Flow-Driven ESG Returns[*]

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Abstract

I show that the returns from sustainable investing are strongly driven by price pressure from flows towards sustainable funds, causing high realized returns that do not reflect high expected returns. Using a structural model, I estimate investors' ability to accommodate the demand from sustainable funds, which is given by their elasticity of substitution between stocks. I show that every dollar flowing from the market portfolio into sustainable mutual funds increases the aggregate value of green stocks by $0.4. The price pressure from flows supports the effectiveness of impact investing by lowering green firms' cost of capital. In the absence of flow-driven price pressure, sustainable funds would have underperformed the market from 2016 to 2021. To this end, I develop a new measure of total capital flows into managed portfolios. The price pressure from total ESG flows is highly correlated with empirically observed returns, both in the time-series and in the cross-section. I support the structural estimates with reduced-form evidence, showing that index inclusions and mandate-driven portfolio additions by sustainable mutual funds significantly boost the prices of green stocks.

1 Introduction

Over the past decade, the sustainable investment industry has grown drastically. The high demand for sustainable investments has fueled the emergence of new funds that incorporate environmental, social, and governance (ESG) criteria into their investment decisions. Despite the enormous growth in the ESG investment industry, both the price impact and the expected returns of sustainable investing are widely debated. Academic and practitioner views on the expected returns from sustainable investments are often diametrically opposed. The pervasive theoretical view is that if investors have a preference for sustainability, the additional utility gained by investing sustainably should be perfectly offset by lower expected returns. Investors bid up the price of sustainable companies, and risk-adjusted expected returns must unambiguously be lower. In other words, investors cannot do well by doing good. Empirically, however, sustainable funds have performed well in recent years suggesting that ESG-concerned investors are in fact doing well by doing good. At the same time, the extent to which sustainable investors can impact prices is highly debated. For every buyer there is a seller. Hence, divesting from oil companies simply implies a change in ownership towards funds without a sustainability mandate. The impact of sustainable investing therefore depends on how much prices have to change in order to induce other investors to hold the divested oil shares.

This paper reconciles the price impact and realized returns of sustainable investing. I show that the high realized returns from sustainable investing are primarily driven by the price impact of flows towards sustainable funds. Flows towards ESG funds - regardless of whether they are motivated by growing ESG concerns or past fund performance - create buying pressure on the stocks that the funds overweight. This buying pressure affects prices, if the market's willingness to accommodate the demand by substituting between stocks is finite. In other words, if the aggregate demand curve for green stocks is downward-sloping, then ESG flows increase the price of green stocks. In equilibrium, the price impact of flows towards ESG funds is driven by two factors: The deviation of ESG funds from the market portfolio and the aggregate willingness to substitute between stocks (henceforth, elasticity of substitution). If the investors holding green stocks substitute elastically between stocks, then the price pressure due to ESG flows has a negligible impact. Small price changes induce investors to rebalance their portfolios by substituting away from the overpriced green stocks. On the other hand, if the holders of green assets do not aggressively rebalance their portfolios, i.e. if they are inelastic, then flows have a large price impact. I show that institutions' ability to accommodate ESG demand

is limited as their elasticity of substitution between stocks is low. Thus, flow-driven trades by ESG funds have a large impact on prices, both in the cross-section of individual ESG stocks and in the time-series of ESG portfolio returns. Therefore, the *realized* returns from sustainable investing over the past decade have a large flow-driven component. The outperformance of ESG funds should hence not be interpreted as *expected* outperformance going forward.

I start by identifying a set of 551 sustainable mutual funds (henceforth ESG funds) by matching their names with a list of sustainability keywords. Using data on mutual funds' portfolio holdings, I then construct a representative ESG portfolio that pools the holdings of ESG mutual funds. The representative ESG portfolio outperformed the aggregate mutual fund portfolio with a significant 5-factor alpha of 1.51% annually. Exposure to the Green Factor by Pástor et al. (2021) does not explain the outperformance. The ESG portfolio's deviations from the aggregate mutual fund portfolio are a revealed preference measure of how sustainable a stock is (perceived to be). I define 'green' stocks as the ones overweighted by ESG funds relative to other mutual funds. Thus, in this paper 'green' refers to all dimensions of sustainability, not only environmental concerns. Quantifying the flow-driven component of the realized returns from the ESG portfolio requires a measure of total ESG flows. To this end, I propose a new measure of capital flows into managed portfolios. The measure includes the portfolio tilts of all institutional investors and is constructed by projecting fund-specific holdings onto managed portfolios in the portfolio-weight as opposed to the return space. Total institutional flows into the ESG portfolio amounted to $1.3 trillion, which dwarfs the flows into ESG mutual funds of $350 billion.[1]

In order to quantify price impact of ESG flows, I estimate a structural model that jointly matches flows and realized returns along the lines of Koijen and Yogo (2019). I use the estimation proposed by van der Beck (2022), which identifies elasticities from investors' trades, as opposed to their portfolio holdings in levels. The model allows for estimating institutions' elasticity of substitution between green and other stocks. I use demand shocks from dividend reinvestments by Schmickler and Tremacoldi-Rossi (2022) as an instrument to address the endogeneity of prices in the elasticity estimation.[2] I show that the estimates are robust to an alternative identification that uses changes in benchmarking intensities by Pavlova and Sikorskaya (2022) as an exogenous shock to supply. The estimated elastic-

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[1]See Morningstar's 2021 Sustainable Funds U.S. Landscape Report.

[2]Starting with Edmans et al. (2012), flow-induced trades by mutual funds have been commonly used as exogenous demand shocks to identify causal relationships. See Wardlaw (2020) for a summary of the literature. Note, that the instrument used in this paper is immune to the Wardlaw-critique (see van der Beck (2022) for details).

ities can be combined with ownership shares into a cross-sectional multiplier matrix. The multiplier matrix is the cross-sectional pendant to the macro multiplier in Gabaix and Koijen (2021). I find that, ceteris paribus, a 1% demand shock for a green stock leads to a 1.11% percent increase in the price of that stock. Furthermore, cross-elasticities suggest that as money is flowing out of the fossil fuel industry, investors substitute towards green stocks, creating positive spillover effects.

I apply the model to the assess the flow-driven component in the realized returns of green stocks. The price pressure due to a $1 flow into the ESG portfolio funds is given by the product of the multiplier matrix and the deviation of the ESG portfolio from market weights. I show that every dollar flowing from the market portfolio into the representative ESG portfolio increases the aggregate value of green stocks by $0.4. I then compute the counterfactual realized returns if the total ESG flows were instead invested in the market portfolio. The price pressure from ESG flows accounts for virtually all of the outperformance of the ESG portfolio over the market portfolio in recent years. In the absence of ESG flows, the ESG portfolio would have underperformed the market with an annualized 5-factor alpha of -0.3%. This suggests that, in the absence of flow-driven price pressure, investors would have had to pay a premium for investing according to their ESG preferences. Moving to the cross-section, I show that green stocks with higher flow-driven demand had significantly higher abnormal returns. The average price impact implied from cross-sectional regressions is 1.17, which is strikingly close to the structural estimate of 1.11. Furthermore, the stocks with higher multipliers implied by the structural model indeed have a higher price impact in the cross-section, i.e. they are more affected by ESG demand.

Lastly, I provide reduced-form evidence on the price pressure of ESG demand from inclusions in the Vanguard 4Good index, as in Berk and van Binsbergen (2022). I show that not all inclusions are followed by index-tracking mutual funds. However, the inclusions that are followed by index trackers are associated with significantly higher returns. The price impact implied by the index inclusions is 1.69, which is close to the structurally estimated ESG multiplier. I then show how to decompose ESG mutual funds' portfolio additions into a mandate-driven and a fundamental component, which extends the concept of ESG index inclusions to a broader set of stocks. The mandate-driven portfolio additions across ESG mutual funds represent non-fundamental shocks to ESG demand and are significantly related to contemporaneous returns, controlling for changes in fundamentals and known return predictors. The magnitude of the estimated price impact is once again in line with the structural multiplier. Lastly, I show that there is substantial heterogeneity in the price impact of different ESG

mutual funds - both in terms of magnitude and direction. Many 'sustainable' mutual funds deviate very little from S&P500 weights. Others positively affect the aggregate market capitalization of the fossil fuel industry. I outline how the model can be used to distinguish ESG funds by their *true* impact on green firms' cost of capital rather than by flamboyant fund prospectuses.

Related Literature

The empirical evidence on the *realized* returns from ESG investing over the past two decades is mixed and tends to depend on the sustainability measure, time horizon, and asset universe under investigation. Hong and Kacperczyk (2009) find that stocks in the tobacco, alcohol, and gaming industry (i.e. sin stocks) outperform other stocks. Bolton and Kacperczyk (2021a) and Bolton and Kacperczyk (2021b) find evidence for a carbon premium, implying that high-emission stocks have higher returns after controlling for known risk factors. Similarly, Hsu et al. (2020) find significant outperformance of high chemical emission stocks versus low ones.[3] Except for Hong and Kacperczyk (2009), who argue for a taste-based explanation along the lines of Fama and French (2007), these papers suggest that sustainable firms offer hedges against adverse climate events and hence require lower returns in equilibrium.

Conversely, many papers show that sustainable stocks had higher realized returns than other stocks. Edmans (2011) shows that a portfolio of firms with high employee satisfaction has a significantly positive alpha. In et al. (2020) find that an ESG portfolio, which longs low emission and shorts high emission stocks earns a significantly positive annualized alpha of 3.5–5.4%. Similarly, Görgen et al. (2020) find that from 2010 to 2017 brown (high carbon) firms performed worse than green firms on average. Hong et al. (2019) find that the risk of drought negatively predicts a country's stock returns. These papers typically propose under-reaction as a reason why sustainability is associated with a positive return premium. Pedersen et al. (2020) propose an equilibrium model with green preferences and ESG scores that are informative about stocks' risk and return. Their model shows that green stocks can have higher returns if ESG scores positively predict returns in a way that has not been appreciated by all investors. In support of the under-reaction hypothesis, Derrien et al. (2021) find that analysts downgrade their earnings forecast in response to negative ESG incidents. Glossner (2021) shows that ESG incidents predict future ESG incidents and that the stock market underestimates the

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[3]Other papers documenting a positive return premium on brown investments in equities, bonds, real estate, and option markets include Faccini et al. (2021), Huynh and Xia (2021), Seltzer et al. (2022), Bernstein et al. (2019), Baldauf et al. (2020), Painter (2020), Goldsmith-Pinkham et al. (2021) and Ilhan et al. (2021).

adverse value effects of negative poor ESG practices. Glossner (2021) also suggests that ESG mutual funds benefit from the under-reaction to ESG news. Similarly, I argue that ESG mutual funds benefit from flow-driven price pressure on green stocks.

The theories developed in Pástor et al. (2021) and Pedersen et al. (2020) imply that the *expected* returns of green stocks should be lower than for brown stocks as investors have a taste for green assets. However, if green preferences (e.g. via climate concerns) strengthen unexpectedly over the estimation horizon, green stocks may have higher realized returns than brown firms. Alternatively, if climate risks increase unexpectedly, the hedging benefits of holding green stocks improve, which pushes up their price, resulting in higher realized returns. Thus unexpected shifts in the aggregate demand for green assets may drive a wedge between expected and realized returns. This divergence between realized and expected returns may explain the strong ambiguity in the empirical findings mentioned above. In a follow-up paper, Pastor, Stambaugh and Taylor (henceforth PST, 2022) regress the realized returns of a green-minus-brown (GMB) factor onto several proxies of unexpected shocks to climate concerns. They then approximate the wedge between *expected* and *realized* factor returns as the return component explained by green demand. As one particular proxy for green demand (by investors rather than consumers) they use flows to ESG mutual funds and find no significant correlation to contemporaneous GMB returns. However, ESG flows may not directly target the GMB portfolio. Instead, they flow into the aggregate ESG mutual portfolio, the returns of which are highly significantly correlated to total ESG flows. It is important to note, that this interpretation of the relationship between green demand and realized returns is slightly different from the mechanism proposed in this paper. In PST (2022), ESG demand only correlates with returns as long as it represents aggregate shifts in green preferences (or equivalently, wealth-weighted individual tastes as in Fama and French (2007)). Thus, if flows to green funds were driven by e.g. past return performance instead of growing climate concerns, prices would remain unchanged. Similarly, ESG demand shocks for individual stocks have negligible price effects as they do not change the exposure to common risk factors and have little impact on aggregate market risk.[4] Nevertheless, despite the different interpretations of the correlation between flows and returns, this paper shares the objective of measuring how the demand for green stocks affects the wedge between realized and expected returns. The joint endogeneity of prices and holdings makes identifying the causal relationship between demand shocks and realized returns extremely difficult. Simple regressions of returns onto flows are typically biased as the number of endogenous variables

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[4] See Petajisto (2009) for a simple calibration.

affecting both demand and prices are countless. Hence, this paper circumvents direct regressions of returns onto flows and instead estimates the coefficient linking flows to returns within a structural model. Perhaps most closely related is the paper by Berk and van Binsbergen (2022), who calibrate the potential impact of ESG divestment in a frictionless CAPM world. They argue that the equilibrium price impact of sustainable investing is negligible because the high return correlation between green and brown stocks makes them strong substitutes. Therefore, inducing other investors to hold brown stocks requires little price concessions. Petajisto (2009), however, shows that the price impact implied by the CAPM greatly underestimates the estimates from the index inclusion literature. In other words, the frictionless mean-variance benchmark considerably overestimates investors' elasticity of substitution between stocks. I directly estimate demand elasticities from holdings data and show that the market's elasticity of substitution between green and brown stocks is indeed very low. Thus investors require large price concessions to accommodate the flow-driven trades by ESG funds. Using index inclusion as in Berk and van Binsbergen (2022), I find that the stocks purchased by ESG index trackers have significantly higher contemporaneous returns.

The paper also relates to the extensive literature on demand-driven price pressure. Shleifer (1986) shows that index inclusion leads to positive realized returns as a result of buying pressure by index funds. Coval and Stafford (2007), Frazzini and Lamont (2008), Edmans et al. (2012) and Lou (2012) find evidence for cross-sectional price pressure resulting from mutual funds' flow-driven trades. More recently, Parker et al. (2020) find that the rebalancing of target date funds affects both the cross-section of realized returns and the aggregate stock market. Using a Morningstar ratings reform as an instrument, Ben-David et al. (2020) show that demand pressures affect the cross-section of realized style returns. Similarly, I show that mandate-driven portfolio additions by ESG funds affect individual stock returns. More closely related, Gabaix and Koijen (2021) use a structural approach to estimate the multiplier linking flows and aggregate stock market returns. They find that a \$1 *unexpected* flow raises the value of the aggregate equity market by around \$5. Using aggregate dividend reinvestments as an instrument, Hartzmark and Solomon (2021) find, that even *expected* uninformed flows into and out of the aggregate stock market have a price multiplier of 1.5 to 2.3. Pavlova and Sikorskaya (2022) introduce a new measure, Benchmarking Intensity, which quantifies the fraction of a stock's total market cap that is held by benchmarked investors. They show that changes in a stock's Benchmarking Intensity are an effective change in supply that is significantly related to contemporaneous returns around the Russell 1000/2000 cutoff. They find that institutional trades have a price multiplier of

1.5. As a robustness check, I use changes in Pavlova and Sikorskaya's Benchmarking Intensity as an instrument to identify investors' demand elasticities. The resulting ESG multipliers are strikingly similar to the flow-based identification. The estimated elasticities furthermore exhibit the same cross-sectional patterns.

Lastly, this paper relates to the growing literature on demand system asset pricing following the influential work by Koijen and Yogo (henceforth KY, 2019). KY (2019) present a structural model that estimates investor-specific demand curves from quarterly 13F filings and links the estimated demand coefficients to equilibrium asset prices. In a follow-up paper, Koijen et al. (2022) estimate investors' demand for environmental scores and show that long-term investors, passive funds, and banks benefit the most from growing climate concerns. Similarly, Noh and Oh (2022) regress institutional portfolio weights onto ESG-Scores and show that ESG demand predicts firm-level improvements in Co2 emissions.[5] In this paper, I refrain from explicitly estimating investors' green preferences as there are many unobserved characteristics correlated with ESG-Scores that drive demand. A technology fund, for example, has an inherently high preference for sustainability simply because tech stocks tend to have higher ESG-Scores. A valid identification of green preferences, therefore, requires exogenous variation in ESG-Scores uncorrelated with investors' unobservable investment mandates and portfolio tilts. Van der Beck (2022) proposes identifying the demand elasticities in KY (2019) from investors' trades, that is changes in their portfolios, as opposed to their cross-sectional holdings. This alleviates the concern of slow-moving unobservable variables (such as investment mandates) that drive investors' holdings in the cross-section and are correlated with prices. The estimation in changes furthermore allows identifying elasticities with existing instruments from the reduced-form literature on price pressure.[6] This paper uses the estimation from van der Beck (2022) to identify the substitutability of green and brown stocks and links it to the realized returns from ESG investing.

The remainder of this paper is structured as follows. Section 2 describes the data. In Section 3, I construct the representative ESG portfolio. Section 4 briefly outlines the structural model and estimates the markets' willingness to substitute between stocks. Section 5 uses the model to quantify the

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[5]A growing number of papers applies the framework by KY (2019) to estimate the impact of counterfactual experiments on equilibrium asset prices. Han et al. (2021) evaluate the impact of mutual fund risk shifting on the beta anomaly. Bretscher et al. (2020) estimate a demand system for corporate bonds. Jiang et al. (2020) use the demand system to decompose the variation in the US net foreign asset position into its underlying determinants. Van der Beck and Jaunin (2021) investigate the impact of retail traders on the equity market through the demand system approach. Haddad et al. (2021) suggest that the elasticity in KY (2019) is potentially endogenous as investors strategically update their elasticity in response to the aggregate elasticity.

[6]E.g. Index inclusions by Shleifer (1986), mutual fund fire sales by Coval and Stafford (2007), flow-driven trades by Lou (2012), and dividend reinvestments by Schmickler and Tremacoldi-Rossi (2022) and Hartzmark and Solomon (2021).

impact of aggregate ESG flows on the time-series of ESG returns. Section 6 investigates stock-specific flows and the cross-section of ESG returns. Section 7 provides robustness tests and applications. Section 8 concludes.

2 Data and Variable Construction

A Prices and Fundamentals

Stock price data on common ordinary shares (share code 10 and 11) traded on the NYSE, AMEX and Nasdaq (exchange code 1, 2 and 3) are from CRSP. Accounting data are from Compustat. Stocks are indexed by n. Stock n's market equity as of date t is denoted by $P_{t,n}$. I normalize shares outstanding to 1, such that prices and market equity coincide. I construct the stock-specific characteristics book equity, market beta, profitability, investment, idiosyncratic volatility, turnover, momentum and industry affiliation.[7] For industry classifications, I use the Fama and French 12 industries. I furthermore construct monthly cash dividends (distribution code 1000-1399) by summing over payment dates from CRSP's daily security file. Sin stocks are defined following Hong and Kacperczyk (2009) as companies involved in the production of alcohol, tobacco and gaming. I further define controversial stocks following MSCI's exclusionary screens as companies in the biotech, firearms, oil, military and cement industry. Because a firm's sustainability is difficult to quantify and because ratings across providers often diverge strongly (see Berg et al. (2019)), I construct an objective measure using portfolio tilts of ESG mutual funds (see next section). As a robustness check, I also use CO_2 emissions and ESG Scores from Refinitiv as a measure of a firm's greenness.

B Holdings and Flows

In the US, institutional investment managers who have discretion over \$100M or more in designated 13F securities must report their respective holdings via quarterly SEC 13F filings. I obtain institution-level holdings from 2010 to 2021 from Thomson's Institutional Holdings Database (s34 file). The holdings data are subsequently merged with characteristics data from CRSP and Compustat.[8] Institutions are indexed by i. I define institution i's quantity demanded $Q^i_{t,n}$ in stock n at time t as the shares held normalized by shares outstanding.[9] Institution-level and mutual fund portfolio weights $w^i_{t,n} = \frac{Q^i_{t,n} P_{t,n}}{A^i_t}$

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[7]See Appendix Section D.5 for details on the construction of these variables.

[8]See KY (2019) for further details on the construction of the database.

[9]Formally $Q^i_{t,n} = \frac{\text{Shares Held}^i_{t,n}}{\text{Shares Outstanding}_{t,n}}$, where Shares Held$^i_{t,n}$ is the number of shares reported in i's 13F Filing.

are constructed as the dollar holdings in each stock (price times shares held) divided by their assets under management A_t^i. An institution's assets under management are given by the sum of its dollar holdings. In order to ensure market clearing, I follow KY (2019) and construct a household sector as the residual shares outstanding not held by 13F institutions.[10]

Monthly data on mutual funds' holdings, net returns and total net assets, as well as other fund-specific characteristics are obtained from the CRSP survivorship-bias-free mutual fund database. For over 90% of all mutual funds, CRSP provides holdings at a higher frequency than Thomson's Quarterly Mutual Fund Holdings Database (s12 file). I construct mutual fund portfolios using both databases and opt for CRSP holdings when moving to a higher frequency. For all mutual funds, I compute flows as $f_t^i = \frac{A_t^i - A_{t-1}^i(1+r_t^i)}{A_{t-1}^i}$ where A_t^i are the fund's total net assets and r_t^i is the monthly return between $t-1$ and t as reported on CRSP.

3   ESG Mutual Funds

A   Identifying ESG Mutual Funds

I use fund names from CRSP's Mutual Fund Database to identify a comprehensive set of ESG mutual funds. To this end, I match fund names with a list of sustainability keywords and identify 551 ESG funds. Specifically, I define a mutual fund to be an 'ESG fund' if its name contains at least one (or any abbreviation) of a list of sustainability keywords.[11] Appendix Section A.1 reports the largest 30 identified ESG funds as well as robustness checks to the identification of the ESG label. I then match the ESG funds with their quarterly and monthly stock holdings from both CRSP and Thomson's Mutual Fund Holdings Database (s12 file). Table 1 provides summary statistics on the sample of ESG funds and their aggregate portfolio.

[Table 1 about here.]

From 2010 to 2021 the average ESG fund held around 200 stocks in its portfolio. The average assets have remained relatively stable and only increased in recent years to $630 Million. The fifth column of Table 1 reports the total number of ESG name changes in a given year. Out of the sample of ESG

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[10]Furthermore, institutions with less than $10 million under management or without any holdings in the inside and/or outside assets are attributed to the household sector, which therefore includes households, small asset managers, and other non-13F institutions.

[11]The list of sustainability keywords used is: *Environment, social, governance, green, sustainable, responsible, SRI, ESG, climate, clean, carbon, impact, fair, gender, solar, earth, renewable, screen, ethical, conscious, CSR, thematic.* See Appendix Section A.1 for details

funds, 99 went from 'non-ESG' to 'ESG' by changing their name to include a sustainable keyword while leaving the fund and portfolio identifier unchanged. The column 'Excess Flows' reports the average flow into ESG funds in excess of the average flow into non-ESG funds. Over the past 5 years, the ESG funds received around 2-3% higher quarterly inflows than other funds. Appendix Section A.2 provides an in-depth analysis of ESG flows controlling for fund characteristics, performance, and portfolio holdings. In a difference-in-difference setting using, I show that having an ESG keyword in the fund-name buys additional quarterly inflows of 1.8%.

B   The Representative ESG portfolio

Using Thomson's Mutual Fund Holdings Database (s12 file), I construct the aggregate portfolio held by the sample ESG mutual funds. To this end, let $Q_{t,n}^{ESG} = \sum_{i \in I^{ESG}} Q_{t,n}^i$ denote the aggregate holdings of the set of identified ESG funds mutual funds I^{ESG}. The representative ESG mutual fund's portfolio weights are given by ESG funds' total dollar holdings divided by their aggregate assets under management. Formally

$$w_{t,n}^{ESG} = \frac{P_{t,n} Q_{t,n}^{ESG}}{\sum_{n=1}^{N} P_{t,n} Q_{t,n}^{ESG}} \tag{1}$$

By using weights instead of dollar holdings, the representative ESG portfolio (henceforth ESG portfolio) is invariant to the number of identified funds, as long as the sample is representative of the average ESG fund. The three rightmost columns of Table 1 report summary statistics on the aggregate ESG portfolio. Total assets grew from \$30 to \$233 billion. At the same time, the fraction of total ESG assets that track an ESG index has also steadily increased to 50%. To what extent do the aggregated holdings across ESG funds reflect the market portfolio? Note, that as more money is flowing into ESG funds, the ESG and the market portfolio converge *by construction*. In the limit, all money is invested in ESG funds and the ESG portfolio coincides with the market portfolio. 'Active Share' is defined as the deviation of the ESG portfolio from the aggregate mutual fund portfolio (henceforth market portfolio). The ESG portfolio tilts around 70% of its assets away from the market portfolio. However, in the most recent years, the active share has declined to 57%.[12] Despite portfolio heterogeneity across ESG funds, their main portfolio tilts go in similar directions. Therefore, while the set of identified ESG funds depends on the kind and amount of keywords used, the aggregate portfolio is extremely robust to different subsets of ESG funds. Appendix Section A.1 provides a detailed investigation of the

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[12]Formally, active share is defined as the deviation of the $\frac{1}{2} \sum_{n \in N^i} |w_{t,n}^{ESG} - w_{t,n}^{MF}|$ where $w_{t,n}^{ESG}$ are the aggregate portfolio weights across all ESG funds and $w_{t,n}^{MF}$ is the aggregate portfolio of all mutual funds.

robustness of the ESG portfolio. Using the ESG portfolio, I construct a revealed-preference measure $\tau_{t,n}$ of investors' green tastes for a stock given by

$$\tau_{t,n} = w_{t,n}^{ESG} - w_{t,n}^{MF} \tag{2}$$

where $w_{t,n}^{MF}$ is the aggregate mutual fund portfolio, which is constructed as in (1) but summing over all mutual funds instead of the subset of ESG funds. Empirically $w_{t,n}^{MF}$ is extremely close to the market capitalization-weighted portfolio, so that defining $\tau_{t,n}$ in excess of market weights leaves all results of the paper unchanged. Stocks with a higher $\tau_{t,n}$ are perceived to be more sustainable as they are overweighted by the representative ESG portfolio. Note, that the revealed preference measure $\tau_{t,n}$ is also a zero-investment long-short portfolio, that is long \$1 in the ESG portfolio and short \$1 in the aggregate mutual fund portfolio. I define stocks with $\tau_{t,n} > 0$ as green stocks and stocks with $\tau_{t,n} < 0$ as other (non-green) stocks. This revealed-preference measure is available for all stocks at a monthly frequency over a large time horizon. It furthermore does not rely on subjective sustainability metrics or third-party ESG scores. $\tau_{t,n}$ is therefore a more objective representation of the market's perception of sustainability. Note, that the purpose of this paper is not to identify a measure of *true* sustainability, but to assess the cross-sectional price distortions due to ESG flows. The most adequate measure of sustainability is hence the measure that people implicitly use when they invest sustainably.

In Appendix Section A.1, I confirm that $\tau_{t,n}$ is robust to the subset of ESG funds used for its computation. I compute two different ESG portfolios using random (non-overlapping) subsets of funds and show that the corresponding $\tau_{t,n}$ are highly cross-sectionally correlated ($\rho > 60\%$). A thorough investigation of the difference between *true* and *perceived* sustainability is beyond the scope of this paper, which addresses the distortion of realized returns due to ESG tastes, regardless of whether they are *correct* or not. I nevertheless confirm that $\tau_{t,n}$ is significantly related to commonly used sustainability metrics. The ESG portfolio significantly tilts towards stocks with high ESG scores and underweights sin stocks, stocks in the fossil fuel industry, and high CO_2 emitters.[13]

C   Realized ESG Returns

Next, I investigate the realized performance of the ESG portfolio $w_{t,n}^{ESG}$, the aggregate mutual fund portfolio $w_{t,n}^{MF}$, and the long-short ESG portfolio $\tau_{t,n} = w_{t,n}^{ESG} - w_{t,n}^{MF}$. The portfolios are rebalanced

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[13]See Appendix Section A.3 for details.

quarterly based on the funds' SEC filings.[14] Table 2 reports the annualized returns and alphas of the portfolios.

[Table 2 about here.]

The first two columns report the annualized returns of the market portfolio and the ESG portfolio. Between 2016 and 2021 the ESG portfolio had a significant 2% higher annualized return than the market portfolio. The four right columns report the returns and alphas of the long-short ESG portfolio $\tau_t \in \mathbb{R}^N$. The returns of τ_t will henceforth be referred to as ESG returns. Intuitively, one would expect significantly negative alphas capturing the taste premium investors are willing to give up in order to invest according to their ESG preferences. However, long-short returns and alphas are significantly positive. From 2016 to 2021, the long-short ESG portfolio had a significant annual CAPM alpha of 2.4%.[15] The last column controls for PST's (2022) Green Factor, as well as the Carhart 4-Factors. The alpha merely drops to 1.5% and remains significant with t-Statistic of 2.01. Overall, Table 2 suggests that investors have been *rewarded* instead of *penalized* for investing according to their ESG preferences. The weights in the long-short ESG portfolio τ_t can be interpreted as a measure of investors' perception of sustainability. Thus, regardless of their *true* sustainability, the stocks that investors deemed more sustainable tended to have higher returns than others.

Despite the apparent outperformance of the ESG portfolio, the goal of this paper is not to add to the debate about whether or why sustainable investing has higher or lower *expected* returns in equilibrium. This paper tries to answer the question of how, ceteris paribus, the cross-section of *realized* returns responds to flows to the ESG portfolio. Thus we can assess, to what extent the realized returns from sustainable investing have been driven by flows towards sustainable funds. However, total flows in the ESG portfolio are not directly observable. The next section shows how to construct aggregate ESG flows from institutional portfolio holdings.

D Measuring Total Flows in the ESG Portfolio

Total flows into the ESG portfolio are difficult to observe. According to Morningstar, labelled ESG mutual funds held $350 billion in total assets, which was less than 1% of the total $37 trillion held

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[14]The portfolios are not necessarily tradeable as funds usually delay their SEC report by up to 45 days.

[15]Note, that these are not the *true* returns an investor would have achieved by investing in the asset-weighted portfolio of (ESG) mutual funds because of fees and because many of these funds trade actively within quarters.

by all ETFs and Mutual funds in the US.[16] However, this does not include the (unobservable) ESG tilts of other mutual funds, investment advisors, pension funds, banks, insurance companies, and other institutions. Therefore, the flows into labelled ESG mutual funds only represent a small subset of total ESG flows. In order to get a sense of total ESG flows, I use 13F filings to estimate each institution's 'ESG share'. Here, I merely present the main procedure. Technical details are delegated to Appendix B. For simplicity, I omit the institution and quarter labels i and t. I project each 13F institution's portfolio w_n in the cross-section onto a set of S managed portfolios w_n^s:

$$\forall i, t: \quad w_n = \sum_{s=1}^{S} \beta^s w_n^s + a_n \tag{3}$$

The managed portfolios are constructed such that the weights add up to 1 across all stocks currently held by the institution N^i. For example, the 'managed' market-weighted portfolio ($s = Mkt$) is given by $w_n^{Mkt} = P_n / \sum_{n \in N^i} P_n$. The residual a_n from the projection is an active zero-cost long-short portfolio in the spirit of Cremers and Petajisto (2009).[17] Thus the coefficients β_t^s sum to 1 and can be interpreted as the asset shares of managed portfolios within institution i. The coefficient on the ESG-managed portfolio, β^{ESG}, measures the institution's ESG share. I then compute the total ESG flow as the sum of institution-specific ESG flows

$$F_{t+1}^{ESG} = \sum_{i=1}^{I} A_{t+1}^{i,ESG} - A_t^{i,ESG}(1 + R_{t+1}^{ESG}) \tag{4}$$

where $A_t^{i,ESG} = \beta_t^{i,ESG} A_t^i$ are the total assets of institution i allocated to the ESG portfolio at time t and R_{t+1}^{ESG} is the return on the ESG portfolio. This measure of total ESG flows is highly robust to controlling for different managed portfolios in the estimation of $\beta_t^{i,ESG}$.[18] Figure 1 plots the total flow into the ESG portfolio from 2012 to 2022.

[Figure 1 about here.]

Total ESG flows have increased rapidly since 2017 and amount to approximately \$1.3 trillion as of 2022, which far exceeds the flows into explicitly labelled ESG mutual funds. Having constructed total

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[16]See Morningstar's 2021 Sustainable Funds U.S. Landscape Report. The assets of labelled ESG funds from the previous section are of a similar magnitude.

[17]In fact, $1/2 \sum_{n \in N^i} |a_n|$ and the active share in Cremers and Petajisto (2009) coincide if $a_n = w_n - w_n^{Mkt}$. This is the case if the coefficient on the market portfolio β^{Mkt} is equal to 1 and the coefficients on all other managed portfolios are equal to 0.

[18]See Appendix B for details.

ESG flows, we are now in the position to assess their impact on the realized returns of the ESG portfolio. The key difficulty in measuring flow-driven price impact lies in the joint endogeneity of prices and demand, which prevents simple regressions of realized returns onto flows. The next section introduces a structural approach to estimating the price impact of ESG flows.

4 A Structural Model of Price Pressure

A Setup and Variable Definitions

This section provides a structural approach to estimating the link between demand shocks and prices. The setup closely follows van der Beck (2022). Here, I merely state the variables and main structural estimation equations. There are N stocks indexed by $n = 1, ..., N$ and T time periods $t = 1, ..., T$. Shares outstanding are normalized to 1 such that the price of a stock, $P_{t,n}$, coincides with market equity. Lowercase letters denote logs (if not otherwise specified) and one-period changes in variables are denoted by $\Delta x_t = x_t - x_{t-1}$. There are I investors indexed by $i = 1, ..., I$ that hold a subset $N^i \subset N$ of all stocks. $Q_t^i \in \mathbb{R}^{N^i}$ denotes the vector of shared held by i. The optimal portfolio $Q_t^i = f^i(P_t, V_t)$ is a function of the vector of current stock prices $P_t \in \mathbb{R}^N$ and a collection of other exogenous observable and unobservable variables V_t (such as the assets under management, interest rate, fundamentals, or investment constraints). An investor's elasticity of demand with respect to the price (henceforth elasticity of demand) is defined as the percentage change in holdings when the price of a stock increases by 1 %. Formally,

$$\zeta_{t,n}^i = -\frac{\partial Q_{t,n}^i / Q_{t,n}^i}{\partial P_{t,n} / P_{t,n}} \tag{5}$$

Similarly, the cross-elasticity of demand is given by $\zeta_{t,nm}^i = -\frac{\partial Q_{t,n}^i / Q_{t,n}^i}{\partial P_{t,m} / P_{t,m}}$ and measures how much of n investor i sells when m's price increases by 1%.[19] The stock-specific and cross elasticities can be stacked in an $N^i \times N^i$ elasticity matrix ζ_t^i for every investor. The aggregate elasticity of demand is defined as the ownership-weighted sum of the investor-specific elasticity matrices,

$$\zeta_t = \sum_{i=1}^{I} \text{diag}(Q_t^i) \zeta_t^i \tag{6}$$

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[19]Note, that for $m = n$ the cross-elasticities $\zeta_{t,nn}^i$ are equal to stock-specific elasticities $\zeta_{t,n}^i$.

with elements equal to $\zeta_{t,nm} = \sum_{i=1}^{I} Q_{t,n}^i \zeta_{t,nm}^i$. Stocks that are primarily held by passive index funds (with $\zeta_t^i = 0$) have a low aggregate elasticity. The distribution of ownership, therefore, affects the aggregate elasticity. For example, the rise of passive investing increases the ownership of less elastic investors which drives down the aggregate elasticity, unless the active investors substantially increase their elasticity (see Haddad et al. (2021)).

Lastly, let $\Delta d_{t,n}$ denote a demand shock for n between t and $t+1$, expressed as a fraction of shares outstanding. The demand shock could be flow-induced purchases of green stocks by an ESG fund or the inclusion of a stock in an ESG index and the corresponding purchases by index trackers.

B Demand-Driven Price Impact

Now assume that an ESG fund receives large inflows and proportionally expands its existing positions resulting in an exogenous demand shock $\Delta d_t \in \mathbb{R}^N$. Equilibrium prices adjust in order to accommodate the demand shock resulting in realized log returns $\Delta p_t \in \mathbb{R}^N$. Proposition 1 in van der Beck (2022) shows that a first order approximation to Δp_t for a large class of models (including e.g. the CAPM or Demand System Approach to Asset Pricing) is given by

$$\Delta p_t = \mathcal{M}_t \Delta d_t + \epsilon_t \tag{7}$$

where $\mathcal{M}_t \in \mathbb{R}^{N \times N}$ is a price pressure matrix equal to the inverse of the market's aggregate elasticity of demand

$$\mathcal{M}_t = \zeta_t^{-1}. \tag{8}$$

See van der Beck (2022) for a proof. ϵ_t captures other sources of return variation such as factor exposures or fundamental news and is orthogonal to the demand shock Δd_t. As the focus of this paper is purely empirical, equation (7) can also be viewed as an assumption as in Greenwood and Thesmar (2011). The link between demand shocks and prices is given by the inverse of the market's elasticity of demand $\mathcal{M}_t$, henceforth referred to as the multiplier matrix. The more elastic investors are (i.e. the larger the diagonal elements in ζ_t^i), the less prices of green stocks have to move, in order to accommodate the demand shocks from flows to ESG funds. Cross-elasticities drive the off-diagonal elements in $\mathcal{M}_t$ and are responsible for flow-induced spill-over effects to other stocks. If investors accommodate flow-driven price pressure on green stocks primarily by substituting towards brown industries, the relative price impact of ESG investing may be negligible.

Example. In order to bolster intuition for the importance of cross-elasticities, consider the following simplified example: There are two stocks, a green stock g and a brown stock b with equal market capitalization, and a representative investor with a 2×2 elasticity matrix. Her demand elasticities with respect to g and b are the same, i.e. $\zeta_g = \zeta_b$. Also, her elasticity of substitution is the same moving from g to b and vice versa, i.e. $\zeta_{b,g} = \zeta_{g,b}$. Now assume that there is an exogenous ESG flow in g and b equal to \$1 and -\$1 respectively. The flow-driven price pressure (7), is given by $\begin{bmatrix} \zeta_g & -\zeta_{g,b} \\ -\zeta_{g,b} & \zeta_g \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$. The difference in market capitalization of g and b after the demand shock is given by $\frac{2}{\zeta_g + \zeta_{g,b}}$.[20] First, the greater the stock-specific elasticity (i.e. the more willing the investor is to sell green and buy brown shares) the smaller the price impact. Second, the greater the cross-elasticity (i.e investors' substitution towards brown stocks as a result of the price increase of the green stock) the smaller the equilibrium price impact. The equilibrium impact of ESG investing, therefore, depends on i) how willing the arbitrageurs are to provide green shares and ii) which stocks they substitute towards.

C   Structural versus Reduced-Form Estimation

As outlined above (and expressed in detail in van der Beck (2022)) the matrix $\mathcal{M}_t$, which links demand shocks and the cross-section of realized returns, can be obtained structurally from investors' demand elasticities. Before diving into estimating elasticities from holdings data, it is worth stepping back and asking whether a structural estimation is truly necessary. One could imagine a much simpler identification from directly regressing realized ESG returns onto demand shocks similar to PST (2022). For example, Pavlova and Sikorskaya (2022) regress returns onto changes in benchmarking intensities and obtain a multiplier of around 1.5. After all, estimating demand elasticities via regressions of demand onto prices is subject to the same endogeneity concerns that contaminate regressions of prices onto demand: Both are jointly determined in equilibrium. Assume, that we had access to non-fundamental demand shocks for green stocks Δd_t from e.g. a stock's inclusion in an ESG index as in Berk and van Binsbergen (2022).[21] The shocks could be used to directly estimate the multiplier using (7) as a linear regression. Nevertheless, there are three distinct benefits of the structural approach. First, it gives rich insights into the underlying investor-specific determinants of the flow multiplier.

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[20]To see this, note that the difference in market equity between the green and brown stock is given by $\begin{bmatrix} 1 & -1 \end{bmatrix} \begin{bmatrix} \zeta_g & -\zeta_{g,b} \\ -\zeta_{g,b} & \zeta_g \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \frac{2(\zeta_g - \zeta_{g,b})}{\zeta_g^2 - \zeta_{g,b}^2} = \frac{2}{\zeta_g + \zeta_{g,b}}$.

[21]See Shleifer (1986), Coval and Stafford (2007) or Schmickler and Tremacoldi-Rossi (2022) for other examples of non-fundamental demand shocks

Second, one can obtain stock-specific and time-varying effects even if we estimate a scalar elasticity for every investor. Because the ownership $Q_{t,n}^i$ varies across stocks and time, ownership-weighted sums across elasticities $\sum_{i=1}^{I} Q_{t,n}^i \zeta^i$ vary across stocks and time. Third, one can use a large cross-section of holdings data over a long history to identify ζ_t as opposed to the small number of potential ESG demand shocks.

Lastly, note that the elasticities themselves are not *deep* parameters and could be a function of trading costs, risk aversion, or investment constraints. The model and its estimation are therefore 'semi-structural'. Understanding the drivers of demand elasticities and in particular downward-sloping demand curves is an important avenue for future research.

D Estimating Elasticities

As in van der Beck (2022), I define institutions' demand as $\Delta q_{t,n}^i = \log Q_{t,n}^i - \log Q_{t-1,n}^i \approx \Delta Q_{t,n}^i / Q_{t-1,n}^i$. Thus $\Delta q_{t,n}^i$ simply measures the percentage change in shares held by institution i in stock n between two quarters. Similarly, percentage changes in the price are given by $\Delta p_{t,n} = \log P_{t,n} - \log P_{t-1,n} \approx \Delta P_{t,n} / P_{t-1,n}$. These variable definitions directly emerge from the definition of the elasticity (5). Up to a first order, an investor's demand elasticity can be obtained from regressions of trades $\Delta q_{t,n}^i$ onto log returns $\Delta p_{t,n}$.

$$\Delta q_{t,n}^i = -\zeta^i \Delta p_{t,n} + \epsilon_{t,n}^i \tag{9}$$

where $\epsilon_{t,n}^i$ captures demand shocks due to e.g. fundamentals, flows or trading constraints. The reduced-form specification essentially corresponds to a first difference estimator of the logit demand specification in KY (2019). van der Beck (2022) provides a detailed investigation of the relationship between the two estimators, which is summarized in Appendix D.3 of this paper. Note, that the scalar regression coefficient ζ^i is a reduced-form approximation of an investor's elasticity, which does not ensure that the investor's total assets remain unchanged. Appendix D.3 shows how to incorporate (9) in a logit framework that satisfies the budget constraint and allows constructing the full time-varying elasticity matrix $\zeta_t^i \in \mathbb{R}^{N \times N}$ from the scalar regression coefficient ζ^i and portfolio holdings.

E Identification

A causal identification of demand elasticities requires exogenous variation in prices that is orthogonal to the investor's own demand shocks. In other words, we can use the exogenous demand shocks

of one investor to identify the elasticity of another investor. As for every buyer there is a seller, exogenous demand shocks by one investor can essentially be viewed as shifting the supply curve. The literature has proposed a variety of potential instruments such as index inclusions, mutual fund flows or dividend reinvestments.[22] An advantage of estimating elasticities via trades (instead of holdings as in KY (2019)) is that essentially all of the instruments from the event-study literature on price pressure can be re-employed to identify demand elasticities. Van der Beck (2022) uses flow-driven trades by mutual funds as an exogenous shock to identify elasticities. Many mutual funds scale their existing holdings in response to in- and outflows (see Lou (2012)). Aggregating the flow-driven trades across all mutual funds provides exogenous cross-sectional demand shocks under the (strong) assumption that the flows were not driven by the funds' underlying fundamentals. To address these concerns, van der Beck (2022) constructs surprise flows by orthogonalizing the cross-sectional of mutual funds flows with respect to the funds' underlying holdings and characteristics.[23] However, it remains unclear whether a simple orthogonalization provides true exogenous flow shocks. In this paper, I take one step further and construct exogenous flow shocks from dividend reinvestments as in Schmickler and Tremacoldi-Rossi (2022). I closely follow their construction of dividend-induced mutual fund trades. Let $D_{t,n}$ denote stock n's dividends per share paid in quarter t. For every fund i, I construct dividend flow df_t^i as the total dividend payout across all stocks in the portfolio relative to assets under management:

$$df_t^i = \sum_{n \in N^i} D_{t,n} Q_{t-1,n}^i / A_{t-1}^i \tag{10}$$

In appendix C.13, I show that mutual funds tend to proportionally reinvest aggregate dividend payouts in their existing portfolios.[24] The hypothetical trading in stock n due to reinvested dividend flows is given by $df_t^i Q_{t-1,n}^i$. I construct an instrument for each investor i by summing the dividend-induced trades (DIT) by all other mutual funds,

$$DIT_{t,n}^{-i} = \sum_{j \in MF, j \neq i} df_t^j Q_{t-1,n}^j \tag{11}$$

Note, that the dividend announcement date of stock n, which contains fundamental information, often lies in the same quarter as the dividend payment. To avoid including the fundamental news coming

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[22]See Chang et al. (2015), Lou (2012), and Schmickler (2020) for respective examples.

[23]Similarly, Schmickler (2020) constructs high-frequency flow shocks to address contemporaneous return chasing in mutual fund flows.

[24]Chen (2020) arrives at a similar result

from n's own dividend announcement, I construct $DIT_{t,n}$ using $df_{t,-n}^i = \sum_{m \neq n} D_{t,m} Q_{t,m}^i / A_t^i$ instead of df_t^i.[25]

Having constructed investor-specific instruments, the elasticities can be obtained in a simple two-stage least squares procedure. Let $\Delta \hat{p}_t^i$ denote the fitted value from regressing returns onto the investor-specific instrument $f_{t,n}^{-i}$. The second stage regression of investor-specific trades Δq_t^i onto the investor-specific instrumented return $\Delta \hat{p}_t^i$ allows identifying their demand elasticities ζ_t^i. Formally, for every investor the two stages are given by:

$$
\begin{aligned}
\text{1st Stage:} \quad & \Delta p_{t,n}^i = \theta^i DIT_{t,n}^{-i} + \epsilon_{t,n}^i \\
\text{2nd Stage:} \quad & \Delta q_{t,n}^i = -\zeta^i \Delta \hat{p}_{t,n}^i + \epsilon_{t,n}^i
\end{aligned}
\tag{12}
$$

where $\epsilon_{t,n}^i = \sum_{k=1}^K X_{t,n,k} \beta_k^i + u_{t,n}^i$ includes the control variables log book equity, profitability, investment, and market beta. The trading due to aggregate dividend flows $DIT_{t,n}^{-i}$ is plausibly more exogenous than ordinary flow-induced trading. The drawback of this instrument is, however, that we cannot obtain negative demand shocks as dividends are strictly positive. Thus the identified elasticities only capture how stock price *increases* affect demand. As a robustness check, Appendix C.4 reports the estimated elasticities identified from flow-shock induced trading, which can take on both positive and negative values. I also explore the stability of the estimates by using changes in 'Benchmarking Intensity' (BMI) by Pavlova and Sikorskaya (2022) as an alternative instrument in the first stage. The next section and Appendix Section C.3 provide further details.

F The Multiplier Matrix

I estimate ζ^i over the panel of quarterly holdings from 2010 to 2021.[26] The multiplier matrix $\mathcal{M} \in \mathbb{R}^{N \times N}$ is given by the inverse of the aggregate (ownership-weighted) elasticity. I omit the time t subscript for notational simplicity. The diagonal elements of $\mathcal{M}$ are the stock-specific multiplier effects. The n-th diagonal element $\mathcal{M}_{n,n} = \frac{\Delta p_n}{\Delta d_n}$ measures the price impact of demand shocks for n onto the price of n. The off-diagonal elements are the spillover effects to other stocks. In particular, $\mathcal{M}_{m,n} = \frac{\Delta p_m}{\Delta d_n}$ measures the price impact of demand shocks for n onto the price of m. Let $N^G \subset N$ denote the subset of green stocks. We are interested in the price impact of demand shocks for green stocks N^G onto the cross-section of all stocks N. Omitting the time subscript, one can partition the

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[25]See Schmickler and Tremacoldi-Rossi (2022).
[26]The estimated investor-specific coefficients are reported in Appendix Table D.16.

multiplier matrix into submatrices by green ($g \in N^G$) and other ($b \notin N^G$) stocks as

$$\mathcal{M} = \begin{bmatrix} \mathcal{M}_{gg} & \mathcal{M}_{gb} \\ \mathcal{M}_{bg} & \mathcal{M}_{gb} \end{bmatrix}. \tag{13}$$

The important elements are $\mathcal{M}_{gg}$ and $\mathcal{M}_{bg}$, which capture the effect of green demand shocks onto green stocks (gg) and of green demand shocks onto non-green stocks (bg) respectively. [27] Intuitively, $\mathcal{M}_{gg}$ measures by how much the prices of other green stocks go up when the demand for any green stock increases by 1%. $\mathcal{M}_{bg}$ measures by how much the prices of non-green stocks increase. The diagonal elements of $\mathcal{M}_{gg}$ are the direct stock-specific effects of green demand, i.e. the price increase of n as a response to a 1% demand shock for n.[28] The cross-multipliers among green stocks are a key determinant of the spillover effects of ESG demand. If market participants accommodate the demand for green stocks by substituting towards other green stocks, the relative repricing of green versus brown stocks due to ESG flow may be strongly amplified.

Table 3 summarizes the elements of the multiplier matrix $\mathcal{M}_t$. The first column reports the direct impact of ESG demand, i.e. the diagonal elements of $\mathcal{M}_{gg}$. The remaining columns report the cross-multipliers, i.e. the spillover effects onto other green and non-green stocks.

[Table 3 about here.]

The average multiplier of the demand for green stocks is around 1.11, implying that (on average) a 1% increase in the demand for a green stock leads to a 1.11% increase in the price of that stock. The stock-specific multiplier is positive for all stocks because demand is downward-sloping for all investors.[29] This is the key channel through which continued capital flows into green firms can lead to high realized returns. Among the cross-multipliers, there is great heterogeneity across stocks which implies that the spillover effects of ESG demand shocks are highly nontrivial. Notably, there are more positive spillover effects of ESG demand towards other green stocks than towards non-green stocks. On average, a positive demand shock for a green stock leads to a price increase in roughly 40% of all other green stocks.

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[27]Formally, letting $N^B = N - N^G$ denote the number of non-green stocks, the dimensions of the matrices are given by $\mathcal{M}_{gg} \in \mathbb{R}^{N^G \times N^G}$, $\mathcal{M}_{bb} \in \mathbb{R}^{N^B \times N^B}$, $\mathcal{M}_{gb} \in \mathbb{R}^{N^G \times N^B}$ and $\mathcal{M}_{bg} \in \mathbb{R}^{N^B \times N^G}$.

[28]Note, that because ownership shares $Q_{t,n}^i$ vary across stocks, the elasticity matrix is not symmetrical. Therefore $\mathcal{M}_{gb}$ and $\mathcal{M}_{bg}$ are different objects.

[29]Unlike in KY (2019), this is not an assumption. The estimation in changes yields downward-sloping demand curves for all investors without a coefficient constraint. See van der Beck (2022) for details.

How sensitive are the multiplier estimates to an alternative identification? In Appendix Section C.3 I identify investor-specific elasticities using an alternative instrument, namely changes in benchmarking intensity (BMI) by Pavlova and Sikorskaya (2022). A stock's BMI measures the fraction of the total market capitalization held by benchmarked investors. Changes in BMI reduce the effective supply of a stock and can be used to identify investor-specific elasticities. The multipliers obtained from the BMI-based elasticities are of strikingly similar magnitude. Using the alternative identification, a 1% demand shock for the average green stock raises its price by 1.17%. As a final robustness check, Appendix Section C.4 estimates investor-specific elasticities from surprise-flow induced trading as in van der Beck (2022). Using surprise-flows as an instrument, I estimate that a 1% demand shock for the average green stock raises its price by 2.78%.

5   The Aggregate Impact of ESG Flows

Having estimated the market's willingness to accommodate ESG demand we are now in the position to estimate the impact of flows on the realized returns from ESG investing.

A   ESG Flow Multiplier

What is the impact on valuations, if investors reallocate $1 from the market portfolio towards the ESG portfolio? A $1 ESG flow translates into stock-specific demand shocks given by $\tau_{t,n} = w_{t,n}^{ESG} - w_{t,n}^{MF}$. Equation (7) then implies, that the equilibrium change in prices $\Delta P_{t+1}^{ESG} \in \mathbb{R}^N$ due to ESG flows is simply

$$\Delta P_{t+1}^{ESG} = \mathcal{M}_t \tau_t. \tag{14}$$

Note, that the net flows are equal to zero as $\sum_{n=1}^{N} \tau_{t,n} = 0$. One could alternatively model nonzero net equity flows, as inflows to ESG funds could also come from e.g. households that were not previously invested in the stock market. Such flows would affect both aggregate stock market and ESG returns. As the focus of this paper lies on the *excess* returns of ESG funds (over the aggregate mutual fund portfolio), net-zero flows are a more suitable way of modelling ESG demand.

Summing the flow-induced change in market equity across all green stocks yields the aggregate dollar impact of a one-dollar ESG flow on all green firms (or at least the ones perceived to be green).[30]

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[30]Note, that (7) is expressed in percentage terms (i.e. the return $\Delta p_{t+1,n}$ resulting from a demand shock in percent of shares outstanding). It can also be expressed in terms of dollar terms by multiplying by prices $P_{t,n}$ (which are equal to market equities due to the normalization). Let $N^G \subset N$ denote the subset of green stocks (for which $\tau_{t,n} > 0$). The

This effect will henceforth be referred to as the ESG flow multiplier. The ESG flow multiplier is driven by two components: First, flows play a stronger role in cross-sectionally inelastic markets with a low aggregate demand elasticity for green stocks and therefore a high multiplier matrix $\mathcal{M}_t$. Intuitively, if price inelastic investors (i.e. investors with a low $\zeta_{t,n}$) are the main shareholders of green stocks (i.e. they have a high ownership $Q_{t,n}^i$), then aggregate elasticity for green stocks is low and prices have to adjust a lot in order to accommodate flow-induced demand. Second, the impact of ESG flows depends on the deviation of the ESG portfolio from the market portfolio $\tau_{t,n}$. If ESG funds' deviation from the aggregate mutual fund portfolio is negligible, then flows towards sustainable funds have no impact on the price regardless of the multiplier effect $\mathcal{M}_t$.

[Figure 2 about here.]

Panel (a) of Figure 2 plots the ESG flow multiplier over time. The ESG flow multiplier is around 0.5 and has declined to 0.3 in recent years. Thus, withdrawing \$1 from the market portfolio and investing it in the ESG portfolio leads to an increase in green stocks' aggregate market capitalization of around \$0.3-0.5. The decline in the ESG multiplier is directly related to the decline in the active share of the ESG portfolio in recent years. As the ESG portfolio moves closer to the market portfolio, net zero ESG flows lead to smaller demand shocks and therefore a smaller price impact. While arguably more objective than third-party ESG scores, using $\tau_{t,n}$ as a measure of sustainability remains a subjective choice. In order to provide a broader perspective on the efficacy of ESG investing, I also compute the impact of a divestment strategy that divests \$1 from a value-weighted portfolio of all fossil companies. Panel (b) of Figure 2 plots the impact of the divestment strategy on the aggregate market capitalization of fossil fuel and green companies. Every dollar withdrawn from the fossil fuel industry reduces its aggregate market capitalization by \$1-1.2. These estimates suggest that divestment strategies can have a large effect on stock prices and therefore firms' cost of capital. Even though green stocks are not directly affected by the divestment strategy, their aggregate value is affected via spillover effects. This underlines the importance of accounting for the off-diagonal elements in $\mathcal{M}_t$. As market participants accommodate the demand shock from the divestment strategy by buying fossil fuel companies they simultaneously buy green companies (potentially to maintain a constant industry exposure). This exerts price pressure on the latter resulting in positive spillover effects.

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total impact on green stocks then given by $\sum_{n \in G} \Delta P_{t+1,n}^{ESG}$ where $\Delta P_{t+1,n}^{ESG}$ are the stock-specific entries of ΔP_{t+1}^{ESG}.

B   Counterfactual ESG Returns in the Absence of Flows

The ESG flow multiplier paired with the large ESG flows of \$1.3 trillion suggest that the flow-driven demand for green stocks has potentially large aggregate pricing implications. In order to assess the quantitative return distortion from total ESG flows, F_{t+1}^{ESG}, I conduct a simple simulation. I simulate counterfactual realized ESG returns if the quarterly flows to ESG funds F_{t+1}^{ESG} were instead reinvested in the aggregate mutual fund portfolio w_t^{MF}.[31] Table 4 reports the counterfactual ESG returns in the absence of flow-driven price pressure.

[Table 4 about here.]

The first row reports the empirically observed annualized ESG return, which is defined as the excess return of the ESG portfolio over the aggregate mutual fund portfolio $\tau_t = w_t^{ESG} - w_t^{MF}$. The second row reports the counterfactual ESG return without price pressure from flows towards labelled ESG mutual funds. The raw return and alphas drop by merely 10 basis points. The impact of capital flows towards specifically labelled sustainable mutual funds is therefore negligible. Without the price pressure from *total* ESG flows, however, the raw return and alphas drop by 200 basis points and are all zero. Thus, when assessing the impact of ESG investing, it is important to account for the ESG tilts by all institutions, including large investment advisors, banks, and pensions funds. The results emphasize the sizeable gap between realized and expected returns from ESG investing that is driven by total sustainable flows. Taking the estimates at face value, this suggests that without a continued flow to the ESG portfolio, ESG investing does not have positive abnormal returns. In other words, it is the price pressure from ESG flows that made 'doing well by doing good'-investing possible.

C   ESG Flows and Returns: Reduced-Form Evidence

The structural approach presented above allows for circumventing the issue that flows and returns are jointly endogenous. Within the model, ESG flows have a large impact on ESG returns. This result is based on three findings: Large flows towards the ESG portfolio (F_{t+1}^{ESG}), a low elasticity of substitution between green and brown firms ($\mathcal{M}_t$), and a considerable deviation of the ESG portfolio from the market portfolio (τ_t). If ESG returns are truly flow-driven, then aggregate ESG flows should

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[31]A first order approximation of the simulated price pressure from \$$X$ net-zero ESG flows is given by $\Delta P_t^{\text{sim}} = \mathcal{M}_t(w_t^{ESG} - w_t^{MF}) * \$X$. The counterfactual returns in the absence of price pressure are then given by $r_{t,n}^{cf} = r_{t,n} - \Delta P_{t+1,n}^{\text{sim}}/P_{t,n}$. Counterfactual ESG returns are then given by $\sum_{n=1}^{N} r_{t,n}^{cf} \tau_{t,n}$. See Appendix D.4 for details.

be correlated to realized ESG returns. Figure 3 plots the quarterly flow into the ESG portfolio along with the excess return on the ESG portfolio.

[Figure 3 about here.]

The correlation between quarterly ESG flows and returns is 74%. While this correlation is by no means causal evidence for flow-driven price pressure, it is nevertheless strikingly high. Notably, PST (2022) find that ESG returns and flows into labelled ESG mutual funds are not significantly correlated. Table 5 replicates their result and provides further evidence on the potential importance of flows in explaining ESG returns.

[Table 5 about here.]

I first regress ESG returns on the total ESG flow and the flow to labelled ESG mutual funds separately. Both measures of ESG flows are significantly related to ESG returns with an R^2 of 29%. Note that simple regressions of the returns onto flows cannot identify price pressure: Beliefs about the climate, the fundamentals of ESG firms, and positive feedback trading, drive both flows into ESG funds, as well as the return on their underlying assets. I merely present these correlations as suggestive evidence for a potential link between ESG flows and returns. The second set of columns replicates the findings of PST (2022). I regress their GMB factor return onto total ESG flows, ESG mutual fund flows, and instrumented flows using quarterly lags. Confirming their results, I find no significant relationship between GMB returns and ESG flows. This underlines the importance of computing the suitable flow into the object of interest. It is unclear whether flows to ESG mutual funds are indeed directed at the GMB portfolio. While many investors follow the MSCI ESG ratings used in PST (2022), the direction of ESG flows critically depend on how the ratings are used to construct portfolio weights. Thus ESG flows may not directly target the GMB portfolio. I circumvent this issue by investigating flows and returns of the same portfolio (w_t^{ESG}).

6 The Cross-Sectional Impact of ESG Flows

This section puts the hypothesis of flow-driven ESG returns to a stronger test. If flow-driven purchases by institutions drive aggregate ESG returns, they should also affect the cross-section of ESG returns. In other words, green stocks that experience higher flow-driven demand should exhibit higher realized returns in the cross-section.

A   Stock-Specific ESG Flows and Returns

While the flows into individual within the ESG portfolio are not directly observable, they can be approximated by aggregating the flow-driven trades of all investors. Total flow-driven trades in stock n are given by

$$\Delta d_{t+1,n} = \sum_{i=1}^{I} Q_{t,n}^i f_{t+1}^i \tag{15}$$

where I includes mutual funds and other 13F institutions (banks, pension funds, insurance companies etc.). f_{t+1}^i is the flow (relative to lagged assets) into investor i and $Q_{t,n}^i$ the lagged ownership in stock n. Precise data on flow-driven trades are only available for mutual funds. Because SEC 13F forms are filed at the management company level, flows towards ESG funds *within* a manager are difficult to capture.[32] Appendix B provides a detailed description on how to approximate flow-driven trades for 13F institutions. Note that because $Q_{t,n}^i$ are ownership shares, $\Delta d_{t+1,n}$ can be interpreted as demand shocks in percent relative to shares outstanding. Thus a flow-driven demand shock of $\Delta d_{t+1,n} = 0.01$ implies a 1% increase in the demand for the stock. If flows affect the cross-section of ESG returns, then $\Delta d_{t,n}$ should be significantly related to the cross-section of ESG returns. Let $\Delta p_{t+1,n}$ denote the quarterly return on stock n. I compute abnormal returns $\alpha_{t+1,n}$ by cross-sectionally orthogonalizing returns with respect to market beta, log market equity, log market-to-book ratio, profitability and investment.[33] I then compute the cumulative flow-driven demand Δd_n and abnormal returns for every stock Δp_n by summing over the sample period from 2016 to 2021.

B   Price Pressure in the Cross-Section of ESG stocks

The structural model predicts that flow-driven price pressure is given by multiplying the vector of flow-driven demand shocks Δd_t by the multiplier matrix $\mathcal{M}_t$. Thus, the model implies a 1:1 mapping between $\mathcal{M}_t \Delta d_t$ and the cross-section of realized ESG returns. Panel (a) of Figure 4 plots the abnormal returns on all green stocks along with the flow-driven price pressure. I fit a linear regression through the scatter points, which shows that the cross-section of green returns is significantly related to flow-driven price pressure (t-Statistic > 7). Furthermore, both value- and equal-weighted regression lines are close to the diagonal. This is strong evidence in favor of the overall magnitude of the demand elasticities

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[32]For example, a \$1 billion exogenous flow from the Vanguard S&P500 ETF to the Vanguard FTSE Social Index Fund would only show up as a demand shock for greener stocks in Vanguard's aggregate share holdings while leaving its total assets under management unchanged.

[33]Formally, I run the quarterly cross-sectional regressions of log returns $r_{t+1,n}$ onto lagged characteristics $X_{t,n}^k$ and extract the residual: $r_{t+1,n} = \beta_t^0 + \sum_{k=1}^{K} \beta_t^k X_{t,n}^k + \Delta p_{t+1,n}$.

obtained from holdings data.[34] On average, the multiplier matrix $\mathcal{M}_t$ correctly maps the cross-section of demand shocks into the realized return space. Panel (b) of Figure 4 plots the price pressure ($\mathcal{M}\Delta d$) for all green stocks against their abnormal return α_n. Once again, the cross-section of abnormal ESG returns is significantly related to price pressure with a t-statistic of 5.25. We furthermore cannot reject the null hypothesis that the slopes of the fitted lines are different from the diagonal.

[Figure 4 about here.]

C Testing different Elasticity Estimates

The flow-driven demand shocks allow for a more granular test of the price impact implied by demand-based asset pricing models. Note, that equation (7) is a first-order approximation to the demand shock in a large class of models, including the Demand System Approach to Asset Pricing by KY (2019).[35] We can test different elasticity estimates by comparing the cross-section of flow-driven ESG returns to the price pressure obtained from different multipliers $\mathcal{M}_t$.

[Table 6 about here.]

Panel (a) of Table 6 compares the regression slope and R^2 across different multipliers. The first column regresses the cross-section of abnormal ESG returns α_n onto the raw flow-driven demand shocks Δd_n, which implies a diagonal multiplier matrix equal to the identity matrix. The slope coefficient is 1.13 with a t-statistic of 6.84. This implies that a 1% demand shock for a green stock increases its price by 1.13%. The average multiplier across all green stocks obtained from the structural model is 1.11, which is strikingly close to the reduced-form estimate. Raw flow-driven demand furthermore explains around 4% of the cross-section of ESG returns. The second column regresses the cross-section of abnormal returns onto demand shocks scaled by the multiplier matrix as in Figure 4. The explained variation of the cross-section of ESG returns rises to 5%. This does not necessarily imply that the additional information contained in the stock-specific and cross-elasticities is small. It rather confirms that the cross-section of individual stock returns is driven by unobservable latent demand shocks unrelated to flow-driven demand (see KY (2019)). The third column uses the elasticity matrix obtained using the methodology in KY (2019). Recall that they identify elasticities using portfolio holdings in levels, whereas this paper identifies elasticities from quarterly trades (i.e. changes in portfolios). The

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[34]If true multipliers were significantly higher than the model-implied estimates (i.e. investors respond more strongly to price changes than implied by the model) then the slope of the regression line would be much steeper.

[35]See van der Beck (2022) for details.

regression slope drops to 0.49 (t-Statistic of 7.22) which implies that the price pressure estimated from holdings in levels is slightly too large. This may be owed to the endogeneity problem of identifying elasticities from holdings as opposed to trades.[36]

Lastly, I provide a simple test of whether the stock-specific multipliers, i.e. the diagonal elements in $\mathcal{M}$ contain additional information about price pressure beyond traditional characteristics. To this end, let $\frac{\alpha_n}{\Delta d_n}$ denote a primitive measure of stock-specific price pressure. It is the abnormal return on stock n from 2016 to 2022 divided by the cumulative flow-driven demand Δd_n. I regress $\frac{\alpha_n}{\Delta d_n}$ in the cross-section onto the stock-specific multipliers, $\mathcal{M}_n$, controlling for log market equity and market beta. Panel (b) of Table 6 reports the estimated coefficients. The price impact of flow-driven demand in cross-section of green stocks is significantly larger for smaller stocks. More importantly, it is significantly positively related to the stock-specific price impact implied by the structural model (with a t-Statistic of 3.6).

7   Applications and Robustness Tests

A   ESG Index Inclusion

The structural approach presented in this paper allows for circumventing the issue that ESG flows and returns are jointly endogenous. It is nevertheless reassuring if the structural estimates are at least to some extent backed by simple reduced-form evidence, such as demand shocks from ESG index inclusions. A well-known ESG index is the FTSE USA 4 Good Index (henceforth 4G index). Berk and van Binsbergen (2022) use a stock's membership in the FTSE USA 4 Good Index as a proxy for aggregate ESG demand and find that there are no price effects associated with inclusion in the index. They conclude that impact investing does not affect firms' cost of capital. However, it is unclear how much money is actually flowing into the stocks added to the index. In other words, are the assets indexed to the 4G Index large enough to generate meaningful demand shocks based on its reconstitution?

To further investigate this, I construct mutual fund demand $\Delta q_{t,n}^{MF}$ as the change in ownership by mutual funds for every stock n and quarter t. Table 7 reports regressions in the style of Berk and van Binsbergen (2022). $\Delta I_{t,n}^{4G}$ is a variable equal to 1 in the quarter of inclusion in the 4G Index, -1 in the quarter of exclusion, and 0 otherwise. I first regress index flow onto $\Delta I_{t,n}^{4G}$ including the controls used

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[36]See van der Beck (2022) for details.

in Berk and van Binsbergen (2022).[37] Addition to 4G Index is associated with a significant increase in total mutual fund ownership of 1.3 percent. In other words, when a stock is included in the 4G Index, mutual funds contemporaneously purchase 1.3 percent of the stock's shares outstanding (on average). This suggests that the 4G Index is sufficiently widely followed such that reconstitutions cause meaningful shocks to index investor demand. The third column of the table replicates the specification in Berk and van Binsbergen (2022) at a quarterly frequency by regressing quarterly stock returns onto $\Delta I_{t,n}^{4G}$. As in their study, the coefficient is insignificant and very small, suggesting that the ESG flows do not generate meaningful price pressure. However, for only 56% of all index reconstitutions, mutual fund flow $\Delta q_{t,n}^{MF}$ has the same sign as $\Delta I_{t,n}^{4G}$.[38] In order to identify relevant (i.e. widely followed) reconstitution events, I use ownership changes of index trackers. I interact the 4G index reconstitutions with a dummy variable equal to 1 if the demand by index trackers has the same sign as the reconstitution.[39] The coefficient on the interaction term is large and statistically significant. This suggests that ESG index inclusion has a strong effect on prices, as long as mutual funds actually purchase the stock when it is included. In other words, conditional on inclusion in the 4G index, the demand by index trackers has a large impact on the prices of green firms. Furthermore, the implied price impact is in line with the multiplier obtained from the structural model. In the quarter of inclusion in the 4G index, the stocks followed by index trackers receive a 3.13% demand shock by mutual funds and experience 5.3% higher return, which implies an ESG demand multiplier of $\frac{5.3}{3.2} = 1.69$.

[Table 7 about here.]

B Mandate-Driven Portfolio Reconstitutions

Mutual fund purchases based on additions and deletions from the 4G Index represent a small set of potentially exogenous ESG demand shocks. In this section, I generalize the idea of ESG index inclusion to construct a larger set of exogenous ESG demand shocks. In order to disentangle non-fundamental from fundamental ESG demand, it will be useful to define two kinds of demand shocks:

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[37]Because additions and deletions are encoded as 1 and -1 respectively, I refer to all index reconstitutions as additions.

[38]From 2012 to 2021 and using quarterly data, I obtain 342 reconstitution events of the 4G index, conditional on the stock already being in the FTSE USA Index. For 192/342=56% out of these events, the aggregate ownership change of mutual funds has the same sign as the reconstitution.

[39]In particular, I a construct investor-demand dummy $\mathbb{1}_{\text{Demand}}$ equal to 1 if the sign of index fund flow during the reconstitution quarter is the same as the sign of the reconstitution $\Delta I_{t,n}^{4G}$. Index fund flow is defined as the change in ownership by index trackers. To identify index funds, I use the label 'Pure Index Fund' provided by the CRSP mutual fund database, which are mutual funds with an index-fund flag equal to 'D'.

Intensive and extensive. Intensive demand shocks are changes in the shares held by an investor that do not originate from or result in zero holdings. Extensive demand shocks are portfolio additions and deletions, i.e. changes in shares held originating from or resulting in zero holdings. A key difference between the two is that extensive demand shocks likely contain an exogenous (non-fundamental) component that is related to the investment mandate of the fund. For example, an ESG investor may include a stock in her portfolio once the company's Co2 Emissions fall below the industry median. Similarly, a value fund includes a stock if it falls in the top quintile of book to market ratios. While not all of the extensive demand shock is non-fundamental (Co2 emissions dropped because of a change in production which affects profits) at least part of it is driven by the fund's exogenous portfolio constraint: "Buy the bottom 50% of Co2 emitters". Let $\Delta Q_{t,n}^{\perp}$ denote the total amount of shares purchased due to specific ESG mandates and portfolio constraints. Because $\Delta Q_{t,n}^{\perp}$ is orthogonal to fundamental news, a significant relationship with contemporaneous returns $r_{t,n}$ would confirm that non-fundamental ESG demand affects prices. Appendix Section B.3 shows how to construct $\Delta Q_{t,n}^{\perp}$ from mutual funds' extensive and intensive trades.

In order to test whether non-fundamental ESG demand impacts prices, I estimate panel regressions of quarterly returns onto $\Delta Q_{t,n}^{\perp}$ controlling for known return predictors such as market beta, size, value, profitability, and investment. Table 8 reports the estimated coefficients on $\Delta Q_{t,n}^{\perp}$ for different specifications.

[Table 8 about here.]

The coefficient on $\Delta Q_{t,n}^{\perp}$ is highly statistically significant with a t-Statistic of 11.02. Note, that $\Delta Q_{t,n}^{\perp}$ only captures the exogenous demand shocks of labelled ESG mutual funds, which represent a subset of all ESG investors. If we scale $\Delta Q_{t,n}^{\perp}$ by the inverse market share of labelled ESG funds relative to total ESG assets, we can identify the structural parameter linking exogenous ESG demand and prices.[40] The coefficient on scaled $\Delta Q_{t,n}^{\perp}$ is 0.95, which implies that when ESG funds purchase 1% of a company's shares outstanding, the price increases by roughly 0.95%. The implied multiplier is 0.95 which is close to the estimate from the structural model of 1.11. I also sort $\Delta Q_{t,n}^{\perp}$ into quartiles by absolute values and assign dummy variables equal to 1 if $\Delta Q_{t,n}^{\perp}$ in the respective quartile is positive and -1 if $\Delta Q_{t,n}^{\perp}$ in the respective quartile is negative. The results show that stocks with higher mandate-driven ESG demand experience stronger price pressure. The coefficient on $\Delta Q_{t,n}^{\perp}$ is significant across

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[40]Formally, total $\Delta Q_{t,n}^{\perp} = S_t^{ESG} \Delta Q_{t,n}^{\perp,\text{Total}}$ where $Q_{t,n}^{\perp,\text{Total}}$ is total mandate-driven ESG demand and S_t^{ESG} is the market share of labelled ESG mutual funds. Thus $Q_{t,n}^{\perp,\text{Total}} = \frac{1}{S_t^{ESG}} \Delta Q_{t,n}^{\perp}$.

all specifications. Thus ESG investors' trades that are driven by portfolio constraints and investment mandates have a significant impact on prices. Furthermore, the magnitudes are consistent with the elasticities estimated from holdings data.

C Impact-Investing at the Fund Level

The interaction between the multiplier matrix $\mathcal{M}_t$ and fund-specific deviations from the market portfolio allows for assessing the efficacy of impact-investing at the fund level. A fund's impact is driven by its deviation from the market portfolio and by the extent to which the deviations are concentrated towards inelastic stocks.[41] A fund's ability to affect green firms' cost of capital is strongly limited, if it overweights stocks that are held by elastic investors and by investors who respond by substituting towards brown stocks. Green stocks that are associated with a high multiplier are best suited for impact investing as flows induce a large realized return and hence a lower cost of capital. Also, note that $\mathcal{M}_t$ is an $N \times N$ matrix that accounts for flow-driven spillover effects to all stocks. If the market accommodates green demand primarily by substituting towards other green stocks, then $\mathcal{M}_{t,gg}$ is high, causing an amplified relative price impact. Table 9 reports the impact of a \$1 flow from the market portfolio towards the largest ESG mutual funds averaged over the past 5 years.

[Table 9 about here.]

There is great heterogeneity in the funds' impact on green stocks. A \$1 flow to the Calvert Social Investment Fund boosts the aggregate value of green stocks by \$0.82. In contrast, the same flow towards the Vanguard FTSE Social Index Fund raises the value of green stocks by only \$0.39. Furthermore, many sustainable funds unintentionally boost the value of fossil fuel companies. A \$1 flow towards the iShares MSCI USA ESG ETF increases the aggregate value of fossil fuel companies by 0.03\$ and decreases the value of green stocks by 0.04\$. On the one hand, this heterogeneity is owed to the fact that there is no objective measure of a fund's *true* sustainability. Asset managers use different sustainability metrics, which often diverge substantially (see Berg et al. (2019) and Berg et al. (2021)). On the other hand, funds differ strongly in their deviation from the market portfolio. Some funds, such as the Vanguard FTSE Social Index Fund or the iShares MSCI USA ESG ETF, deviate very little from S&P500 index weights and hence primarily serve as a way for investors to feel good about themselves without having a *true* impact. Surprisingly, flows towards many sustainable funds

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[41]Formally, fund i's impact is given by $\mathcal{M}_t w_{t,n}^i - w_{t,n}^{MF}$. These are the cross-sectional price changes due to a 1 dollar from from the aggregate mutual fund portfolio towards i.

raise the aggregate valuation of fossil fuel companies. Even though an ESG fund may underweight an industry as a whole, by tilting towards more inelastic stocks it can positively affect the aggregate valuation of that industry. Similarly, if the fund tilts towards stocks that have high cross-elasticities with underweighted stocks it unintentionally boosts the valuation of the wrong companies. Overall table 9 emphasizes that while sustainable flows do impact firms' realized returns and cost of capital, the choice of the appropriate fund is crucial to affect change in the preferred direction.

8   Conclusion

This paper investigates the extent to which the realized returns from ESG investing are owed to price-pressure arising from flows towards sustainable funds. Flow-driven price pressure is the product of sustainable funds' deviation from the market portfolio and the market's elasticity of substitution between stocks. I find that every dollar flowing from the market portfolio towards the ESG portfolio increases the aggregate value of green firms by \$0.4. As a result, ESG funds would have likely underperformed the market in the absence of flow-driven price pressure on green stocks. Thus, one should be careful when using the *realized* outperformance of sustainable investments in recent years to judge their *expected* outperformance going forward.While the low aggregate elasticity of substitution is worrying for the overall stability and efficiency of equity markets, it supports the effectiveness of impact investing. Flows towards green funds that invest in cross-sectionally inelastic stocks substantially reduce the cost of capital of the firms in the funds' portfolios. As the framework allows quantifying the effect of flows on green firms' cost of capital, it enables differentiating sustainable funds by an objective *real-impact* criterion.

The large impact of flows on realized ESG returns does not necessarily affect *expected* ESG returns going forward. Assessing the extent to which *expected* returns are affected by past demand pressures is non-trivial as it depends on the transitory versus permanent nature of ESG flows. If ESG inflows are expected to be permanent, then the permanent flow leads to a permanently higher valuation of green stocks. Thus, the reduction in expected returns due to flow-induced price pressure is relatively small. If, however, ESG inflows unexpectedly revert, the realized future return may be strongly negative. The question, whether ESG funds will receive outflows in the future ultimately depends on whether ESG flows are performance- or taste-based. It is likely that at least some flows to ESG funds are driven by past performance rather than *true* shifts in green preferences. Even if none of the flows to

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ESG funds are performance-driven, green preferences fluctuate over time and may well decline during bad economic times.

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Figure 1: **Total ESG Flow**

The figure plots the total flow into the ESG portfolio from 2012 to 2022. I compute the ESG flow for each 13F institution as the return-adjusted change in ESG-assets under management and then then sum across all institutions. I report rolling 4-quarter averages and plot the cumulative sum of all flows since 2012. The dotted line plots the ESG flow when controlling for exposures to 12 (Fama-French) industry portfolios in the estimation of β_t^{ESG}.
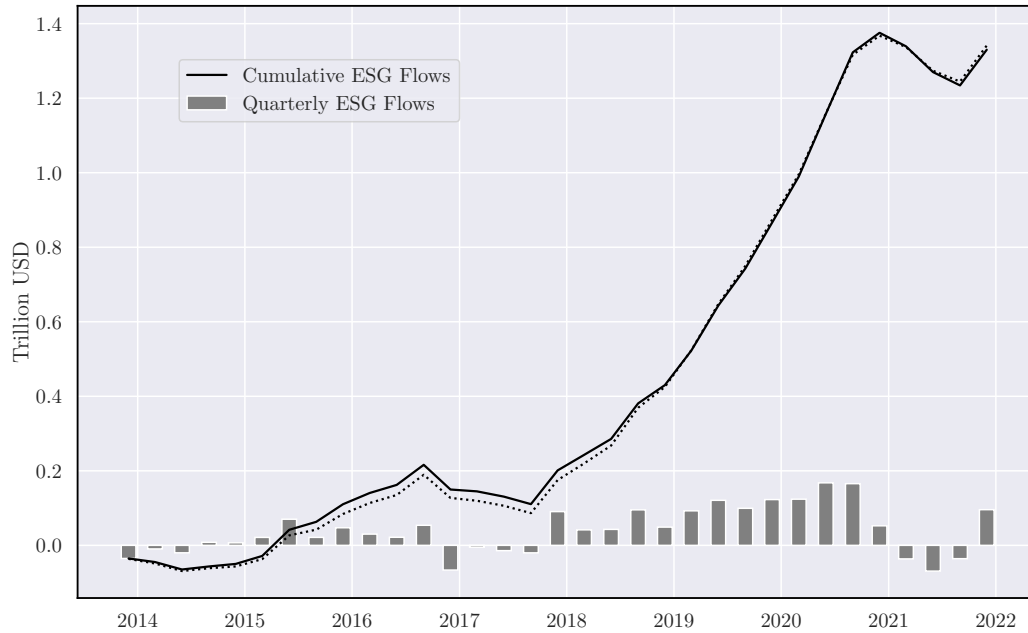
Figure 2: **ESG Flow Multiplier**

The figure plots the ESG flow multiplier, i.e. the aggregate change in market cap in green stocks due to a $1 ESG flow. Formally, the aggregate effect of ESG flows on green stocks is given by $\sum_{n \in N^G} \Delta P_{t+1,n}^{ESG}$ where $\Delta P_t^{ESG} = \mathcal{M}_t \tau_t$ is the vector of price changes following the $1 ESG flow. The dotted line reports the ESG multiplier without cross-spillover effects (setting the diagonal elements in $\mathcal{M}$ to 0. Panel (b) plots the impact of a divestment strategy that divests $1 from a value-weighted portfolio of all fossil companies. The black line shows the direct impact on the aggregate valuation of fossil fuel companies. The green line shows the indirect spillover effects to green stocks.

(a) ESG Flow Multiplier
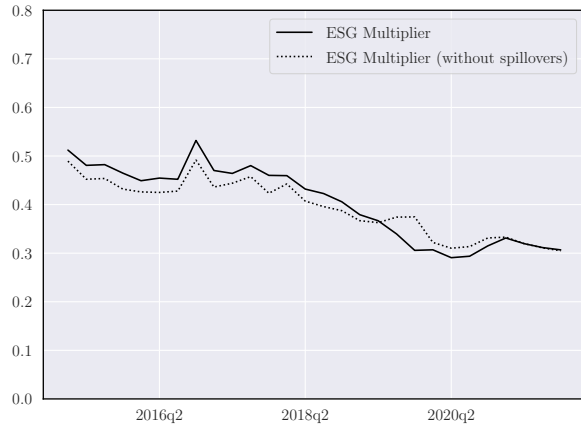
(b) Fossil-Fuel Divestment Multiplier
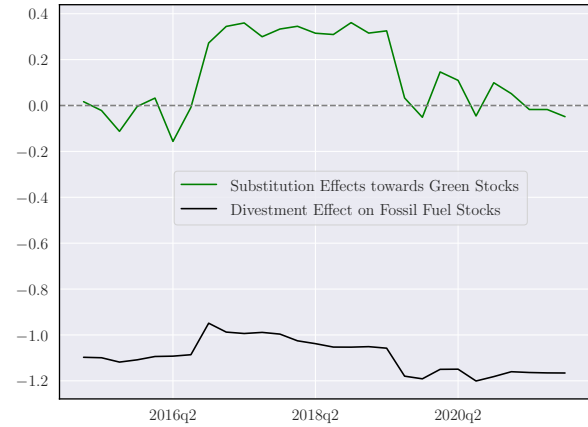
Figure 3: **Aggregate ESG Flows and Returns**

The figure plots the quarterly excess return on the ESG portfolio $\tau_t = w_t^{ESG} - w_t^{MF}$ against the quarterly ESG flow F_{t+1}^{ESG} measured in percent relative to the total stock market capitalization. I plot rolling 4-quarter averages of returns and flows.
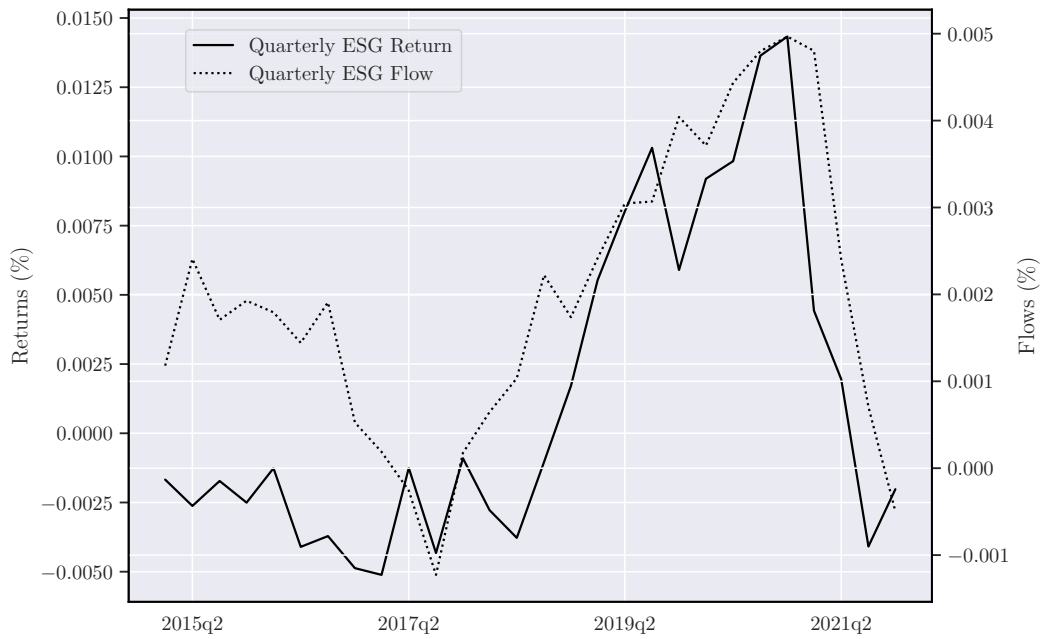
Figure 4: **ESG Demand in the Cross-Section of ESG Returns**

The figure reports binned scatter plots of the cross-section of ESG returns against flow-driven price pressure $\mathcal{M}_t \Delta d_{t,n}$. For each stock, I compute the cumulative price pressure and returns from 2016 to 2022. Panel (a) plots price pressure against raw cumulative returns Δp_n. Panel (b) plots price pressure against abnormal returns α_n obtained from cross-sectional regressions of returns onto known predictors.

(a) Raw Returns

(b) Abnormal Returns

Table 1: **ESG Funds Summary Statistics**

The table reports yearly averages of quarterly metrics describing the sample of ESG funds. The first 5 columns report statistics at the ESG fund level. Excess Flows measure the average quarterly flow across all ESG funds in excess of the average quarterly flow across non-ESG funds. The number of name changes captures the total number of funds that change their name in a given year by including an ESG keyword. The last 3 columns report statistics for the aggregated portfolio of all ESG funds. Index ESG funds are ESG funds that directly track (or are based on) an index. The fraction of indexed AUM is computed as index ESG funds' total AUM relative to the total AUM of all ESG funds. Active share (Cremers and Petajisto (2009)) is computed as the deviation of the ESG portfolio $w_{t,n}^{ESG}$ from market capitalization weights $w_{t,n}^{m}$, i.e. $\frac{1}{2}\sum_n |w_{t,n}^{ESG} - w_{t,n}^{m}|$. For all other variables, I report the average across quarters within a given year.

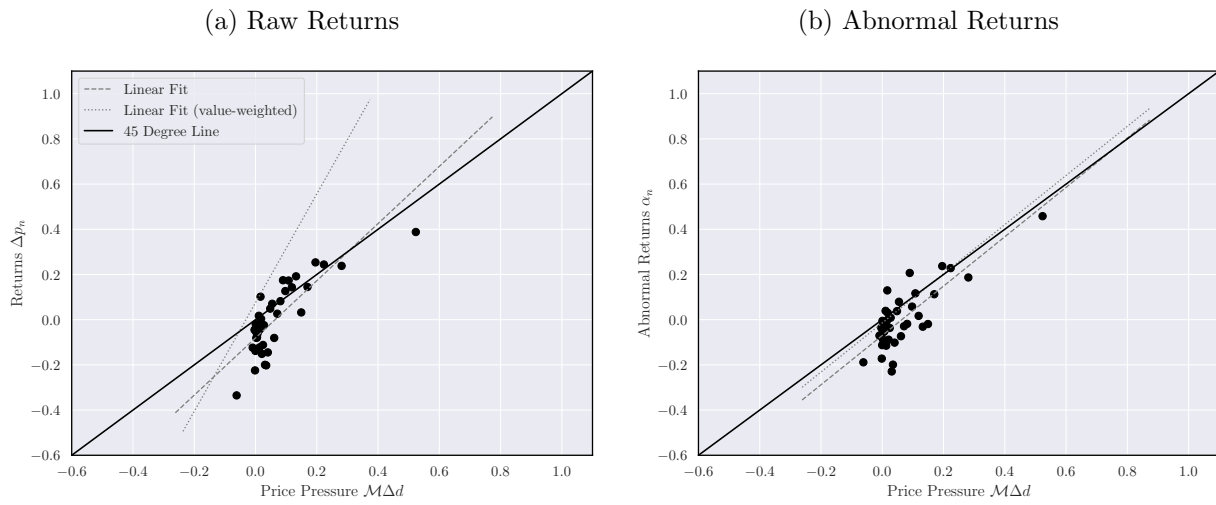| | ESG Fund-Level Statistics | | | | | Aggregate Statistics on w_t^{ESG} | | |
Year	# Funds	Avg. # Stocks	Avg. AUM ($ Billion)	Excess Flows (%)	# Name Changes	AUM ($ Billion)	% Indexed AUM	Active Share
2010	89	95	0.34	0.54	2	30.60	0.11	0.71
2011	82	128	0.38	-1.26	0	31.17	0.13	0.70
2012	88	139	0.28	-0.69	2	25.02	0.16	0.70
2013	83	119	0.34	0.73	1	28.82	0.17	0.69
2014	88	115	0.43	-0.55	3	37.66	0.19	0.67
2015	101	133	0.36	-0.45	3	36.80	0.24	0.68
2016	117	153	0.31	0.35	6	36.62	0.25	0.67
2017	158	153	0.30	2.21	7	48.03	0.21	0.65
2018	199	147	0.32	1.46	19	63.19	0.22	0.63
2019	237	149	0.34	2.09	16	79.71	0.28	0.61
2020	288	165	0.43	3.24	19	126.68	0.40	0.56
2021	368	156	0.63	2.23	21	233.48	0.50	0.57

Table 2: **ESG Returns**

The table reports annualized average returns and alphas from 2016 to 2021. The two left columns report average annualized returns on the market portfolio w_t^{MF} and the representative ESG portfolio w_t^{ESG}. The three right columns report the annualized alphas of the long-short ESG portfolio $\tau_t = w_t^{ESG} - w_t^{MF}$. The ESG portfolios are rebalanced quarterly. Alphas are computed with respect to the CAPM, the CAPM plus the Green Factor in PST (2022), and the Carhart 4-factor model plus the Green Factor. The standard errors are robust to heteroskedasticity and autocorrelation.

	Mutual Fund Portfolio w_t^{MF}	ESG Portfolio w_t^{ESG}	Long-Short ESG Portfolio ($\tau_{t,n}$)			
			Return	α (CAPM)	α (CAPM + Green)	α (CH4 + Green)
2012-2022						
Return (%)	15.57	16.37	0.72	0.96	0.48	0.42
t-statistic	3.20	3.41	1.57	2.03	1.01	0.90
2016-2022						
Return (%)	16.98	19.11	2.01	2.40	1.87	1.51
t-statistic	2.05	2.36	2.91	3.47	2.55	2.01

Table 3: **The Elements of Multiplier Matrix**
The table summarizes the stock-specific and cross-elements of the multiplier matrix for green demand shocks. The first column reports the stock-specific multipliers, i.e. the percent increase in price of a green stock following a 1% increase in demand for that stock. The other columns report the off-diagonal elements of the multiplier matrix, i.e. cross-multipliers, which capture spillover effects to other stocks. Cross-multipliers are separated into spillover effects within green stocks ($\mathcal{M}_{gg}$) and from green stocks to brown stocks ($\mathcal{M}_{bg}$).

| | $\mathcal{M}_g$ | Cross-Multipliers ($\times 10^4$) | |
		$\mathcal{M}_{gg}$	$\mathcal{M}_{bg}$
Mean	1.11	-0.86	-1.40
Std.	(0.1)	(9.66)	(8.40)
10th Pctl.	1.01	-2.30	-3.23
Median	1.09	-0.05	-0.12
90th Pctl.	1.25	0.43	0.36
Fraction Positive Spillovers		38%	32%

Table 4: **Counterfactual ESG Returns without Flow-Driven Price Pressure**

The table reports the true (empirically observed) realized returns of the long-short ESG portfolio τ_t and the counterfactual returns observed in the absence of price pressure from i) labelled ESG mutual fund flows and ii) total ESG flows. I report raw returns and alphas with respect to the CAPM, the CAPM plus the Green Factor from PST (2022), and the Carhart 4-Factor Model plus the Green Factor.

	Return	α (CAPM)	α (CAPM + Green)	α (CH4 + Green)
True Returns: Empirically Observed				
Return (%)	2.01	2.40	1.87	1.51
t-statistic	2.91	3.47	2.55	2.01
Counterfactual Returns: In Absence of Flows from labelled ESG Mutual Funds				
Return (%)	1.92	2.32	1.78	1.42
t-statistic	2.78	3.35	2.43	1.90
Counterfactual Returns: In Absence of Total ESG Flows				
Return (%)	0.04	0.57	-0.05	-0.30
t-statistic	0.05	0.77	-0.07	-0.38

Table 5: **The Correlation of ESG Flows and Returns**

The table reports regressions of the form

$$R_t^{ESG} = \alpha + \beta F_t^{ESG} + \epsilon_t$$

where R_t^{ESG} is an ESG return and F_t^{ESG} a measure of ESG flows. The first set of columns uses the τ-portfolio under 1) total ESG flows and 2) labelled ESG mutual fund flows. The second set of columns uses quarterly GMB (green-minus-brown) factor returns PST (2022). In specification (3) I instrument for the ESG flow by its lag F_{t-1}^{ESG} as in PST (2022). The first stage t-Statistic is 7.6. I only report IV results for ESG mutual fund flows, as the relevance condition does not hold for total ESG flows. For all specifications except for (3), I use rolling 4-quarter average flows. T-statistics are reported in parentheses. Significance at the 90, 95 and 99% confidence levels is indicated by *,**,*** respectively.

	ESG Return τ_t		GMB Factor Returns (PST, 2022)		
	(1)	(2)	(1)	(2)	(3)
const	-0.00	-0.00	0.02	0.02	0.02
	(-1.00)	(-0.21)	(2.17)	(2.66)	(2.15)
Total ESG Flow	2.47***		1.46		
	(3.45)		(1.46)		
ESG Mutual Fund Flow		47.65***		6.01	
		(3.40)		(0.08)	
IV (lagged Flow)					15.46
					(0.24)
R^2	0.29	0.29	0.01	0.00	-

Table 6: **The Cross-Section of ESG Returns and different Elasticity Measures**

Table (a) reports the slope coefficient β_1 and R^2 of regressions of the following form

$$\alpha_n = \beta_0 + \beta_1 \text{Pressure}_n + \epsilon_n$$

where Pressure_n is 1) raw demand Δd_n, 2) demand multiplied by the multiplier matrix estimated in this paper, and 3) demand multiplied by the multiplier matrix estimated in KY (2019). Panel (b) plots the coefficient estimates of a panel regression of price impact $\frac{\alpha_n}{\Delta d_n}$ onto the diagonal elements of the elasticity matrix, controlling for log market equity and beta. T-statistics are reported in parentheses.

(a) Comparing Multiplier Estimates

	Raw Demand Δd_n	Demand × Multiplier $\mathcal{M}\Delta d_n$	Demand × KY-Multiplier $\mathcal{M}_{\text{KY}}\Delta d_n$
$\Delta \alpha_n$	1.13	1.09	0.44
	(6.84)	(7.28)	(5.90)
R^2	0.04	0.05	0.03

(b) Price Pressure in the Cross-Section

	Price Impact $\alpha_n/\Delta d_n$
const	1.809
	(1.418)
diag $\mathcal{M}$	2.813***
	(3.598)
Log ME	-0.211***
	(-4.488)
Beta	0.154
	(1.313)

Table 7: **How much money is following the FTSE 4 Good Index?**

The table reports different regressions in the style of Berk and van Binsbergen (2022). $\Delta I_{t,n}^{4G}$ is equal to 1 in the quarter of inclusion in the FTSE 4 Good Index, -1 in the quarter of exclusion, and 0 otherwise. $I_{t,n}^{4G}$ is a dummy equal to 1 in all quarters after inclusion. $\Delta I_{t,n}$ and $I_{t,n}$ are defined equivalently, but for the FTSE USA index. The stocks in the FTSE 4 Good Index are a strict subset of the stocks in the FTSE USA index. $\mathbb{1}_{\text{Demand}}$ is a dummy equal to 1 if aggregate purchases by index mutual funds have the same sign as the $\Delta I_{t,n}^{4G}$. The first two columns use quarterly mutual fund flow as a dependent variable. Columns three and four use quarterly stock returns. T-statistics are in parentheses. Standard errors are double clustered at the stock and year-month level. Significance at the 90, 95 and 99% confidence levels is indicated by *,**,*** respectively.

| | Mutual Fund Flow $\Delta q_{t,n}^{MF}$ | | Quarterly Returns $\Delta p_{t,n}$ | |
	(1)	(2)	(1)	(2)
const	0.002	0.002	0.047**	0.047**
	(1.64)	(1.64)	(2.43)	(2.43)
$I_{n,t}$	-0.001	-0.001	-0	-0.001
	(-0.93)	(-1.01)	(-0.06)	(-0.10)
$I_{n,t}^{4G}$	-0.001	-0.001	-0.005	-0.005
	(-1.2)	(-1.18)	(-0.8)	(-0.78)
$\Delta I_{n,t}$	-0.001	-0.001	-0.001	-0.001
	(-0.51)	(-0.54)	(-0.03)	(-0.04)
$\Delta I_{n,t}^{4G}$	0.013***	-0.007*	0.009	-0.062*
	(4.5)	(-1.91)	(0.29)	(-1.75)
$\Delta I_{n,t}^{4G} \times \mathbb{1}_{\text{Demand}}$		0.032***		0.115**
		(4.52)		(2.21)

Table 8: Price Impact of Non-Fundamental ESG Demand

The table reports the results of panel regressions of quarterly returns onto non-fundamental ESG demand $\Delta Q_{t,n}^{\perp}$. Specification (1) uses the raw $\Delta Q_{t,n}^{\perp}$, which are mandate-driven portfolio additions by labelled ESG mutual funds. Specification (2) scales $\Delta Q_{t,n}^{\perp}$ by the inverse market share of labelled ESG funds relative to total ESG assets. Specification (3) includes changes in fundamentals as additional controls. Specification (4) splits $\Delta Q_{t,n}^{\perp}$ into quartile dummies. Robust t-Statistics are reported in parentheses. Significance at the 90, 95 and 99% confidence levels is indicated by *,**,*** respectively.

	Quarterly Returns			
	(1)	(2)	(3)	(4)
$\Delta Q^{\perp}$	58.95***			
	(11.02)			
$\Delta Q^{\perp}$ Scaled		0.95***	0.88***	
		(10.44)	(9.88)	
$\mathbb{1}(\Delta Q^{\perp}$ Quartile 1)				-0.008***
				(-3.240)
$\mathbb{1}(\Delta Q^{\perp}$ Quartile 2)				0.001
				(0.250)
$\mathbb{1}(\Delta Q^{\perp}$ Quartile 3)				0.001
				(0.330)
$\mathbb{1}(\Delta Q^{\perp}$ Quartile 4)				0.026***
				(13.150)
Fundamental Controls	Yes	Yes	Yes	Yes
Changes in Fundamentals	No	No	Yes	No
Time FE	Yes	Yes	Yes	Yes

Table 9: **Flow Impact at the Fund Level**

The table reports the impact of a \$1 flow towards some of the largest ESG mutual funds in the US. I compute the impact at every quarter and then average across quarters from 2016 to 2021. I report the impact on green stocks for which $\tau_{t,n} > 0$, as well as fossil fuel and sin stocks. The second column reports the funds' active deviation from the S&P 500 computed as $\frac{1}{2} \sum_n |w_{t,n}^i - w_{t,n}^{SP}|$.

		Impact of 1\$ Flow onto...		
	Deviation from S&P500	Green Stocks	Fossil Fuel Stocks	Sin Stocks
TIAA-CREF Funds: Social Choice Equity Fund	0.546	0.272	0.013	-0.008
Calvert Social Investment Fund	0.819	0.613	-0.006	-0.010
Putnam New Opportunities Fund	0.762	0.173	-0.052	-0.027
Vanguard FTSE Social Index Fund	0.391	0.098	-0.047	-0.030
Calvert Social Index Fund	0.339	0.097	-0.041	-0.021
Virtus Small-Cap Sustainable Growth Fund	0.971	-0.105	0.052	0.016
iShares FTSE KLD 400 Social Index Fund	0.594	0.313	-0.000	-0.015
Brown Advisory Winslow Sustainability Fund	0.833	0.432	-0.006	-0.009
iShares MSCI USA ESG ETF	0.515	-0.043	0.030	0.007

Appendix A   The ESG Portfolio

A.1   Robustness of the ESG portfolio

The ESG portfolio is constructed using ESG mutual funds' portfolio holdings. To this end, I identify a large set of ESG mutual funds via their fund name as reported by CRSP. A mutual fund is an ESG fund if its name contains at least one (or any abbreviation) of a list of sustainability keywords :*Environment, social, governance , green, sustainable, responsible, SRI, ESG, climate, clean, carbon, impact, fair, gender, solar, earth, renewable, screen, ethical, conscious, CSR, thematic.* The total list of keywords is much larger. For brevity, this list excludes all keywords that are not actually used in funds' names. Figure A.10 plots the 30 largest ESG funds and their assets under management as of December 2021.

Table A.10: **Largest 30 ESG Funds**
The table the largest 30 ESG funds and their assets under management identified by the list of sustainability keywords. Assets under management are reported in billion USD.

Fund Name	Assets	Fund Name	Assets
iShares ESG Aware MSCI USA ETF	25.70	iShares MSCI KLD 400 Social ETF	4.20
Vanguard FTSE Social Index Fund	16.79	Xtrackers MSCI USA ESG Leaders Equity ETF	4.14
TIAA-CREF Social Choice Equity Fund	7.75	Sustainable Equity Fund	3.86
iShares ESG Aware MSCI EAFE ETF	7.62	International Sustainability Core 1 Portfolio	3.47
Brown Advisory Sustainable Growth Fund	7.38	CCM Community Impact Bond Fund	3.40
Core Impact Bond Fund	7.27	Vanguard ESG International Stock ETF	3.17
Putnam Sustainable Leaders Fund	6.82	Calvert Small Cap Fund	3.06
Calvert Impact Fund	6.75	Invesco Floating Rate ESG Fund	2.86
Vanguard ESG US Stock ETF	6.50	FT Clean Edge Green Energy Index Fund	2.82
iShares ESG Aware MSCI EM ETF	6.22	Pax Global Environmental Markets Fund	2.74
US Sustainability Core 1 Portfolio	5.86	Invesco Solar ETF	2.73
iShares Global Clean Energy ETF	5.61	AB Sustainable Global Thematic Fund	2.65
Calvert US Large-Cap Core Resp. Index Fund	5.26	Pax Sustainable Allocation Fund	2.62
iShares MSCI USA ESG Select ETF	4.82	Calvert Bond Fund	2.49
iShares ESG MSCI USA Leaders ETF	4.31	PIMCO Total Return ESG Fund	2.46

Note, that the ESG portfolio w_t^{ESG} is scale-invariant and does not depend on the number of identified ESG funds. Its representativeness therefore only depends on whether the subset of ESG funds identified via the list of keywords is represenative of the total ESG fund population. In other words, how stable is w_t^{ESG} for different samples of ESG funds. At every quarter, I sort the sample of ESG funds by their assets under management and split the sample in two groups based on whether a fund has an odd or even rank. I then aggregate the holdings for the two groups and compute two

representative ESG portfolios $w_t^{ESG,even}$ and $w_t^{ESG,odd}$. The two portfolios are therefore computed using two different (non-overlapping) subsets of funds. I also define two measures of greenness τ_t^{even} and τ_t^{odd} as the deviation of $w_t^{ESG,even}$ and $w_t^{ESG,odd}$ from the aggregate mutual fund portfolio w_t^{MF}.[42].

Figure A.5 plots the quarterly cross-sectional correlation of the two ESG portfolios and the two taste measures. I plot both raw (i.e. equal-weighted) correlations, and market cap-weighted correlations.

Figure A.5: Representativeness of the ESG Portfolio

Panel (a) plots quarterly cross-sectional correlations between $w_t^{ESG,even}$ and $w_t^{ESG,odd}$. Panel (b) plots the quarterly cross-sectional correlations between τ_t^{even} and τ_t^{odd}, which are deviations of the ESG portfolios from the aggregate mutual fund portfolio w_t^{ESG}. I compute both equal-weighted and market cap-weighed correlations and plot 3-month rolling averages of the cross-sectional correlation coefficients.

| (a) Correlation $w_t^{ESG,even}$ and $w_t^{ESG,odd}$ | (b) Correlation τ_t^{even} and τ_t^{odd} |
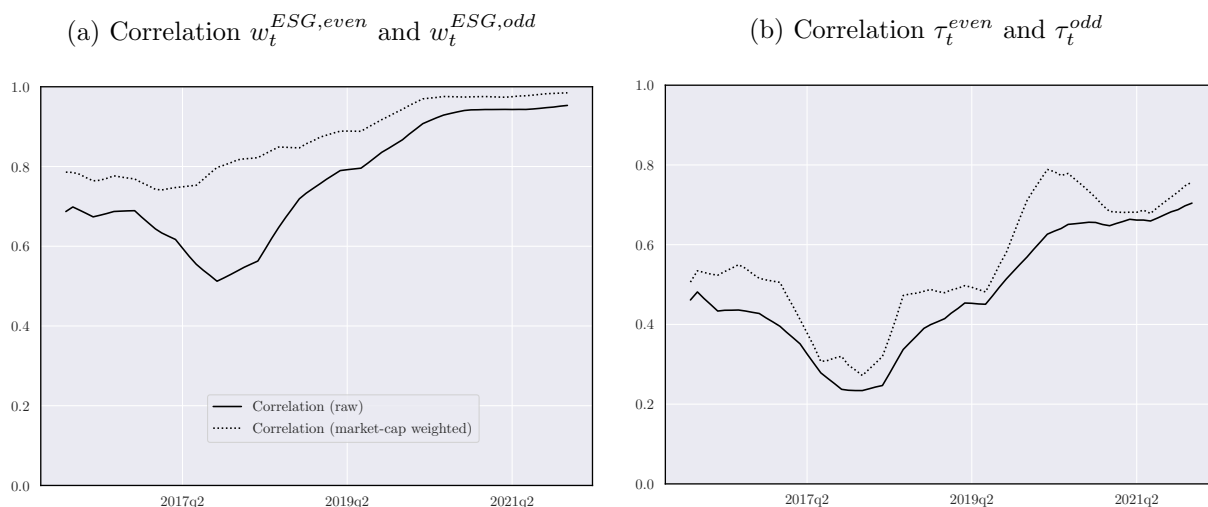
The two ESG portfolios are highly correlated with correlations above 90% for the later part of the sample. This correlation is not just by driven the common tilt towards the aggregate mutual fund portfolio. The ESG portfolio's deviations from the aggregate mutual fund portfolio, τ_t^{even} and τ_t^{odd}, are also highly correlated with an average correlation above 50%. Market-cap weighted correlations are slightly higher implying that there is stronger agreement among ESG funds for larger stocks.

A.2   Investor Preference for ESG Labels

In light of the large flows to sustainable funds in recent years, a natural question that arises is whether including an ESG keyword in the fund title leads to increased inflows. In other words, can fund managers effectively *buy* additional flows by simply changing their fund's name?

Let $\mathbb{1}_{ESG,t}^i$ denote a dummy variable equal to 1 if fund i has an ESG keyword in its name at date t. As a first preliminary test, I regress the panel of quarterly aggregated flows onto $\mathbb{1}_{ESG,t}^i$ controlling

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[42]Formally $\tau_t^{even} = w_t^{ESG,even} - w_t^{MF}$ and $\tau_t^{odd} = w_t^{ESG,odd} - w_t^{MF}$

for lagged flows, fund size, fund performance, portfolio tilts and factor exposures. Panel (a) of Table A.11 reports the estimated coefficient on the ESG dummy across different specifications.

Table A.11: **ESG Labels and Flows**

The table reports the results to panel regressions of quarterly flows onto ESG indicators from 2010 to 2020. Panel (a) reports the coefficient on the ESG dummy equal to 1 if fund i has an ESG keyword in its name as of time t. The first column reports the specification without any controls except quarter fixed effects. The second column includes fund-level controls given by log assets under management, annual return, Sharpe ratio, Fama and French 3-Factor alpha, and flows lagged up to 9 quarters. The third column includes portfolio-level controls given by exposure to momentum, value and size factors as well as characteristic scores for momentum, value, size and greenness. Panel (b) reports the coefficients to the three dummy variables indicating whether a fund is an ESG fund at some point in the sample ($\mathbb{1}^i_{ESG}$), whether it changed its name to an ESG title at some point in the sample, and whether a previously non-ESG fund added an ESG keyword to its title ($\delta^i_{ESG,t}$). Standard errors across specifications are clustered at the fund level. Significance at the 99%, 95% and 90% level is indicated with ***,**,* respectively.

(a) ESG Fund Indicator $\mathbb{1}^i_{ESG,t}$				(b) Name Change $\delta^i_{ESG,t}$			
	Flows f^i_{t+1}				Flows f^i_{t+1}		
	(1)	(2)	(3)		(1)	(2)	(3)
$\mathbb{1}^i_{ESG,t}$	0.041***	0.023***	0.020***	$\mathbb{1}^i_{ESG}$	0.047***	0.025***	0.022***
	(0.005)	(0.003)	(0.003)		(0.006)	(0.004)	(0.004)
Time FE	Yes	Yes	Yes	$\mathbb{1}^i_{treat}$	-0.074***	-0.038***	-0.032***
Fund Controls	No	Yes	Yes		(0.008)	(0.004)	(0.005)
Ptfl. Controls	No	No	Yes	$\delta^i_{ESG,t}$	0.021**	0.021***	0.018**
					(0.009)	(0.006)	(0.008)
				Time FE	Yes	Yes	Yes
				Fund Controls	No	Yes	Yes
				Ptfl. Controls	No	No	Yes

The estimates reveal that having an ESG keyword in the title leads significantly larger quarterly flows of 2%. Given that average quarterly flows are of the same magnitude, the flow gains from being regarded as an ESG fund are extremely large. The flow gain remains large and statistically significant at any reasonable confidence levels despite controlling for various fund-level characteristics including the lagged fund return, Sharpe ratio, Fama and French 3-Factor alpha, fund size (log assets under managament) and lagged flows up to 8 quarters. I also control for portfolio exposures to momentum, value and size obtained from regressing monthly fund returns onto factor returns. Lastly, I control for fund-level characteristic scores as in Lettau et al. (2018), which are portfolio-weighted averages of the stock characteristics.[43]

Nevertheless, it is possible (although unlikely) that ESG funds differ from other funds along some other dimension not captured by directly observable fund characteristics or common risk exposures and portfolio tilts. To address remaining endogeneity concerns, I use funds' name changes as exogenous

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[43]For every fund, I compute scores for greenness, value, size and momentum.

variation in ESG titles. As mentioned in the previous section, 88 out of the 551 identified ESG funds have changed their name at some point between 2010 and 2020 by including an ESG keyword in the title. The name changes can be used akin to a difference-in-difference estimator in order to control for unobservable flow heterogeneity at the fund level. More formally, note that one can decompose the ESG dummy $\mathbb{1}_{ESG,t}^i$ into three sub-variables: i) A dummy $\mathbb{1}_{ESG}^i$ equal to 1 if the fund had an ESG keyword in the title at some point between 2010 and 2020, ii) a treatment dummy $\mathbb{1}_{treat}^i$ equal to 1 if the fund switched to an ESG title at some point between 2010 and 2020, and iii) a time-varying indicator $\delta_{ESG,t}^i$ equal to 1 *after* a previously non-ESG fund added an ESG keyword to its title. Any flow heterogeneity from having an ESG keyword in the title that is driven by some unobservable fund-level fixed effect is captured by $\mathbb{1}_{ESG}^i$ and $\mathbb{1}_{treat}^i$, such that $\delta_{ESG,t}^i$ captures the pure effect of the name change. Panel (b) reports the estimates across different specifications. Despite having very few name changes in the sample, the coefficient on the name change indicator $\mathbb{1}_{ESG}^i$ is statistically significant and roughly equal to 2%. Thus controlling for various fund-level characteristics, changing the fund's name to include an ESG keyword boosts quarterly flows by 2%. Note, that the treatment dummy $\mathbb{1}_{treat}^i$ is significantly negative. Thus funds with strong outflows seem to have a greater incentive to include trending ESG keywords in their name, which significantly alleviates subsequent outflows. This is an interesting avenue for further research.

A.3 Perceived versus True Sustainability

Do sustainable mutual funds invest sustainably? As already suggested in table 1, the ESG portfolio w_t^{ESG} tilts over 50% of its assets away from the aggregate mutual fund portfolio w_t^{MF}. However, this does not imply that ESG funds (in aggregate) tilt towards *truly* sustainable stocks. The difficulty in answering the question about *true* sustainability lies in the lack of an objective definition. Particularly the social and governance component of ESG investing may strongly depend on personal preferences and ethical convictions. While the environmental component may be more easily objectifiable (e.g. via Co2 Emission data), it is still subject to large variations in preferences. For example, is the least polluting company among all fossil fuel companies a sustainable company? Analyzing, which companies are *truly* sustainable lies beyond the scope of this paper. I nevertheless assess whether the ESG portfolio's deviations from the market portfolio align with a set of sustainability characteristics. To this end, I estimate two regressions. The first is a panel OLS regression of $\tau_{t,n}$ onto the sustainability characteristics. The second is a probit regression of a greenness dummy $\mathbb{1}_{\tau>0}$ (which is equal to 1,

if the stock is overweighted by the ESG portfolio) onto the same set of sustainability characteristics. As sustainability characteristics, I use Refinitiv ESG Scores, a Co2 emissions indicator, a sin stock dummy, a fossil fuel industry dummy and a Vanguard 4 Good dummy equal to 1, if the stock is in the Vanguard 4 good index. The Co2 emissions indicator is equal to 1 at time t, if the stock is in the highest decile of Co2 scope 1 emissions across all stocks in the sample. I furthermore control for log market equity, market beta and volatility in both specifications. Table A.12 reports the results.

Table A.12: **ESG tastes and sustainability characteristics**

The table reports the results of two regressions. The first is a panel regression including time fixed effects of $\tau_{t,n}$ onto different sustainability characteristics. The second is a probit regression of a greenness dummy $\mathbb{1}_{\tau>0}$ (which is equal to 1, if the stock is overweighted by the ESG portfolio) onto the same set of sustainability characteristics. The control variables in all specifications are log market equity, market beta and volatility. *,**,*** denote significance at the 90, 95 and 99% confidence level.

| | Sustainability Characteristics | | | | | | |
	ESG Score	High Co2 Emissions	Sin Stock	Fossil Fuel	Vanguard 4 Good Index	Controls	R^2
Panel Regression $\tau_{t,n}$							
Coefficient	0.21***	-0.21***	-0.58***	-0.21***	0.51***	Yes	5.92%
t-stat	11.01	-16.28	-13.57	-11.80	39.05		
Probit Regression $\mathbb{1}_{\tau>0}$							
Coefficient	0.78***	-0.33***	-0.47***	-0.14***	0.46***	Yes	5.53%
t-stat	28.83	-23.20	-9.82	-5.39	41.88		

The coefficients on virtually all sustainability characteristics are highly significant with the right sign. The ESG portfolio tilts significantly towards stocks with high ESG scores as well as stocks that are in the Vanguard 4 Good Index. It significantly underweights sin stocks, stocks in the fossil fuel industry and high Co2 emitters. This is strong evidence, that ESG funds (on aggregate) do tilt towards what may be labelled as *objective* sustainability. Kim and Yoon (2022), Liang et al. (2021) and Gibson et al. (2022), on the other hand, show that investors who are part of the Principles for Responsible Investment initiative do not have better ESG scores. The opposing results underline the above-mentioned concerns that treating readily available scores by ESG ratings providers as *objective* or *true* sustainability is problematic. Recent evidence furthermore suggests, that ESG scores by ratings providers are inflated by greenwashing and empty sustainability claims (see Yang (2021) and Bams and van der Kroft (2022)).

Appendix B   Measuring ESG Flows

B.1   Aggregate ESG Flows

Price pressure in aggregate ESG returns is driven by flows towards the ESG portfolio w_t^{ESG}. Total cumulative flows into labelled ESG mutual funds from Section 3 amount to roughly \$175 billion as of December 2021. However, the flows into labelled ESG do not include the (unobservable) ESG tilts of other mutual funds, large investment advisors, pension funds, banks, insurance companies, and other institutions. Unfortunately, precise data on flows are only available for mutual funds. 13F institutions report their holdings at the management company level. Thus flows towards ESG funds *within* a manager show up as active trades a_{t+1}^i instead of flow-driven trades $Q_t^i f_{t+1}^i$. To illustrate this point, consider the following simple example.

Example. Manager i manages two investment funds, an ordinary index fund and an ESG fund that overweights green stocks and underweights brown stocks. Between t and $t+1$ investors withdraw money from the index fund and invest it in the ESG fund provided by the same manager. Thus total flows f_{t+1}^i are 0, but the manager buys some green stocks ($\Delta Q_{t+1,\text{green}} > 0$) and sells some brown stocks ($\Delta Q_{t+1,\text{brown}} < 0$). In the aggregated 13F holdings, these trades only show up as active trades a_{t+1}^i, even though they are purely flow-driven.

In order to address this issue I propose decomposing 13F institutions' portfolios into different fund-level portfolios via a simple cross-sectional projection. For simplicity of notation, I am dropping the fund superscripts i. For every 13F-quarter pair, I am projecting the portfolio weights onto a set of $s = 1, ..., S$ managed portfolios (or individual funds)

$$
\min_{\{\beta_t^s\}_{s=1}^S} \quad ||w_{t,n} - \sum_{s=1}^S \beta_t^s w_{t,n}^s||_2 \tag{16}
$$
$$
\text{s.t.} \quad 0 \le \beta_t^s \le 1 \quad \forall s = 1, ..., S
$$

Thus β_t^s are the wealth-shares of individual funds belonging to institution i and $w_{t,n}^s$ their corresponding portfolios. As a set of managed portfolios $w_{t,n}^s$, I choose the equal-weighted portfolio $w_{t,n}^E = 1/N^i$, the market cap-weighted portfolio $w_{t,n}^{Mkt} = P_{t,n}/\sum_{n \in N^i} P_{t,n}$ and the ESG portfolio $w_{t,n}^{ESG}$. (16) is essentially equal to a constrained cross-sectional regression of portfolio weights $w_{t,n}$ onto a constant (the equal-weighted portfolio $w_{t,n}^E$) and characteristics (the other managed portfolios). The managed portfolios are constructed such that the weights sum to 1 across the institution's current holdings N^i.

This implies rescaling the ESG portfolio $w_{t,n}^{i,ESG} = w_{t,n}^{ESG}/\sum_{n \in N^i} w_{t,n}^{ESG}$ such that $\sum_{n \in N^i} w_{t,n}^{ESG} = 1$. The residual from the projection $a_{t,n} = w_{t,n} - \sum_{s=1}^{S} \beta_t^s w_{t,n}^s$ is a long-short active portfolio that is orthogonal to the managed portfolios $w_{t,n}^s$. The inclusion of the equal-weighted portfolio $w_{t,n}^E$ furthermore ensures that $a_{t,n}$ is a net-zero investment portfolio, i.e. $\sum_{n \in N^i}^{N} a_{t,n} = 0$. The active deviation relative to the managed portfolios (as a fraction of total assets) is given by

$$\text{Active Share}_t = \frac{1}{2} \sum_{n \in N^i} |a_{t,n}| \tag{17}$$

Thus the projection of a fund's weights onto managed portfolios can be viewed as an extension to the 'Active Share' proposed by Cremers and Petajisto (2009). If the coefficient on the market portfolio β_t^{Mkt} is equal to 1 and the coefficients on all other managed portfolios are equal to 0, then $a_{t,n} = w_{t,n} - w_{t,n}^{Mkt}$ and the two measures of activeness coincide.

Because the weights in the zero-cost portfolio sum to 0, and all the managed portfolio weights $w_{t,n}^s$ sum to 1 respectively, it must hold that $\sum_{s=1}^{S} \beta_t^s = 1$. The coefficients β_t^e, β_t^m and β_t^{ESG} can therefore be interpreted as the wealth shares of the individual funds $w_{t,n}^E$, $w_{t,n}^m$ and $w_{t,n}^{ESG}$ within the management company i. Figure B.6 summarizes the ESG tilt across 13F investors. Panel (a) plots the equal- and value-weighted average ESG tilt across all 13F institutions from 2012 to 2022. The value-weighted ESG tilt β_t^{ESG} steadily grew from 7 to 18% in the past 10 years. As a robustness check, I also add 12 Fama-French industry portfolios to the projection (16). The aggregate ESG tilt and the corresponding total flows to the ESG portfolio are unaffected by controlling for industry exposures.

Figure B.6: **ESG Tilts across 13F Investors**

Panel (a) plots the average equal- and value-weighted ESG tilt β_t^{ESG} across all 13F institutions. Formally, I compute $\frac{1}{I}\sum_{i=1}^{I}\beta_t^{i,ESG}$ and $\sum_{i=1}^{I}v_t^i\beta_t^{i,ESG}$ where $v_t^i = A_t^i/\sum_{i=1}^{I}A_t^i$ are AUM-weights. Panel (b) plots the fraction of Closet-ESG investors, both in terms of number of institutions and in terms of assets. Closet-ESG investors are defined as investors with an ESG-share of over 50%. The grey lines report values obtained when controlling for industry exposures in the estimation of β_t^{ESG}.

(a) Average ESG Tilt	(b) Closet-ESG Investors

Using the investor-specific ESG tilts $\beta_t^{i,ESG}$ and their total assets under management A_t^i, we can compute the total ESG assets held by investor i as $A_t^{i,ESG} = A_t^i\beta_t^{i,ESG}$. Following the literature on mutual fund flows, I define the flow in the ESG portfolio of investor i as the change in ESG assets in excess of the valuation gains due to ESG returns. Formally,

$$F_{t+1}^{i,ESG} = A_{t+1}^{i,ESG} - A_t^{i,ESG}(1 + R_{t+1}^{ESG}) \tag{18}$$

where R_{t+1}^{ESG} is the return on the ESG portfolio. Note that empirically, this return may differ across investors because 13F institutions hold different subsets of stocks $N^i \subseteq N$. Summing across all investors yields the total flow by 13F investors in the ESG portfolio.

Lastly, note that the ESG tilt β_t^{ESG} allows distinguishing 13F investors by their tilt towards sustainable stocks. I define 'Closet-ESG' investors as 13F institutions that hold over 50% of their assets in the ESG portfolio (i.e. $\beta_t^{ESG} > 0.5$). Between 2016 and 2021, the total number Closet-ESG funds grew from 8 to 133. Panel (b) plots the number of Closet-ESG funds and their total assets. The fraction of assets held by Closet-ESG funds increased over tenfold over the past 10 years.

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B.2 Stock-Specific ESG Flows

If one had access to the flows and holdings of *all* investors $i = 1, ..., I$, one could decompose each investor's trades $\Delta Q^i_{t+1,n}$ into a flow-driven and an information-related component as in e.g. Greenwood and Thesmar (2011) or Lou (2012):

$$\Delta d^i_{t+1,n} = \underbrace{f^i_{t+1} Q^i_{t,n}}_{\text{Flow-Driven Demand}} + \underbrace{a^i_{t+1,n}}_{\text{Active Demand}} \tag{19}$$

However, the only investor group for which we have precise data on both flows f^i_{t+1} and holdings $Q^i_{t,n}$ at the fund level are mutual funds. 13F institutions only report quarterly holdings $Q^i_{t,n}$. As mentioned above, the aggregation of 13F holdings across funds within a management company makes it difficult to construct flow-driven trades for 13F investors. However, we can approximate the flow-driven trades in green stocks using the investor-specific flows in the ESG portfolio $F^{i,ESG}_{t+1}$ and the corresponding weights $w^{i,ESG}_t$.[44] For each 13F institution that is not a mutual fund, I construct $f^i_{t+1} = F^{i,ESG}_{t+1} / A^{i,ESG}_t$ as the relative flow to the ESG portfolio and $Q^i_{t,n} = (w^{i,ESG}_t A^{i,ESG}_t) / P_{t,n}$ as the corresponding stock-specific holdings within the ESG portfolio. Total flow-driven demand for each green stock is given by summing the flow-driven demand across all mutual funds and 13F investors. In order to avoid double-counting we I omit all 13F institutions that are classified as mutual funds using the corrected type codes from KY (2019).

$$\forall n \in N^G : \quad \Delta d_{t+1,n} = \sum_{i=1}^{I} Q^i_{t,n} f^i_{t+1} \tag{20}$$

where $N^G \subset N$ denotes the subset of green stocks. Because shares outstanding are normalized to 1, $Q^i_{t,n}$ are ownership shares and $\Delta d_{t+1,n}$ are demand shocks in percent relative to shares outstanding. Lastly, note that one could construct $\Delta d_{t+1,n}$ for alternative subsets of stocks by decomposing 13F holdings into other managed portfolios and computing the within-manager flow to the portfolio of interest.

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[44]Recall that the ESG portfolio weights are investor-specific because I normalize them within each investor's universe $w^{i,ESG}_{t,n} = w^{ESG}_{t,n} / \sum_{n \in N^i} w^{ESG}_{t,n}$.

B.3 Extracting Non-fundamental ESG Demand

Let $\mathbb{1}^X_{t,n}$ denote indicator variables equal to 1 if a trade between $t-1$ and t is an extensive trade.[45] Let $\Delta Q^X_{t,n}$ denote extensive green demand. It is the sum of all extensive trades in stock n by ESG mutual funds between $t-1$ and t:

$$\Delta Q^X_{t,n} = \sum_{i \in I^{ESG}} \mathbb{1}^X_{t,n}(Q^i_{t,n} - Q^i_{t-1,n}) \tag{21}$$

Similarly, the intensive green demand is given by $\Delta Q^I_{t,n} = \sum_{i \in I^{ESG}}(1 - \mathbb{1}^X_{t,n})(Q^i_{t,n} - Q^i_{t-1,n})$. As described above, the goal is to extract the mandate-driven (i.e. non-fundamental) component of $\Delta Q^X_{t,n}$. Under the assumption that all fundamental information contained in extensive trades is also present in intensive trades, we can extract the mandate-driven component from extensive green demand $Q^X_{t,n}$. To this end, I cross-sectionally orthogonalize extensive green demand with respect to intensive green demand,

$$\forall t \quad : \Delta Q^X_{t,n} = \beta_t \Delta Q^I_{t,n} + Controls + \Delta Q^\perp_{t,n} \tag{22}$$

where $Controls$ includes changes in book equity, total assets and profitability between $t-1$ and t. One could argue, that intensive trades by ESG funds do not capture all of the fundamental information in extensive trades. I therefore also orthogonalize with respect to total intensive trades (i.e. trades summed across all investors and not just ESG funds). This should eliminate any variation in ESG funds' extensive trades that is driven by fundamental information. The residual from the regressions, $\Delta Q^\perp_{t,n}$, is the component of ESG funds' purchases that is exclusively driven by exogenous portfolio constraints or mandates. That is, it is a proxy for non-fundamental ESG demand. However, because $\Delta Q^\perp_{t,n}$ is constructed using only a subset of all ESG investors, regressions of returns onto $\Delta Q^\perp_{t,n}$ do not capture structural parameters. In order to approximate total mandate-driven ESG demand, let S^{ESG}_t denote the wealth share of labelled ESG mutual funds relative to total ESG assets A^{ESG}_t. Figure B.7 plots S^{ESG}_t over time.

---

[45]Formally

$$\mathbb{1}^X_{t,n} = \begin{cases} 0 & \text{if } Q_{t-1,n} = 0 \text{ or } Q_{t,n} = 0 \\ 1 & \text{otherwise} \end{cases}.$$

Figure B.7: **Wealth Share of Labelled ESG Mutual Funds**
The figure reports the wealth share of labelled ESG mutual funds as a fraction of total ESG assets A_t^{ESG}. Total ESG assets are constructed as the sum of individual investors' ESG holdings $A_t^{i,ESG}$ from Section 3.
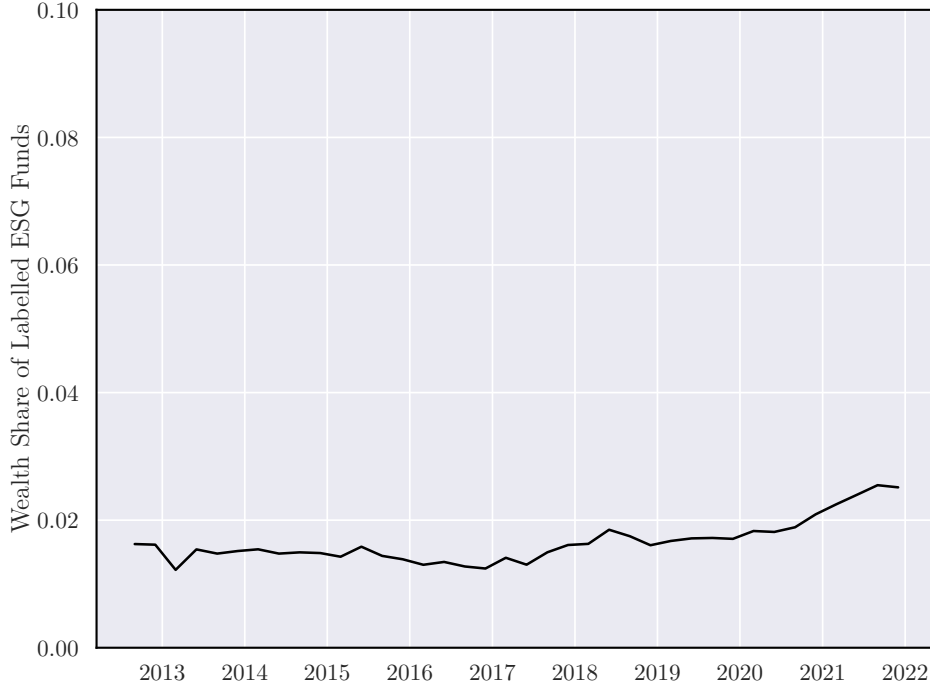
The figure suggests that demand from labelled ESG mutual funds is roughly 2% of total ESG demand. Total mandate-driven ESG demand can be approximated as $\frac{1}{S_t^{ESG}}\Delta Q_{t,n}^{\perp}$. The coefficient obtained from regressions of returns onto total mandate-driven ESG demand should then reveal the structural parameter. Lastly, note that for simplicity of exposition, the estimation is split into the construction of $\Delta Q_{t,n}^{\perp}$ and regressions of returns onto $\Delta Q_{t,n}^{\perp}$. This is equivalent to simple regressions of returns onto the raw $\Delta Q_{t,n}^{X}$, controlling for intensive trades $\Delta Q_{t,n}^{I}$.

Appendix C   Identification

C.1   *Dividend Reinvestments*

Do mutual funds reinvest total dividend payout in their existing portfolio? I assess the extent to which mutual funds invest a stock's dividend payout in all other stocks within their portfolios. Let $\Delta q_{t,n}^i = Q_{t,n}^i/Q_{t-1,n}^i - 1$ denote the percentage change in shares held between two quarters. If mutual funds reinvest dividend payouts across their entire portfolio, then $\Delta q_{t,n}^i$ should be significantly related

to the dividend flow from all *other* stocks $df_{t,-n}^i$. I test this in a pooled regression given by

$$\Delta q_{t,n}^i = \theta df_{t,-n}^i + Controls + \epsilon_{t,n}^i \qquad (23)$$

where *Controls* includes a constant, time fixed effects, total fund flows f_t^i and log returns $\Delta p_{t,n}$. Table C.13 reports the coefficient estimates across different specifications.

Table C.13: **Dividend Reinvestments**
The table reports the estimated coefficients from the pooled regression of trades $\Delta q_{t,n}^i$ onto dividend flows from other stocks $df_{t,-n}^i$. Standard errors robust to heteroskedasticity and autocorrrelation are reported in parentheses. Significance at the 90, 95 and 99% confidence levels is indicated by *,**,*** respectively.

	Quarterly trades $\Delta q_{t,n}^i$					
	(1)	(2)	(3)	(4)	(5)	(6)
Dividend Flow $df_{t,-n}^i$	4.88***	5.83***	2.52***	2.44***	1.21**	1.91***
	(0.807)	(0.836)	(0.545)	(0.408)	(0.502)	(0.554)
Total Flow f_t^i	-	-	0.61	0.67	0.27	0.21
	-	-	(0.046)	(0.035)	(0.027)	(0.025
Stock Return $\Delta p_{t,n}$	-	-	-0.02	-0.03	-0.04	-0.04
	-	-	(0.003)	(0.003)	(0.012)	(0.018)
Div. per Share $D_{t,n}$	-	-	-	-0.01	0.02	-
	-	-	-	(0.001)	(0.008)	-
Quarter FE	No	Yes	Yes	Yes	Yes	Yes
Large Dividend Flow ($df_{t,-n}^i > 1\%$)	No	No	No	No	Yes	Yes
Exclude Dividend Stocks	No	No	No	No	No	Yes

The dividend-scaling coefficient θ is significantly positive across all specifications. Thus, on average mutual funds reinvest their dividend payouts across all other stocks in their portfolios. Specification (5) estimates the impact of large dividend flows that exceed 1% of the funds' total assets. The scaling coefficient is close to 1, suggesting that when funds receive large total dividend flows, they proportionately scale up all their existing positions. Specification (6) excludes dividend paying stocks. While this greatly reduces the number of observations, the dividend scaling coefficient remains highly statistically significant. Lastly, note the effect of total relative flows f_t^i on quarterly trades is highly statistically significant across all specifications. The estimated coefficient is comparable in magnitude to Lou (2012). Mutual funds scale their existing portfolio holdings in response to both, total in- and outflows, and total payouts from dividends.

C.2 Instrument Relevance

The significant relationship between flow-driven purchases and contemporaneous returns (i.e. the relevance of the instrument) has been shown at least since Lou (2012). Schmickler and Tremacoldi-Rossi (2022) furthermore show that the trades induced by dividend flows are significantly related to contemporaneous stock returns. This paper uses their instrument to identify exogenous price shocks in the first stage. Recall, that the first stage regression is given by

$$\Delta p^i_{t,n} = \theta^i DIT^{-i}_{t,n} + \epsilon^i_{t,n}$$

where $DIT^{-i}_{t,n}$ is the dividend-based instrument and $\epsilon^i_{t,m}$ includes the control variables log book equity, profitability, investment, and market beta. I estimate the first stage in a pooled panel regression for the subset of stocks held by Thomson Reuters' institutional type codes. Figure C.8 reports the t-statistic of θ^i for each institutional type. The t-statistic exceed the critical weak-instrument threshold of of 4.05 (see Stock and Watson, 2005) for all institutional types.

Figure C.8: **Weak Instrument Test**
The figure reports the t-statistic on the coefficient θ^i for each institutional type. The red dotted line indicates the weak instrument threshold of 4.05 (see Stock and Watson, 2005).
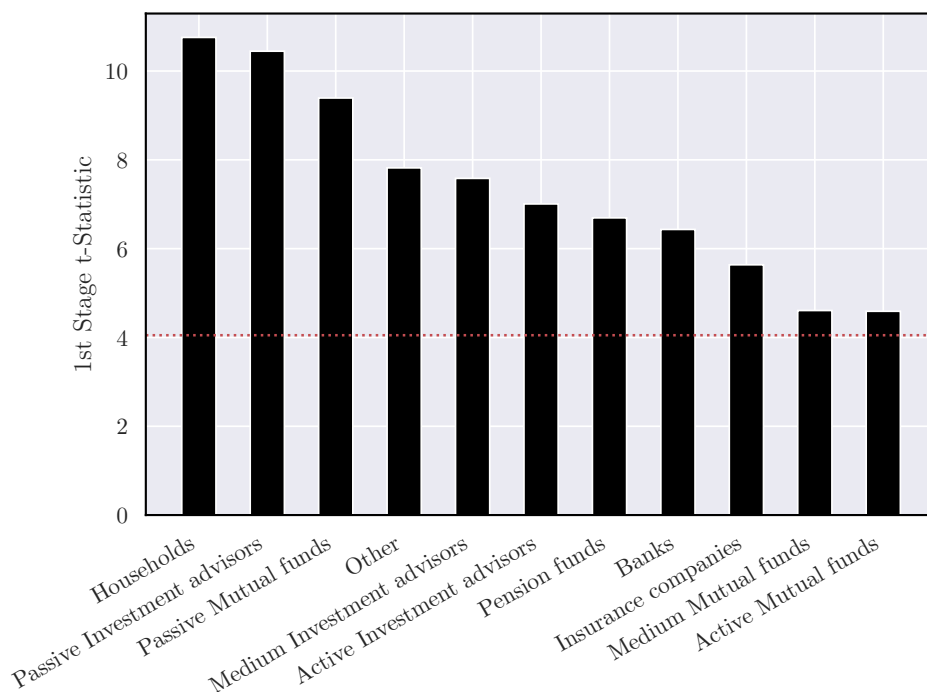
C.3 Identification using Benchmarking Intensity

The central object of the relationship between flow-driven demand and realized returns is investors' elasticity of demand. The parameter estimates critically depend on a valid instrument, i.e. *exogenous* variation in prices that is orthogonal to the investor's own latent demand shocks. In this section I explore the stability of the estimates to an entirely different instrument. In particular, I use the benchmarking intensity by Pavlova and Sikorskaya (2022) as exogenous supply shocks to identify investors' demand elasticities. I kindly thank Anna Pavlova and Taisiya Sikorskaya for generously sharing their data with me.

Benchmarking Intensity. If the aggregate demand for equities is downward-sloping, changes in the supply of stocks can have significant price effects. These supply shifts can in turn be used to identify investors' demand elasticities. If benchmarked (or passive) investors increase their holdings in a given stock, they are effectively reducing its supply. Pavlova and Sikorskaya (2022) construct each stock's benchmarking intensity as the AUM-weighted sum across index weights:

$$BMI_{t,n} = \frac{\sum_x A_t^x w_{t,n}^x}{P_{t,n}} \tag{24}$$

where $w_{t,n}^x$ is the portfolio weight of stock n in index x at time t and A_t^x is the total amount of exchange traded funds' and mutual funds' assets benchmarked to index x. Changes in a stock's benchmarking intensity between two quarters, $\Delta BMI_{t,n}$, represent a change in the stock's effective supply and may be used as an exogenous shock to identify elasticities. However, changes in benchmarking intensity may be driven by fundamental news (or price increases themselves) that cause index additions and deletions. Pavlova and Sikorskaya (2022) address the potential endogeneity by only using changes in benchmarking intensity across the Russell 1000/2000 cutoff. However, the amount of observations around the Russell cutoff are not sufficient to estimate the structural model in Section 4. Despite the potential endogeneity concerns, I therefore use the raw $\Delta BMI_{t,n}$ across all stocks and quarters to identify investor-specific demand elasticities. While this instrument is imperfect, it serves as a useful robustness check that similar elasticity estimates can be obtained using a completely different instrument from a separate study.

Table C.14: **Multiplier Matrix identified from Benchmarking Intensity**
The table summarizes the price impact $\mathcal{M}$ of green demand onto green g and non-green stocks b. (i.e. diagonal and off-diagonal elements of the multiplier matrix $\mathcal{M}$) identified from from changes in Benchmarking Intensity $\Delta BMI_{t,n}$ (see Pavlova and Sikorskaya (2022).

| | $\mathcal{M}_g$ | Cross-Multipliers $(\times 10^4)$ | |
		$\mathcal{M}_{gg}$	$\mathcal{M}_{bg}$
Mean	1.17	-0.82	1.50
Std.	(1.06)	(29.48)	(33.99)
10th Pctl.	0.35	-8.46	-6.27
Median	0.83	0.00	0.18
90th Pctl.	2.5	6.61	10.87
Fraction Positive Spillovers		50%	61%

Table C.15 summarizes the impact of ESG demand shocks identified from changes in benchmarking intensities. The estimates are close to the estimates identified from the flow-based instrument (see Table 3). The average price impact of the demand for green stocks is 1.17% respectively. Recall, that the multiplier identified from the flow-based instrument is 1.11%. Thus the multiplier identified via benchmarking intensity is slightly higher but lie in the same ballpark.

C.4 Identification using Flow Shocks

Following van der Beck (2022), I construct an alternative instrument for each investor by aggregating the surprise flow-induced trades by all other mutual funds,

$$f_{t,n}^{-i} = \sum_{j \neq i}^{I} f_{t+1}^{j,\perp} Q_{t,n}^{j} \tag{25}$$

where $f_{t+1}^{j,\perp}$ is the flow into fund j between t and $t+1$ orthogonalized for fund characteristics, holdings and returns. In particular, I obtain the surprise flow $f_t^{j,\perp}$ as the residual in cross-sectional regressions of fund flows f_t^j onto fund characteristics. The characteristics are portfolio weighted greenness, value, size, momentum, profitability, investment and idiosyncratic volatility as well as the funds' own contemporaneous returns. Thus the flow shocks are orthogonal to the fund's portfolio tilts. This addresses the endogeneity concern that flows are driven by fundamental news regarding the fund's underlying assets. See van der Beck (2022) for details.

Table C.15: **Multiplier Matrix identified from Flow Shocks**
The table summarizes the price impact $\mathcal{M}$ of green demand onto green g and non-green stocks b. (i.e. diagonal and off-diagonal elements of the multiplier matrix $\mathcal{M}$) identified from flow shocks (see van der Beck (2022).

| | $\mathcal{M}_g$ | Cross-Multipliers $(\times 10^4)$ | |
		$\mathcal{M}_{gg}$	$\mathcal{M}_{bg}$
Mean	2.78	-16.56	-9.81
Std.	(0.72)	(62.99)	(40.27)
10th Pctl.	1.81	-41.63	-24.23
Median	2.82	-3.68	-1.31
90th Pctl.	3.67	0.00	0.56
Fraction Positive Spillovers		10%	21%

Appendix D   Details on Estimation and Variable Construction

D.1   Pooling by Institutional Types

In order to pool investors into groups, I start by computing each investor's active share as of quarter t as

$$\text{Active Share}_t^i = \frac{1}{2} \sum_n |w_{t,n}^i - w_{t,n}^M| \tag{26}$$

which measures a fund's deviation from holding a passive market portfolio. I define index funds as 13F institutions with Active Share$_t^i < 0.01$. These are all investors who tilt less than 1% of their portfolio away from passive market weights. For the remaining investors, I use Thomson's institutional type code labels, which split investors into banks, pension funds, investment advisors, insurance companies, mutual funds and other. I divide the largest investor groups, investment advisors and mutual funds, into activeness terciles based on their Active Share$_t^i$. The resulting groups are labelled *rigid*, *medium* and *elastic*. I estimate group-specific demand curves using the two-step procedure in (12) by pooling the observations of all institutions within a group.

D.2   Estimated Coefficients by Investor Type

I estimate elasticities over the panel of quarterly holdings from 2010 to 2020 including time fixed effects. Table D.16 reports the estimated coefficients for all investors. The first row reports the estimates for a pooled regression across all investors. The pooled elasticity is 1.05, which implies that on average

institutions sell 1.05% of their holdings in a stock when the price increases by 1%.[46] The remaining rows report the elasticities obtained in a pooled estimation across institutional types. There is great heterogeneity in the estimated elasticities ζ^i across types. ζ^i is the lowest for insurance companies and large passive investment advisors investors such as Blackrock, Fidelity and Vanguard. Active mutual funds are the most elastic investors with an elasticity of 3.2. The second column reports the elasticities estimated from the cross-section of quarterly holdings $Q_{t,n}^i$ instead of trades $\Delta q_{t,n}^i$. The estimates are considerably smaller for the majority of investors.

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[46]Note. that ζ^i only approximates the true elasticity. The next section provides a thorough description on how to structurally construct exact elasticities.

Table D.16: **Demand Curves by Investor Type**

The table reports the estimated demand curves for different groups of investors. The trades $\Delta q^i_{t,n}$ are pooled over stocks, quarters and institutional types, such that one demand curve is estimated per investor group. Formally, the estimation equation is given by

$$\forall j = 1, ..., J \quad : \Delta q^j_{t,n} = -\zeta^j \Delta \hat{p}_{t,n} + \epsilon_{t,n}.$$

where $\Delta \hat{p}_{t,n}$ is the fitted return from dividend flow demand shocks and $\epsilon_{t,n}$ includes the control variables log book equity, profitability, investment and market beta. Institutional types (split by active share) are denoted by $j = 1, ...J$ and include mutual funds, investment advisors, households, pension funds, insurance companies, and other 13F institutions. Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation.

	ζ^i Identified from Trades $\Delta q_{t,n}$ van der Beck (2022)	ζ^i Identified from portfolio holdings $Q_{t,n}$ Koijen and Yogo (2019)
Pooled All		
	1.054 (0.033)	0.282 (0.001)
Pooled by Type		
Mutual Funds		
High Active Share	3.198 (0.305)	0.744 (0.004)
Medium Active Share	2.660 (0.298)	0.477 (0.004)
Low Active Share	1.296 (0.092)	-0.142 (0.003)
Investment advisors		
High Active Share	0.924 (0.120)	0.795 (0.002)
Medium Active Share	0.250 (0.103)	0.624 (0.001)
Low Active Share	0.424 (0.046)	0.521 (0.001)
Banks	1.292 (0.118)	0.238 (0.002)
Pension funds	0.838 (0.081)	0.322 (0.002)
Insurance companies	0.387 (0.168)	0.321 (0.003)
Other 13F Instiutions	0.039 (0.226)	-0.415 (0.003)
Households	0.724 (0.244)	0.530 (0.009)

D.3 Incorporation in Logit Framework and Asset Substitution

Motivated by the fact that portfolio weights are log-normally distributed in the data, KY (2019) propose (and microfound) a logit framework for the demand of investor i:

$$\log \delta^i_{t,n} = (1 - \zeta^i) \log P_{t,n} + \varepsilon^i_{t,n} \tag{27}$$

where $\delta_{t,n}^i = w_{t,n}^i / w_{t,0}^i$ is the portfolio weight relative to the weight in an outside asset $w_{t,0}^i$ and $\varepsilon_{t,n}^i$ includes a constant, observable characteristics and a residual. The portfolio constraint that $\sum_{n \in N^i} w_{t,n}^i = 1 - w_{t,0}^i$ implies that

$$w_{t,n} = \frac{\delta_{t,n}^i}{1 + \sum_{m=1}^{N} \delta_{t,m}^i}. \tag{28}$$

The logit framework ensures that portfolio holdings add up to total assets and that holdings cannot be negative (as observed in the 13F filings). Note that we can rewrite $\log \delta_{t,n}^i = \log Q_{t,n}^i + \log P_{t,n}^i - \log w_{t,0}^i A_t^i$. Rearranging and taking first differences yields[47]

$$\Delta q_{t,n}^i = -\zeta_t^i \Delta p_{t,n} + \epsilon_{t,n}^i \tag{29}$$

where $\epsilon_{t,n}^i = \Delta \log(w_{t,0}^i A_t^i) + \Delta \varepsilon_{t,n}^i$. The first-difference estimator has the distinct advantage of eliminating any time-invariant drivers of cross-sectional portfolio holdings that are correlated to prices. In a simple simulation, van der Beck (2022) shows that (29) successfully eliminates the ommited variable bias from unobservable portfolio tilts that are slow-moving and correlated to the cross-section of prices.

A first-order approximation of investor's demand elasticity is given by the scalar regression coefficient $-\frac{\Delta q_{t,n}^i}{\Delta p_{t,n}} = \zeta^i$. However, this measure of elasticity does not ensure that the investor's portfolio weights add up to 1, (or alternatively: that her assets A_t^i remain unchanged). In order to ensure that the budget constraint holds we need to plug the estimated coefficient into (28). To this end, note that $\log w_{t,n}^i = \log Q_{t,n}^i + \log P_{t,n}^i - \log A_t^i$. Differentiating and rearranging yields the following elasticity

$$-\frac{\partial \log Q_{t,n}^i}{\partial \log P_{t,n}} = \zeta^i + \underbrace{w_{t,n}^i(1 - \zeta^i)}_{\text{Portfolio Constraint}}. \tag{30}$$

The elasticity is given by ζ^i plus a correction term, which ensures that portfolio weights add up to 1.[48] Precisely because of the portfolio constraint, price changes have spillover effects to other stocks.

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[47]KY (2019) actually propose re-estimating 27 over the cross-section of portfolio weights every quarter t resulting in time-varying coefficients ζ_t^i. Empirically, however, the coefficients remain very stable in the time-series. Thus the correction term for time-varying coefficients in the first-difference estimator is small and can be ignored. In fact, estimating constant demand coefficients ζ^i in a panel regression including time-fixed effects leads to essentially the same demand curves (see van der Beck and Jaunin (2021) and ?)

[48]The correction term is negative, if the investor is very elastic $\zeta^i > 1$. In this case the dollar holdings (not the number of shares held!) in stock n is decreasing in price of n and we have to make a downward adjustment to the elasticity to satisfy the portfolio constraint.

Cross-elasticities are given by

$$-\frac{\partial \log Q_{t,n}^i}{\partial \log P_{t,m}} = w_{m,t}^i(1-\zeta^i).^{49} \tag{31}$$

We can stack the elasticities into an elasticity matrix $-\frac{\partial \log Q_t^i}{\partial \log P_t'} \in \mathbb{R}^{N \times N}$ given by

$$-\frac{\partial \log Q_t^i}{\partial \log P_t'} = \zeta^i I + (1-\zeta^i)1w_t', \tag{32}$$

where I is the identity matrix and 1 is a vector of ones. Thus the logit framework allows transforming the simple scalar regression coefficient ζ^i into a demand-elasticity matrix that accounts for spillover effects across the entire cross-section of holdings.

D.4 Details on the Flow-Simulation

Let $\Delta P_{t+1}^{\text{ESG-Flow}}$ denote vector of price pressures (expressed in dollars) resulting from \$X flow from the market portfolio towards the ESG portfolio. Equation (7) implies that

$$\Delta P_{t+1}^{\text{ESG-Flow}} = \mathcal{M}_t(w_t^{ESG} - w_t^{MF}) * \$X$$

Note, that (7) is expressed in percentage terms (i.e. the return $\Delta p_{t+1,n}$ resulting from a demand shock in percent of shares outstanding). It can also be expressed in terms of dollar terms by multiplying by prices $P_{t,n}$ (which are equal to market equities due to the normalization). The price pressure in percentage terms for each stock n is given by

$$\Delta p_{t+1,n}^{\text{ESG-Flow}} = \frac{\Delta P_{t+1,n}^{\text{ESG-Flow}}}{P_{t,n}}$$

Note, that true (empirically observed) realized returns of the ESG portfolio are given by $R_{t+1}^{ESG} = \sum_n \tau_{t,n} r_{t+1,n} = \tau_t' r_{t+1}$. The structurally implied price pressure from \$X ESG flows is given by

$$Pressure_{t+1}^{ESG} = \sum_{n=1}^{N} \tau_{t,n} p_{t+1,n}^{\text{ESG-Flow}}$$

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[49] Again, if $\zeta^i > 1$ an increase in the price of stock m reduces the dollar holdings in stock m and the freed up cash is invested in all other stocks, causing spillover effects proportional to the size of the shock to m given by $w_{m,t}^i$.

A first order approximation of the counterfactual ESG returns in the absence of flow-driven price pressure is therefore given by

$$\tilde{R}_{t+1}^{ESG} = R_{t+1}^{ESG} - Pressure_{t+1}^{ESG}$$

. Table D.17 reports the ESG portfolio's counterfactually observed alpha in the absence of price pressure arising from simulated sustainable flows of $10 and $25 billion quarterly.

Table D.17: **ESG Alpha without Flow-driven Price Pressure**
The table reports annualized long-short returns and alphas of the ESG portfolio from 2016 to 2021. On the left I report the empirically observed alphas. On the right, I report the counterfactually observed alphas without the price pressure from simulated sustainable flows. The long-short ESG portfolio τ_t is the zero-investment portfolio that goes long the ESG portfolio w_t^{ESG} and short the aggregate mutual fund portfolio w_t^{MF}. Alphas are computed with respect to the CAPM, the CAPM plus the Green Factor in PST (2022), and Carhart 4-factor model plus the Green Factor. The standard errors are robust to heteroskedasticity and autocorrelation.

	Return	α (CAPM)	α (CAPM + Green)	α (CH4 + Green)
True Returns: Empirically Observed				
Return (%)	2.01	2.40	1.87	1.51
t-statistic	2.91	3.47	2.55	2.01
Counterfactual Returns: In Absence of Flows of Simulated Flow $25B				
Return (%)	0.66	1.05	0.5	0.12
t-statistic	0.86	1.36	0.6	0.14

The price pressure from quarterly ESG flows of $10 billion is already sufficient to account for almost all of the outperformance of ESG funds. Furthermore, in the absence of $25 billion quarterly ESG flows, the counterfactual returns and alphas of the ESG-taste portfolio are all negative. In contrast, the realized (i.e. truly observed) returns and alphas are all significantly positive. These results emphasize the sizeable gap between realized and expected returns from ESG investing that is driven by flows to sustainable funds. This suggests that without continued flow to sustainable funds, ESG investing may have negative alpha. In other words, it is the price pressure from ESG flows that made 'doing well by doing good'-investing possible.

D.5 Variable Construction

- Book Equity: Book equity is constructed following Fama and French. It is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit, minus the book

value of preferred stock.

- Market beta: Stocks' market betas are estimated in a regression of monthly returns over the one-month T-bill. We use 60-month rolling windows and require a minimum of 24 months of returns.

- Profitability: I use the Fama and French definition, i.e. revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in $t-1$.

- Investment: Investment is the annual growth rate of assets computed as a log difference.

- Idiosyncratic volatility: Idiosyncratic volatility is computed as the monthly time series standard deviation of residual returns. Residual returns are obtained from regressing daily returns onto daily realization of the market, size and value factor.

- Turnover: Turnover is the total share volume in a given month (as reported on CRSP) divided by the total shares outstanding.

- Momentum: Momentum is computed as the total return over the past 11-months, excluding the most recent month.

- Sin Stocks: Tobacco and alcohol stocks are defined as belonging to the Fama and French SIC classification groups 4 and 5 respectively. Gaming stocks are identified using NAICS codes 7132, 71312, 713210, 71329, 713290, 72112, and 721120.

- MSCI Controversial Stocks: Stocks in the biotech, firearms, oil, military and cement industry are identified using SIC codes 2833–2836, 1300, 1310–1339, 1370–1382, 1389, 2900–2912, 2990–2999, 3240–3241, 3760–3769, 3795, 3480–3489 and NAICS codes 336992, 332992–332994.

- Co2 Emissions: Total Co2 Emissions are scaled by revenue. As the fraction of US stocks with available Co2 emissions is relatively small, I compute an additional proxy for Co2 emissions which fills missing observations with the median emissions within Fama and French 48 industries.