Liquidity Clienteles, Correlated Demand and Excess Comovement of Exchange-Traded Fund Returns

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ABSTRACT

This study shows that return differences between Exchange-Traded Funds and their underlying portfolio Net Asset Values – which contain no fundamental risk – comove excessively across ETFs. Excess comovements are strong across ETFs in matching investment styles, but insignificant across opposite styles. The degree of return comovements is positively related to proxies for correlated demand shocks, flows to institutional ETF owners in matching styles, ETF liquidity and measures of aggregate market uncertainty. These results agree with a clientele based explanation, whereby investors with high liquidity needs and correlated demand self-select into ETFs due to their high perceived liquidity.

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1 Introduction

In frictionless markets with rational investors, the price of a security will equal its fundamental value, and any comovement in returns must be due to comovement in fundamentals. However, in economies with frictions or with irrational investors, and in which there are limits to arbitrage, comovement in returns may be partially delinked from fundamentals giving rise to what is known as *excess comovement.* Several theoretical models build on the price impact of correlated investor demand to explain the existence of excess comovement[2].

In this paper I analyze excessive return comovements by using a set of twin-based securities. The return differential between an Exchange Traded Fund (ETF) and its underlying portfolio of securities (NAV) contains no fundamental risk but the two components are subject to different sources of transient price pressure. Any remaining comovement among ETF-NAV return differentials can therefore be considered excessive. This approach is in sharp contrast to prior studies that test the theoretical predictions of excess comovement by studying return patterns around "exogenous" events, or by relying on a CAPM type model to filter out the fundamental component of returns[3].

My conjecture that ETF returns comove excessively with one another starts with the idea that ETFs attract a clientele of high-turnover investors that impound non-fundamental demand shocks to ETF prices at a higher rate relative to the securities in their baskets. This liquidity clientele effect is motivated by Amihud and Mendelson's (1987) model, which predicts that short-horizon investors self-select into more liquid assets, such as ETFs.

ETFs are generally perceived to be more liquid than their underlying securities. Broman and Shum (2014) show that ETF spreads are, on average, smaller relative to their corresponding underlying portfolio spreads, and turnover is higher. This may happen because market making in portfolios (ETFs) is less risky due to lower adverse selection costs compared with individual securities. In addition, ETFs provide a "hidden" layer of liquidity via the share creation mechanism[4] that allows institutional investors to access liquidity via the primary market for

[2] see Barberis and Shelifer (2003), Barberis, Shleifer and Wurgler (2005) and Greenwood and Thesmar (2011).
[3] e.g. Barberis, Shleifer and Wurgler (2005), Prinsky and Wang (2006), Green and Hwang (2009), Kumar, Page and Spalt (2013)
[4] The creation/redemption process is an arbitrage mechanism that allows select institutional investors to trade on price differentials between the ETF and the NAV by creating (or redeeming) ETF shares in exchange for the underlying basket of securities.

ETFs whenever it is more cost efficient to transact in the underlying assets. This option-like feature of ETFs implies that the lower bound for their liquidity is determined by the liquidity of the ETF in the secondary market, and the underlying securities in the primary market. Retail investors will also find the liquidity of ETFs desirable since they have lower expense ratios than even their cheapest mutual fund counterparts.

Clientele differences combined with *correlated demand* among ETFs can give rise to excess comovement in returns. This can happen if high-turnover investors restrict their trades to the ETF space, forming a preferred habitat as in Barberis, Shleifer and Wurgler (2005). Even if such investors do not trade solely in ETFs, excess comovement can exist as long as ETF investors have correlated liquidity needs (Greenwood and Thesmar, 2011). The correlated demand of style investors can also give rise to excess comovements (as in Barberis and Shleifer, 2003); they may find ETFs attractive not only because of their high liquidity, but also because managers cater to investor demand by offering funds tied directly to popular investment styles, and because it is generally easier and cheaper to engage in style investing in ETFs.

Excess comovement of ETF returns implies that ETFs are exposed to an additional source of non-fundamental risk, particularly in the short-run. In this case the investors who may be the most attracted to ETFs (high-turnover investors) are also the ones that will suffer the most from this additional source of risk. Recent survey evidence by Greenwich Associates (2013) confirms that ETFs are increasingly being used by institutional investors for short-term strategies such as tactical asset allocation, as a short-term liquidity vehicle for hedging, for transition management and cash equitization.

To make my tests as clean as possible, I focus on a sample 163 physically replicated ETFs that are traded in the U.S. and that track only U.S. equity indices. These funds have over $530 billion in total assets as of 12/2012. In contrast to related studies on twin securities; cross-listed stocks (e.g. Gagnon and Karolyi, 2010), international closed-end funds (Bodurtha, Kim and Lee, 1995), or even domestic closed-end funds (Lee, Shleifer and Thaler, 1991), my sample is unlikely to be affected by either non-synchronicity or stale pricing. The former is not a concern since ETFs and their underlying securities are traded in the same time-zone. Stale pricing is unlikely to occur because both ETFs and their underlying securities are generally actively traded.

To preview my results, I find strong comovement patterns among ETF-NAV returns within the small- and large-cap styles, as well as among the value- and growth styles. The valuation-based comovements are interesting because there are no significant differences in liquidity characteristics between value and growth funds suggesting that correlated trading at the style level may help explain these comovement patterns. To illustrate the economic impacts, a 1 Std. Dev. increase in the own-style mispricing factor is on average associated with an increase in weekly ETF-NAV return differentials by 9.3 to 11.7 bps (or 61 to 70 % of the Std. Dev. of ETF-NAV returns) for value funds (smallest impact) to small-cap funds (biggest impact). Beyond the size and valuation styles, there are no remaining comovements across ETFs in opposite styles. These results are strongest at the daily and weekly return horizons, but remain significant even at the monthly horizon. The economic magnitude of these effects is likely to be underestimated because ETF returns are calculated based on mid-point prices (as opposed to closing prices) that understate the true amount of mispricing; I use mid-point prices to minimize the possibility that commonality in bid-ask bounce is affecting the return comovements.

To further bolster my case that these comovement patterns are driven by correlated non-fundamental demand, I show that similar comovement patterns exist in the abnormal trading activity of ETFs and in shocks to ETF liquidity (relative to its underlying portfolio). More importantly, I find that these proxies for correlated demand shocks predict one-quarter ahead ETF return comovements. Several measures of ETF liquidity also positively predict return comovements, which is to be expected if ETFs attract investors with high liquidity needs. Controlling for an ETFs liquidity characteristics, return comovements should be greater when market-wide arbitrage costs are high because they leave more “room” for excess comovement (Kumar and Lee, 2006; Kumar and Spalt, 2013). Consistent with this idea, I find that return comovements are higher when funding liquidity is low, or when market volatility is high.

In contrast to Kumar and Spalt (2013) who show that retail investor accentuate return comovements and institutional investors mitigate them, my finding of excess comovements is likely to be driven by institutional investors because they account for roughly 80 % of the trading in ETFs (Aggarwal and Schofield, 2012). Consistent with this idea, I show that average flows to institutional owners of ETFs at the investment style level predict one-quarter ahead excess comovements. The results in this paper therefore contribute to our limited understanding of institutional investors in facilitating excess comovements. Anton and Polk (2014) is the only other paper to my knowledge that also shows that institutional investors (specifically active mutual funds) facilitate excess comovements through their common ownership.

The high degree of excess comovement among ETFs raises the question of how important this issue can be among other securities subject to similar shocks, but with greater limits-to-arbitrage. Namely, stock returns may also be exposed to similar non-fundamental sources of risk. DeLisle, French and Schutte (2013) document a large increase in stock return comovements since the 1990s. This increase in comovements coincides with a large increase in index investing, particularly via ETFs. I provide preliminary evidence to support the idea that stock return comovements and ETF excess return comovements share a common driver, possibly related to correlated non-fundamental demand via habitat effects or style investing.

It is important to understand what affects asset prices in the ETF market due to the potential for spillovers across markets. Staer (2014) shows that ETF fund flows have a large impact on underlying stock returns, almost half of which is reversed within a few days. Ben-David, Franzoni and Moussawi (2014) find that higher ETF ownership of stocks is associated with more volatile stock returns and a stronger mean-reverting component in stock returns, while Da and Shive (2013) link higher ETF ownership to stronger underlying stock return comovements. My conjecture that ETFs attract high-turnover investors with correlated trading needs is consistent with these findings.

I also consider several alternative explanations for the documented return comovements. First, the comovement patterns might be driven by similarities among ETFs in their rate of information diffusion. Given that differences in information diffusion between two actively traded securities (ETFs and their underlying U.S. equity securities) are unlikely to persist beyond the intra-daily horizon, my finding of excess comovement at the weekly and monthly horizons is inconsistent with the information diffusion hypothesis. Moreover, many of the style-based comovement patterns in returns and demand shock proxies are more consistent with correlated demand at the style level. Second, Cherkes, Sagi and Stanton (2008) derive a model to explain the Closed-End Fund discount puzzle that builds on the idea that CEF premiums are positively related to CEF liquidity (relative to its underlying portfolio). In the context of this paper, changes in premium could reflect changes in fund liquidity. Correlated changes could potentially explain the style-based return comovements. To test this prediction, I regress ETF-NAV returns on the change in relative liquidity of other ETFs in the same style. The results provide no support to this alternative story. Third, I consider whether ETF-NAV returns reflect differences in systematic risk between ETFs and NAVs, as captured by the Fama-French 3-Factors or the funding liquidity factor of Hu, Pan and Wang (2013). The results are once again nonexistent.

Among the most widely cited evidence in favor of correlated demand-based theories of excess comovement are the comovements observed around index additions (with other index stocks) and stock splits (with low-priced stocks)[5]. The critical assumption, that the event is exogenous remains controversial and has recently been challenged by Kasch and Sarkar (2012) and Perez, Shkilko and Tang (2012). There is also a broader debate in the literature as to whether the observed comovement patterns among small-cap stocks (Banz, 1981) or value/growth stocks (Fama and French, 1993, 1995) can be explained by common variation in cash flows or discount rates[6]; or by unmodeled irrational behavior (see Barberis and Thaler, 2003), and to what extent limits-to-arbitrage can explain these findings (Brav, Heaton, Li, 2010). My contribution in this regard is to provide a more controlled experiment that is better suited for separating the two sources (fundamental vs. non-fundamental) of return comovements.

This paper is also related to a growing literature on the relationship between correlated trading and return comovements. Kumar and Lee (2006) find not only that retail trades are systematically correlated, but also that such trades can help explain some of the anomalous return comovements among stocks with high arbitrage costs. Correlated retail demand has also been linked to investors' tendency to place similar speculative bets (Dorn, Huberman and Sengmueller, 2008). Kumar, Page and Spalt (2013b) show that stocks with lottery-like feature comove too much with one another due to the correlated trading activity of gambling-motivated investors. Greenwood (2007) constructs a simple trading strategy that bets on the reversion of the prices of over-weighted Nikkei 225 stocks that comove too much in the short-run and finds this trading strategy to yield significant risk-adjusted profits.

The article proceeds as follows. Section 2 provides some background information on ETF arbitrage. Section 3 presents the main hypotheses. Section 4 describes the data, defines the key variables and presents summary statistics. Section 5 presents the empirical tests for excess comovement, while section 6 investigates correlated demand and the determinants of return comovement. Section 7 explores alternative explanations. Section 8 concludes.

[5] See e.g. Barberis, Shleifer and Wurgler (2005), Green and Hwang (2009), Kumar, Page and Spalt (2013).
[6] See e.g. Fama and French (1993), (1995); Campbell, Polk and Vuolteenaho (2009); Campbell *et al.* (2013)

2 Background on ETF arbitrage and institutional details

ETFs have an open-ended structure via the share creation and redemption process that facilitates arbitrage. This process is only available to some institutional investors (called Authorized Participants, or APs), which have signed an agreement with the ETF sponsor. APs can buy or sell ETF shares in bundles (or creation units) directly from the ETF sponsor in exchange for the underlying basket of securities at the end of the trading day (at 4 P.M. EST). Although this process is limited to APs (typically market makers, broker/dealers or large institutions), they can also create (or redeem) shares directly for their clients who wish to transact in ETFs.

To illustrate the arbitrage process via the share creation mechanism, consider a situation where the ETF is trading at a premium (ETF price is above the NAV). An AP would then buy the underlying basket (at the NAV), exchange the basket for new ETF shares with the ETF sponsor and sell the newly created shares on the secondary market. The process works in reverse when the ETF is trading at a discount (ETF price is below the NAV).

The direct cost of creating ETF shares are small for U.S. equity funds (the focus of this paper). The size of a creation unit is typically 50,000 or 100,000 shares with dollar values ranging from $300,000 to $10 million. The fixed creation costs range from $500 to $3,000. For SPY, the world's largest and most actively traded ETF tracking the S&P 500, the fixed fee of $3,000 amounts to about 5 bp for one creation unit worth $6 million, or 1 bp for five creation units worth about $30 million (Petajisto, 2013). For a sample of equity U.S. ETFs[7], Broman and Shum (2014) report that share creations/redemptions occur on 30.9 (22.7) % of trading days on average (median) and conditional on such days, the magnitudes are $69.6 million ($12.4 million) or 244.3 percent (27.4 percent) of daily dollar volume. These magnitudes indicate that investors frequently create multiple creation units at a given point in time, possibly to reduce costs.

Arbitrage activity is also undertaken by market participants other than APs, such as hedge funds and high-frequency traders (Marshall, Nguyen, and Visaltanachoti, 2013). For instance, when the ETF is trading at a premium, an investor can purchase the underpriced asset (NAV), short-sell the overpriced asset (ETF) and wait for prices to converge to realize an arbitrage profit. ETF prices can also be arbitraged against other ETFs (Marshall, Nguyen, and Visaltanachoti, 2013; Petajisto, 2013) or against futures contracts (Richie, Daigler, and Gleason, 2008).

[7] Their sample is identical to mine. More details to follow in the data section.

3 Theoretical framework: liquidity clienteles, correlated demand and limited arbitrage

The theoretical channel for excess comovement in ETF returns relies on clientele effects, correlated demand and limited arbitrage. I will discuss each in turn. I begin by specifying a general risk-return relation for the ETF and the underlying portfolio Net Asset Value (NAV):

$$
\begin{aligned}
R_{i,t}^{NAV} &= E\left(R_i^{NAV}\right) + \sum_{p=1}^{P} \beta_{i,p} f_p + e_{i,t}^{NAV} \\
R_{i,t}^{ETF} &= E\left(R_i^{ETF}\right) + \sum_{p=1}^{P} \beta_{i,p} f_p + e_{i,t}^{ETF}
\end{aligned} \tag{1}
$$

$$
R_{i,t}^{E-N} \equiv R_{i,t}^{E-N} - R_{i,t}^{E-N} = e_{i,t}^{ETF} - e_{i,t}^{NAV} \tag{2}
$$

where $E(R_i)$ = expected return of ETF/NAV i, f_p = systematic risk factor p (zero-mean),

$\beta_{i,p}$ = the p^{th} factor sensitivity of ETF i

The ETF and the NAV are claims to the same fundamental assets. In efficient markets the expected returns and factor sensitivities of both assets must be the same. This assumption gives us Eq. (2). Despite the enhanced pricing efficiency of ETFs via the share creation mechanism, arbitrage remains, however, limited (more in the next section). For this reason it is important to verify that the expected return of $R_{i,t}^{E-N}$ is zero (confirmed in section 4.2) and that $R_{i,t}^{E-N}$ is uncorrelated with systematic risk factors (confirmed in section 7).

My conjecture is about the existence of a clientele factor $C_{k,t}$ in the ETF residual[8]*:*

$$
e_{i,t}^{ETF} = \gamma_i C_{k,t} + u_{i,t}^{ETF} \tag{3}
$$

$C_{k,t}$ = clientele specific common factor for characteristic, or style k.

This factor arises because ETFs are likely to attract a clientele of high-turnover investors that impound non-fundamental demand shocks to ETF prices at a higher rate relative to the securities in their baskets. This *liquidity clientele* effect is motivated by Amihud and Mendelson's (1987) model, which predicts that short-horizon investors self-select into more liquid assets, such as ETFs. Supporting this conjecture, Broman and Shum (2014) show that ETFs have on average smaller proportional quoted spreads relative to their underlying portfolio. The authors also show

[8] Another interpretation is that the ETF is more exposed to the clientele factor C relative to the NAV.

that the ETF liquidity relative to its underlying portfolio is a key determinant of investor demand (fund flows and ownership by institutions with high ex-ante liquidity needs).

Relative ETF liquidity may be positive because market making in portfolios (ETFs) is less risky due to lower adverse selection costs compared with individual securities. In addition, ETFs provide a "hidden" layer of liquidity via the share creation/redemption mechanism that allows institutional investors to access liquidity via the primary market whenever it is more cost efficient to transact in the underlying assets. This option-like feature of ETFs implies that the lower bound for their liquidity is determined by the liquidity of the ETF in the secondary market, and the liquidity of the underlying securities in the primary market.

The existence of a liquidity clientele in ETFs is also supported empirically by Ben-David, Franzoni and Moussawi (2014), who find evidence consistent with the transmission of non-fundamental volatility to the underlying securities via arbitrage activity. In addition, investors who are forced to trade frequently due to income shocks (Lynch and Tan 2011), exogenous liquidity shocks (Huang, 2003), or because they need to hedge against non-traded risk exposure (Lo, Mamaysky and Wang 2004), may be particularly attracted to ETFs with high liquidity. Retail investors with high liquidity needs will also find ETFs attractive because they generally do not even have the capacity to invest cost-efficiently in the underlying stocks. There are few other alternatives for such investors because ETFs generally have lower expense ratios than even their cheapest mutual fund counterparts. Retail investors do pay attention to trading costs: Barber, Odean and Zheng (2005) show that salient, attention-grabbing information such as front-end loads and commissions, are important for mutual fund investors' purchase decisions. In the case of ETFs, the most salient costs are likely to be quoted spreads and expense ratios, which are widely disseminated, while commissions are generally small, and sometimes even free[9].

An additional requirement for the existence of a common clientele factor is that ETF investors have *correlated non-fundamental demand*. This can happen if high-turnover investors restrict their trades to the ETF space, forming a preferred habitat as in Barberis, Shleifer and Wurgler (2005). As noted by the authors, transactions costs can give rise to preferred habitat. When these investors' risk-aversion, sentiment or liquidity needs change, they will engage in correlated trading, thereby inducing a common factor in ETF returns. The preferred habitat model is similar to the noise-trader model in Lee, Shleifer and Thaler (1991) where

[9] Many ETFs have free commissions: for a list see http://etfdb.com/type/commission-free/all/.

unpredictable changes in investor sentiment lead to changes in the demand for closed-end fund shares. Greenwood and Thesmar (2011) derive similar predictions without preferred habitats; they rely instead on correlated liquidity needs among groups of investors. Summarizing,

Hypothesis 1: *ETF returns comove excessively with the returns of other ETFs.*

Another possibility is correlated demand at the style level. In Barberis and Shleifer's (2003) model investors allocate funds at the style level (e.g. small or value) as opposed to at the individual asset level. If some of these style investors are also noise traders with correlated sentiment (e.g., Baker and Wurgler, 2006), then coordinated shifts in investor preference for certain investment styles will induce a common factor in the returns of assets in the same style. The strong demand for investment styles is evident from the large number of ETFs, mutual funds, and hedge funds that follow distinct styles and which are used by both individual and institutional investors[10]. Moreover, style investors may be particularly attracted to ETFs because ETF managers cater to investor demand by offering funds tied directly to popular investment styles. It is also easier to move money in and out of two different styles with ETFs than with stocks and generally cheaper to enter into long-short strategies (e.g. Value-Growth) given the relatively low short-selling costs of ETFs[11]. Thus,

Hypothesis 2: *ETF returns comove excessively with the returns of other ETFs that have similar style characteristics.*

Models of excess comovement also have obvious cross-sectional extensions. Namely, if the degree of commonality in non-fundamental demand shocks varies across ETFs, this variation should be cross-sectionally related to the amount of excess comovement in returns (Greenwood, 2007; Greenwood and Thesmar, 2011).

Hypothesis 3: *The amount of excess comovement in ETF returns is positively related to the degree of commonality in non-fundamental demand.*

3.1 Limits-to-Arbitrage

Without *limits-to-arbitrage* shocks to asset prices should revert instantaneously. In reality arbitrage remains limited by transactions costs, holding costs and other implicit restrictions (e.g.

[10] see e.g. Brown and Goetzmann (1997); Fung and Hsieh (1997); and Chan, Chen, and Lakonishok (2002)
[11] "No Shortage of Share Lending" featured in Journal of Indexes, February 17, 2010.

short-selling constraints). As for transactions costs, both ETF and underlying portfolio spreads matter because arbitrage trades require access to both markets. Price impact is also of particular concern. Staer (2014) reports that a 1 Std. Dev. increase in aggregate share creations ($2.47 billion) is on average associated with a 52 bp concurrent increase in market returns; almost 40 % of the initial price impact reverts within five days. An arbitrageur incurs holding costs, especially idiosyncratic risk (see Pontiff, 2006), whenever she has to delay liquidating the position[12].

The potentially high price impact costs of ETF share creations combined with the large size of typical creation events (Broman and Shum, 2014) indicate that an AP might need several days to accumulate a position that is large enough to offset the creation without undue price impact. This makes it harder to trade on small price deviations by using the share creation process. Traditional long-short arbitrage trades with smaller trade sizes can be used to avoid some of the price impact costs. However, such arbitrage trades are exposed to holding costs.

Greenwood's (2005) model can be used to justify limits-to-arbitrage further. In their model market-makers (or APs in the ETF market) are risk-averse and require compensation for providing liquidity. Thus, when a non-fundamental shock hits the ETF market, APs absorb the liquidity demand by shorting the ETF and simultaneously hedging their short ETF position by purchasing the underlying basket. Because APs are risk averse, they require compensation for the additional inventory that they are taking on. Similar predictions arise in Cespa and Foucault's (2014) model with multiple investor classes and some degree of market fragmentation. However, a strict adherence to either model would not allow for mispricing among securities with identical fundamentals. Ben-David, Franzoni and Moussawi (2014) discuss a dynamic extension of Cespa and Foucault's (2012) model to justify temporary price discrepancies between identical assets.

4 Data

My data selection starts with all U.S. traded Exchange-Traded Funds that exist both in Bloomberg and Morningstar Direct. I keep funds that i) invest in U.S. equity, ii) are physically

[12] For ETF arbitrage, delays can occur because share creations only take place at end-of-day NAVs, while the underlying portfolio may have to be accumulated over an extended period of time for several reasons. First, APs need to hedge their exposure to the underlying securities when an ETF is sold in the secondary market until enough demand is available to meet the minimum creation size. Second, many ETFs have a cut-off time in the afternoon to submit creation orders implying that arbitrageurs do not get to see the end-of-day NAVs before making the decision to trade. Third, arbitrageurs may wish to avoid price impact costs by splitting up the purchases over an extended period of time. Moreover, search and delay costs are more likely to arise when the position to be liquidated is large.

replicated and "passively" managed and iii) have at least 3 years of data available[13]. In recent years a number of active, or "smart beta", funds have emerged to give investor's access fundamentally-weighted indices (see the Economist 07/2013). These funds are excluded because their holdings change frequently, which makes it more difficult to measure their NAVs and portfolio liquidity. I also exclude active ETFs so that investors are not picking an ETF because of its investment strategy or manager performance, and other exotic ETFs (leveraged, inverse and futures-based ETFs). These three exclusion criteria decrease the sample of ETFs from 354 to 221 to 163. In terms of assets under management (AUM), the total AUM of U.S. equity funds was $632 billion in September 2012 according Blackrock (2012), while the AUM of my 163 funds was $537 billion. I also drop SPY, the world's largest ETF, from the sample because it would dominate some of the AUM-weighted results that I subsequently use[14]. This further reduces the sample AUM to $416 billion. Given the dramatic expansion in scope and size of the ETF market in the last five to ten years, earlier data may not be as representative of current market conditions, which is why I decided to focus on a recent sample period, from January 2006 to December 2012. I also conduct robustness tests on a sample starting in June 2002.

The sample of ETFs, along with NAVs[15], shares outstanding and prices for the underlying indices, is obtained from Bloomberg. My second source is CRSP, which I use to obtain price, return and volume data for all funds. Third, I use the ubiquitous 3-by-3 Morningstar style classification (Small-, Mid- and Large-Cap; Value-Blend-Growth) to identify the investment style of a fund. I use the size and valuation styles based on the evidence in Froot and Teo (2009) and Kumar (2009) that both retail and institutional investors allocate capital at the size and value-growth level. The Morningstar classification has three key advantages. First, it coincides with the dichotomy often used by practitioners. Second, Morningstar is a leading fund information provider and its classification system is publicly available. Third, many ETFs are named after their Morningstar style analogs e.g. SPDR S&P 600 Small-Cap Value or iShares Russell 3000 Growth fund. Investors do pay attention to fund names as illustrated by Cooper, Gulen and Rau (2005). They show that mutual funds that take rename their fund to match the

[13] I exclude the first 6 months of a funds history since the data can be unreliable, leaving me with an estimation sample of at least 2.5 years. For instance, ETFs may be illiquid when they are first created. Also, due to the low number of shares outstanding and the minimum fixed size of a creation/redemption basket, ETF's can experience dramatic creation/redemption activity early in the funds lifecycle.

[14] The main results of this paper also hold for SPY.

[15] For ETF's by the iShares provider I use the NAV data that is directly available from their website as they contain fewer data errors, as suggested by Petajisto (2013).

current “hot style “subsequently experience abnormal inflows, even when the name change is unrelated to performance or any real change in holdings to match the new style.

Table 1 gives snapshots of the ETF sample used in this study. At the beginning (01/2006), my sample contains 95 ETFs with $154.69 billion in AUM. Subsequently there are 155 ETFs with $198.22 billion in AUM (07/2007), and 162 ETFs with $416.82 billion at the end of the sample (12/2012). These 162 ETFs consist of 23 small-, 50 mid- and 89 large-cap funds and a roughly equal distribution of value-growth-blend funds within each size-category. Within each size-category (small- to large), value and growth ETFs are generally smaller than their blend counterparts. Although roughly half of the funds can be classified as sector funds, their share of the total AUM is less than one third throughout the sample and they are roughly equally split between the three size categories. The vast majority of funds are also fully replicated.

[Table 1]

4.1 Key Variables

ETF mispricing is typically measured by the premium, or the log-difference between the market price of an ETF and the market value of the ETF’s portfolio on a per-share basis (NAV[16]):

$$P_{i,t}^{E-N} = \ln\left(ETF_{i,t}\right) - \ln\left(NAV_{i,t}\right) \tag{4}$$

where: $ETF_{i,t}$ = bid-ask midpoint price for ETF i on day t, $NAV_{i,t}$ = Net Asset Value

Hypothesis 1 and 2 predict comovements among ETF-NAV return differences $R_{i,t}^{E-N}$. When log-returns are used, $R_{i,t}^{E-N}$ corresponds to the change in premium, with the definition being exact on days when the ETF does not pay any dividends[17]. I will use log-returns throughout this study to keep the link clear between return differences and changes in premium.

There are a handful of extreme observations that need to be dealt with. Premiums greater than 20 % are mainly due to data errors (Petajisto, 2013); these are replaced by 1/3 of the previous day’s premium (the normal rate of mean of mean-reversion in the data)[18]. When the mid-quote based premium is more than ten percentage points greater than the end-of-day based

[16] NAV also includes accrued income from securities lending, dividends and cash,
[17] ETF’s typically pay dividends every quarter or semi-annually, so this is not of any real concern.
[18] In addition, NAV returns are assumed to be identical to underlying index returns. Since most funds in my sample are fully replicated (see Table 1), this is an innocuous assumption. Based on this we can infer that the ETF return must equal the underlying index return minus the change in premium.

premium in absolute terms, I use the latter instead (same filter for ETF returns). Finally, premiums and ETF-NAV return differences and are winsorized fund-by-fund at 5 Std. Dev. from the mean to reduce the impact of any remaining outliers.

4.2 Descriptive Statistics

Table 2 provides descriptive statistics for ETF premiums and ETF-NAV returns (changes in premiums). Both are zero on average, and at the median supporting my assumption that ETF and NAV returns have the same expected returns. There is, however, considerable variation around the mean as indicated by the standard deviation of 0.27 % and 0.39 % for the level and change in premiums. The extreme right and left tails (1 and 99 percentiles) are roughly +/- 73 bps for levels of premiums, and +/- 1 % for changes in premiums. These numbers are based on closing ETF prices and because they represent actual trades, the figures are more representative of the magnitude of mispricing that investors can expect to face. In studying return comovements, I use mid-quote prices rather than end-of-day prices for levels (and changes) in premiums to minimize the possibility that return comovements are affected by commonality in bid-ask bounce. Engle and Sarkar (2006) also suggest using mid-point prices in order to mitigate concerns about the illiquidity of the shares of smaller ETFs. In this case, the standard deviation of the premium (levels and changes) is roughly half of that reported for premiums based on closing prices. The absolute value of mid-quote premiums is smallest for large-cap funds (5.4 bps) followed by mid- (6.5 bps) and small-cap funds (8.1 bps) suggesting that arbitrage costs are highest for mid- and small-cap funds.

[Table 2]

5 Empirical tests of excess comovement

In order to empirically identify the common clientele factor $C_{k,t}$ in ETF returns from Eq. (3), I first take the ETF-NAV return difference to control for fundamental variation in returns:

$$R_{i,t}^{E-N} = R_{i,t}^{ETF} - R_{i,t}^{NAV} = \gamma_i C_{k,t} + u_{i,t}^{ETF} - u_{i,t}^{NAV} = \gamma_i C_{k,t} + u_{i,t}^{E-N} \quad (5)$$

As a proxy for $C_{k,t}$, I use the equally-weighted[19] ETF-NAV return of all other ETFs with a particular characteristic or style k, denoted $R_{k,t}^{E-N}$. Excess comovement of ETF returns implies a positive association between $R_{i,t}^{E-N}$ and $R_{k,t}^{E-N}$ because R_{t}^{E-N} is unrelated to systematic risk factors (more in section 7). The key results are robust to orthogonalizing $R_{i,t}^{E-N}$ with these risk factors.

I begin by analyzing comovements among ETFs in the same size category. Size (of the underlying index) is not only related to a popular investment style, it also captures an important liquidity characteristic: small-cap ETFs typically have the lowest quoted spreads relative to their underlying portfolio followed by mid- and large-cap ETFs (Broman and Shum, 2014). I estimate the following regression:

$$R_{i,t}^{E-N} = \alpha_i + \lambda_i P_{i,t-1}^{E-N} + \beta_{i,S} R_{S,t}^{E-N} + \beta_{i,M} R_{M,t}^{E-N} + \beta_{i,L} R_{L,t}^{E-N} + e_{i,t} \tag{6}$$

where the dependent variable is the ETF-NAV return difference and the three style factors are equally-weighted ETF-NAV returns of other small-, mid- and large-cap ETFs (excluding *i*). Hypothesis 2 predicts that the own-category beta (e.g. the large-cap beta $\beta_{i,L}$ of a large-cap ETF) is greater than zero on average, which would indicate excess comovement at the style level. Hypothesis 1 is a more general prediction about excess comovement among ETFs (the average of $\beta_{i,S}, \beta_{i,M}, \beta_{i,L}$ is positive).

Regression (6) also includes the lagged level of premiums ($P_{i,t-1}^{E-N}$) to account for mean-reversion in premium changes (or the ETF-NAV return, $R_{i,t}^{E-N}$). This mean-reversion arises fundamentally because the level of premium is stationary, in which case changes in premiums must be mean-reverting. I run time-series regressions of (6) separately for each ETF using all available observations and report the mean of the estimated coefficients across all ETFs, while taking into account the cross-equation correlations in the estimated betas when computing the standard errors for the mean. Following Hameed, Kang and Viswanathan (2010), I calculate the standard error for the mean estimated coefficient as:

$$Std.Dev.\left(\overline{\beta}\right) = Std.Dev.\left(\frac{1}{N}\sum_{i=1}^{N}\beta_i\right) = \frac{1}{N}\sqrt{\sum_{i=1}^{N}Var\left(\beta_i\right) + \sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N}\rho_{i,j}\sqrt{Var\left(\beta_i\right)Var\left(\beta_j\right)}} \tag{7}$$

where $\sqrt{Var(\beta_i)}$ = the White standard error of the coefficient

$\rho_{i,j}$ = the estimated correlation between the residuals for ETF *i* and *j*.

[19] I also verify that similar results hold for AUM-weighted factors.

[Table 3]

Table 3 provides average beta-coefficients for each size-factor by size-category for the daily, weekly and monthly return horizons. Focusing first on the weekly horizon, the results show that the returns of large- (small-) cap funds comove significantly *only* with the large- (small) cap factor. The economic magnitudes are also considerable. To illustrate, a 1 Std. Dev. increase in the *own* category factor is on average associated with an increase in ETF-NAV returns by 5.7 bps (or 47 % of the Std. Dev. of ETF-NAV returns) and 9.8 bps (or 58 % Std. Dev.) for large- and small-cap ETFs respectively. The own-category results for mid-cap ETFs are economically weaker by almost half relative to small-cap funds.

There is also some evidence of return comovements across categories. For instance, the returns of mid-cap ETFs comove excessively not only with other mid-cap ETFs (average $\beta_{i,M}$ = 0.52, significant at 1 % level), but also with large-cap ETFs (average $\beta_{i,L}$ = 0.17, significant at 10 % level) at the weekly level. This is to be expected when the styles that are relevant for investors are not perfectly identified. This is particularly true for mid-cap funds because the mid-cap style is not as well defined as the opposites large- and small.

Next, I examine return comovements among two popular investment styles: value and growth. Any excess comovement in ETF returns within the same style, but not across, would be consistent with style investing (Hypothesis 2). In contrast, such comovement patterns would be hard to reconcile with correlated trading at the preferred habitat, or ETF level (Hypothesis 1), because high-turnover investors would not differentiate between value and growth ETFs as they have similar liquidity characteristics (Broman and Shum, 2014). The regression is then:

$$R_{i,t}^{E-N} = \alpha_i + \lambda_i P_{i,t-1}^{E-N} + \beta_{i,V} R_{V,t}^{E-N} + \beta_{i,G} R_{G,t}^{E-N} + e_{i,t} \tag{8}$$

The results in Table 3 show that the own-category betas are significantly positive for both value and growth ETFs indicating excess comovement among ETFs within the same valuation style. At the weekly level, the economic impacts of a 1 Std. Dev. shock to the own valuation factors are somewhat lower than the size-based comovements at 6.7 bps and 3.1 bps, which correspond to 39 % and 29 % of the Std. Dev. of ETF-NAV returns. These results hold mainly at the daily and weekly return horizons. At the monthly horizon there is evidence of return comovements across styles: growth ETFs comove significantly with value ETFs. These results are likely driven by an incomplete characterization of styles; size is also important.

5.1 Own and distant styles

The results in the previous section indicate that there are strong return comovements among ETFs that belong to the same size and/or valuation categories. However, there is also some evidence of comovement across categories. In the style investing model of Barberis and Shleifer (2003) there are only two styles – own and distant – and securities should comove positively with other securities in the same style, and negatively with securities in the distant style. In order to improve identification of the styles, I match ETFs into two mutually exclusive groups (own- and distant) based on both the size and valuation categories. I estimate the following model:

$$R_{i,t}^{E-N} = \alpha_i + \lambda_i P_{i,t-1}^{E-N} + \beta_{i,OWN} R_{OWN,t}^{E-N} + \beta_{i,DI} R_{DI,t}^{E-N} + e_{i,t} \quad (9)$$

In constructing the own-category return factor for ETF *i*, I include funds that match at least one style. I do not match along both the size and valuation styles because in some style intersections there are only a few funds (e.g. small-cap value), which might produce noisy return factors. Instead, I give equal weight to funds that match only one of the categories, and twice the equal weight for funds that match both categories[20]. For the distant-category factor, I include funds that match neither the size, nor the valuation category of ETF *i*. The distant-category factor is equally-weighted. I report results for the weekly and monthly horizons, for sub-samples of sector vs. non-sector funds and pre (06/2002-08/2008) vs. post financial crisis (04/2009-12/2012). The pre-crisis sample partly covers an earlier time-period not included in the main analysis.

[Table 4]

The results in Table 4, Panel A for the weekly horizon show not only that the own-category betas are on average positive and significant, but also that more than 75 % of the betas are individually significant, and more than 95 % are positive. As predicted by the style investing model, there is also some evidence to suggest that the distant category comovements are negative. The distant category betas are negative on average, but insignificant. This lack of significance seems to be driven by mid-cap funds whose style is not as well defined. Re-running the regression without mid-cap ETFs produces negative and significant distant category betas at the 1 % level. To illustrate, a one Std. Dev. increase in the own (distant) style return factors is associated with a

[20] Blend funds (neither Value, nor Growth) are matched only along the size dimension. The results remain robust if I match on both the size and valuation styles and require at least 5 funds in each size-valuation category.

57.5 % (-6.3 %) standard deviation increase (decrease) in ETF-NAV returns. Similar results are obtained both prior and after the financial crisis (Panel B).

Almost half of the ETFs in my sample are sector funds, though their AUM is less than a third. A priori, it is not clear to what extent sector funds can be neatly classified into the size and value-growth categories. From a style-investors point of view, different sectors might even form their own unique style. Since there are only a few ETFs tracking similar sectors, it would not be feasible to pursue separate sector styles. Instead, I will continue to use the Morningstar classification system for both non-sector and sector funds as it is done in a consistent manner. The value-growth style is based on the coefficient estimates from a regression of fund returns on 10 factors for value/growth, while the size style is based on the market cap of the underlying stocks[21]. In Panel B, I redo the results separately for sector and non-sector funds. The results for sector funds are statistically significant at the 1 % level, but are economically weaker, particularly when comparing median own-style betas ($\beta_{i,OWN} = 0.79$ vs 0.56 for non-sector and sector funds) or model R^2 (64.3 % vs 55.1 %).

To summarize, the results in this section indicate that ETFs comove excessively only with other ETFs in the same size and valuation style. These results hold across daily, weekly and even monthly return horizons. Since the price pressure associated with non-fundamental demand shocks is temporary, the strength of excess comovements should, on the one hand, decline with the length of the return horizon, particularly because the share creation mechanism facilitates arbitrage. On the other hand, if there is some persistence in demand shocks combined with limits-to-arbitrage, then it could help explain the persistence in return comovements over longer horizons.

6 Correlated demand and excess comovement in returns

The demand-based theories of return comovement predict that correlated (non-fundamental) demand shocks can give rise to excess comovement in asset returns. Moreover, if the degree of commonality in demand shocks varies across securities, this variation should be cross-sectionally related to the amount of excess comovement in returns (Hypothesis 3). In order to test this hypothesis, we need empirical proxies for correlated demand shocks. In section 6.1, I propose

[21] For instance, iShares Transportation Average ETF has a strong growth tilt (average P/B of its constituent stocks of 6.08) while Guggenheim S&P 500 Eq Weight Utilities has a strong value tilt (average P/B is 1.57). Both ETFs comove significantly with other growth and value ETFs respectively (unreported).

three such measures. I also show that these demand shock proxies exhibit similar style-based comovements as do ETF-NAV returns. In section 6.2, I explore the determinants of return comovement and the test the cross-sectional prediction of Hypothesis 3.

6.1 Measuring correlated demand shocks

Correlated demand shocks can arise from various sources, such as changes in sentiment, risk aversion, changes in liquidity needs, income shocks or hedging needs. Theoretical models of excess comovements generally do not distinguish between the various sources; neither do I. My goal is simply to link return comovement with correlated demand shocks. To arrive at a proxy for non-fundamental demand shocks, I build on the concept of abnormal trading activity. In the context of portfolio theory, turnover is a natural proxy for trading activity (Lo and Wang, 2000). Hence, I use ETF turnover *relative* to its underlying basket of securities:

$$REL\left(TO\right)_{i,t} = \ln\left(TO_{i,t}^{ETF} \,/ \sum_{k=1}^{K} w_{i,k,t} TO_{k,t}^{UND}\right) \tag{10}$$

where: $TO_{i,t}^{ETF}$ = $VOL_{i,t}^{ETF}/SHR_{i,t}^{ETF}$, or the share volume divided by the number of shares outstanding for ETF *i* on day *t*.

$TO_{k,t}^{UND}$ = turnover of underlying security *k* on day *t*.

$w_{i,k,t}$ = dollar-weight invested by ETF *i* in security *k* at the end of day *t*

A similar measure of portfolio turnover ($w_{i,k,t}TO_{k,t}^{UND}$) is used by Lo and Wang (2000). Higher numbers for *REL*(*TO*) indicate that the ETF is more actively traded relative to its underlying securities, presumably because the ETF attracts high-turnover investors. As a measure for relative turnover shocks, I use the residual estimated from an ARMA(1,1) model for the daily *REL*(*TO*), denoted by $\omega_{i,t}^{RTO}$. A positive $\omega_{i,t}^{RTO}$ signals an unexpected increase in the trading activity of ETF *i* relative to its underlying basket of securities. It is possible that $\omega_{i,t}^{RTO}$ reflects not only non-fundamental, but also fundamental demand shocks. For instance, investors could use ETFs for (fundamental) style-timing strategies. However, if investors collectively use active style-timing strategies (implying correlated demand), they cannot all be based on fundamental information because the average investor cannot beat the market. Hence, commonality in relative turnover shocks should, at least partly, be driven by correlated non-fundamental demand.

To investigate comovements in relative turnover, I adopt the same approach that I used for ETF-NAV returns. Specifically, I regress shocks to relative trading activity on the equally-weighted shock to relative trading activity of other funds in ETF $i's$ own or distant styles (as defined in the previous section):

$$\omega_{i,t}^{RTO} = \alpha_i + \sum_{j=-1}^{+1} \beta_{i,j}^{OWN} \omega_{OWN,t+j}^{RTO} + \sum_{j=-1}^{+1} \beta_{i,j}^{DI} \omega_{DI,t+j}^{RTO} + u_{i,t}^{RTO} \tag{11}$$

The one-day leading and lagged terms are meant capture any lagged adjustment in commonality (Chordia, Roll and Subrahmanyam, 2000). Correlated demand at the style level implies positive concurrent own-style betas ($\beta_{i,0}^{OWN}$). One caveat is that I cannot rule out comovements across styles ($\beta_{i,0}^{DI} > 0$) because $\omega_{i,t}^{RTO}$ may also capture fundamental demand shocks that are likely to be correlated at the market level. Nevertheless, I would expect to find stronger own than distant style comovements if the non-fundamental style component is strong.

As an alternative measure of correlated demand, I use the degree of commonality in relative liquidity. There is an extensive literature documenting that liquidity comoves across stocks. The demand-side view argues that commonality in liquidity arises because of correlated trading activity (Chordia, Roll and Subrahmanyam, 2000; Karolyi, Lee and Van Dijk, 2012), demand by institutional owners (Kamara, Lou and Sadka, 2008), by investor sentiment (Huberman and Halka, 2001) or the price impact of correlated liquidity needs (Greenwood and Thesmar, 2011). In this case we can view commonality in ETF liquidity as a proxy for correlated demand. The supply-side view provides a different interpretation. In this case liquidity commonality is explained by the funding constraints of financial intermediaries. Several theoretical models predict that commonality in liquidity, via illiquidity spirals or feedback loops, increases during periods when arbitrage capital is limited[22]. Even if liquidity commonality is to some extent related to supply effect, the prediction does not change. That is, when the supply of arbitrage capital is limited, liquidity commonality is high, there is more room for mispricing and for excessive return comovements. However, as we shall see in section 6.2, the results are more consistent with the demand-side view of liquidity commonality.

[22] see Karolyi, Lee and Van Dijk (2012) for an extensive list of references.

To measure relative liquidity, I use the difference between the (log of) Amihud's price impact[23] for the underlying portfolio and the ETF:

$$REL\left(LIQ\right)_{i,t} = \sum_{k=1}^{K} w_{i,k,t} \ln\left(\left|R_{i,t}^{UND}\right| / DVOL_{i,t}^{UND}\right) - \ln\left(\left|R_{i,t}^{ETF}\right| / DVOL_{i,t}^{ETF}\right) \qquad (12)$$

where $R_{i,t}^{UND}$ = midpoint return (in %) for security *k* held by ETF *i*, on trading day *t*

$DVOL_{i,t}^{UND}$ = dollar volume (in \$millions) for security *k*, on trading day *t*

Amihud's price impact has been widely used in the literature. Hasbrouck (2009) reports that, "among the daily proxies, the Amihud illiquidity measure is most strongly correlated with the TAQ-based price impact coefficient" (p. 1459). Amihud's measure is also endorsed by several other papers as good proxy for price impact; others have used it to study commonality in liquidity[24]. A similar measure of portfolio liquidity has been used by Idzorek, Xiong and Ibbotson (2012) and Broman and Shum (2014). Having defined $REL(LIQ)$, parallel calculations are done to compute measures of commonality with $REL(TO)$ replaced by $REL(LIQ)$ in Eq. (11). The data for portfolio weights comes from Morningstar Direct[25]. For a more detailed description and summary statistics of the turnover and liquidity variables, see Broman and Shum (2014).

Finally, I use flows to the institutional owners of an ETF as a direct proxy for demand shocks (though not necessarily non-fundamental):

$$Flow_{i,q} = \sum_{n=1}^{N} IO_{i,n,q-1} \Delta_{\%} AUM_{i,n,q} \qquad (13)$$

where: $IO_{i,n,q-1}$ = ownership of ETF *i* by the n[th] institutional owner, end of quarter *q-1*

$\Delta_{\%} AUM_{i,n,q}$ = % change in assets of the n[th] institutional owner of ETF *i*

In words, *Flow* captures aggregate changes in the assets of all investors that own ETF *i*. The ownership of institution *n* ($IO_{i,n,q-1}$) acts as weight for the importance of a particular investor. Suppose that all N institutional investors who hold ETF *i* receive a large sell order in a given quarter, implying correlated demand at the ETF level, then $Flow_{i,q} < 0$. To measure correlated

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[23] Daily observations of the price impact ratio above the 99.5[th] percentile of the sample have been discarded as in Amihud (2002). Similar results obtain if I use the CRSP-based quoted spreads to measure liquidity.
[24] Lesmond (2005), Goyenko, Holden and Trzcinka (2009), Fong, Holden, and Trzcinka (2010) endorse Amihud, while Karolyi, Lee and Van Dijk (2012) and Kamara, Lou and Sadka (2008) use Amihud for liquidity commonality.
[25] Since my holdings data for the underlying holdings of an ETF is generally at the monthly level, this assumes that changes in weights only reflect changes in market values of the constituents.

demand at the style level for ETF i, I calculate the equally-weighted $Flow_{i,q}$ across all ETFs in the own and distant styles, denoted $Flow_{Own,q}$ and $Flow_{Di,q}$. The flow measures are winsorized at the 1st and 99th percentile of the distribution to mitigate the impact of outliers.

The institutional ownership data comes from quarterly 13-F filings with the U.S. Securities and Exchange Commission (SEC) and is provided by Thomson Reuters. After 1978, all institutional investment managers (including foreign investors) with discretionary assets in excess of $100 million are required to report their holdings to the SEC on a quarterly or semi-annual basis. SEC regulation stipulates that all holdings of common stock (including ETFs) greater than 10,000 shares or $200,000 must be disclosed. To arrive at a measure of institutional ownership $IO_{i,n,q-1}$, the number shares held at the quarter-end is divided by the median number of ETF shares outstanding. The median is used to mitigate the impact of outliers and timing errors in the reporting of shares held (Broman and Shum, 2014). The holdings data is also adjusted for errors following Frazzini and Lamont (2008).

6.2 Results for correlated demand

Table 5 presents the results for correlated demand shocks, as estimated from Eq. (11) for shocks to relative turnover (Panel A), or relative liquidity (Panel B). I report the following results: average and median values for the concurrent, lagged, lead, sum coefficients and adjusted R^2; the percentage of funds with positive coefficients, the percentage of funds with positive and significant coefficients, negative and significant coefficients. Test of statistical significance for the average (median) coefficient is based on the cross-sectional t-statistic (sign-test) similar to Chordia, Roll and Subrahmanyam (2000) and Brockman *et al.* (2009). The results show that shocks to relative turnover $\omega_{i,t}^{RTO}$ comove significantly (at the 1 % level) across ETFs in the same style both at the mean and the median. More than 99 % of the concurrent $\beta_{i,0}^{OWN}$ coefficients are positive, and almost 90 % are individually significant at the 5 % level. Although shocks to relative trading activity also comove across styles ($\beta_{i,0}^{DI} > 0$), the magnitude of the $\beta_{i,0}^{DI}$'s are only about a third as large as those for the $\beta_{i,0}^{OWN}$'s and less than 50 % of the concurrent $\beta_{i,0}^{DI}$ coefficients are individually significant at the 5 % level.

[Table 5]

The results for relative liquidity paint an even clearer picture: shocks to relative liquidity comove positively (100 % of ETFs) and significantly (93 % of ETFs) across ETFs in the same style ($\beta_{i,0}^{OWN} > 0$), while there are no significant comovement across ETFs in distant styles ($\beta_{i,0}^{DI} = 0$). These style-based comovements in relative liquidity are more consistent with demand than supply-side explanations given that the theoretical effects behind the latter (illiquidity spirals and feedback loops) are generally described as a market-wide phenomenon.

Overall, the results in this section highlight that measures for demand shocks exhibit similar style-based comovements as do ETF-NAV returns.

6.3 Explaining the amount of return comovement

Hypothesis 3 predicts a link between return and demand shock comovements. In this context, how should one measure the degree of comovement in returns and demand shocks? The existing literature mainly uses the regression R^2 (e.g. Morck, Yeung and Yu, 2000; Hameed, Kang and Viswanathan, 2010; Karolyi, Lee and Van Dijk, 2012), although the beta coefficient is also used (Kamara, Lou and Sadka, 2008). I use the R^2 because the beta is sensitive to scaling effects that arise from differences in factors and their volatilities (i.e. the beta denominator) across ETF styles. It is also difficult to make cross-sectional comparisons of betas in short samples due to the large variation in ETF-NAV return volatilities across ETFs and over time. The R^2-measure does not suffer from these problems as it is a function of both the variance of the dependent variable and the factors. I therefore use the regression R^2 (labelled $R^2_{ret,q}$) from Eq. (9), estimated every quarter q on daily data. Since regression (9) also controls for the lagged level of premium, I decompose the model R^2 as:

$$R_q^2 = \frac{COV\left(R_{i,t}^{E-N}, \lambda_i P_{i,t-1}^{E-N}\right)}{VAR\left(R_{i,t}^{E-N}\right)} + \frac{COV\left(R_{i,t}^{E-N}, \beta_{i,OWN} R_{OWN,t}^{E-N}\right)}{VAR\left(R_{i,t}^{E-N}\right)} + \frac{COV\left(R_{i,t}^{E-N}, \beta_{i,DI} R_{DI,t}^{E-N}\right)}{VAR\left(R_{i,t}^{E-N}\right)} \quad (14)$$

and use the sum of the last two normalized covariance terms, denoted $R^2_{ret,q}$, to measure the degree of return comovement. $R^2_{ret,q}$ can be interpreted as the fraction of the model R^2 attributable to the own and distant category factors (Graham, Li and Qiu, 2013). Similarly, I measure comovements in relative turnover/liquidity shocks from the fraction of model R^2 attributable to the concurrent own and distant-style factors from Eq. (11). The degree of comovement in relative turnover and liquidity is denoted by $R^2_{rto,q}$ and $R^2_{rliq,q}$ respectively.

Figure 1 illustrates the time-series dynamics of the cross-sectional median return comovement ($R^2_{ret,t}$) across the small-, mid- and large-cap styles. We can see that small-cap ETFs have higher return comovements relative to large-cap ETFs throughout the sample. This is not surprising because small-cap ETFs are generally the most liquid relative to their underlying securities (Broman and Shum, 2014), which should make them particularly attractive to high-turnover investors who experience non-fundamental demand shocks at a higher rate relative to the investors in the underlying securities. Similar patterns can also be seen for comovements in relative turnover and liquidity. Figure 2 is constructed in a similar way, except that return comovements are depicted across terciles of ETFs based on the degree of correlated demand shocks in the prior quarter, as proxied by $R^2_{rto,q-1}$ in Panel A, and $R^2_{rliq,q-1}$ in Panel B. We can see that ETFs in the top tercile of relative turnover comovement have higher return comovements in 82 % of quarters (40 % are significant at the 5 % level) relative to ETFs in the lowest tercile. Moreover, ETFs in the highest tercile of relative liquidity comovement have higher return comovements in 100 % of the quarters (100 % are significant at the 5 % level). These preliminary findings agree with Hypothesis 3.

[Figures 1 and 2]

To provide further evidence that ETF return comovements are driven by correlated demand, I estimate pooled OLS regressions of $R^2_{ret,q}$ on proxies for correlated demand shocks ($R^2_{rto,q-1}, R^2_{rliq,q-1}, \left|Flow_{i,q-1}\right|, \left|Flow_{OWN,q-1}\right|, \left|Flow_{DI,q-1,}\right|$), several fund specific and macro variables related to arbitrage costs and liquidity:

$$R^2_{ret,q} = f\left(R^2_{ret,q-1}, R^2_{rto,q-1}, R^2_{rliq,q-1}, \left|Flow_{i,q-1}\right|, \left|Flow_{OWN,q-1}\right|, \left|Flow_{DI,q-1}\right|, Fund_{i,q-1}, Macro_q\right) \quad (15)$$

I also control for style (Morningstar 3-by-3) and sector fixed effects; in some specifications I also add ETF or time fixed effects. Note that the flow measures are in absolute values. This is because $R^2_{ret,t}$ is a measure of the magnitude of comovement.

Return comovements are likely to be higher among funds with more desirable liquidity characteristics. As a direct measure of liquidity, I use the monthly quoted spread for the ETF:

$$QSPR^{ETF}_{i,m} = -1 * \ln\left(\frac{1}{N_m}\sum_{t=1}^{N_m} 100 * \frac{ASK^{ETF}_{i,t} - BID^{ETF}_{i,t}}{\left(ASK^{ETF}_{i,t} + BID^{ETF}_{i,t}\right)/2}\right) \quad (16)$$

where: $ASK_{i,t}^{ETF}(BID_{i,t}^{ETF})$ = CRSP ask (bid) price at the close on trading day *t* for ETF *i*

N_m = nr. of trading days in calendar month *m*

I use the log-transformation to mitigate the impact of outliers and to deal with the apparent non-stationarity in the data. I estimate the portfolio quoted spread by dollar-weighting the monthly quoted spread of each security included in the ETF's basket ($QSPR_{i,m}^{UND} = w_{i,k,m}QSPR_{k,m}^{UND}$). The CRSP-based spread is highly correlated with the (more accurate) TAQ spread in the cross-section (Chung and Zhang, 2014), which is the dimension of primary interest.

I also include the expense ratio because it is a salient attention-grabbing cost for retail investors, and Assets Under Management because AUM and liquidity are correlated. Another related measure is holding costs (a proxy for arbitrage costs), or costs that accrue every period a position remains open. Pontiff (2006) demonstrates theoretically that a rational investor's demand for a mispriced asset increases with the magnitude of mispricing, but decreases with the asset's idiosyncratic risk. An arbitrageur will be exposed to idiosyncratic risk whenever she has to delay liquidating the position. To measure idiosyncratic risk, I use the standard deviation of the change in premium. Gagnon and Karolyi (2010) use a similar measure for cross-listed stocks.

Controlling for an ETFs liquidity characteristics, return comovements should be greater when market-wide arbitrage costs are high because they leave more "room" for excess comovement (Kumar and Lee, 2006; Kumar and Spalt, 2013). I use the funding liquidity factor by Hu, Pan and Wang (2013), which is based on price deviations between on-the-run and off-the-run Treasury securities, averaged across a wide range of maturities. Market volatility is also an important determinant of the risk to market makers of maintaining inventories of their securities (Chordia, Roll, and Subrahmanyam, 2000), and changes in market volatility can cause changes in inventories and create correlated institutional trading. Market volatility is also related aggregate uncertainty in financial markets either via higher transaction costs or lower funding liquidity (i.e., less capital is devoted to ETF arbitrage) as in Brunnermeier and Pedersen (2009). In either case, the prediction is that return comovements should be positively related to market volatility, which I proxy for by the volatility of the NAV returns.

[Table 6]

Before I discuss the results, I present a correlation matrix for the variables included in the regression. Table 6 shows that return comovements $R_{ret,q}^2$ are positively correlated with proxies for correlated demand shocks (ranging from 0.03 for $|Flow_{i,q-1}|$ to 0.47 for $R^2_{rliq,q-1}$) and with proxies for the level of ETF illiquidity (from -0.10 for ETF spreads to -0.39 for expense ratios). Correlations among the correlated demand shock proxies are generally also positive.

[Table 7]

The results in Table 7 suggest that every proxy for correlated demand shocks, when included individually, predict return comovements positively and significantly at the 1 % significance level. The only exception is flows to an ETFs institutional owners. This is not surprising given that this variable is constructed at a very low frequency (quarterly) relative to the frequency at which return comovements are measured (daily). Nevertheless, we see a positive and highly significant relationship between flows to institutional owners matching the style of ETF *i*, which is consistent with correlated demand taking place at the style level. Moreover, return comovements are significantly higher for more liquid ETFs (lower quoted spreads, expense ratios and idiosyncratic risk), for less liquid underlying portfolios, and during times when arbitrage is limited (high market volatility, low funding liquidity). Similar results are obtained when all correlated demand proxies are included simultaneously, and if we control for time or ETF fixed effects in addition to style fixed effects. In omitted robustness tests I also verify that similar results are obtained when comovements are measured using weekly data[26].

Overall, the findings in this section show that return comovements are stronger for ETFs with high correlated demand and more desirable liquidity characteristics, which supports my conjecture that ETF returns comove excessively with one another due to the correlated demand of a high-turnover clientele in ETFs.

6.4 ETF and underlying portfolio return comovement

DeLisle, French and Schutte (2013) document a large increase stock return comovements – as measured by the R^2 from a market model for individual stock returns – since the 1990s. This increase in comovements coincides with a large increase in index investing, particularly via ETFs. Wurgler (2010) discusses the economic benefits and costs associated with index investing. Among the economic costs is the potential for a rise in return comovements via habitat effects or

[26] In this case I estimate relative turnover/liquidity comovements using a more parsimonious model to conserve degrees of freedom (there are only 13 weeks per quarter). Specifically, I exclude leading and lagged terms for the own and distant factors. Recall from Table 5 that these are insignificant for the average/median fund.

style investing, the effect of which will be stronger as the degree of overlap among indices increases. This conjecture is not inconsistent with the risk-return relationship that I assumed for the ETF and its underlying portfolio in Eq. (1) and (2). The risk-return relationship can be reinterpreted such that both the ETF and its underlying portfolio are exposed to the common habitat/style factor C_k, but the ETF has a higher exposure ($\gamma_i^{ETF} > \gamma_i^{NAV}$) because it is likely to attract high-turnover investors who are more exposed to non-fundamental demand shocks relative to the investors in the underlying securities. The implication of this is two-fold. First, the excessive return comovements documented in this study would be underestimated because we could only identify the differential exposure between ETF and NAV returns ($\gamma_i^{ETF} - \gamma_i^{NAV}$). Second, there would be a positive relationship between the degree of return comovement among ETFs, and degree of comovement among their underlying securities. To test this idea, I expand on Eq. (15) by including measures of underlying stock return comovements.

To measure underlying stock return comovements for ETF i's portfolio during quarter q, I first calculate the degree of return comovement for each individual stock j held by ETF i. This is done by regressing the daily stock return ($R_{j,d}^{UND}$) on the Fama and French 3-factors (*MKT*, *SMB* and *HML*) and calculating the fraction of model R^2 attributable to the *MKT* factor, and combined for the *SMB* and *HML* factors. Next, I calculate the dollar-weighted average R^2:

$$
\begin{aligned}
R_{i,MKT,q}^2 &= \sum_{j=1}^{N} w_{i,j,q} R_{j,MKT,q}^2 = \sum_{j=1}^{N} w_{i,j,q} \frac{COV\left(R_{j,d}^{UND}, \beta_{j,MKT} MKT_d\right)}{VAR\left(R_{j,d}^{UND}\right)} \\
R_{i,STYLE,q}^2 &= \sum_{j=1}^{N} w_{i,j,q} R_{j,SMB,q}^2 + \sum_{j=1}^{N} w_{i,j,q} R_{j,HML,q}^2 \\
&= \sum_{j=1}^{N} w_{i,j,q} \frac{COV\left(R_{j,d}^{UND}, \beta_{j,SMB} SMB_d\right)}{VAR\left(R_{j,d}^{UND}\right)} + \sum_{j=1}^{N} w_{i,j,q} \frac{COV\left(R_{j,d}^{UND}, \beta_{j,HML} HML_d\right)}{VAR\left(R_{j,d}^{UND}\right)}
\end{aligned} \tag{17}
$$

The decomposition of total R^2 to the fraction attributable to the *MKT* and style factors *SMB* and *HML* is motivated by the idea that some of the comovement patterns among small and value/growth stocks could be driven by correlated non-fundamental demand. I therefore expect a positive link between ETF return comovements $R_{i,ret,q}^2$ and underlying portfolio return comovements $R_{i,MKT,q}^2$ and $R_{i,STYLE,q}^2$, particularly with the latter.

[Table 8]

Table 8 provides the results. As expected, both $R^2_{i,MKT,q}$ and $R^2_{i,STYLE,q}$ enter with a positive and significant coefficient (at the 1 % level). What is noteworthy is that the coefficient for $R^2_{i,STYLE,q}$ remains highly significant (but only marginally significant for $R^2_{i,MKT,q}$) even after controlling for time fixed effects implying that there is a common cross-sectional driver of ETF and stock return comovements, presumably related to correlated demand at the style level. The results remain strong (in fact even stronger) if we control for ETF fixed effects suggesting time-invariant ETF characteristics due not subsume the effect.

7 Alternative explanations

Differences between ETF and NAV returns might also be related to factors other than price pressure induced by correlated demand. In this section I consider three alternative explanations.

7.1 Information diffusion

The information diffusion view of excess comovement asserts that fundamental shocks (with permanent price impact) are incorporated faster into the prices of some securities as opposed to others (Barberis, Shleifer and Wurger, 2005). In this case there will be a common factor in the returns of securities that incorporate information at similar rates. For instance, if information diffuses faster into ETF prices, then ETF premiums may reflect news that is embedded in ETF price, but not in the prices of underlying securities (NAV). Consequently, changes in premiums (or ETF-NAV return) can be contemporaneously correlated across ETFs.

The results in this paper do not support the information diffusion view. First, differences in information diffusion between two actively traded securities (ETFs and their underlying portfolios) are unlikely to persist beyond the intra-daily horizon. The key results in this study are, however, robust at the weekly and monthly horizons. Moreover, the style-based return comovements are hard to reconcile with information diffusion, particularly those documented among ETFs in the same value/growth style because there are no significant differences in liquidity between value and growth ETFs. Finally, I show strong evidence of predictability in the degree of excess return comovement using several proxies for correlated demand shocks. Some degree of persistence in demand shocks combined with limits-to-arbitrage could explain this predictability as well as the persistence in return comovements over longer horizons.

The existing literature also provides some evidence against the information diffusion hypothesis. Ben-David, Franzoni and Moussawi (2014) show that greater (exogenous) stock ownership by ETFs is associated with higher stock return volatility and a stronger mean-reverting component in stocks returns implying that the higher volatility arises from non-fundamental sources. Further evidence is provided by Staer (2014) who shows that much of the initial price impact of ETF flows on underlying stock returns reverts within five days.

7.2 Correlated changes in liquidity

Cherkes, Sagi and Stanton (2008) propose a theoretical model to explain the closed-end fund discount puzzle that builds on the idea that CEF premiums are positively related to the liquidity of the CEF *relative* to its underlying portfolio and expense ratios. Thus, changes in premium could reflect changes in fund liquidity (as expense ratios rarely change). A similar argument has been empirically tested by Chan, Hong, and Subrahmanyam (2008) in the context of cross-listed (ADR) stocks. The authors find that changes in ADR premiums (calculated relative to their home market share prices) are positively related to ADR liquidity relative to home share liquidity.

In order for changes in *relative* liquidity to be able to explain the return comovements documented previously, changes in liquidity must also be correlated across ETFs. To investigate this issue, I regress changes in premiums (i.e. ETF-NAV returns) on shocks to relative ETF liquidity ($\omega_{i,t}^{rliq}$ based on Eq. (12)) and the average shock to relative liquidity of other ETFs in own- and distant-styles ($\omega_{Own,t}^{rliq}$, $\omega_{Di,t}^{rliq}$).

[Table 9]

The results in Table 9 provide no evidence to suggest that ETF-NAV returns can be explained by shocks to relative ETF liquidity, or by shocks to relative liquidity of other ETFs in the own- or distant-styles. The results remain unchanged if I follow Chan, Hong, and Subrahmanyam (2008) and calculate the dependent variable and liquidity measures as the difference between the average of daily values in the current month and the average in the previous month[27]. These results suggest that correlated changes in liquidity are unlikely to have an economically important effect on ETF-NAV returns.

[27] Results omitted for conciseness, but are available upon request.

7.3 Exposure to systematic risk factors

Differences in systematic risk between ETF and NAV returns might be able to explain the comovement patterns documented earlier. To investigate this possibility, I regress ETF-NAV return differences on the Fama and French 3-factors (*MKT*, *SMB* and *HML*[28]) and the lagged premium ($P_{i,t-1}^{E-N}$) to control for mean-reversion in ETF-NAV returns.

[Table 10]

Table 10 shows that daily ETF-NAV returns are negatively and significantly exposed to the market factor (holds for the average ETF in every style); large-cap ETFs are positively exposed to *SMB* (small-cap ETFs have insignificantly negative exposure), while Value ETFs are negatively exposed to the HML factor (growth ETFs also have a marginally negative exposure). These results do not line up with the explanation that ETF returns are fundamentally more risky relative their NAV returns. The economic significance is marginal as indicated by the minor increase in R^2 compared to the baseline model that only controls for mean-reversion in ETF-NAV returns, and by the fact that these findings are wiped out at lower return horizons.

Another possibility is that ETFs are differentially exposed to systematic liquidity risk, especially because there are large differences in liquidity between the ETF and its underlying portfolio. This story is, however, unlikely because recent evidence on the pricing of liquidity risk in U.S. stocks suggests that the characteristic liquidity premium has declined considerably over time and is priced only among the smallest stocks, while systematic liquidity is priced primarily among NASDAQ stocks (Ben-Rephael, Kadan and Wohl, 2013). In contrast, my results are not driven by small-cap ETFs. To formally investigate this issue I augment the Fama-French 3-factor model with the market-wide funding liquidity factor based on Hu, Pan and Wang (2013), which is available at the daily level from the author's website. The results show that HPW's funding liquidity variable enters with a positive and significant coefficient for large-cap ETFs, not small-caps as we might have expected based on the prior literature (see Panel B). As before, the results are wiped out at lower horizons. Thus, differences in systematic risk are unlikely to be able to explain the comovement patterns documented earlier among ETF-NAV returns.

[28] It is possible that ETF-NAV returns are correlated with *SMB* and *HML* if these return premiums are related to correlated non-fundamental demand. However, identification of this relationship is likely to be weak given that SMB and HML are not filtered from fundamental sources of risk.

8 Summary and Conclusions

In this paper I analyze excessive comovements in returns directly by using a set of twin-based securities: the return differential between an Exchange Traded Fund (ETF) and its underlying portfolio of securities (NAV) contains no fundamental risk, but the two are subject to different sources of transient price pressure. My conjecture is that the correlated demand by a liquidity-based clientele in ETFs is the source of excess comovement in ETF returns.

My findings indicate that ETFs comove excessively with other ETFs that have similar style characteristics (size and value/growth), while there are no excess comovements among ETFs in distant styles (matching neither size, nor valuation). Similar comovement patterns are found in the abnormal trading activity of ETFs and in shocks to ETF liquidity (relative to its underlying portfolio). More importantly, I find that these proxies for correlated demand shocks predict one-quarter ahead ETF return comovements. In accordance with liquidity being a factor in inducing clientele differences between ETFs and their underlying portfolio, I show that return comovements are higher for funds with more desirable liquidity characteristics.

These excess ETF return comovement are found to persist across daily, weekly and even monthly return horizons. This is consistent with some degree of persistence in demand shocks combined with arbitrage costs that prevent from arbitrageurs from fully eliminating the mispricing.

I also consider, and reject, several alternative theories based on non-investor driven commonalities in fund characteristics that might explain the comovements among ETF-NAV return differentials. The first is based on correlated changes in liquidity within an ETFs own style, while the second considers the possibility that there are differences in systematic risk exposure between ETFs and NAVs. Neither explanation has much explanatory power.

My overall conclusion is that the excess comovement in ETF returns is mainly driven by the correlated non-fundamental demand of a liquidity-based clientele.

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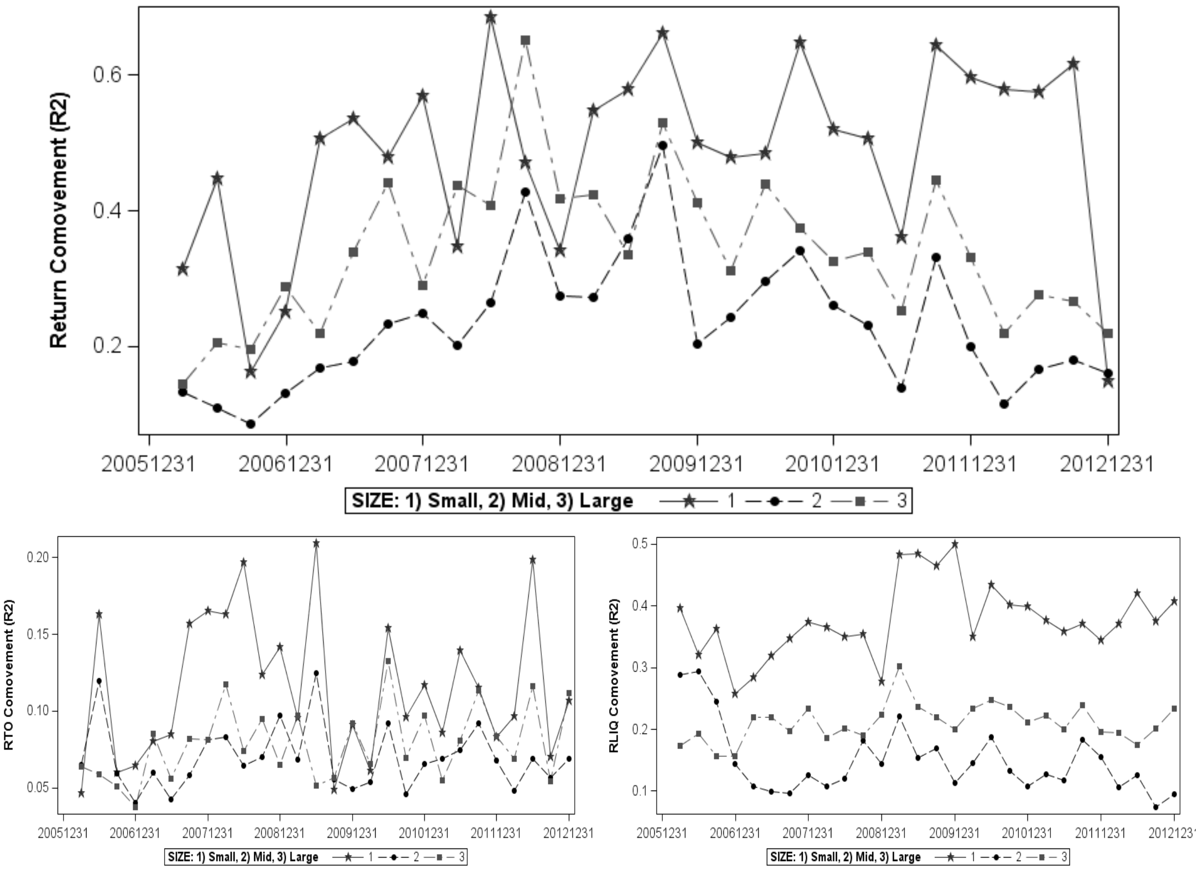
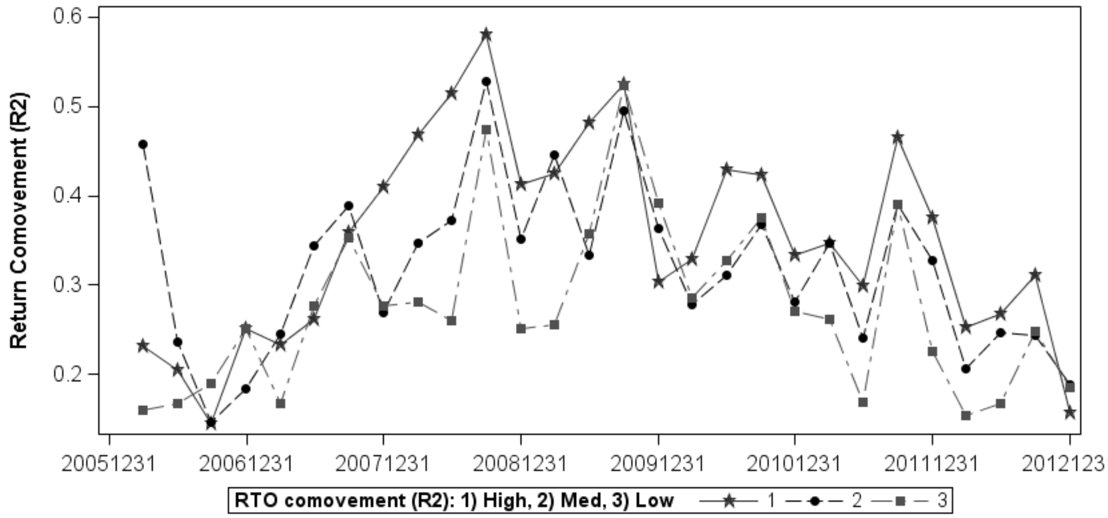


Figure 1: Comovement in returns, turnover and liquidity

The cross-sectional median excess return comovement is plotted for the small, mid and large cap styles (UP). The bottom two graphs plot the cross-sectional median comovement in relative turnover (LEFT) and relative liquidity (RIGHT). Comovements are based on the model R^2, or the fraction of the variation in the dependent variable (ETF-NAV returns, relative turnover or liquidity) attributable to the own and distant style factors.

Panel A: Cross-sectional mean of $R^2_{ret,q}$ by $R^2_{rto,q-1}$ tercile



Panel B: Cross-sectional mean of $R^2_{ret,q}$ by $R^2_{rliq,q-1}$ tercile

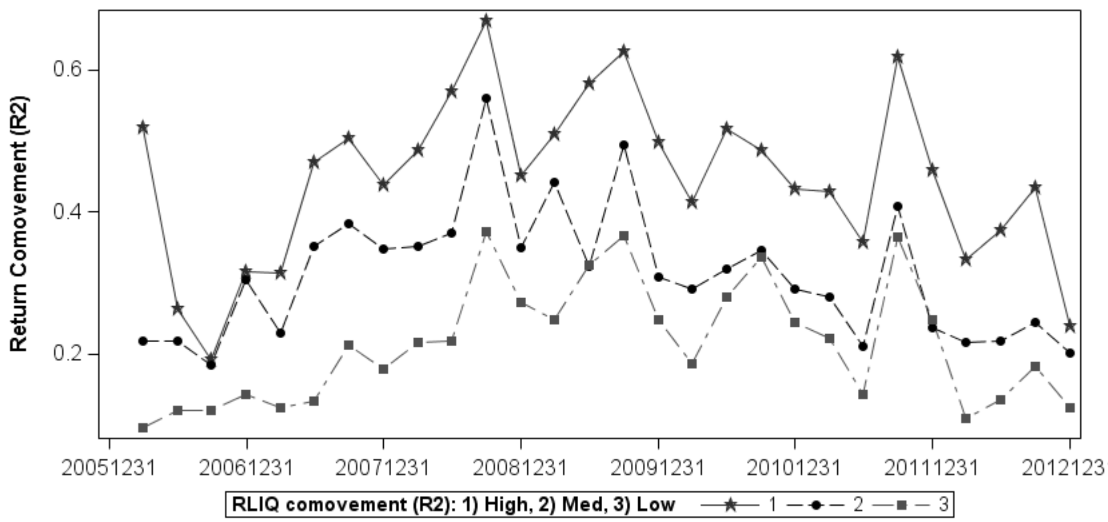


Figure 2: Excess comovement and correlated demand

The cross-sectional median excess return comovement is plotted over time for three groups. Terciles are based on comovement in relative turnover ($R^2_{rto,q-1}$) and comovement in relative liquidity ($R^2_{rliq,q-1}$) in Panels A and B respectively. Comovements are based on the model R^2, or the fraction of the variation in the dependent variable (ETF-NAV returns, relative turnover or liquidity) attributable to the own and distant style factors.

Table 1: Snapshot of ETF statistics

This table reports the number of ETFs and the Assets under Management at the beginning, the middle and at the end of the sample. The statistics are given by the style of the fund, which are based on Morningstar's Size-Valuation matrix. Sector funds are included into the Size-Valuation matrix, which is why I also provide separate statistics for sector vs. non-sector. The last two rows report the replication method used.

	Nr. of ETFs			AUM (in $million)		
Category	**01/2006**	**06/2009**	**12/2012**	**01/2006**	**06/2009**	**12/2012**
Large Cap	**61**	**85**	**89**	**100 664**	**133 489**	**280 486**
Large Value	21	27	28	30 121	38 801	73 222
Large Blend	18	27	29	30 266	50 581	111 962
Large Growth	22	31	32	40 278	44 108	95 302
Mid Cap	**19**	**49**	**50**	**31 779**	**36 689**	**85 348**
Mid Value	5	13	14	5 242	6 202	11 301
Mid Blend	6	15	15	19 557	19 155	41 452
Mid Growth	8	21	21	6 981	11 332	32 595
Small Cap	**15**	**21**	**23**	**22 243**	**28 045**	**50 983**
Small Value	3	5	6	3 338	5 312	8 798
Small Blend	6	9	10	14 063	16 689	32 206
Small Growth	6	7	7	4 842	6 045	9 979
Value	29	45	48	38 701	50 315	93 321
Blend	30	51	54	63 885	86 425	185 620
Growth	35	59	60	52 101	61 484	137 876
Non-Sector	53	72	77	124 284	149 794	301 862
Sector	42	83	85	30 404	48 430	114 955
Fully Replicated	80	134	140	136 798	173 495	370 782
Optimized	15	21	22	17 890	24 729	46 035
All	95	155	162	154 687	198 224	416 816

Table 2: Descriptive Statistics

P_i^{E-N} (R_i^{E-N}) is the level of (change in) premium calculated as the log-price (return) difference the ETF price and the NAV price. Both levels and changes in premiums are reported in percentage. Closing and mid-point refers to premiums calculated using closing or mid-point prices/returns. Summary statistics for premiums are for daily observations.

Variable	Mean	Median	Std. Dev.	1 %	99 %
Closing: $P_i^{E-N} = ln\left(P_i^{ETF}/P_i^{NAV}\right)$	-0.002	0.000	0.272	-0.757	0.719
Mid-point: $P_i^{E-N} = ln\left(P_i^{ETF}/P_i^{NAV}\right)$	-0.005	-0.006	0.116	-0.299	0.323
Large-Cap	-0.001	-0.000	0.109	-0.252	0.298
Mid-Cap	-0.008	-0.009	0.126	-0.327	0.364
Small-Cap	-0.018	-0.017	0.122	-0.381	0.337
Blend	-0.007	-0.006	0.120	-0.297	0.302
Value	-0.004	-0.004	0.110	-0.294	0.331
Growth	-0.005	-0.006	0.117	-0.306	0.333
Closing: $R_i^{E-N} = R_i^{ETF} - R_i^{NAV}$	0.000	0.000	0.388	-1.039	1.039
Mid-point: $R_i^{E-N} = R_i^{ETF} - R_i^{NAV}$	0.000	0.000	0.159	-0.430	0.427
Large-Cap	0.000	0.000	0.161	-0.482	0.461
Mid-Cap	0.000	0.000	0.180	-0.477	0.486
Small-Cap	-0.000	0.000	0.148	-0.381	0.377
Blend	-0.000	0.000	0.168	-0.410	0.404
Value	0.000	0.000	0.149	-0.437	0.423
Growth	0.000	0.000	0.159	-0.443	0.447
Closing: $\left\|P_i^{E-N}\right\|$	0.135	0.073	0.236	0.000	1.065
Mid-point: $\left\|P_i^{E-N}\right\|$	0.061	0.036	0.099	0.000	0.438
Large-Cap	0.054	0.032	0.095	0.000	0.401
Mid-Cap	0.065	0.038	0.109	0.000	0.484
Small-Cap	0.081	0.055	0.093	0.000	0.466
Blend	0.060	0.036	0.104	0.000	0.430
Value	0.059	0.035	0.093	0.000	0.454
Growth	0.062	0.037	0.099	0.000	0.438

Table 3: Excess comovement across ETFs grouped by size or value/growth

This table reports the results from estimating the following *panel* regression:

$$(1): R_{i,t}^{E-N} = \alpha_i + \lambda_i P_{i,t-1}^{E-N} + \beta_{i,S} R_{S,t}^{E-N} + \beta_{i,M} R_{M,t}^{E-N} + \beta_{i,L} R_{L,t}^{E-N} + e_{i,t}$$

$$(2): R_{i,t}^{E-N} = \alpha_i + \lambda_i P_{i,t-1}^{E-N} + \beta_{i,V} R_{V,t}^{E-N} + \beta_{i,G} R_{G,t}^{E-N} + e_{i,t}$$

where the dependent variable is the ETF-NAV return difference, P_i^{E-N} is the ETF premium and the return factors are equally weighted ETF-NAV return differences of (1) other Small-, Mid- and Large-Cap ETFs, or (2) other Value and Growth ETFs. Hypothesis 2 predicts significant own-category betas (in **bold**). I report average *betas* by category and across the factors. T-statistics for the mean are adjusted for cross-correlation as in Hameed, Kang and Viswanathan (2010). */**/*** denotes statistical significance at the 10, 5 and 1 % level. Panels A, B and C report results for the daily, weekly and monthly return horizon respectively. N is the total number of observations across all ETFs in a category. R^2 is the average R-squared.

Factors	**(1): Size Categories**				**(2): Value/Growth categories**	
	Small	Mid	Large	Factors	Value	Growth
			Panel A: Daily Frequency			
$R_{L,t}^{E-N}$	-0.021	0.154***	**0.709*** **	$R_{G,t}^{E-N}$	0.091	**0.564*** **
	(0.53)	(2.79)	(16.63)		(1.48)	(12.11)
$R_{M,t}^{E-N}$	0.117***	**0.484*** **	0.051	$R_{V,t}^{E-N}$	**0.639*** **	0.096***
	(2.96)	(8.6)	(1.29)		(12.69)	(2.86)
$R_{S,t}^{E-N}$	**0.716*** **	0.042*	-0.011			
	(37.35)	(1.79)	(0.66)			
R^2	0.697	0.569	0.622	R^2	0.587	0.576
N	37,346	79,530	143,575	*Nobs*	77,287	97,534
			Panel B: Weekly Frequency			
$R_{L,t}^{E-N}$	-0.050	0.171*	**0.677*** **	$R_{G,t}^{E-N}$	0.137	**0.399*** **
	(0.67)	(1.87)	(9.88)		(1.24)	(3.63)
$R_{M,t}^{E-N}$	0.138*	**0.515*** **	0.063	$R_{V,t}^{E-N}$	**0.619*** **	0.176**
	(1.86)	(6.19)	(1.00)		(6.63)	(2.22)
$R_{S,t}^{E-N}$	**0.700*** **	0.037	-0.023			
	(21.33)	(1.12)	(0.87)			
R^2	0.748	0.618	0.658	R^2	0.610	0.621
N	7,765	16,366	29,633	*Nobs*	15,962	20,283
			Panel C: Monthly Frequency			
$R_{L,t}^{E-N}$	0.033	0.001	**0.535*** **	$R_{G,t}^{E-N}$	-0.014	**0.180**
	(0.29)	(0.01)	(5.83)		(0.08)	(1.2)
$R_{M,t}^{E-N}$	0.161	**0.500*** **	0.295*	$R_{V,t}^{E-N}$	**0.645*** **	0.335***
	(0.9)	(2.69)	(1.90)		(3.49)	(2.71)
$R_{S,t}^{E-N}$	**0.571*** **	0.131*	-0.023			
	(8.56)	(1.76)	(0.41)			
R^2	0.650	0.532	0.653	R^2	0.553	0.575
N	1,760	3,710	6,709	*Nobs*	3,621	4,588

Table 4: Excess Comovement across Multiple Style Dimensions

This table reports the results from estimating the following panel regression:

$$R_{i,t}^{E-N} = \alpha_i + \lambda_i P_{i,t-1}^{E-N} + \beta_{i,OWN} R_{OWN,t}^{E-N} + \beta_{i,DI} R_{DI,t}^{E-N} + e_{i,t}$$

where the dependent variable is the ETF-NAV return difference and P_i^{E-N} is the ETF premium. The two return factors are weighted ETF-NAV return differences of other ETFs that match 1) the same size and/or the valuation category of ETF *i* (OWN) and 2) neither the size, nor the valuation category of ETF *i* (Distant). Equal weight is given to funds that match only one style dimension (size or valuation), and twice the equal weight is given to funds that match both style dimensions (size and valuation). Blend funds (neither value, nor growth) are matched only by their size category. ETFs in the distant category are all equally-weighted. I report average *betas* across all ETFs. T-statistics for the mean are adjusted for cross-correlation as in Hameed, Kang and Viswanathan (2010). T-statistics at the 5th, 50th and 95th refer to fund specific t-statistics and are based on white standard errors. */**/*** denotes statistical significance at the 10, 5 and 1 %.

Statistic	$\boldsymbol{\beta_{i,OWN}}$	[t-stat]	$\boldsymbol{\beta_{i,DI}}$	[t-stat]	$\boldsymbol{\beta_{i,OWN}}$	[t-stat]	$\boldsymbol{\beta_{i,DI}}$	[t-stat]
Panel A: Return horizon								
	Weekly return horizon				**Monthly return horizon**			
Mean	0.781	[10.86]	-0.053	[-0.82]	0.762	[7.45]	-0.028	[-0.31]
P05	0.034	[0.08]	-0.890	[-2.70]	-0.331	[-0.59]	-0.931	[-2.54]
P25	0.409	[1.88]	-0.213	[-1.47]	0.408	[1.46]	-0.288	[-1.00]
P50	0.775	[3.50]	-0.059	[-0.44]	0.701	[2.58]	0.001	[0.03]
P75	1.032	[5.99]	0.156	[0.82]	1.049	[3.86]	0.185	[0.92]
P95	1.745	[10.99]	0.695	[2.73]	1.820	[6.15]	0.776	[2.04]
R2	0.651				0.595			
N	53,764				13,664			
Panel B: Sub-samples								
	Period: 06/2002-08/2008 (weekly)				**Period: 04/2009-12/2012 (weekly)**			
Mean	0.605	[11.40]	-0.018	[-0.36]	0.722	[12.44]	-0.051	[-1.06]
P05	-0.043	[-0.19]	-0.577	[-2.82]	0.119	[0.33]	-0.616	[-3.25]
P25	0.379	[2.17]	-0.106	[-0.76]	0.458	[2.67]	-0.178	[-1.69]
P50	0.575	[3.90]	-0.009	[-0.09]	0.685	[4.20]	-0.047	[-0.44]
P75	0.744	[6.12]	0.141	[1.14]	0.970	[7.19]	0.103	[0.79]
P95	1.346	[9.32]	0.442	[2.99]	1.556	[12.17]	0.458	[2.63]
R2	0.569				0.615			
N	31,028				31,516			
	Non-Sector Funds (weekly)				**Sector Funds (weekly)**			
Mean	0.782	[7.93]	-0.038	[-0.43]	0.744	[5.02]	-0.019	[-0.14]
P05	-0.127	[-0.18]	-1.125	[-2.76]	-0.552	[-0.97]	-0.931	[-2.05]
P25	0.547	[2.21]	-0.283	[-1.21]	0.364	[1.06]	-0.288	[-0.86]
P50	0.790	[3.18]	-0.064	[-0.35]	0.575	[1.88]	0.052	[0.19]
P75	1.115	[4.51]	0.129	[0.83]	0.929	[3.10]	0.215	[0.95]
P95	1.734	[7.32]	0.585	[1.80]	2.758	[4.30]	1.047	[2.05]
Adj. R2	0.643				0.551			
N	28,066				25,698			

Table 5: Comovement in relative trading activity and liquidity

Daily shocks to relative turnover (liquidity) for ETF i are regressed on equally-weighted shocks in relative turnover (liquidity) of other ETFs in the own- and distant styles:

$$\omega_{i,t}^{RTo} = \alpha_i + \sum_{j=-1}^{+1} \beta_{i,j}^{Own} \omega_{Own,t+j}^{RTo} + \sum_{j=-1}^{+1} \beta_{i,j}^{Di} \omega_{Di,t+j}^{RTO} + u_{i,t}^{RTo}$$

$$\omega_{i,t}^{RLiq} = \alpha_i + \sum_{j=-1}^{+1} \beta_{i,j}^{Own} \omega_{Own,t+j}^{RLiq} + \sum_{j=-1}^{+1} \beta_{i,j}^{Di} \omega_{Di,t+j}^{RLiq} + u_{i,t}^{RLiq}$$

The regressions include lagged, concurrent and lead values for the factors. I report the average and median values for the concurrent, lagged, lead, sum coefficients and Adjusted R^2; the percentage of funds with positive coefficients, the percentage of funds with positive and significant coefficients, negative and significant coefficients. Test of statistical significance for the mean is based on the cross-sectional t-statistic for the average coefficient, while the significance for the median is based on a sign-test. */**/*** denotes statistical significance at the 10, 5 and 1 % level.

	Own-style betas				**Distant-style betas**				
	Conc	**Lag**	**Lead**	**Sum**	**Conc**	**Lag**	**Lead**	**Sum**	**Adj. R^2**
				Panel A: Relative turnover					
Mean	0.616	0.041	0.036	0.693	0.246	-0.009	-0.006	0.231	0.060
	(25.63)	(2.90)	(2.89)	(22.82)	(14.45)	(-0.69)	(-0.52)	(9.68)	
Median	0.593***	0.020	0.040	0.705***	0.213***	0.001	0.004	0.221***	0.054
% pos	100.00	59.26	63.58	98.77	90.74	50.62	50.62	79.63	
% pos & sig	88.89	5.56	8.02	88.89	49.38	2.47	1.85	46.30	
% neg & sig	0.00	0.62	3.09	0.00	0.00	2.47	4.94	4.32	
				Panel B: Relative liquidity					
Mean	0.918	-0.002	-0.018	0.897	0.036	0.001	0.012	0.049	0.202
	(24.70)	(-0.26)	(-1.88)	(22.99)	(1.90)	(0.09)	(1.34)	(2.09)	
Median	0.870***	-0.006	-0.019	0.874	0.044	0.006	0.013	0.030	0.156
% pos	100.00	47.53	45.06	97.53	55.56	51.85	52.47	53.70	
% pos & sig	92.59	3.09	2.47	89.51	26.54	4.32	3.70	35.80	
% neg & sig	0.00	5.56	8.02	1.23	21.60	1.23	3.09	23.46	

Table 6: Correlations

The variables included in the correlation matrix are the degree of ETF return comovements ($R^2_{ret,q}$), degree of relative turnover and liquidity comovement ($R^2_{rto,q-1}$ and $R^2_{rliq,q-1}$), flows to ETF i's institutional owners ($Flow_{i,q-1}$), equally-weighted flows to institutional owners of other ETFs matching the style of ETF i ($Flow_{Own,q-1}$) and equally-weighted flows to institutional owners of ETFs not matching the style of ETF i ($Flow_{Di,q-1}$). Fund specific variables included are expense ratios (EXP), log of assets under management (AUM), idiosyncratic risk (ID RISK), proportional monthly ETF and underlying portfolio quoted spreads (ETF QSPR, UND QSPR; signed to indicate liquidity). Macro variables include the volatility of NAV returns (STD(NAV)) and fund liquidity (NOISE). The timing of variables (*q* or *q-1*) corresponds to that used in the regressions in Table 7.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
(1) $R^2_{ret,q}$	1.00												
(2) $R^2_{rto,q-1}$	0.17	1.00											
(3) $R^2_{rliq,q-1}$	0.46	0.30	1.00										
(4) $\lvert Flow_{i,q-1}\rvert$	0.03	0.04	-0.03	1.00									
(5) $\lvert Flow_{Own,q-1}\rvert$	0.09	0.06	-0.04	0.41	1.00								
(6) $\lvert Flow_{Di,q-1}\rvert$	0.07	0.05	-0.03	0.41	0.88	1.00							
(7) STD(NAV), q	0.07	-0.05	-0.10	0.11	0.11	0.13	1.00						
(8) NOISE, q	0.15	0.01	0.00	0.24	0.38	0.39	0.76	1.00					
(9) Exp. Ratio, q-1	-0.38	-0.15	-0.49	-0.02	-0.01	-0.01	0.07	-0.02	1.00				
(10) ln(AUM), q-1	0.19	0.13	0.40	0.08	-0.07	-0.08	-0.10	-0.09	-0.51	1.00			
(11) ID RISK, q-1	0.03	-0.05	-0.04	0.13	0.20	0.24	0.68	0.68	0.04	-0.11	1.00		
(12) ETF QSPR, q-1	0.10	0.10	0.26	-0.07	-0.26	-0.29	-0.46	-0.59	-0.31	0.59	-0.57	1.00	
(13)UND QSPR, q-1	-0.13	0.03	-0.02	-0.13	-0.24	-0.28	-0.55	-0.67	-0.04	0.15	-0.63	0.65	1.00

Table 7: Explaining the degree of excess return comovement

This table reports results from regressions of the amount of return comovement ($R^2_{ret,q}$) for ETF i on the following measures of correlated demand shocks: commonality in abnormal trading activity ($R^2_{rto,q-1}$), commonality in relative liquidity ($R^2_{rliq,q-1}$), flows to ETF i's institutional owners ($Flow_{i,q-1}$), equally-weighted flows to institutional owners of other ETFs matching the style of ETF i ($Flow_{Own,q-1}$) and equally-weighted flows to institutional owners of ETFs not matching the style of ETF I ($Flow_{Di,q-1}$). Comovements are based on the model R2, or the fraction of the variation in the dependent variable (ETF-NAV returns, relative turnover or liquidity) attributable to the own and distant style factors. Other variables included are fund expense ratios, assets under management (AUM), idiosyncratic risk (ID RISK), proportional monthly ETF and underlying portfolio quoted spreads (ETF QSPR, UND QSPR; signed to indicate liquidity), volatility of NAV returns (STD(NAV)), fund liquidity (NOISE). All variables are measured at the end of quarter q-1 except for the macro variables STD(NAV) and NOISE that are contamporaneous. */**/*** denotes statistical significance at the 10, 5 and 1 % level. Standard errors are clustered by fund.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$R^2_{ret,q-1}$	0.369***	0.352***	0.373***	0.372***	0.342***	0.338***	0.173***
	(18.96)	(16.73)	(17.50)	(18.42)	(15.68)	(14.75)	(7.37)
Exp. Ratio, q-1	-0.148***	-0.126***	-0.160***	-0.153***	-0.135***	-0.123***	-0.050
	(3.79)	(3.30)	(3.94)	(3.84)	(3.45)	(2.95)	(0.48)
AUM, q-1	-0.451	-0.730*	-0.510	-0.437	-0.923**	-0.815**	-1.907***
	(1.21)	(1.91)	(1.35)	(1.21)	(2.37)	(2.06)	(2.66)
ID RISK, q-1	-21.035***	-24.245***	-18.973***	-19.736***	-23.467***	-8.968*	-29.081***
	(4.03)	(3.85)	(3.76)	(3.97)	(3.80)	(1.73)	(5.04)
ETF QSPR, q-1	2.984***	2.689***	3.139***	3.206***	3.487***	4.312***	5.215***
	(3.39)	(3.10)	(3.42)	(3.64)	(3.79)	(4.03)	(5.55)
UND QSPR, q-1	-2.586**	-2.160*	-2.410*	-2.445*	-2.547*	0.757	-5.646***
	(2.22)	(1.81)	(1.87)	(1.95)	(1.95)	(0.40)	(4.66)
STD(NAV), q	2.520***	2.377***	2.505***	3.169***	3.003***	0.651	4.914***
	(3.64)	(3.42)	(3.55)	(4.44)	(4.02)	(0.62)	(6.50)
NOISE, q	0.571***	0.711***	0.510**	0.270	0.431*		0.164
	(2.86)	(3.58)	(2.42)	(1.24)	(1.83)		(0.74)
$R^2_{rto,q-1}$	0.125***				0.068	0.044	0.081*
	(3.20)				(1.59)	(1.09)	(1.78)
$R^2_{rliq,q-1}$		0.152***			0.155***	0.119***	0.106***
		(5.91)			(5.52)	(4.25)	(3.78)
$\lvert Flow_{i,q-1}\rvert$			0.017		-0.009	0.002	-0.001
			(1.12)		(0.60)	(0.15)	(0.05)
$\lvert Flow_{Own,q-1}\rvert$				0.246***	0.241***	0.435*	0.253***
				(3.34)	(3.17)	(1.86)	(3.22)
$\lvert Flow_{Di,q-1}\rvert$				-0.030	-0.018	0.280	0.021
				(0.34)	(0.20)	(1.14)	(0.23)
Dummies							
Sector	YES	YES	YES	YES	YES	YES	YES
Style	YES	YES	YES	YES	YES	YES	YES
Time	NO	NO	NO	NO	NO	YES	NO
ETF	NO	NO	NO	NO	NO	NO	YES
Adj. R^2	0.427	0.442	0.417	0.423	0.440	0.504	0.496
Nobs	3,700	3,683	3,528	3,711	3,371	3,371	3,371

Table 8: ETF and underlying portfolio return comovement

This table reports results from regressions of the amount of return comovement ($R^2_{ret,q}$) for ETF i on fund characteristics, macro variables, proxies for correlated demand shocks and measures of return comovements for the underlying securities in the ETF's underlying portfolio. Table 7 provides more details on the remaining variables. */**/*** denotes statistical significance at the 10, 5 and 1 % level. Standard errors are clustered by fund.

Variables	**(1)**	**(2)**	**(3)**
$R^2_{ret,q-1}$	0.335***	0.337***	0.166***
	(15.34)	(14.69)	(7.25)
Exp. Ratio, q-1	-0.133***	-0.118***	-0.039
	(3.31)	(2.84)	(0.38)
AUM, q-1	-0.732*	-0.774*	-1.823**
	(1.89)	(1.97)	(2.50)
ID RISK, q-1	-17.688***	-7.869	-21.707***
	(3.12)	(1.57)	(4.34)
ETF QSPR, q-1	3.241***	4.361***	4.841***
	(3.54)	(4.16)	(5.26)
UND QSPR, q-1	-4.952***	0.162	-7.992***
	(3.65)	(0.08)	(6.54)
STD(NAV), q	-0.872	-1.179	0.389
	(0.93)	(1.19)	(0.36)
NOISE, q	0.465**		0.243
	(2.06)		(1.11)
$R^2_{rto,q-1}$	0.072*	0.049	0.084*
	(1.70)	(1.18)	(1.84)
$R^2_{rliq,q-1}$	0.140***	0.113***	0.093***
	(4.94)	(4.02)	(3.34)
$\lvert Flow_{i,q-1} \rvert$	-0.013	0.001	-0.002
	(0.83)	(0.05)	(0.11)
$\lvert Flow_{Own,q-1} \rvert$	0.247***	0.444*	0.259***
	(3.24)	(1.90)	(3.30)
$\lvert Flow_{Di,q-1} \rvert$	-0.028	0.307	0.004
	(0.32)	(1.26)	(0.05)
$R^2_{UND,MKT,q}$	0.251***	0.134*	0.282***
	(5.73)	(1.91)	(6.81)
$R^2_{UND,STYLE,q}$	0.272***	0.248***	0.343***
	(3.88)	(3.45)	(4.12)
Dummies			
Sector	YES	YES	YES
Style	YES	YES	YES
Time	NO	YES	NO
ETF	NO	NO	YES
Adj. R^2	0.447	0.505	0.504
Nobs	3,371	3,371	3,371

Table 9: Changes in premiums and liquidity

This table reports regressions of the change premiums (ETF-NAV returns) on the lagged premium (not shown), shock to relative ETF liquidity ($\omega_{i,t}^{rliq}$), shock to the equally-weighted relative liquidity of ETFs in the Own and Distant categories ($\omega_{OWN,t}^{rliq}$ and $\omega_{DI,t}^{rliq}$). I report average coefficient across all ETFs. T-statistics for the mean are adjusted for cross-correlation as in Hameed, Kang and Viswanathan (2010). */** denotes statistical significance at the 10 and 5 % level. ΔR^2 is the average improvement in R-squared compared to the model where ETF-NAV returns are only regressed against the lagged level of premium.

	Daily horizon		**Weekly horizon**		**Monthly horizon**	
	(a)	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
$\omega_{i,t}^{rliq}$	0.0011	0.0009	0.0017	0.0001	0.0098	0.0064
	(0.76)	(0.37)	(0.58)	(0.03)	(1.19)	(0.53)
$\omega_{OWN,t}^{rliq}$		0.0002		-0.0015		0.0054
		(0.07)		(-0.30)		(0.45)
$\omega_{DI,t}^{rliq}$		0.0007		0.0021		0.0071
		(0.39)		(0.60)		(0.79)
ΔR^2	0.001	0.001	0.002	0.005	0.010	0.031
N	247,303	247,238	52,933	52,933	12,175	12,175

Table 10: Differences in systematic risk?

This table reports regressions of ETF-NAV returns on the lagged level of premium to control for mean-reversion, *MKT*, *SMB*, *HML* and funding liquidity (NOISE) factors, estimated fund-by-fund using all available observations. T-statistics for the mean are adjusted for cross-correlation as in Hameed, Kang and Viswanathan (2010). */**/*** denotes statistical significance at the 10, 5 and 1 % level. ΔR^2 is the average improvement in R-squared compared to the model where ETF-NAV returns are only regressed against the lagged level of premium.

		Daily horizon		Weekly horizon		Monthly horizon	
Factor	**By style**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
MKT	All	-0.0193***	-0.0197***	-0.0052	-0.0055	0.0003	0.0008
	Small	-0.0203***	-0.0203***	-0.0054	-0.0053	0.0034	0.0053
	Large	-0.0184***	-0.0189***	-0.0045*	-0.0049**	-0.0009	-0.0010
	Value	-0.0217***	-0.0223***	-0.0049*	-0.0051*	-0.0008	-0.0003
	Growth	-0.0190***	-0.0190***	-0.0052	-0.0055	0.0003	0.0008
SMB	All	0.0055	0.0073	0.0073	0.0068	-0.0014	-0.0011
	Small	-0.0124*	-0.0110	-0.0013	-0.0012	-0.0064	-0.0048
	Large	0.0121**	0.0137***	0.0081	0.0074	0.0000	-0.0003
	Value	0.0081	0.0109*	0.0070	0.0067	0.0009	0.0008
	Growth	0.0086*	0.0098**	0.0073	0.0068	-0.0014	-0.0011
HML	All	-0.0117***	-0.0108***	0.0030	0.0035	0.0013	0.0013
	Small	-0.0119**	-0.0116**	0.0044	0.0043	0.0019	0.0014
	Large	-0.0095**	-0.0082*	0.0033	0.0041	0.0016	0.0017
	Value	-0.0219***	-0.0209***	0.0017	0.0021	0.003	0.0029
	Growth	-0.0030	-0.0028	0.0030	0.0035	0.0013	0.0013
NOISE	All		0.0145*		-0.0115		0.0076
	Small		0.0100		0.0065		0.0268
	Large		0.0174**		-0.0193		-0.0001
	Value		0.0210**		-0.0110		0.0044
	Growth		0.0118*		-0.0115		0.0076
ΔR^2	All	0.078	0.078	0.019	0.032	0.061	0.098
N	All	258,529	254,405	53,764	53,288	13,664	13,502