%	0,89
IEU	iShares S&P Europe ETF	10/10/2007	16.24	723,220,357	14,343	0.58%	0,86
IEM	iShares MSCI Emerging Markets ETF	10/10/2007	16.24	810,899,141	1,768	0.69%	0,32
IWLD	iShares Core MSCI World ex Australia ESG ETF	28/4/2016	7.68	305,734,914	6,021	0.10%	0,50
IVV	iShares S&P 500 ETF	10/10/2007	16.24	4,325,162,95	5,890	0.04%	0,93
IHWL	iShares Core MSCI World ex Australia ESG (AUD Hedged) ETF	28/4/2016	7.68	196,128,617	2,645	0.13%	0,70
IHVV	iShares S&P 500 AUD Hedged ETF	18/12/2014	9.04	617,496,927	12,812	0.10%	0,95
IJH	iShares S&P Midcap ETF	10/10/2007	16.24	185,627,539	28,084	0.09%	0,87
WDMF	iShares Edge MSCI World Multifactor ETF	14/10/2016	7.22	184,461,461	6,354	0.35%	0,84
WVOL	iShares Edge MSCI World Minimum Volatility ETF	14/10/2016	7.22	183,452,931	12,516	0.30%	1,10
IZZ	iShares FTSE China Large-Cap ETF	15/11/2007	16.14	185,753,085	3,483	0.77%	1,39
AUMF	iShares Edge MSCI Australia Multifactor ETF	14/10/2016	7.22	34,607,193	5,812	0.30%	0,81
MVOL	iShares Edge MSCI Australia Minimum Volatility ETF	14/10/2016	7.22	34,491,084	12,863	0.30%	1,56
IOZ	iShares Core S&P/ASX 200 ETF	9/12/2010	13.07	3,242,253,91	24,285	0.05%	1,01
ILC	iShares S&P/ASX 20 ETF	9/12/2010	13.07	406,458,908	29,523	0.24%	1,37
IHD	iShares S&P/ASX High Dividend Yield ETF	9/12/2010	13.07	276,499,953	19,983	0.30%	0,79
ISO	iShares S&P/ASX Small Ordinaries ETF	9/12/2010	13.07	119,622,601	196,855	0.55%	0,62
SYI	SPDR MSCI Australia Select High Dividend Yield Fund	29/9/2010	13.26	250,908,206	14,305	0.20%	0,64
QMIX	SPDR MSCI World Quality Mix Fund	14/9/2015	8.30	27,152,743	65,528	0.18%	0,62
WEMG	SPDR S&P Emerging Markets Carbon Control Fund	4/11/2013	10.16	19,656,155	6,199	0.65%	0,42
WDIV	SPDR S&P Global Dividend Fund	4/11/2013	10.16	307,262,107	19,459	0.35%	0,59
WXOZ	SPDR S&P World ex Australia Carbon Control Fund	19/3/2013	10.79	250,523,258	21,044	0.30%	1,74
OZF	SPDR S&P/ASX 200 Financials ex A-REITs Fund	13/4/2011	12.73	106,157,039	1,965	0.40%	0,30
OZR	SPDR S&P/ASX 200 Resource Fund	13/4/2011	12.73	112,129,017	5,267	0.40%	0,36
STW	SPDR S&P/ASX 200 Fund	27/8/2001	22.36	4,269,612,60	466,913	0.05%	0,88
SFY	SPDR S&P/ASX 50 Fund	27/8/2001	22.36	703,589,685	25,924	0.29%	0,91
SSO	SPDR S&P/ASX Small Ordinaries Fund	13/4/2011	12.73	25,748,024	35,304	0.50%	0,91
WXHG	SPDR World ex Australia Carbon Control (Hedged) Fund	9/7/2013	10.48	135,044,806	47,625	0.35%	0,95
Average			12.05	564,872,493	32,516	0.36%	0.83
Min			5.14	19,656,155	491	0.04%	0.18
Max			22.36	4,325,162,95	466,913	0.77%	1.74

This table presents the profiles of ETFs, which include their ticker, name, inception date, age as at 31/12/2023, average daily assets (in Australian dollars) during the period 2019-2023, average traded volume (in shares) over the same period, the expense ratio, and the average intraday volatility.

The average ETF in the sample is 12 years old. The youngest ETF is 5 years old (i.e., the Global X S&P Biotech ETF), while the oldest ETFs are the SPDR S&P/ASX 200 fund and the SPDR S&P/ASX 50 fund, which both were incepted on August 27, 2001, and are 22 years old. In addition, 23 ETFs are older than the sample's average age. Overall, the analysis of ages indicates that the examined ETFs are quite mature.

When it comes to the size of ETFs, as it is measured in assets under management terms, Table 1 reports an average assets figure of A$564 million. The average assets of four ETFs exceed one billion Australian dollars. Without these outliers, the average ETF in the sample managed about A$263 million over the period under examination.

In regard to the tradability of equity ETFs in Australia, an average daily volume of 32.5 thousand shares is provided in Table 1. The extreme volume records are 491 shares at a minimum and 467 thousand shares at a maximum. The most tradable ETF in the sample is the SPDR S&P/ASX 200 fund.

On the fees charged by the examined ETFs, Table 1 reports an average expense ratio of 36 basis points (bps). The range between extreme expense ratios is quite large at 73 bps, as the minimum and maximum expense ratios are equal to 4 bps and 77 bps, respectively. When examining expense ratios a bit further, we can observe that the highest ratios are charged by ETFs with international focus on Europe, Japan, emerging markets, and so on. ETFs that target to specialized sectors, such as the solar battery value chain industry, also have higher expense ratios than ETFs with broad local focus.

Finaly, the average intraday volatility of the sample is equal to 83 bps. This is a rather tolerable figure. The extreme scores of average intraday volatilities of the sample are equal to 18 bps (at a minimum) and 174 bps (at a maximum).

Table 2 presents the descriptive statistics of the examined ETFs' daily returns and flows over the period 2019-2023. Descriptive statistics include average terms, standard deviation, minimum and maximum scores. Total (cumulative) returns over the entire period under study are reported too.

Table 2. Returns and Flows.

	Returns					Flows			
Ticker	Average	StDev	Min	Max	Total	Average	StDev	Min	Max
ACDC	0.060	1.147	-7.454	6.491	96.098	-0.056	1.136	-6.426	7.380
ESTX	0.036	1.223	-10.585	8.231	44.157	-0.036	1.210	-8.038	10.479
TECH	0.047	1.605	-13.805	10.310	54.000	-0.046	1.589	-10.207	13.667
ROBO	0.041	1.234	-9.229	5.645	52.364	-0.040	1.222	-5.588	9.136
ZYUS	0.012	1.329	-11.614	11.073	3.933	-0.012	1.317	-10.946	11.466
CURE	0.027	2.287	-13.579	9.051	0.787	-0.023	2.266	-8.961	13.443
ZYAU	-0.005	1.193	-10.424	8.179	-14.053	0.005	1.181	-8.097	10.320
IJR	0.051	1.601	-11.459	9.874	61.017	-0.049	1.585	-9.776	11.337
IHOO	0.039	1.266	-15.181	10.010	47.736	-0.037	1.254	-9.858	15.069
IXJ	0.042	1.145	-9.015	8.831	56.119	-0.041	1.134	-8.744	8.920
IOO	0.060	1.253	-10.489	10.803	93.276	-0.059	1.240	-10.696	10.383
IVE	0.028	1.129	-10.003	8.217	31.843	-0.028	1.118	-8.135	9.903
IJP	0.027	1.070	-6.503	7.656	30.973	-0.026	1.059	-7.587	6.433
IKO	0.025	1.570	-15.502	10.021	17.693	-0.024	1.555	-9.921	15.345
IXI	0.028	1.049	-7.649	11.020	32.671	-0.027	1.039	-10.912	7.569
IAA	0.016	1.454	-9.513	10.796	7.672	-0.016	1.439	-10.685	9.406
IEU	0.034	1.232	-11.015	8.234	38.901	-0.034	1.220	-8.153	10.903
IEM	0.013	1.291	-12.172	9.694	6.153	-0.013	1.278	-9.602	12.051
IWLD	0.043	1.258	-12.740	10.081	55.025	-0.040	1.246	-9.980	12.630
IVV	0.062	1.317	-11.263	11.299	-87.019	-0.061	1.304	-11.184	11.152
IHWL	0.041	1.334	-12.431	11.498	50.339	-0.040	1.321	-11.383	12.307
IHVV	0.039	1.471	-17.499	12.078	-85.855	-0.037	1.457	-11.935	17.354
IJH	0.055	1.515	-14.125	10.506	-82.765	-0.054	1.500	-10.401	13.958
WDMF	0.029	1.085	-9.386	7.881	34.342	-0.029	1.074	-7.803	9.292
WVOL	0.023	0.844	-7.302	8.321	28.610	-0.021	0.836	-8.238	7.229

IZZ	-0.019	1.808	-9.981	20.282	-35.861	0.020	1.789	-20.072	9.876
AUMF	0.021	1.103	-8.617	6.683	20.823	-0.020	1.092	-6.616	8.531
MVOL	0.020	0.986	-9.472	6.297	21.198	-0.017	0.979	-6.180	9.377
IOZ	0.028	1.108	-9.679	7.006	31.417	-0.026	1.096	-6.932	9.573
ILC	0.028	1.138	-9.157	7.884	31.228	-0.027	1.127	-7.799	9.065
IHD	0.019	1.154	-8.596	7.025	17.108	-0.019	1.142	-6.955	8.514
ISO	0.008	1.254	-9.102	5.169	0.439	-0.008	1.241	-5.117	9.011
SYI	0.015	1.261	-10.580	6.908	8.950	-0.014	1.248	-6.839	10.474
QMIX	0.037	0.963	-8.202	7.329	51.249	-0.036	0.954	-7.256	8.078
WEMG	0.009	0.950	-7.084	5.143	6.363	-0.009	0.941	-5.091	7.060
WDIV	0.004	0.891	-8.378	5.336	-0.391	-0.003	0.882	-5.283	8.295
WXOZ	0.036	1.106	-11.850	7.764	45.365	-0.035	1.095	-7.686	11.690
OZF	0.027	1.397	-11.087	9.177	23.479	-0.026	1.383	-9.085	10.976
OZR	0.041	1.605	-12.567	8.255	41.835	-0.040	1.589	-8.173	12.442
STW	0.027	1.099	-9.649	5.889	29.671	-0.026	1.088	-5.793	9.565
SFY	0.027	1.099	-9.605	6.260	29.748	-0.026	1.088	-6.198	9.519
SSO	0.011	1.280	-13.437	5.218	2.994	-0.010	1.268	-5.166	13.303
WXHG	0.019	1.300	-20.190	10.713	13.586	-0.018	1.287	-10.606	19.995
Average	0.029	1.265	-10.864	8.701	21.238	-0.028	1.253	-8.607	10.755
Min	-0.019	0.844	-20.190	5.143	-87.019	-0.061	0.836	-20.072	6.433
Max	0.062	2.287	-6.503	20.282	96.098	0.020	2.266	-5.091	19.995

This table presents the returns and flows of ETFs over the period 2019-2023.

Returns are computed with Net Asset Values (NAVs), which have been found on the websites of ETF' managing companies. Employing the approach followed by a plethora of researchers (e.g., Sirri and Tufano Flows, 1998), flows are calculated by combining changes in assets under management and returns in the following formula:

$$\text{Flow}_{\,i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * \left(1 + R_{i,t}\right)}{TNA_{i,t-1}} \tag{1}$$

where $TNA_{i,t}$ is the inflow of the ith ETF on day t and $R_{i,t}$ is the return of this ETF on the same day. Similar to NAVs, data on daily assets have been found on the websites of the managing companies.

The average daily and total return of ETFs over the entire period under study has been positive (i.e., 3 bps and 2,123 bps, respectively). At the individual level, most of the examined ETFs present positive daily and cumulative returns. Moreover, the sample's average standard deviation in returns (i.e., risk) is equal to 127 bps. The range of the average extreme return scores is quite wide at 1,956 bps. On the other hand, the average daily flow is negative at -0.028. The volatility of flows is commensurate with return volatility at 125 bps. This is also the case about the spread between minimum and maximum flow records.

4.2. Research Methods

In testing the relation between fund flows and returns, we follow the approach adopted by Ben-Raphael et al. (2011). First, we examine the impact on concurrent flows by their lagged values up to four days. The time series regression model applied for each individual ETF in the sample is the following:

$$Flow_{i,t} = \lambda_{i,t} + \sum_{s=-1}^{s=-4} Flow_{i,s} + u_{i,t} \tag{2}$$

Then, we assess the impact on fund flows by lagged returns up to four days too. Again, this impact is examined for each single ETF in the sample with the following time series regression model:

$$Flow_{i,t} = \lambda_{i,t} + \sum_{s=-1}^{s=-4} Ret_{i,s} + u_{i,t} \tag{3}$$

At the third stage, we combine lagged flows and lagged returns up to four days to identify the impact on concurrent flows, as shown in the following time series regression model:

$$Flow_{i,t} = \lambda_{i,t} + \sum_{s=-1}^{s=-4} Flow_{i,s} + \sum_{s=-1}^{s=-4} Ret_{i,s} + u_{i,t} \tag{4}$$

In the final step, we add a control variable to model (4), which is the lagged intraday volatility of each ETF up to four days. We choose this factor as a control variable because the literature has shown that intraday volatility matters when trying to predict the return of ETFs.[8] Based on this evidence, we assume that intraday volatility can affect fund flows too. The applied model is as follows:

$$Flow_{i,t} = \lambda_{i,t} + \sum_{s=-1}^{s=-4} Flow_{i,s} + \sum_{s=-1}^{s=-4} Ret_{i,s} + \sum_{s=-1}^{s=-4} IntrVol_{i,s} + u_{i,t} \tag{5}$$

After assessing the determinative factors of fund flows, we focus on the corresponding factors for concurrent returns. We do so by applying for each ETF in the sample the four models above replacing daily flows with daily returns as the dependent variable of the models.

5. Empirical Results

5.1. Fund Flows

The results of the regression models (2) to (5) on ETF flows are provided in Table 3. The table presents the average, minimum and maximum coefficient of the entire sample for each independent variable considered along with the number of positive (significant and insignificant) and negative (significant and insignificant) estimates. Average, minimum and maximum R-squared values are reported too.

Table 3. Regression Results on Flows.

	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Constant	-0.035	-0.093	0.024	0	2	7	34
Flows(-1)	-0.181	-0.365	0.085	1	0	39	3
Flows(-2)	0.034	-0.050	0.127	17	19	1	6
Flows(-3)	0.007	-0.073	0.099	10	12	4	17
Flows(-4)	-0.059	-0.141	-0.005	0	0	26	17

[8] For instance, Xu et al. (2020) find that in the case of commodity ETFs the ability to predict returns strengthens on days of higher volatility and larger jumps.

R-squared	0.052	0.005	0.127				
	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Constant	-0.035	-0.093	0.023	0	2	7	34
Return(-1)	0.179	-0.084	0.361	38	4	1	0
Return(-2)	-0.033	-0.125	0.050	1	7	17	18
Return(-3)	-0.007	-0.098	0.073	4	19	10	10
Return(-4)	0.058	0.006	0.140	27	16	0	0
R-squared	0.052	0.005	0.127				
	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Constant	-0.034	-0.099	0.027	0	3	5	35
Flows(-1)	0.181	-7.852	7.273	5	24	5	9
Flows(-2)	-1.104	-7.993	8.071	5	12	4	22
Flows(-3)	0.177	-9.397	11.490	5	17	3	18
Flows(-4)	-0.553	-2.415	3.090	1	17	4	21
Return(-1)	0.734	-1.008	1.689	5	24	5	9
Return(-2)	-1.601	-2.793	2.967	5	11	4	23
Return(-3)	0.216	-1.247	1.375	5	17	3	18
Return(-4)	0.348	-6.793	3.037	1	18	4	20
R-squared	0.058	0.007	0.182				
	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Contant	-0.040	-0.180	0.292	1	6	6	30
Flows(-1)	0.135	-7.050	6.588	6	21	5	11
Flows(-2)	-0.859	-8.114	3.897	5	12	3	23
Flows(-3)	0.039	-9.578	7.985	7	16	3	17
Flows(-4)	-0.178	-6.596	6.643	1	17	4	21
Return(-1)	0.250	-6.842	6.587	6	22	5	10
Return(-2)	-0.880	-8.057	3.862	5	11	3	24
Return(-3)	0.030	-9.517	7.926	7	16	4	16
Return(-4)	-0.138	-6.496	6.662	1	17	4	21
IntrVol(-1)	-0.035	-0.384	0.286	7	8	19	9
IntrVol(-2)	0.060	-0.147	0.474	11	22	1	10
IntrVol(-3)	-0.072	-0.389	0.086	1	10	17	15
IntrVol(-4)	0.067	-0.175	0.310	20	15	2	6
R-squared	0.068	0.012	0.184				

This table presents the results of four time series regression models via which the flows of ETFs are regressed on the lagged flows, the lagged returns and the lagged intraday volatilities. The study period spans from 2019 to 2023.

When it comes to model (2), the results indicate a negative relation of concurrent flows with their one-lagged values. The corresponding coefficient is equal to -0.181, while 39 estimates are significantly negative. The majority of the two-lagged coefficients are positive (totally 36 positive estimates), but only 17 of them are statistically significant. Half of the three-lagged flow estimates are positive, but only 10 of them are significant. On the other hand, only 4 negative estimates are significant. Finally, all the four-lagged flow estimates are negative, with 26 of them being statistically significant. Overall, the results of model (2) on fund flows indicate a clearly reverting behavior of ETF flows from one day to the next, while the sign of the impact on concurrent flows by the flows of the previous two to four days varies.

The results of model (3) document a clearly positive impact of the one-lagged returns on concurrent flows. The respective average estimate is 0.179. Moreover, the model produces 42 positive estimates, with 38 of them being significant. All the four-lagged return estimates are positive too, with 26 of them being significant. The results on the two- and three-lagged returns are mixed. Overall, the results of model (3) on ETF flows demonstrate that a positive relation exists between concurrent flows and the returns of the previous day, indicating a return chasing behavior for the vast majority of the examined ETFs similar to that reported by Clifford et al. (2014) and Yousefi (2021).

The results of model (4), which combines both lagged flows and lagged returns to explain concurrent flows, are quite different to the "individual" results obtained through models (2) and (3). The negative relation between flows and one-lagged flows revealed by model (2) is not verified by the results of model (4). Only 14 estimates are negative and just 5 of them are significant. A similar comment could be made about the positive relation between flows and one-lagged returns established on the basis of model's (3) results. In particular, model (4) provides only 5 significantly positive estimates for the one-lagged return factor. The results on other lagged flow and return factors are mixed, indicating no specific patterns with respect to their impact on concurrent flows.

The results of model (5), which along with lagged flows and returns, considers lagged intraday volatility up to four days, picture a rather inconsistent impact on concurrent flows by the lagged flows and lagged returns, similar to that of model (4). On the other hand, the impact of the lagged intraday volatility seems to be quite significant in several cases. In particular, 7 and 19 one-lagged intraday volatility estimates are significantly positive and negative, respectively. 11 two-lagged estimates are positive and significant and just 1 is significantly negative. 1 three-lagged coefficient is significantly positive and 17 are significantly negative. Finally, 20 four-lagged volatility estimates are positive and significant and 2 are significantly negative.

Based on the results of model (5), we may conclude that the lagged intraday volatility matters when trying to predict concurrent flows. However, the extent and the sign of intraday volatility's impact on fund flows is rather fund-specific.

To summarize the regression results on fund flows, we note that, based on the outcomes of models (2) and (3), we can conclude that a significantly negative relation exists between concurrent flows and one-lagged flows, while the relation of flows with the previous day's returns is positive and strong. However, given that models (4) and (5) provided mixed results on these relationships, we should emphasize that the validity of these relationships depends to some extent on the specification of the model used to explain the fund flows of the Australian equity ETFs.

5.2. Returns

The results of models (2) to (5) on returns are presented in Table 4. The presentation of regression results in Table 4 is similar to that in Table 3 on fund flows. The average one-lagged flow coefficient from model (2) is 0.183, with the majority of the single estimates being significantly positive (i.e., 38 estimates). Based on this finding, the positive impact of the one-lagged returns on the concurrent flows applies to the opposite direction too, that is, the impact of the one-lagged flow to the concurrent return is positive and significant. The results on the two- and the three-lagged flows are mixed, regarding both the sign and the number of statistically significant estimates. On the other hand, all the four-lagged flow coefficients are positive, with 26 of them being statistically significant. When it comes to the autocorrelation in returns, the results of model (3) show that concurrent returns are negatively related to their one-lagged values, with the relevant estimate being equal to -0.181 and the single estimates being significantly negative in 38 cases. This evidence reveals a reverting behavior in daily returns. Furthermore, 36 two-lagged return estimates are positive, but half of them are statistically significant. In the case of the three-lagged returns, half of estimates are positive and half are negative, but, in total, only 14 coefficients are statistically significant. Finally, all four-lagged estimates are negative, with 26 of them being significant.

Table 4. Regression Results on Returns.

	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Constant	0.036	-0.022	0.094	7	34	0	2
Flows(-1)	0.183	-0.086	0.368	38	4	1	0
Flows(-2)	-0.034	-0.129	0.051	1	7	17	18
Flows(-3)	-0.007	-0.100	0.074	5	17	10	11
Flows(-4)	0.059	0.004	0.143	26	17	0	0

R-squared	0.052	0.005	0.127				
	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Constant	0.036	-0.022	0.094	7	34	0	2
Return(-1)	-0.181	-0.365	0.085	1	0	38	4
Return(-2)	0.034	-0.050	0.127	17	19	1	6
Return(-3)	0.007	-0.073	0.099	10	12	4	17
Return(-4)	-0.058	-0.141	-0.005	0	0	26	17
R-squared	0.052	0.005	0.127				
	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Constant	0.039	-0.023	0.116	9	32	0	2
Flows(-1)	0.169	-0.088	0.315	38	4	1	0
Flows(-2)	0.208	-2.691	2.572	6	21	4	12
Flows(-3)	0.953	-1.511	2.364	3	18	7	15
Flows(-4)	0.940	-1.616	2.517	4	22	1	16
Return(-1)	-0.167	-0.323	0.082	1	0	38	4
Return(-2)	0.247	-2.413	2.363	6	23	4	10
Return(-3)	0.937	-1.265	1.789	3	18	7	15
Return(-4)	0.876	-1.453	2.189	4	22	1	16
R-squared	0.092	0.008	0.267				
	Average	Min	Max	Sign>0	Insign>0	Sign<0	Insign<0
Contant	0.042	-0.294	0.183	7	30	1	5
Flows(-1)	-0.173	-6.507	7.364	5	12	5	21
Flows(-2)	1.047	-3.926	8.265	3	24	5	11
Flows(-3)	-0.045	-7.983	9.673	4	17	5	17
Flows(-4)	0.194	-6.773	6.680	4	22	1	16
Return(-1)	-0.289	-6.509	7.152	5	11	6	21
Return(-2)	1.040	-3.890	8.207	3	25	5	10
Return(-3)	-0.019	-7.923	9.611	4	17	6	16
Return(-4)	0.140	-6.791	6.579	4	22	1	16
IntrVol(-1)	0.036	-0.289	0.388	19	10	7	7
IntrVol(-2)	-0.061	-0.480	0.147	1	11	11	21
IntrVol(-3)	0.073	-0.087	0.395	17	16	0	10
IntrVol(-4)	-0.068	-0.314	0.177	2	7	20	14
R-squared	0.068	0.012	0.184				

This table presents the results of four time series regression models via which the returns of ETFs are regressed on the lagged flows, the lagged returns and the lagged intraday volatilities. The study period spans from 2019 to 2023.

The results of model (4) verify the positive impact of the one-lagged flow to returns, as 38 estimates are significantly positive. The majority of the rest lagged flow estimates are statistically insignificant. Model (4) verifies the negative impact on return by their one-lagged values, as 38 estimates are significantly negative. Similar to the lagged flow estimates from day two to day four, the majority of the corresponding lagged return estimates are not significant in statistical terms.

Model (5) fails to verify the positive impact of the one-lagged flows on concurrent returns, as an average negative one-lagged flow coefficient is obtained, while the majority of the single estimates (i.e., 33 estimates) are insignificant. Most of the rest lagged flow estimates are not significant. On the other hand, the negative correlation between concurrent and one-lagged returns is partially verified by the results of model (5). In particular, the corresponding average estimate is negative at -0.289 and 27 individual estimates are negative, but only 6 of them are statistically significant. The majority of the two- to four-lagged return coefficients are insignificant.

As far as lagged intraday volatility is concerned, the results from model (5) reveal a slightly positive impact of the one-day lagged values of intraday volatility to returns. The respective average is equal to 0.036 and 29 single estimates are positive, with 19 of them being significant. The impact on returns by the two-lagged volatility seems to be negative, as the majority of the corresponding coefficients (i.e., 33 estimates) are negative, but only 11 of them are significant. 33 estimates of the three-lagged intraday volatility values are positive, with 17 being statistically significant. Finally, 34 estimates of the four-lagged intraday volatility factor are negative, with 29 of these estimates being statistically significant.

Overall, the results of the applied regression models on the returns of the equity ETFs in Australia establish a positive relationship between concurrent returns and the previous day's flows, as well as a reverting behavior of returns compared to their one-day lagged values. The regression analysis also indicates that the lagged intraday volatility can be a valuable factor to consider when trying to predict the returns of ETFs in the very near future, i.e., during an interval of one week.

6. Conclusion

The relationship of fund flows with returns is evaluated in this paper with daily data from the Australian ETF market over the period 2019-2023. Being motivated by the findings in the literature on various markets and investment vehicles, which indicate that this relationship is significant, we seek to answer whether flows affect returns and vice versa. The sign of this impact is sought after too. Our sample focuses on the equity niche of the Australian ETF industry and includes 43 ETFs. The relationship between flows and returns is evaluated with the use of four alternative autoregressive models, which consider the lagged values of flows, returns and intraday volatility up to four days as determinative factors of flows and returns.

The results of the regression analysis establish a negative relationship between flows and their values on the previous day. The opposite is found about the impact of the one-day lagged returns on concurrent flows. The latter findings implies a return chasing behavior on behalf of ETF investors in Australia. This behavior means that investors choose to put their money on winning ETFs. In regard to the impact of lagged intraday volatility on fund flows, our analysis reveals that this factor can be quite significant in explaining the flows of the examined ETFs.

When it comes to the impact of lagged flows on concurrent returns, the results accentuate a significantly positive impact on return by the previous day's flows. On the contrary, the impact of the corresponding lagged returns on concurrent returns is clearly negative, indicating a reverting pattern in the behavior of daily returns. The impact of the lagged intraday volatility on returns is also found to be quite significant when trying to predict the return of ETFs.

Overall, we deem that our results can have significant practical implications, especially for short-term or even daily traders with ETFs. Our evidence on the positive relation between returns and one-lagged flows and the reverting pattern in daily returns could be the basis for profitable investing strategies. However, one should not underestimate that, to some degree, our results depend on the specification of the model used to assess the relationship between funds flows and returns.

In any case, our study is a first effort towards explaining the relationship between performance and money flows in the Australian ETF industry. Our study can be the basis for future research on the topic with probably a larger data set, covering more ETF categories, such as fixed-income and commodity ETFs, and longer time frames.

Funding Statement

This research received no external funding.

Conflict of interest

The author claims that the manuscript is completely original. The author also declares no conflict of interest.

Author contributions

This article has been solely written in its entirety by the author.

References

Ben-Rephael, A., Kandel, S., and Wohl, A. (2011). The Price Pressure of Aggregate Mutual Fund Flows, *Journal of Financial and Quantitative Analysis* 46(2), 585-603. https://doi.org/10.1017/S0022109010000797

Boney, V.R., Doran, J.S., and Peterson, D.R. (2007). The Effect of the Spider Exchange Traded Fund on the Demand for S&P Index Mutual Funds, *ETFs and Indexing* (Vol. 2007), 61-74.

Capon, N., Fitzsimons, G.J., and Prince, R.A. (1996). An Individual Level Analysis of the Mutual Fund Investment Decision, *Journal of Financial Services Research* 10, 59-82. https://doi.org/10.1007/BF00120146

Ciccone, J., Marchiori, L., and Morhs, R. (2022). The Flow-Performance Relationship of Global Investment Funds, *Journal of International Money and Finance* 127, October 2022, 1-24. https://doi.org/10.1016/j.jimonfin.2022.102690

Clifford, C., Fulkerson, J., and Jordan, B. (2014). What Drives ETF Flow?, *Financial Review* 49(3), 619-642. https://doi.org/10.1111/fire.12049

Del Guercio, D., and Tkac, P. (2002). The Determinants of the Flows of Funds of Manager Portfolios: Mutual fund vs. Pension Funds, *Journal of Financial and Quantitative Analysis* 37(4), 523-557. https://doi.org/10.2307/3595011

Ferreira, M.A., Keswani, A., Miguel, A.F., Ramos, S.F. (2012). The Flow-Performance Relationship Around the World, *Journal of Banking and Finance* 36(6), 1759-1780. https://doi.org/10.1016/j.jbankfin.2012.01.019

Gallagher, D.R., and Segara, R. (2002). The Performance and Trading Characteristics of Exchange-Traded Funds, *Journal of Investment Strategy* 1(2), 49-60.

Ivanov, S.I. (2016). Analysis of the Factors Impacting ETFs Net Fund Flow Changes, *Studies in Economics and Finance* 33(2), 244-261. https://doi.org/10.1108/SEF-06-2014-0114

Kalaycıoğlu, S. (2004). Exchange Traded Fund Flows, Working Paper, William E. Simon Graduate School of Business Administration, University of Rochester, Rochester, NY.

Narend, S., and Thenmozhi, M. (2016). What Drives Fund Flows to Index ETFs and Mutual Funds? A Panel Analysis of Funds in India, *Decision* 43, 17-30. https://doi.org/10.1007/s40622-016-0124-6

Ippolito, R. (1992). Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry, *Journal of Law and Economics* 35(1), 45-70.

Patel, J., Zeckhauser, R., and Hendricks, D. (1991). The Rationality Struggle: Illustration from Financial Markets, *American Economic Review* 81(2), 232-236.

Sirri, E.R., and Tufano, P. (1992). The Demand for Mutual Fund Services by Individual Investors, Working Paper, Harvard Business School.

Sirri, E.R., and Tufano, P. (1998). Costly Search and Mutual Fund Flows, *Journal of Finance* 53(5), 1589-1622.

Smith, K.V., 1978, Is Fund Growth Related to Fund Performance?, *Journal of Portfolio Management* 4, 49-54.

Staer, A., 2017, Fund Flows and Underlying Returns: The Case of ETFs, *International Journal of Business* 22(4), 275-304.

Sun, L., and Small, G. (2022). Has Sustainable Investing Made an Impact in the Period of Covid-19?: Evidence from Australian Exchange Traded Funds, *Journal of Sustainable Finance and Investment* 12(1), 251-273. https://doi.org/10.1080/20430795.2021.1977577

Hu, L., Yin, X., and Zhao, J. (2022). Are the Flows of Exchange-Traded Funds Informative?, *Financial Management* 51(4), 1165-1200. https://doi.org/10.1111/fima.12396

Hu, Y., Bouri, E., Saeed, T., and Wen, Z. (2020). Intraday Return Predictability: Evidence from Commodity ETFs and their Related Volatility Indices, *Resources Policy* 69, 1-10. https://doi.org/10.1016/j.resourpol.2020.101830

Yusefi, H. (2021). How Fund Flows Affect Future Performance? Evidence from Exchange-Traded Funds (ETFs), In Two Essays on the Information Embedded in Flow of Exchange-Traded Funds (ETFs), Doctoral Dissertation, Old Dominion University.