Information and liquidity linkages in ETFs and underlying markets*

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Abstract

We show that exchange-traded funds (ETFs) establish strong information links with the underlying equities but weak ones with the underlying corporate debt securities. This has several distinct effects on each asset class. First, ETFs propagate liquidity shocks to equities but not to debt securities. Second, ETF flows affect the underlying equities' returns to a much higher degree than debt securities' returns. Third, higher ETF ownership increases equities' volatility but decreases debt securities' volatility. The results are consistent with the view that the higher accessibility of equities facilitates the formation of close information links with ETFs through arbitrage, which makes equities' prices sensitive to ETF demand shocks and creates the potential for illiquidity contagion when this link is disrupted. In contrast, the hard-to-access nature of corporate debt securities results in weak information links with ETFs which reduces commonalities between the two markets.

JEL classification: G12, G14, G23

Keywords: Information links, ETFs, liquidity, returns, volatility

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Non-technical summary

Exchange-traded funds (ETFs) are index products that have grown substantially over the past decade, with Irish ETFs representing 14% of total Irish investment fund assets as of 2019. By allowing their shares to be traded continuously on an exchange, ETFs have become a popular instrument through which investors can gain access to a wide variety of asset classes, from liquid equities to more hard-to-access corporate bonds. Their growth has attracted both academic and regulatory interest on how they can affect the underlying markets they invest in.

ETF shares and the underlying securities are subject to arbitrage activity that exploits price differences when they arise, ensuring that the ETF share price closely mirrors the value of the underlying securities. In addition, ETF shares can incorporate information before it is reflected in the prices of the underlying securities, creating an information link through which ETFs can propagate shocks to them via this arbitrage activity. In this paper, we provide novel evidence using a rich regulatory dataset of Irish ETF holdings on how ETFs can affect the underlying equities' and corporate debt securities' liquidity, price and volatility through information links.

By looking at both equities and corporate debt securities, we are able to assess the differential effects of ETFs on the two asset classes. Since equities are exchange-traded, we expect them to be more accessible compared to the over-the-counter-traded corporate debt securities and hence easier to conduct arbitrage with ETF shares due to lower transaction costs. As such, ETFs will form stronger information links with equities compared to corporate debt securities, so the effects will be stronger on the former compared to the latter.

Consistent with this hypothesis, we find that ETFs can propagate liquidity shocks to the underlying equities but not to the corporate debt securities, because when ETFs lose their informativeness when they become more illiquid the information link with equities breaks down, propagating the liquidity shock to them. In contrast, ETF illiquidity has no effect on the underlying corporate debt securities' liquidity due to the absence of a strong information link. In addition, we find that ETF price demand shocks can have a substantial effect on the underlying equities' prices as information gets incorporated, but the effect on the underlying corporate debt securities' prices is much smaller, consistent with our hypothesis that the information link is stronger in the former compared to the latter. Finally, we document an increase of the underlying equities' volatility as ETFs' ownership of them increases, but an equivalent reduction of volatility of the underlying corporate debt securities for an increase of ETF ownership. This suggests that as ETFs invest more in the equities, they facilitate arbitrage activity which strengthens the information link and increases activity in the equities, leading to higher volatility. In contrast, higher ETF ownership of corporate debt securities encourages investors to migrate to ETFs because of their higher accessibility, weakening the information link and decreasing the volatility of the corporate debt securities.

Our findings shed light on how ETFs affect the underlying securities differently according to their accessibility. In addition, the effects can occur across multiple aspects of the underlying securities including their liquidity, price and volatility, and understanding the underlying mechanism driving these effects is crucial in providing a holistic view of how ETFs can propagate shocks.

1. Introduction

Turmoil in one market can affect other markets when assets are linked through information channels, creating comovements in liquidity, prices and volatility. Information links between assets exist when investors use information from one asset to infer the price of another. However, these links can trigger contagion effects when investors mistakenly believe that idiosyncratic shocks in one asset reveal information about the other asset, increasing volatility (King and Wadhwani, 1990), or when a liquidity dry-up in one asset makes investors unable to reliably price the other, propagating liquidity shocks (Cespa and Foucault, 2014).

In this paper, we provide novel evidence for this transmission mechanism by looking at the Irish exchange-traded funds (ETFs) and their underlying equities and corporate debt securities using a proprietary dataset from the Central Bank of Ireland. ETF shares can be traded intra-daily on an exchange, which attracts high-frequency trading. In addition, ETF shares and the underlying securities are subject to arbitrage activity that exploits price differences, which creates a link between the two markets. Finally, ETFs as index products emphasize the systematic factor of the underlying assets, so they can become the key mover of the index as well as the underlying assets if they dominate the markets (Bhattacharya and O'Hara (2020), Glosten et al. (2020)). As a result, ETFs provide a natural testing ground to assess the effects of information links between markets.

We investigate the effects of ETFs on the underlying equities' and corporate debt securities' liquidity, returns and volatility. By looking at both equities and debt securities, we are able to assess how the ETF effects differ according to the unique characteristics of each market. Specifically, we argue that the strength of the information link and the resulting degree of liquidity, returns and volatility comovement depends on the accessibility of the underlying markets, i.e. the ease with which investors can trade in them. This is because a higher accessibility incentivises market participants to actively trade the underlying assets in order to exploit arbitrage opportunities with

ETF shares, which strengthens the information link. On the other hand, a lower accessibility of the underlying markets incentivises market participants to migrate to the ETFs to satisfy their liquidity demand, which weakens the information link and the transmission of shocks between markets.

We expect ETFs to form stronger information links with the underlying exchange-traded equities than with the underlying over-the-counter-traded (OTC) corporate debt securities due to the lower accessibility of the latter arising from the significant search and transaction costs of OTC markets (Vayanos and Wang, 2007). The difference in accessibility between equities and corporate debt securities has been further amplified by the post-crisis banking regulations which have caused a deterioration of corporate debt markets' liquidity due to the dealers' contraction of market-making activities (Bessembinder et al. (2018), Bao et al. (2018)), while equity markets' liquidity has recovered from the crisis period (Anand et al., 2013). Even though there certainly exist individual equities that are less liquid than corporate debt securities, the findings of these papers suggest that there is a significant overall divergence in the liquidity of these two markets which affects their accessibility.

While the literature on ETFs and underlying equities has found strong effects on price and liquidity comovements due to arbitrage (Da and Shive (2015), Agarwal et al. (2017), Ben-David et al. (2018)), the literature on ETFs and underlying corporate debt securities has shown theoretically and empirically that the illiquid and hard-to-access nature of these securities imposes limits to arbitrage and can lead to persistent price distortions (Pan and Zeng (2017), Bhattacharya and O'Hara (2018)). This weakens the information link, leading liquidity traders to migrate from the underlying corporate debt securities to the ETFs which offer lower transaction and adverse selection costs (Dannhauser, 2017). As a result, we hypothesize that the ETFs will have stronger effects on the underlying equities than on the corporate debt securities.

We start our empirical analysis by testing whether ETFs propagate liquidity shocks to the underlying securities based on the theoretical framework of Cespa and Foucault (2014). The authors argue that the presence of information links can lead to illiquidity contagion when investors are unable to price one asset due to the illiquidity of the other, citing the dry-up of liquidity of ETFs during the 2010 Flash Crash as an example. Arbitrageurs can dampen this effect by providing capital to both assets but their absence can exacerbate contagion. We find that a one-standard-deviation increase in ETF bid-ask spreads is associated with a next-day increase in equities' bid-ask spreads of 0.8 basis points (bps). However, debt securities' bid-ask spreads are not affected by a change of ETF bid-ask spreads. Furthermore, we find that arbitrage activity plays an active role in dampening illiquidity contagion between ETFs and equities as predicted by Cespa and Foucault (2014) due to the provision of arbitrage capital in both assets, but not so between ETFs and debt securities where arbitrageurs are less active.

The results are consistent with the two market setups outlined in the theoretical framework: in a fully interconnected market the liquidity of the two assets is interrelated through the information channel, while in a fully segmented market there are no liquidity spillovers. These two theoretical setups represent the opposite ends of a spectrum, and our empirical results suggest that ETFs lie within these two extremes. On the one hand, ETFs and the underlying equities are closer to the fully interconnected market where investors use information from each asset to price the other (strong information link). On the other hand, ETFs and the underlying corporate debt securities are closer to the fully segmented market where investors largely ignore the information present in asset prices because it can be noisy, so a deterioration of liquidity in one asset does not have cross-asset effects (weak information link).

In the second part of our analysis, we investigate the effect of information links on the underlying securities' returns. If the assets are closely linked, the theoretical framework of Cespa and Foucault (2014) predicts that demand shocks in one asset can have an impact on the price of the other asset. However, when the markets are fully segmented such an effect does not exist. We estimate regressions of daily security returns on security-level ETF flows, which proxy the expected demand for each security caused by aggregate additional ETF demand, in order to establish whether changes in ETF demand affect the underlying returns. We find that a one-standard-deviation increase of lagged ETF flows is associated with a 69 bps increase of daily stock returns but only 0.4 bps increase of daily debt securities' returns. The results show that ETF demand affects equities' prices more strongly than debt securities' prices, consistent with our argument of a strong information link between ETFs and equities but a weak one between ETFs and corporate debt securities.

Finally, we look at the effect of ETF ownership, i.e. the fraction of the securities' market capitalisation owned by ETFs, on the strength of the information link and the volatility of the securities. If ETF ownership facilitates arbitrage between ETFs and the underlying securities, the two markets become more interconnected by strengthening the information link and the activity on the underlying securities increases, with a subsequent increase in their volatility (Ben-David et al., 2018). In contrast, if the underlying assets are hard-to-trade, a higher ETF ownership is associated with a migration of liquidity traders from the underlying assets to the ETFs due to the latter's higher accessibility (Dannhauser, 2017). This segments the markets by weakening the information link and lowers activity in the underlying assets and hence their volatility (Grossman, 1989). We thus expect that higher ETF ownership is associated with an increase of equities' volatility but a decrease of debt securities' volatility. Consistent with this prediction, we find that a one-standard-deviation increase in ETF ownership is associated with an increase of equities' volatility by 1% of a standard deviation but a decrease of debt securities' volatility by 1% of a standard deviation.

Against the backdrop of a significant growth of ETFs over the past decade, our results have important policy implications. First, the accessibility of the underlying markets and by extension the ease with which investors can exploit arbitrage opportunities is an important factor in determining whether ETFs can propagate shocks to them. Second, ETFs can affect the assets they invest in via various channels including their liquidity, price as well as volatility, and understanding the underlying mechanism that drives the effects on these channels is crucial in providing a holistic view of how ETFs can transmit shocks.

Our paper contributes to the literature on links between assets. King and Wadhwani (1990) argue that asset prices are linked via information channels, which partly explains the simultaneous drop of assets during the market crash of 1987. Duffie et al. (2014) show theoretically the existence of strategic complementarities in information acquisition in segmented markets. They also show cross-class externalities, including pure learning externalities between linked markets. Rahi and Zigrand (2009) show theoretically how arbitrageurs integrate markets by exploiting asset mispricings, which is the way ETFs and underlying markets propagate information.

We also contribute to the literature on illiquidity contagion. When arbitrage capital becomes scarce, prices can deviate significantly from their fundamental values (Hu et al., 2013). We empirically test the theoretical predictions of Cespa and Foucault (2014) by investigating whether liquidity shocks can propagate from ETFs to the underlying securities, and the role of arbitrageurs in mitigating this effect.

Finally, our paper is related to the growing literature on ETFs and how they affect asset prices. Da and Shive (2015) document the positive association between ETF ownership and return comovement of underlying stocks due to arbitrage while Agarwal et al. (2017) document a similar pattern with the liquidity of the underlying stocks. Evans et al. (2017) find a positive relationship between ETF ownership and bid-ask spreads of the underlying stocks. Bhattacharya and O'Hara (2018) show theoretically that ETFs investing in hard-to-access markets such as corporate bonds can transmit noise and form weak information links while Pan and Zeng (2017) show theoretically and empirically that the illiquidity of corporate bond markets limits arbitrage opportunities with ETFs. Glosten et al. (2020) show that ETFs increase the informational efficiency of the underlying stocks by incorporating systematic information faster and transmitting it to the underlying securities. Ben-David et al. (2018) argue that ETF ownership increases the non-fundamental volatility of underlying stocks, adding an undiversifiable risk which increases their risk premia. In contrast, Agapova and Volkov (2018) find that ETF ownership reduces the volatility of the underling bond securities. We propose the presence of information links as an explanation behind the different effects of ETFs to the underlying equities and corporate debt securities.

The rest of the paper is structured as follows. Section 2 provides the ETF institutional details, section 3 describes the data used in this study, section 4 presents the empirical results and section 5 concludes.

2. Institutional Details

ETFs are investment companies that track the performance of a securities index, similarly to index mutual funds. The main difference is that ETFs allow their shares to be traded continuously intra-daily on an exchange. ETFs can replicate an index either by holding all or a representative sample of the securities comprising the index (physical ETFs) or by entering into derivatives contracts, usually total return swaps, where the return on the index is swapped with the return on another benchmark (synthetic ETFs). Other types of ETFs also exist, such as leveraged ETFs that attempt to deliver a multiple of the index return, and inverse ETFs that seek to deliver the inverse of the index return.

ETF shares can be created and redeemed like other open-ended funds. However, this can only be done by a select group of market participants called Authorised Participants (APs), who have a legal agreement with the ETFs to trade directly with them. The APs do this because they can profit from bid-ask spreads on the secondary market and by creating and redeeming ETF shares when their value deviates from the net asset value (NAV) of the underlying securities. The trading of shares between the APs and the ETF in exchange for the underlying securities or cash constitutes the primary market. Other market participants trade ETF shares on an exchange or over-the-counter through market makers (which can also be APs), which constitutes the secondary market. The secondary market trading allows the ETF share price to move even in the absence of fund flows.

The continuous trading of ETF shares ensures that their price does not deviate significantly from the underlying NAV. If there is a positive demand shock on the ETF shares such that they trade at a premium relative to the NAV, the APs can buy the underlying securities at the NAV, submit them to the ETF in order to create new ETF shares on the primary market and sell them for a profit on the secondary market. This creates an upward pressure on the underlying securities and a downward pressure on the ETF shares until prices converge. Conversely, when a negative demand shock causes the ETF shares to trade at a discount relative to the NAV, the APs can buy the shares on the secondary market and redeem them on the primary market in exchange for the underlying securities, which can be subsequently sold at the NAV for a profit. This creates a downward pressure on the underlying securities and positive pressure on the ETF shares. ETF arbitrage can also be achieved by other market participants on the secondary market by buying the inexpensive asset and short selling the expensive one until prices converge for a profit. Of course, this mechanism is not a pure arbitrage opportunity as prices may not converge fast enough. Through this arbitrage mechanism, demand shocks on ETF shares can propagate to the underlying securities.

While there also exist other products such as index mutual funds that contain systematic information regarding the underlying assets, and could also create information links with them, ETFs are unique in allowing continuous trading of their shares rather than only once per day. Hence, they are more suitable for speculative and hedging purposes which fosters the creation of information links.

3. Data

We use a proprietary dataset on Irish-domiciled ETFs and their holdings from the Central Bank of Ireland (CBI) database.[1] All funds report their holdings to the CBI on a quarterly basis and are categorised internally into the following types according to their investment strategy: equity, bond, hedge, mixed, money market (MM), real estate (RE) and other funds. An ETF can belong to any of these types, although in practice the vast majority are either equity or bond funds. As of September 2018, there were 694 Irish-domiciled ETFs holding a total of EUR 424 billion of assets, which is around two-thirds of the total held by euro area ETFs. The majority of these assets was invested in physical ETFs (EUR 374 billion), and EUR 271 billion was invested in equities while EUR 116 billion was invested in bonds. Together, equities and bonds comprised more than 90% of total assets held by Irish ETFs.

Our equities sample covers the period from March 2014, the earliest available date for which reliable data exist, up to December 2018. We have a total of 16,937 equities held by Irish ETFs at various points during the sample period. We use Bloomberg to download data for each stock. We obtain daily data on price, shares outstanding, volume, percentage bid-ask spread, total assets, book value of debt, revenue, cost of goods sold, as well as bid and ask percentage volumes to identify the direction of trades. We use this data to construct the main variables as well as controls.

Moving to corporate debt securities, we obtain daily data on their individual characteristics from IHS Markit including mid price, bid-asks-spread, maturity date, number of trades and volume. Credit ratings data is obtained from the CBI database and is mapped to a scale from 1 (highest rating) to 22 (lowest rating) following Dimitrov et al. (2015). The sample covers the period from January 2016, the earliest available date in the Markit database, up to December 2018. We have a total of 22,534 corporate debt securities held by the Irish ETFs during this period. We provide

[1] `https://www.centralbank.ie/docs/default-source/statistics/statistical-reporting-requirements/fund-administrators/money-market-and-investment-funds-return-(mmif)/mmif-notes-on-compilation.pdf`

Table 1: Amounts invested by Irish ETFs in equities and debt securities per country of security in EUR million

Country	Amount	% of total assets	% of country market cap
Panel A: Equities			
US	136,150	50.16	0.49
UK	18,324	6.75	0.59
Japan	18,020	6.64	0.34
Germany	15,438	5.69	0.82
France	12,501	4.06	0.55
Panel B: Corporate debt securities			
US	23,006	34.96	0.11
UK	6,923	10.52	0.25
France	6,474	9.84	0.32
Netherlands	6,393	9.72	0.41
Germany	3,572	5.43	0.23

details on the construction of the variables in Appendix A.

Table 1 reports the amounts invested in equities and debt securities by Irish ETFs per country of security as of September 2018. Only the five largest countries according to amount invested are shown. The table also reports the amount held in each country as a percentage of total assets and the amount invested as a percentage of the total market capitalisation (equities) or amount outstanding (debt securities) of the country. Amounts are in EUR million.

As can be seen, 50% of total assets held in equities or EUR 136 billion are invested in US equities, followed by UK, Japan, Germany and France with smaller fractions. Irish ETFs hold on average 0.5% of the total market capitalisation of each country. For corporate debt securities, 35% of total assets or EUR 23 billion are invested in US debt, followed by UK, France, the Netherlands and Germany. On average, Irish ETFs hold 0.3% of the total amount outstanding of debt issued by entities in each country.

Table 2 provides summary statistics for the variables that we use in the analysis. Panels A and B present summary statistics for the monthly equities and debt securities samples while panels C and D present the statistics for the daily equities and debt securities samples.

Looking at Panel A, we observe that the daily stock volatility, calculated as the standard deviation of daily stock returns over the period of a month, has a maximum value in our sample of 94.914%. Such high values reflect the fact that we include all the equities holdings and do not confine our analysis to US equities which are not as volatile.[2] ETF ownership of equities ranges from −0.170% (a negative value indicates short positions) to 23.200%, almost a quarter of a stock's market capitalisation. Hedge funds have the largest short position (−21.097%) while equity funds have the largest long position (38.580%).

In Panel B, daily volatility of corporate debt securities can similarly take high values up to 99.410%, although the highest ETF ownership is lower compared to equities at 14.649%. In addition, there are no short ETF positions on debt securities as observed by the minimum value of ETF ownership of 0%. Hedge funds again have the largest short position (−4.504%) while bond funds have the largest long position (27.383%), both smaller than the corresponding positions for equities.

Moving to Panel C, the stock-level ETF flows, a weighted average of the daily flows occurring in all ETFs investing in each security, take values from EUR −42.522 million to EUR 45.851 million. Stock-level ETF bid-ask spreads range from −0.003% to 2.789%. ETF mispricing, the difference between ETFs' share price and the underlying portfolio's NAV, ranges from EUR −0.001 million to EUR 1246.021 million.

In Panel D, corporate debt ETF flows range from EUR −5.928 million to EUR 5.737 million, lower than for equities which reflects the reduced arbitrage activity. ETF bid-ask spreads range from 0% to 0.842% while ETF mispricing ranges from EUR 0 to EUR 138.017 million.

[2]We have repeated our analysis by removing the outliers of the variables of interest to ensure that our analysis is robust.

Table 2: Summary statistics for the variables used in the study. Columns denote, respectively, the name of the variable, number of observations, mean value, standard deviation, minimum value, 25th, 50th, 75th percentiles and maximum value.

Variable	N	Mean	SD	Min	25th	50th	75th	Max
Panel A: Monthly sample (equities)								
Daily stock volatility (%)	602,961	2.245	1.583	0.000	1.377	1.900	2.665	94.914
ETF ownership (%)	615,173	0.071	0.193	−0.170	0.000	0.000	0.061	23.200
Equity fund ownership (%)	615,173	0.327	0.774	−1.826	0.000	0.026	0.330	38.580
Hedge fund ownership (%)	615,173	0.021	0.208	−21.097	0.000	0.000	0.000	9.700
MM fund ownership (%)	615,173	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mixed fund ownership (%)	615,173	0.027	0.199	−0.522	0.000	0.000	0.003	20.998
Bond fund ownership (%)	615,173	0.000	0.030	−0.081	0.000	0.000	0.000	9.507
Other fund ownership (%)	615,173	0.003	0.140	−0.302	0.000	0.000	0.000	30.300
RE fund ownership (%)	615,173	0.003	0.114	−0.009	0.000	0.000	0.000	18.827
Log(Market Cap (EUR million))	615,173	8.033	9.161	−3.577	5.824	6.793	7.831	12.982
1/Price	615,173	3.086	108.677	0.000	0.051	0.152	0.744	20000.000
Amihud ratio (%)	615,173	0.001	0.103	0.000	0.000	0.000	0.000	44.289
Bid-ask spread (%)	613,940	0.603	1.883	0.004	0.142	0.258	0.522	179.605
Book-to-market	615,173	1.494	2.603	0.000	0.591	1.004	1.539	140.345
Past 12-month returns (%)	615,173	15.404	70.624	−99.957	−15.034	5.358	30.240	8487.126
Gross profitability	615,173	0.163	0.331	−69.369	0.030	0.083	0.206	9.465

Table 2: Continued

Variable	N	Mean	SD	Min	25th	50th	75th	Max
Panel B: Monthly sample (corporate debt)								
Daily debt volatility (%)	548,609	0.278	0.539	0.000	0.079	0.177	0.350	99.410
ETF ownership (%)	548,609	0.216	0.558	0.000	0.000	0.000	0.107	14.649
Equity fund ownership (%)	548,609	0.001	0.023	0.000	0.000	0.000	0.000	5.761
Hedge fund ownership (%)	548,609	0.014	0.201	−4.504	0.000	0.000	0.000	18.981
MM fund ownership (%)	548,609	0.008	0.233	0.000	0.000	0.000	0.000	19.599
Mixed fund ownership (%)	548,609	0.072	0.352	−0.109	0.000	0.000	0.000	16.263
Bond fund ownership (%)	548,609	0.570	1.552	−0.510	0.000	0.000	0.333	27.383
Other fund ownership (%)	548,609	0.026	0.227	−2.280	0.000	0.000	0.000	15.992
RE fund ownership (%)	548,609	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Credit rating	539,598	7.985	3.730	1.000	6.000	8.000	10.000	22.000
Time to maturity	548,609	9.619	13.760	0.000	2.875	5.249	9.032	99.775
Age	548,609	4.057	3.579	0.019	1.561	3.129	5.353	32.493
Log(Amount outstanding (EUR million))	547,638	20.392	20.115	11.025	19.807	20.125	20.592	23.588
Bond zero	548,609	0.659	0.380	0.000	0.273	0.857	1.000	1.000
Log(Trades)	548,609	4.014	4.885	0.000	0.000	1.609	3.989	8.889
Amihud ratio (%)	303,413	0.000	0.000	0.000	0.000	0.000	0.000	0.170
Bid-ask spread (%)	548,609	0.534	2.863	0.000	0.186	0.351	0.639	198.020
Turnover	547,638	0.003	0.385	0.000	0.000	0.000	0.002	132.124
Log(Average trade size)	303,413	13.238	13.360	6.908	11.986	12.794	13.462	15.425

Table 2: Continued

Variable	N	Mean	SD	Min	25th	50th	75th	Max
Panel C: Daily sample (equities)								
Security-level ETF flows (EUR million)	12,780,975	0.003	0.109	−42.522	0.000	0.000	0.000	45.851
Security-level ETF bid-ask spread (%)	12,780,975	0.008	0.028	−0.003	0.000	0.001	0.005	2.789
Ret$[t, t-1]$ (%)	12,240,572	0.038	2.713	−99.327	−1.104	−0.004	1.098	450.291
Log(Market Cap (EUR million))	12,780,975	8.036	9.169	−3.699	5.823	6.794	7.833	13.048
1/Price	12,780,975	3.061	108.908	0.000	0.050	0.149	0.724	25000.000
Amihud ratio (%)	12,204,888	0.001	0.393	0.000	0.000	0.000	0.000	781.250
Bid-ask spread (%)	12,675,871	0.564	1.706	0.004	0.140	0.255	0.510	197.563
Book-to-market	12,665,539	1.499	3.845	0.000	0.589	1.001	1.536	1872.746
Past 12-month returns (%)	12,780,975	15.688	70.851	−99.957	−14.909	5.510	30.556	8643.620
Gross profitability	12,662,938	0.164	0.360	−69.369	0.030	0.084	0.207	31.230
Order imbalance	12,580,958	−0.006	0.330	−158.702	−0.046	−0.002	0.035	209.540
ETF mispricing (EUR million)	12,780,975	0.201	5.448	−0.001	0.000	0.001	0.009	1246.021
FD	11,322,719	0.751	0.159	0.116	0.651	0.854	0.874	0.937

Table 2: Continued

Variable	N	Mean	SD	Min	25th	50th	75th	Max
Panel D: Daily sample (corporate debt)								
Security-level ETF flows (EUR million)	12,137,327	0.001	0.034	−5.928	0.000	0.000	0.000	5.737
Security-level ETF bid-ask spread (%)	12,137,327	0.001	0.004	0.000	0.000	0.000	0.001	0.842
Ret$[t, t-1]$ (%)	12,913,942	0.004	1.334	−99.507	−0.082	0.000	0.085	1934.592
Credit rating	12,549,641	7.971	3.717	1.000	6.000	8.000	10.000	22.000
Time to maturity	12,913,942	9.626	13.711	0.000	2.932	5.284	9.079	100.005
Age	12,913,942	3.958	3.574	0.000	1.457	3.047	5.270	32.554
Log(Amount outstanding (EUR million))	12,891,097	20.390	20.115	11.025	19.807	20.119	20.592	23.588
Bond zero	12,913,942	0.661	0.379	0.000	0.273	0.864	1.000	1.000
Log(Trades)	12,913,942	4.003	4.890	0.000	0.000	1.609	3.970	9.325
Amihud ratio (%)	5,977,483	0.000	0.018	0.000	0.000	0.000	0.000	10.988
Bid-ask spread (%)	12,913,942	0.542	2.894	0.000	0.192	0.356	0.649	198.020
Turnover	12,891,097	0.004	0.574	0.000	0.000	0.000	0.002	298.550
Log(Average trade size)	7,090,874	13.266	13.381	6.908	12.007	12.825	13.495	15.425
ETF mispricing (EUR million)	12,137,327	0.058	0.754	0.000	0.000	0.001	0.007	138.017
FD	12,342,449	0.807	0.113	0.053	0.765	0.874	0.874	0.937

4. Empirical analysis

4.1. ETFs and illiquidity contagion

We begin our analysis by investigating the potential of ETFs to transmit liquidity shocks to the underlying securities. We test our hypothesis that the magnitude of illiquidity spillover will be stronger from ETFs to the underlying equities than to the underlying debt securities using the theoretical framework of Cespa and Foucault (2014). The authors argue that the magnitude of illiquidity spillover is determined by the strength of the information link, the presence of arbitrage capital and the dealers' risk tolerance. While the framework allows for the possibility that the underlying securities could also affect ETFs, we focus on one side of the relationship because ETFs attract high-frequency trading and thus can incorporate information faster than the underlying securities, especially when the latter are hard-to-trade (Aramonte and Avalos, 2020). This can result in ETFs affecting the underlying securities rather than the other way around (Bhattacharya and O'Hara, 2018).

Our measure of liquidity is the bid-ask spread. We define the security-level ETF bid-ask spread as follows:

$$ETF\ bid - ask\ spread_{i,t} = \sum_{j=1}^{J} w_{i,j,t} bid - ask\ spread_{j,t} \tag{1}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the portfolio of ETF j in day t, and $bid - ask\ spread_{j,t}$ is the bid-ask spread of ETF j in day t. The weights do not sum to 1 for each security but they represent the "information proportionality" of each ETF. As an example, a hypothetical ETF that invests 99% of its assets on a specific security should have a price that closely mirrors that of the security, and investors would assign a large weight on its informativeness. As a result, the ETF's bid-ask spread is weighted accordingly to capture the impact of a decrease of its liquidity on the underlying security's liquidity due to the breakdown of the information link, depending on how informative the ETF's price is.

We proxy the degree of arbitrage activity by constructing the security-level ETF mispricing variable following Ben-David et al. (2018).

$$ETF\ mispricing_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t} \mid Mispricing_{j,t} \mid}{MktCap_{i,t}} \tag{2}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the portfolio of ETF j in day t, $AUM_{j,t}$ are the total assets of ETF j in day t, and $MktCap_{i,t}$ is the market capitalisation of security i in day t. $\mid Mispricing_{j,t} \mid$ denotes the difference between the ETF j's share price and NAV divided by its share price in day t. Larger mispricing indicates the absence of arbitrageurs in the market that exploit the price differences. We create a dummy variable that takes the value of 1 for values of ETF mispricing higher than the 90th percentile and interact it with the ETF bid-ask spread in order to estimate the effect of high mispricing (absence of arbitrageurs) on illiquidity contagion.

In addition, we measure dealers' risk tolerance by using the VIX index for equities and the MOVE index for debt securities as a proxy of market stress. As Cespa and Foucault (2014) argue, higher market stress implies a lower risk tolerance of dealers, which strengthens illiquidity contagion. Similarly to mispricing, we create dummy variables that take the value of 1 for values of the corresponding variables higher than the 90th percentile and interact them with the ETF bid-ask spread.

In our regressions we include security and day fixed effects, and standard errors are clustered at the country and day levels. Furthermore, we include a number of lagged control variables. For equities we include, following Ben-David et al. (2018), market capitalisation, the inverse of the stock price as a measure of size, the Amihud (2002) measure and the bid-ask-spread to account for persistence in illiquidity. In addition, we include a number of control variables that are standard predictors of returns, including the book-to-market ratio, the cumulative past 12-month returns and gross profitability. Finally, we include order imbalance which is calculated as the euro value of buy minus sell trades divided by market capitalisation. For debt securities we include as control variables the credit rating, time to maturity, the percentage of days in a month that the security didn't trade (Bond zero), the bid-ask spread and the security's turnover defined as the average daily volume over a month as a percentage of its amount outstanding. We omit the amount outstanding because it remains constant for each security and is collinear with the security fixed effects.[3]

The results for equities and debt securities are presented in Tables 3 and 4 respectively. We use lagged ETF bid-ask spread in order to avoid simultaneity bias as both assets could influence each other. In column (1) we present results without including the stress index (VIX or MOVE) or mispricing interactions, in column (2) we include the stress index interaction, in column (3) we include the mispricing interaction while in column (4) we include all interactions.

Looking at the full model specification for equities in column (4) of Table 3, we document an increase of 0.8 bps of bid-ask spreads for a one-standard-deviation increase of ETF bid-ask spreads, which provides evidence for illiquidity contagion. However, this relationship is dampened during times of high market stress as indicated by the negative VIX interaction coefficient of -0.4 bps. This is in contrast to the theoretical predictions of Cespa and Foucault (2014), who argue that low dealer risk tolerance (as proxied by high values of the VIX index) exacerbates illiquidity contagion. A potential driver behind this result could be that the dealers who specialise in one asset and propagate liquidity shocks when the informativeness of the other asset evaporates coexist with dealers who trade both assets for hedging purposes.[4] These dealers could then shift their capital

[3]In unreported results we also included as control variables the Amihud measure of illiquidity, the logarithm of the number of trades per month and the average trade size over a month. However, the inclusion of these controls greatly reduces our sample size due to limited observations of these variables. We ran the regressions in the reduced sample with and without these controls and the results for our variables of interest did not change. As such, we do not include them in the final regressions in order to preserve our sample size.

[4]In their model, Cespa and Foucault (2014) assume that dealers specialise in one asset, so they infer its price using information from the other asset (cross-asset learning). This enables illiquidity contagion when the informativeness of the other asset evaporates and excludes cross-market hedging effects when dealers diversify their risk by trading both assets.

to the underlying securities when ETFs become illiquid, dampening illiquidity contagion. On the other hand, the ETF mispricing interaction coefficient is positive 0.7 bps which shows that the absence of arbitrageurs exacerbates illiquidity contagion. This is in line with Cespa and Foucault (2014), since arbitrageurs dampen illiquidity contagion by providing capital to both assets.

Moving to debt securities, we do not observe a significant relationship between ETF bid-ask spreads and debt securities' bid-ask spreads.[5] Furthermore, ETF mispricing is not significant, indicating that arbitrage activity does not affect illiquidity contagion between ETFs and debt securities. The MOVE interaction coefficient is similarly insignificant. Overall, the findings indicate the presence of a strong information link between ETFs and equities which increases the interconnectedness of the market and the potential for illiquidity contagion, but a weaker link between ETFs and debt securities which segments the market and reduces contagion effects.

In Appendix B we provide results using alternative thresholds of 70th and 80th percentiles for the stress indices and ETF mispricing. While the results for debt securities remain insignificant (Tables B3 - B4), we observe that for equities ETF mispricing is insignificant when we use the 70th percentile (Table B1) and marginally significant when we use the 80th percentile (Table B2), and its magnitude increases as the threshold becomes higher. This result shows that illiquidity contagion between ETFs and equities is directly linked to the level of arbitrage activity: as arbitrageurs increasingly exit the market, the proportion of illiquidity contagion attributed to this phenomenon also increases. Furthermore, as can be seen from the descriptive statistics of ETF bid-ask spread for the different thresholds of ETF mispricing using the daily equities sample in Table B5, higher ETF mispricing is associated with higher average ETF bid-ask spreads. This provides further evidence to our argument that the information link is strengthened through arbitrage and relies on the liquidity of the markets. The exit of arbitrageurs from the markets associated with liquidity evaporation in one asset results in larger illiquidity contagion effects due to them.

[5] All our results hold if we also include government debt securities which represent only a small fraction of total debt securities that Irish ETFs invest in.

Finally, looking at the VIX interaction coefficients, we observe that they become smaller in absolute magnitude as the threshold becomes higher, from -0.9 bps and -0.6 bps to -0.4 bps for the 70th, 80th and 90th percentiles respectively. This indicates that the ability of dealers to dampen illiquidity contagion through cross-asset trading becomes increasingly impaired due to their decreasing risk tolerance and withdrawal from the market as it becomes more volatile.

4.2. ETF flows and returns

The previous results indicate that ETFs and equities form strong information links while ETFs and debt securities form weak ones, with implications for liquidity commonality. In this section we assess the effects of ETFs on the underlying securities' returns in order to further analyse the implications of the information channel. Cespa and Foucault (2014) predict that in a fully interconnected market demand shocks to one asset can affect the price of the other while in a fully segmented market they do not. Hence, we expect a stronger effect of ETF demand shocks on equities' returns than on debt securities' returns. As explained in section 2, the APs can transmit demand shocks to the underlying securities through the creation and redemption of ETF shares. Following Ben-David et al. (2018), we construct the security-level ETF flows variable which acts as a proxy for ETF demand shocks:

$$ETF\ flows_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} Flows_{j,t}}{Volume_{i,t}} \tag{3}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the portfolio of ETF j in day t, $Flows_{j,t}$ is the percentage change in shares outstanding of ETF j in day t and $Volume_{i,t}$ is the volume of security i in day t. $Flows_{j,t}$ and $Volume_{i,t}$ are multiplied by their corresponding prices in order to obtain euro security-level ETF flows.

First, we regress stock returns in day t on the lagged flows and the same control variables as before using the entire sample. The results are presented in Table 5, with column (5) containing

Table 3: ETF bid-ask spreads and stock bid-ask spreads. This table reports estimates from OLS regressions of daily stock bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	0.012***	0.013***	0.006***	0.008***
	(3.072)	(3.383)	(2.864)	(3.078)
ETF bid-ask spread (%) * VIX ($t-1$)		−0.004***		−0.004***
		(−4.994)		(−4.032)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.007***	0.007***
			(5.774)	(5.720)
log(MktCap ($t-1$))	−0.002***	−0.002***	−0.002***	−0.002***
	(−3.389)	(−3.388)	(−3.384)	(−3.384)
1/Price ($t-1$)	0.000	0.000	0.000	0.000
	(0.834)	(0.849)	(0.836)	(0.849)
Amihud ratio ($t-1$)	0.111***	0.111***	0.111***	0.111***
	(2.796)	(2.797)	(2.797)	(2.797)
Bid−ask spread ($t-1$)	0.576***	0.576***	0.576***	0.576***
	(15.478)	(15.477)	(15.481)	(15.481)
Book-to-market ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(10.348)	(9.330)	(10.348)	(9.508)
Past 12-month returns ($t-1$)	0.000*	0.000*	0.000*	0.000*
	(1.830)	(1.807)	(1.819)	(1.770)
Gross profitability ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.418)	(−0.345)	(−0.385)	(−0.235)
Order imbalance ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.655)	(−0.620)	(−0.656)	(−0.642)
Ret[$t-1, t-2$]	0.000	0.000	0.000	0.000
	(0.352)	(0.353)	(0.353)	(0.354)
Intercept	0.018***	0.018***	0.018***	0.018***
	(3.712)	(3.712)	(3.707)	(3.707)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,411,458	11,411,458	11,411,458	11,411,458
R^2	0.566	0.566	0.566	0.566

Table 4: ETF bid-ask spreads and debt securities bid-ask spreads. This table reports estimates from OLS regressions of daily debt securities bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	−0.000	−0.000	−0.001	−0.001
	(−1.482)	(−1.523)	(−1.348)	(−1.376)
ETF bid-ask spread (%) * MOVE ($t-1$)		0.000		0.000
		(0.259)		(0.254)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.000	0.000
			(1.063)	(1.058)
Credit rating ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(3.674)	(3.674)	(3.675)	(3.675)
Bid-ask spread ($t-1$)	0.954***	0.954***	0.954***	0.954***
	(57.249)	(57.249)	(57.249)	(57.249)
Time to maturity ($t-1$)	0.000	0.000	0.000	0.000
	(1.067)	(1.067)	(1.067)	(1.067)
Bond zero ($t-1$)	−0.000***	−0.000***	−0.000***	−0.000***
	(−3.044)	(−3.045)	(−3.045)	(−3.045)
Turnover ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.664)	(−0.668)	(−0.562)	(−0.566)
Ret$[t-1, t-2]$	−0.057**	−0.057**	−0.057**	−0.057**
	(−2.416)	(−2.416)	(−2.416)	(−2.416)
Intercept	−0.001	−0.001	−0.001	−0.001
	(−0.984)	(−0.984)	(−0.984)	(−0.984)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,698,589
R^2	0.961	0.961	0.961	0.961

the full model specification which we refer to. As can be seen, there is a statistically significant effect of lagged ETF flows on stock returns, with a one-standard-deviation change in ETF flows being associated with a 69 bps change in stock returns.

Next, we interact ETF flows with the VIX index, which proxies dealers' risk tolerance. We expect a negative relationship because during times of stress when the risk tolerance of the dealers weakens, the information link breaks down lowering the effect of ETF demand shocks. Consistent with this prediction, we find a negative interaction coefficient of -30.3 bps. In addition, we interact ETF flows with ETF mispricing, which proxies the absence of arbitrageurs, and we expect a negative coefficient as these market participants propagate price pressure due to a demand shock from one asset to the other according to Cespa and Foucault (2014). Hence, their absence would subdue the relationship between ETF flows and underlying securities' returns. Indeed, the interaction coefficient is negative -15.6 bps.[6]

Finally, we consider how the different levels of financial development of each country in our sample affect the relationship between ETF flows and underlying securities' returns. Specifically, we use data from the IMF Financial Development Index[7] in order to assess whether the unique market characteristics of each country have an effect on our results. The data measure various aspects of development of financial institutions and financial markets and are reported in annual frequency, ranging from 0 (lowest development) to 1 (highest development). We have experimented with all the variables in the dataset and our results are broadly consistent. Hence, we report results for the overall country financial development, including financial markets and institutions. We create the dummy variable FD that takes the value of 1 if financial development is higher than the median value of development of all countries in our sample and 0 otherwise and interact

[6] In order to exclude the possibility that the results are driven by indexing effects, i.e. the exclusion and inclusion of stocks in the major indices, we have repeated the analysis by removing all observations in the months when all major index rebalances occur. The results remain the same.

[7] `https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B`

it with ETF flows.[8] The latest available year available for the IMF data is 2016, so we assume constant FD values as of 2016 since there is little variation across time.[9] As can be seen, the interaction is negative and significant (-53.3 bps) implying that equities in countries with high financial development are less affected by ETF demand shocks. This is intuitive as such markets are more efficient so the equities' prices better reflect their fundamental values from other sources of information and do not rely on ETFs as much.

In Table C1 provided in Appendix C we repeat the analysis for the five largest countries individually in order to assess whether the effects are consistent across different countries. Irish ETFs do not have a significant effect on US equities, which is intuitive given the size of the US stock market and the relatively small size of Irish ETFs. The only country with significant effects is France (4 bps).

Next, we repeat the analysis for corporate debt securities and present the results in Table 6, with the full model specification again in column (5). We document a small increase in securities' returns of 0.4 bps for a one-standard-deviation increase of lagged ETF flows. The interaction of ETF flows with the MOVE index is insignificant, indicating that the relationship is not affected by a change in the dealers' risk tolerance, which is intuitive given the segmented nature of the market. Including the interaction of ETF flows and mispricing shows that the absence of arbitrageurs completely negates the effect of ETF flows on the underlying securities' returns, with a negative coefficient of -0.4 bps, which combined with the MOVE result indicates that ETF demand shock propagation in this market is driven by arbitrageurs rather than dealers. Finally, the FD interaction is insignificant, which is likely due to the fact that corporate debt securities are OTC traded and are not tied to specific geographical markets, irrespectively of their issuing country. Looking at the five largest individual countries in Table C2 in Appendix C, we don't observe any significant effect of Irish ETF flows on them.

[8] We have also performed the analysis by considering the mean development. The results are robust.

[9] Repeating the analysis for equities from 2014 to 2016 with time-varying FD values yields similar results.

Overall, the results in both the full sample and the individual countries suggest that ETF demand shocks have a much larger effect on equities' than debt securities' returns, consistent with the view that the former form stronger information links with ETFs than the latter.

4.3. ETF ownership and volatility

In this section we investigate whether ETF ownership affects the strength of information links and the underlying securities' volatility. The introduction of a correlated asset in the market such as ETFs can increase trading activity in both assets due to arbitrage opportunities, hence increasing their volatility (Ben-David et al., 2018) and making the two markets more interconnected. On the other hand, if the new asset is more liquid and accessible, it may cause a migration of liquidity traders to the new asset which reduces activity in the illiquid asset and hence its volatility (Grossman, 1989), segmenting the two markets.

We follow Ben-David et al. (2018) and define ETF ownership of security i in month t as the sum of the value of holdings by all ETFs investing in the security, divided by the security's market capitalisation at the end of the month:

$$ETF\ ownership_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t}}{MktCap_{i,t}} \tag{4}$$

where J is the set of ETFs that hold the security i, $w_{i,j,t}$ is the weight of security i in the portfolio of ETF j in month t, $AUM_{j,t}$ are the total assets of ETF j in month t, and $MktCap_{i,t}$ is the market capitalisation of security i in month t. In other words, this variable is the fraction of the total market capitalisation of the security held by Irish ETFs.

Our dependent variable is the daily volatility of security i, calculated by estimating the standard deviation of daily security returns for each month. We include the usual control variables, as well as the percentage of the total stock market capitalisation held by each fund type except for money market funds which have no equity holdings. Finally, we include three lags of volatility to account

Table 5: ETF flows and stock returns. This table reports estimates from OLS regressions of daily stock returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. FD is a dummy variable taking the value of 1 for values higher than its median. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Ret$[t, t-1]$				
	(1)	(2)	(3)	(4)	(5)
ETF flows $(t-1)$ (%)	0.003***	0.003***	0.149***	0.479***	0.690***
	(3.393)	(3.799)	(12.877)	(3.199)	(3.853)
ETF flows (%) * VIX $(t-1)$		−0.224***			−0.303***
		(−3.383)			(−11.393)
ETF flows (%) * ETF mispricing $(t-1)$			−0.147***		−0.156***
			(−12.255)		(−10.142)
ETF flows (%) * FD $(t-1)$				−0.477***	−0.533***
				(−3.186)	(−3.083)
log(MktCap $(t-1)$)	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(−18.480)	(−18.451)	(−18.481)	(−18.481)	(−18.436)
1/Price $(t-1)$	0.000	0.000	0.000	0.000	0.000
	(1.461)	(1.462)	(1.460)	(1.460)	(1.071)
Amihud ratio $(t-1)$	0.291***	0.291***	0.291***	0.291***	0.291***
	(2.997)	(2.996)	(2.997)	(2.996)	(2.997)
Bid-ask spread $(t-1)$	−0.001	−0.001	−0.001	−0.001	−0.001
	(−0.171)	(−0.169)	(−0.178)	(−0.169)	(−0.172)
Book-to-market $(t-1)$	−0.000*	−0.000*	−0.000*	−0.000*	−0.000*
	(−1.828)	(−1.823)	(−1.828)	(−1.827)	(−1.793)
Past 12-month returns $(t-1)$	0.000**	0.000**	0.000**	0.000**	0.000**
	(2.255)	(2.244)	(2.255)	(2.254)	(2.220)
Gross profitability $(t-1)$	0.000	0.000	0.000	0.000	0.000
	(1.163)	(1.160)	(1.163)	(1.162)	(1.163)
Order imbalance $(t-1)$	0.000*	0.000*	0.000*	0.000*	0.000*
	(1.759)	(1.758)	(1.758)	(1.762)	(1.762)
Ret$[t-1, t-2]$	−0.016*	−0.016*	−0.016*	−0.016*	−0.016*
	(−1.845)	(−1.845)	(−1.845)	(−1.846)	(−1.847)
Intercept	0.019***	0.019***	0.019***	0.019***	0.019***
	(18.730)	(18.701)	(18.738)	(18.730)	(18.710)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	11,415,066	11,415,066	11,415,066	11,415,066	11,415,066
R^2	0.092	0.092	0.092	0.092	0.093

Table 6: ETF flows and debt securities returns. This table reports estimates from OLS regressions of daily debt securities returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 90th percentile. FD is a dummy variable taking the value of 1 for values higher than its median. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:			$\text{Ret}[t, t-1]$		
	(1)	(2)	(3)	(4)	(5)
ETF flows $(t-1)$ (%)	0.001	0.000	0.004***	0.004*	0.004**
	(0.835)	(0.706)	(9.539)	(1.915)	(2.566)
ETF flows (%) * MOVE $(t-1)$		0.001			0.000
		(1.648)			(0.269)
ETF flows (%) * ETF mispricing $(t-1)$			−0.004***		−0.004***
			(−9.846)		(−9.692)
ETF flows (%) * FD $(t-1)$				−0.003	0.001
				(−1.413)	(0.349)
Credit rating $(t-1)$	0.000	0.000	0.000	0.000	0.000
	(0.302)	(0.301)	(0.302)	(0.473)	(0.478)
Bid-ask spread $(t-1)$	0.002	0.002	0.002	0.002	0.002
	(0.731)	(0.731)	(0.730)	(0.729)	(0.728)
Time to maturity $(t-1)$	0.000	0.000	0.000	0.000	0.000
	(1.089)	(1.084)	(1.089)	(0.811)	(0.944)
Bond zero $(t-1)$	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(−5.159)	(−5.159)	(−5.159)	(−5.076)	(−5.367)
Turnover $(t-1)$	0.000	0.000	0.000	0.000	0.000
	(0.391)	(0.318)	(0.026)	(0.231)	(0.033)
$\text{Ret}[t-1, t-2]$	−0.045***	−0.045***	−0.045***	−0.045***	−0.045***
	(−3.013)	(−3.013)	(−3.013)	(−3.002)	(−3.002)
Intercept	−0.000	−0.000	−0.000	−0.000	−0.000
	(−0.479)	(−0.479)	(−0.479)	(−0.555)	(−0.510)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,161,001	11,161,001
R^2	0.020	0.020	0.020	0.020	0.020

for volatility clustering.

The results of the OLS regressions of daily stock volatility on ETF ownership are presented in Table 7. We report results for the entire sample as well as for the largest countries individually. We use fixed effects at the security and month levels as before. Standard errors are double-clustered at the country and month levels when the entire sample is used, and at the security and month levels when individual countries are examined.

Looking at the results for the entire sample in column (All), we establish a positive relationship between ETF ownership and stock volatility. Specifically, for a one-standard-deviation increase of ETF ownership, stock volatility increases by 1% of a standard deviation. Examining individual countries, we infer that Irish ETFs do not affect the volatility of US stocks, but have a significant effect for UK (3.4%), Japanese (3.2%), German (5.3%) and French (7.0%) stocks.

In Table 8 we present the results of the same analysis using debt securities. In contrast to equities, we find that a one-standard-deviation increase of ETF ownership corresponds to a decrease of debt securities' volatility by 1% of a standard deviation. However, looking at individual countries, none of the five largest markets have a significant reduction of volatility although all coefficients are negative.

Our contrasting results for equities and debt securities corroborate the findings of the literature (Agapova and Volkov (2018), Ben-David et al. (2018)) and provide further evidence for the links between ETFs and the underlying securities. Increased arbitrage activity between ETFs and equities strengthens the information link between the two markets and increases demand for the equities and their volatility. However, increased ETF ownership in debt securities incentivises liquidity traders to migrate from the debt securities to the ETFs (Dannhauser, 2017), which segments the markets by weakening the information link and lowers the underlying securities' volatility.

Table 7: ETF ownership and stock volatility. This table reports estimates from OLS regressions of daily stock volatility on ETF ownership and control variables. In the (All) column estimates using the entire sample are presented, and in subsequent columns estimates are presented for the largest countries individually. The dependent variable and ETF ownership are standardised. Standard errors are double-clustered at the country and month levels for column (All), and security and month levels for subsequent columns. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Daily volatility (t)					
	(All)	(US)	(UK)	(Japan)	(Germany)	(France)
ETF ownership ($t-1$)	0.010**	0.005	0.034***	0.032**	0.053***	0.070***
	(2.091)	(0.885)	(3.290)	(2.111)	(2.973)	(3.239)
log(MktCap ($t-1$))	−0.206**	−0.338***	−0.231***	−0.025	−0.067	−0.207**
	(−2.553)	(−12.097)	(−3.369)	(−0.537)	(−1.097)	(−2.145)
1/Price ($t-1$)	0.000	0.017***	−0.003	−0.159***	1.398**	1.804***
	(1.154)	(3.706)	(−0.703)	(−4.180)	(2.265)	(3.584)
Amihud ratio ($t-1$)	34.677**	151.919	−4.369*	−518200.397***	297.454	−14395.311
	(2.158)	(0.638)	(−1.859)	(−6.058)	(0.168)	(−0.814)
Bid-ask spread ($t-1$)	0.033***	0.011***	0.064*	0.269***	−0.038	0.060
	(3.674)	(2.980)	(1.716)	(3.234)	(−1.343)	(1.068)
Book-to-market ($t-1$)	0.007	0.003	0.012	0.003	0.003	0.000
	(1.105)	(0.205)	(0.841)	(0.554)	(0.189)	(0.011)
Past 12-month returns ($t-1$)	0.081**	0.002	−0.026	0.128***	0.152***	0.071
	(2.556)	(0.254)	(−1.043)	(7.142)	(2.708)	(1.115)
Gross profitability ($t-1$)	0.008	0.057	−0.163*	0.097	0.040	−0.234
	(0.616)	(1.602)	(−1.937)	(0.892)	(0.281)	(−0.776)
Equity fund ownership ($t-1$)	0.471	2.156*	1.376	0.806	0.135	2.721
	(0.723)	(1.803)	(1.518)	(1.488)	(0.079)	(1.324)
Hedge fund ownership ($t-1$)	−5.933*	−10.963***	3.559	0.476	5.183	−23.706**
	(−1.865)	(−4.351)	(0.899)	(0.232)	(1.447)	(−2.303)
Mixed fund ownership ($t-1$)	−0.013	−11.345***	10.333***	0.510	0.183	6.730
	(−0.011)	(−3.110)	(2.745)	(0.271)	(0.041)	(0.728)
Bond fund ownership ($t-1$)	−4.326	−10.642**	105.404**	114.190*	−77.760	−1330.493***
	(−0.633)	(−2.482)	(2.347)	(1.924)	(−0.459)	(−3.298)
Other fund ownership ($t-1$)	2.937	0.422	−0.029	14.249	1.777**	122.218
	(1.169)	(0.230)	(−0.007)	(0.931)	(2.183)	(1.371)
RE fund ownership ($t-1$)	−0.641	5.163	−24.177	54.889**	11.004	−16.749
	(−1.050)	(1.036)	(−1.472)	(2.183)	(0.516)	(−0.367)
Daily volatility ($t-1$)	0.212***	0.105***	0.185***	0.188***	0.177***	0.052
	(6.218)	(7.821)	(3.266)	(8.033)	(5.684)	(1.453)
Daily volatility ($t-2$)	0.101***	0.055***	0.065*	0.082***	0.084***	0.063**
	(11.100)	(3.509)	(1.678)	(7.424)	(4.057)	(2.165)
Daily volatility ($t-3$)	0.098***	0.088***	0.014	0.154***	0.093***	0.077*
	(7.463)	(4.803)	(0.473)	(10.901)	(5.813)	(1.989)
Intercept	1.367**	2.165***	1.587***	0.077	0.373	1.541*
	(2.446)	(11.491)	(3.158)	(0.245)	(0.812)	(1.900)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	601,694	127,019	27,357	84,924	9,071	6,440
R^2	0.476	0.482	0.459	0.514	0.496	0.411

Table 8: ETF ownership and debt securities volatility. This table reports estimates from OLS regressions of daily debt securities volatility on ETF ownership and control variables. In the (All) column estimates using the entire sample are presented, and in subsequent columns estimates are presented for the largest countries individually. The dependent variable and ETF ownership are standardised. Standard errors are double-clustered at the country and month levels for column (All), and security and month levels for subsequent columns. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Daily volatility (t)					
	(All)	(US)	(UK)	(France)	(Netherlands)	(Germany)
ETF ownership ($t-1$)	−0.010**	−0.008*	−0.010	−0.019*	−0.004	−0.044
	(−2.411)	(−1.857)	(−0.697)	(−1.758)	(−0.377)	(−1.464)
Credit rating ($t-1$)	0.009	0.023*	−0.006	0.066	−0.020	−0.019
	(0.729)	(1.962)	(−0.180)	(1.269)	(−0.767)	(−0.792)
Time to maturity ($t-1$)	0.002	−0.000	0.129***	0.004***	−0.001***	0.000
	(0.113)	(−0.085)	(5.745)	(3.066)	(−3.218)	(0.000)
Bond zero ($t-1$)	−0.030	−0.040	−0.183*	−0.075	−0.041	1.642
	(−1.303)	(−1.006)	(−1.717)	(−0.511)	(−0.359)	(1.481)
Bid-ask spread ($t-1$)	3.224*	10.322**	29.906***	53.877***	3.891	89.145***
	(2.018)	(2.557)	(2.949)	(4.556)	(0.669)	(3.439)
Turnover ($t-1$)	0.005	−0.082	3.962	4.131	0.378	34.298***
	(0.358)	(−1.196)	(0.990)	(0.479)	(0.076)	(3.005)
Equity fund ownership ($t-1$)	−6.153**	−9.953	41.955***	−77.322***	16.056	−5.792
	(−2.106)	(−1.470)	(4.549)	(−3.338)	(0.863)	(−0.324)
Hedge fund ownership ($t-1$)	0.454	−3.802*	−0.578	84.710***	−8.056	5.060
	(0.195)	(−1.951)	(−0.108)	(3.183)	(−0.690)	(0.785)
MM fund ownership ($t-1$)	0.744*	1.050	0.677	0.668	0.509	6.528**
	(1.759)	(1.096)	(0.498)	(0.494)	(1.212)	(2.534)
Mixed fund ownership ($t-1$)	0.262	−0.082	−3.355*	−1.400	1.331	−2.892
	(0.576)	(−0.114)	(−1.734)	(−0.733)	(1.310)	(−0.356)
Bond fund ownership ($t-1$)	−0.116	−0.223	0.358	0.109	−0.113	0.035
	(−0.593)	(−0.729)	(0.630)	(0.097)	(−0.251)	(0.038)
Other fund ownership ($t-1$)	0.018	0.579	−1.262	−1.174	0.089	−3.108
	(0.016)	(0.372)	(−0.493)	(−0.384)	(0.028)	(−0.402)
Daily volatility ($t-1$)	0.214***	0.262***	0.075	0.219***	0.060	0.181
	(8.738)	(5.751)	(1.550)	(4.766)	(1.084)	(0.830)
Daily volatility ($t-2$)	0.073	0.144***	0.052	0.023	0.029	0.017
	(1.645)	(3.546)	(1.395)	(1.033)	(0.897)	(0.730)
Daily volatility ($t-3$)	0.065	0.129***	0.040	0.024	0.025	0.016
	(1.073)	(3.674)	(1.301)	(0.951)	(0.435)	(1.051)
Intercept	−0.100	−0.241**	−1.343***	−0.665	0.174	−1.832
	(−0.640)	(−2.330)	(−4.410)	(−1.669)	(0.660)	(−1.686)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	513,292	244,729	41,948	33,161	29,464	14,549
R^2	0.501	0.590	0.466	0.633	0.301	0.655

5. Conclusion

Our paper provides novel empirical evidence to the information links arising between ETFs and their underlying securities. We investigate two underlying asset classes, equities and corporate debt securities and document the heterogeneous effects of ETFs on their liquidity, returns and volatility.

First, we find that Irish ETFs propagate liquidity shocks to the underlying equities but not to the debt securities. Second, we document a stronger effect of ETF flows on the underlying equities' returns than the underlying debt securities' returns. Third, while higher ETF ownership increases equities' volatility, it decreases debt securities' volatility.

We argue that these effects are due to a strong information link formed between ETFs and equities but a much weaker one between ETFs and debt securities. This link arises due to the accessibility of equity markets which facilitates the exploitation of arbitrage opportunities. However, the hard-to-trade nature of the debt securities inhibits arbitrage, resulting in a weaker information link.

As a result, we document illiquidity contagion occurring between ETFs and equities but not between ETFs and debt securities, since a breakdown of the information link when ETFs become illiquid would affect equities more severely than debt securities. Similarly, the effect of ETF flows on equities' returns is much stronger than the one on debt securities' returns as equities are strongly affected by ETF demand shocks through arbitrage but debt securities are less so. Finally, equities' volatility increases due to increased arbitrage activity as ETF ownership increases, but debt securities' volatility decreases as investors satisfy their liquidity demand through the (more liquid) ETFs.

Our results indicate that ETFs can affect the underlying markets in different ways depending on their accessibility. From a policy perspective, this has important implications in understanding the extent to which ETFs can propagate shocks as well as their effects on different aspects of the underlying assets including their liquidity, price and volatility. Future research should investigate more directly the role of market accessibility and arbitrageurs in driving the results presented in this paper, and examine the effects during a period of severe market stress when ETFs face large redemption shocks from APs.

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Appendix A. Variable Definitions

Table A1: Variable Definitions

Variable	Description	Source
Panel A: Equities		
Daily stock volatility	Standard deviation of daily stock returns within a month.	Bloomberg
ETF ownership	The sum of positions held by ETFs in the stock at each quarter, divided by the stock's daily market capitalisation. We assume that positions remain constant throughout the quarter.	CBI data and Bloomberg
Equity/Hedge/MMF/ Mixed/Bond/Other/ RE fund ownership	The sum of positions held by ETFs of each fund type in the stock at each quarter, divided by the stock's daily market capitalisation. We assume that positions remain constant throughout the quarter.	CBI data and Bloomberg
Log(Market Cap)	The natural logarithm of the product of the stock's shares outstanding and daily price.	Bloomberg
1/Price	The inverse of the daily stock price.	Bloomberg
Amihud ratio	The average of the absolute stock daily return divided by the euro volume within a month.	Bloomberg
Bid-ask spread	The midpoint bid-ask spread.	Bloomberg
Book-to-market	Book value of assets / Market value of assets, where Market value of assets = Market capitalisation + Book value of debt.	Bloomberg
Past 12-month returns	The cumulative daily stock returns of the past 12 months.	Bloomberg
Gross profitability	(Revenue - Cost of goods sold) / Book value of assets, following Novy-Marx (2013).	Bloomberg
Security-level ETF flows	The stock-level weighted ETF flows divided by the stock's volume.	CBI data and Bloomberg
Security-level ETF bid-ask spread	The stock-level weighted ETF bid-ask spreads.	CBI data and Bloomberg
Security-level ETF mispricing	The stock-level weighted ETF mispricing.	CBI data and Bloomberg
Ret$[y, x]$	The cumulative stock return from date x to y.	Bloomberg
Order imbalance	(Ask % volume - Bid % volume) $\times$ Volume / Shares outstanding.	Bloomberg

Table A1: Continued

Variable	Description	Source
Panel B: Debt securities		
Daily debt volatility	Standard deviation of daily debt security returns within a month.	Markit
ETF ownership	The sum of positions held by ETFs in the debt security at each quarter, divided by the security's amount outstanding. We assume that positions remain constant throughout the quarter.	CBI data
Equity/Hedge/MMF/ Mixed/Bond/Other/ RE fund ownership	The sum of positions held by ETFs of each fund type in the debt security at each quarter, divided by the security's amount outstanding. We assume that positions remain constant throughout the quarter.	CBI data
Credit rating	The debt security's credit rating in a scale of 1 (highest rating) to 22 (lowest rating) following Dimitrov et al. (2015).	CBI data
Time to maturity	The debt security's time to maturity in years.	Markit
Age	The debt security's age in years.	CBI data
Log(Amount outstanding)	The natural logarithm of the debt security's amount outstanding.	CBI data
Bond zero	The fraction of days in a month that the debt security did not trade.	Markit
Log(Trades)	The natural logarithm of the debt security's number of trades per month.	Markit
Amihud ratio	The average of the absolute debt security's daily return divided by the euro volume within a month.	Markit
Bid-ask spread	The midpoint bid-ask spread.	Markit
Turnover	The debt security's average daily volume over a month divided by the amount outstanding.	CBI data and Markit
Log(Average trade size)	The natural logarithm of the debt security's average daily volume over a month divided by the average number of trades over a month.	Markit
Security-level ETF flows	The debt security-level weighted ETF flows divided by the security's volume.	CBI data, Bloomberg and Markit
Security-level ETF bid-ask spread	The debt security-level weighted ETF bid-ask spreads.	CBI data, Bloomberg and Markit
Security-level ETF mispricing	The debt security-level weighted ETF mispricing.	CBI data, Bloomberg and Markit
Ret$[y, x]$	The cumulative debt security's return from date x to y.	Markit

Appendix B. Illiquidity contagion alternative thresholds

Table B1: ETF bid-ask spreads and stock bid-ask spreads. This table reports estimates from OLS regressions of daily stock bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 70th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	0.012***	0.017***	0.011**	0.017**
	(3.072)	(3.226)	(2.268)	(2.592)
ETF bid-ask spread (%) * VIX ($t-1$)		−0.009***		−0.009***
		(−3.049)		(−3.014)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.001	0.001
			(0.654)	(0.351)
log(MktCap ($t-1$))	−0.002***	−0.002***	−0.002***	−0.002***
	(−3.389)	(−3.393)	(−3.388)	(−3.392)
1/Price ($t-1$)	0.000	0.000	0.000	0.000
	(0.834)	(0.842)	(0.839)	(0.844)
Amihud ratio ($t-1$)	0.111***	0.111***	0.111***	0.111***
	(2.796)	(2.797)	(2.797)	(2.797)
Bid-ask spread ($t-1$)	0.576***	0.576***	0.576***	0.576***
	(15.478)	(15.466)	(15.478)	(15.466)
Book-to-market ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(10.348)	(10.057)	(10.351)	(10.106)
Past 12-month returns ($t-1$)	0.000*	0.000*	0.000*	0.000*
	(1.830)	(1.833)	(1.827)	(1.829)
Gross profitability ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.418)	(−0.441)	(−0.416)	(−0.440)
Order imbalance ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.655)	(−0.656)	(−0.655)	(−0.657)
Ret[$t-1, t-2$]	0.000	0.000	0.000	0.000
	(0.352)	(0.355)	(0.352)	(0.355)
Intercept	0.018***	0.018***	0.018***	0.018***
	(3.712)	(3.717)	(3.711)	(3.716)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,411,458	11,411,458	11,411,458	11,411,458
R^2	0.566	0.566	0.566	0.566

Table B2: ETF bid-ask spreads and stock bid-ask spreads. This table reports estimates from OLS regressions of daily stock bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. VIX and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 80th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	0.012***	0.014***	0.009***	0.012***
	(3.072)	(3.438)	(2.659)	(3.007)
ETF bid-ask spread (%) * VIX ($t-1$)		−0.006***		−0.006***
		(−3.991)		(−3.792)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.004***	0.003***
			(3.321)	(2.873)
log(MktCap ($t-1$))	−0.002***	−0.002***	−0.002***	−0.002***
	(−3.389)	(−3.390)	(−3.387)	(−3.388)
1/Price ($t-1$)	0.000	0.000	0.000	0.000
	(0.834)	(0.842)	(0.839)	(0.846)
Amihud ratio ($t-1$)	0.111***	0.111***	0.111***	0.111***
	(2.796)	(2.797)	(2.797)	(2.797)
Bid-ask spread ($t-1$)	0.576***	0.576***	0.576***	0.576***
	(15.478)	(15.473)	(15.478)	(15.474)
Book-to-market ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(10.348)	(9.777)	(10.351)	(8.801)
Past 12-month returns ($t-1$)	0.000*	0.000*	0.000*	0.000*
	(1.830)	(1.832)	(1.825)	(1.827)
Gross profitability ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.418)	(−0.434)	(−0.408)	(−0.425)
Order imbalance ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.655)	(−0.655)	(−0.656)	(−0.656)
Ret$[t-1, t-2]$	0.000	0.000	0.000	0.000
	(0.352)	(0.354)	(0.352)	(0.354)
Intercept	0.018***	0.018***	0.018***	0.018***
	(3.712)	(3.714)	(3.710)	(3.712)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,411,458	11,411,458	11,411,458	11,411,458
R^2	0.566	0.566	0.566	0.566

Table B3: ETF bid-ask spreads and debt securities bid-ask spreads. This table reports estimates from OLS regressions of daily debt securities bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 70th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	−0.000	−0.000	−0.002	−0.002
	(−1.482)	(−1.594)	(−1.385)	(−1.409)
ETF bid-ask spread (%) * MOVE ($t-1$)		0.000		0.000
		(1.081)		(1.066)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.001	0.001
			(1.224)	(1.219)
Credit rating ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(3.674)	(3.674)	(3.675)	(3.675)
Bid-ask spread ($t-1$)	0.954***	0.954***	0.954***	0.954***
	(57.249)	(57.249)	(57.249)	(57.249)
Time to maturity ($t-1$)	0.000	0.000	0.000	0.000
	(1.067)	(1.067)	(1.067)	(1.067)
Bond zero ($t-1$)	−0.000***	−0.000***	−0.000***	−0.000***
	(−3.044)	(−3.044)	(−3.045)	(−3.044)
Turnover ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.664)	(−0.714)	(−0.530)	(−0.580)
Ret$[t-1, t-2]$	−0.057**	−0.057**	−0.057**	−0.057**
	(−2.416)	(−2.416)	(−2.416)	(−2.416)
Intercept	−0.001	−0.001	−0.001	−0.001
	(−0.984)	(−0.984)	(−0.984)	(−0.984)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,698,589
R^2	0.961	0.961	0.961	0.961

Table B4: ETF bid-ask spreads and debt securities bid-ask spreads. This table reports estimates from OLS regressions of daily debt securities bid-ask spreads on ETF bid-ask spreads and control variables. ETF bid-ask spreads are divided by market capitalisation and standardised. MOVE and ETF mispricing are dummy variables taking the value of 1 for values higher than their corresponding 80th percentile. Standard errors are double-clustered at the country and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Bid-ask spread (t)			
	(1)	(2)	(3)	(4)
ETF bid-ask spread ($t-1$) (%)	−0.000	−0.000	−0.001	−0.001
	(−1.482)	(−1.562)	(−1.392)	(−1.424)
ETF bid-ask spread (%) * MOVE ($t-1$)		0.000		0.000
		(0.808)		(0.797)
ETF bid-ask spread (%) * ETF mispricing ($t-1$)			0.001	0.001
			(1.254)	(1.237)
Credit rating ($t-1$)	0.000***	0.000***	0.000***	0.000***
	(3.674)	(3.674)	(3.675)	(3.675)
Bid-ask spread ($t-1$)	0.954***	0.954***	0.954***	0.954***
	(57.249)	(57.249)	(57.249)	(57.249)
Time to maturity ($t-1$)	0.000	0.000	0.000	0.000
	(1.067)	(1.067)	(1.067)	(1.067)
Bond zero ($t-1$)	−0.000***	−0.000***	−0.000***	−0.000***
	(−3.044)	(−3.044)	(−3.045)	(−3.045)
Turnover ($t-1$)	−0.000	−0.000	−0.000	−0.000
	(−0.664)	(−0.694)	(−0.551)	(−0.581)
Ret$[t-1, t-2]$	−0.057**	−0.057**	−0.057**	−0.057**
	(−2.416)	(−2.416)	(−2.416)	(−2.416)
Intercept	−0.001	−0.001	−0.001	−0.001
	(−0.984)	(−0.984)	(−0.984)	(−0.984)
Day fixed effects	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes
Observations	11,698,589	11,698,589	11,698,589	11,698,589
R^2	0.961	0.961	0.961	0.961

Table B5: Descriptive statistics of ETF bid-ask spread for different ETF mispricing thresholds using daily equities sample

	Security-level ETF bid-ask spread (%)		
ETF mispricing threshold	70th percentile	80th percentile	90th percentile
Mean	0.025	0.031	0.035
SD	0.062	0.069	0.076
Min	−0.003	−0.003	−0.003
Max	2.512	2.512	2.512
Observations	3,850,844	2,569,245	1,287,646

Appendix C. Country-level ETF flows and security returns

Table C1: ETF flows and country stock returns. This table reports estimates from OLS regressions of daily stock returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. Standard errors are double-clustered at the security and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from March 2014 to December 2018.

Dependent Variable:	Ret$[t, t-1]$				
	(US)	(UK)	(Japan)	(Germany)	(France)
ETF flows $(t-1)$ (%)	0.002	0.007	0.002	0.000	0.040**
	(0.154)	(0.199)	(0.982)	(0.095)	(2.437)
log(MktCap $(t-1)$)	−0.002***	−0.003***	−0.003***	−0.002***	−0.001***
	(−5.316)	(−9.027)	(−11.414)	(−6.904)	(−2.748)
1/Price $(t-1)$	0.000***	0.000**	−0.000	0.003	0.005***
	(3.226)	(2.020)	(−0.677)	(0.799)	(3.528)
Amihud ratio $(t-1)$	13.600	0.022	−917.714***	−9.423	−131.042
	(0.606)	(0.259)	(−2.721)	(−1.212)	(−0.690)
Bid-ask spread $(t-1)$	−0.005	−0.025**	0.030	−0.078***	−0.005
	(−0.975)	(−2.107)	(1.127)	(−4.174)	(−0.359)
Book-to-market $(t-1)$	−0.000	0.000	0.000***	0.000***	0.000
	(−1.426)	(0.797)	(2.588)	(3.664)	(0.798)
Past 12-month returns $(t-1)$	−0.000	0.000	0.000***	0.000**	0.000
	(−1.488)	(0.975)	(2.931)	(2.293)	(1.188)
Gross profitability $(t-1)$	0.002***	0.001***	0.004***	0.001	0.004**
	(2.805)	(2.909)	(6.162)	(0.581)	(2.394)
Order imbalance $(t-1)$	0.000	−0.001***	−0.000	0.005***	−0.001
	(1.107)	(−4.950)	(−0.605)	(6.472)	(−1.361)
Ret$[t-1, t-2]$	−0.020***	−0.012*	−0.006	−0.065***	0.013*
	(−3.186)	(−1.931)	(−1.475)	(−9.301)	(1.912)
Intercept	0.011***	0.019***	0.021***	0.018***	0.009**
	(5.372)	(8.699)	(10.999)	(6.470)	(2.278)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,463,258	518,077	1,598,692	183,816	132,885
R^2	0.132	0.174	0.263	0.203	0.181

Table C2: ETF flows and country debt securities returns. This table reports estimates from OLS regressions of daily debt securities returns on ETF flows and control variables. ETF flows are divided by market capitalisation and standardised. Standard errors are double-clustered at the security and day levels. t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The sample covers the period from January 2016 to December 2018.

Dependent Variable:	Ret$[t, t-1]$				
	(US)	(UK)	(France)	(Netherlands)	(Germany)
ETF flows $(t-1)$ (%)	0.002*	0.000	−0.000	0.000	−0.000
	(1.896)	(0.675)	(−0.022)	(0.647)	(−1.078)
Credit rating $(t-1)$	0.000	−0.000	0.000	0.000	0.000
	(0.413)	(−1.178)	(0.500)	(0.920)	(1.542)
Bid-ask spread $(t-1)$	0.008	0.127*	−0.001	−0.013*	−0.079*
	(1.321)	(1.799)	(−0.086)	(−1.708)	(−1.685)
Time to maturity $(t-1)$	0.000**	0.000***	−0.000***	−0.000***	0.000
	(2.493)	(5.988)	(−8.896)	(−3.497)	(0.000)
Bond zero $(t-1)$	−0.000***	−0.000**	−0.000	0.000	−0.000
	(−3.220)	(−2.300)	(−0.903)	(0.154)	(−0.258)
Turnover $(t-1)$	−0.000	−0.004	−0.015	−0.002	0.010
	(−0.431)	(−0.514)	(−1.582)	(−0.545)	(0.699)
Ret$[t-1, t-2]$	−0.085***	−0.041*	0.001	−0.006	0.000
	(−6.538)	(−1.930)	(0.331)	(−0.583)	(0.041)
Intercept	−0.000	−0.002***	0.000	−0.001	0.000
	(−0.430)	(−4.973)	(0.343)	(−0.823)	(0.448)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Security fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5,493,436	957,172	752,837	663,507	357,513
R^2	0.067	0.124	0.080	0.044	0.097