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Flow-Driven ESG Returns

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Abstract

I show that the recent returns to ESG investing are strongly driven by price impact from flows towards ESG funds. Using data on institutional trades, I estimate the market's ability to accommodate the demand of ESG funds, which is given by the elasticity of substitution between ESG and other stocks. I show that every dollar flowing towards ESG stocks increases their aggregate market value by $0.7. Using a novel measure of total ESG flows, I estimate an annual flow-driven ESG return of 2.07%. In the absence of flows, ESG funds would have not outperformed the market from 2017 to 2022.

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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 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 rebalance their portfolios.

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 sizeable price impact of ESG flows. 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 ESG and non-ESG stocks is limited. 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 ESG stocks substitute elastically between stocks, then the price impact from ESG flows is negligible. Small price changes induce investors to rebalance their portfolios by substituting away from the overpriced ESG stocks. On the other hand, if the holders of ESG stocks do not aggressively rebalance their portfolios, i.e. if they are inelastic, then flows have a large impact on prices and realized returns. Quantifying the flow-driven component of the realized returns to ESG investing involves three main challenges. First, it requires a measure of ESG for all stocks such that we can construct a representative ESG portfolio. Second, we need to measure flows into the ESG portfolio. Third, we have to estimate the price elasticity of demand for ESG stocks.

I start by identifying a set of 384 ESG 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 funds. Since 2017, the representative ESG portfolio outperformed the aggregate mutual fund portfolio by 1.04% annually, controlling for common risk factors. 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 'ESG' stocks as the ones overweighted by ESG funds relative to other mutual funds. Thus, in this paper 'sustainability' refers to all dimensions of ESG, not only environmental concerns.

I then propose a new measure of total institutional capital flows into managed portfolios. To this end, I estimate the ESG tilt of all institutional investors by projecting their portfolios onto the representative ESG portfolio controlling for tilts towards other managed portfolios. Total institutional flows into the ESG portfolio amounted to \$2.5 trillion, which dwarfs the flows into labeled ESG mutual funds of \$350 billion.[1]

In order to estimate the impact of ESG flows on ESG returns, I estimate the market's willingness to substitute between ESG and non-ESG. I identify demand elasticities from investors' trades, as opposed to their portfolio holdings in levels as in Koijen and Yogo (henceforth KY, 2019). 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. The estimated elasticities can be combined with ownership shares into a cross-sectional multiplier matrix. The multiplier matrix can be interpreted as the cross-sectional version of the macro multiplier in Gabaix and Koijen (2021).

I then use the model to assess the flow-driven component in the realized returns of ESG 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 ESG stocks by \$0.7 relative to non-ESG stocks. I then compute the realized returns if total ESG flows were instead invested in the market portfolio. The annual flow-driven ESG return of 2.07% is large and statistically significant. The price pressure from ESG flows accounts for virtually all of the outperformance of the ESG portfolio over the market portfolio. In the absence

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

of flow-driven price impact, the ESG portfolio would have not outperformed the market portfolio in recent years. This suggests that in the absence of ESG flows, 'doing well by doing good'-investing would have not been possible. In other words, investors would have not been compensated for investing in line with their ESG preferences.

The extant empirical evidence on the *realized* returns from ESG investing is mixed and tends to depend on the ESG measure, time horizon, and asset universe under investigation.[2] The theories developed in Fama and French (2007), Pástor et al. (2021) and Pedersen et al. (2020) imply that the *expected* returns of ESG stocks should be lower than for non-ESG stocks as investors have a taste for ESG assets. However, if ESG preferences or climate risks strengthen unexpectedly over the estimation horizon, ESG stocks may have higher realized returns than non-ESG firms. This paper shows that ESG investors' impact on the realized is quantitatively meaningful and should be taken into account when estimating expected ESG returns over the recent sample period. Similarly, Pastor, Stambaugh, and Taylor (henceforth PST, 2022) find that several proxies of shocks to climate concerns can explain the recent outperformance of green stocks. The mechanism does not distinguish, whether ESG correlated with prices because they i) represent demand shocks by ESG investors in price-inelastic markets or ii) merely proxy for common demand shifters by all investors in price-elastic markets. Nevertheless, despite the different interpretations of the correlation between flows and returns, the papers share the objective of measuring how the demand for ESG stocks affects the wedge between realized and expected returns.

Second, the paper relates to the extensive literature on downward-sloping demand curves in asset pricing.[3] Lou (2012) shows that the flow-driven trades by mutual funds have a sizeable impact on the prices of individual stocks. Building on this mechanism, I provide a structural model to estimate the price impact of flows on aggregate style returns. Following the influential work by KY (2019) a rapidly growing literature estimates de-

[2] Papers documenting a positive return premium on unsustainable (or non-ESG) investments include Hong and Kacperczyk (2009), Bolton and Kacperczyk (2021a), Bolton and Kacperczyk (2021b), Hsu et al. (2020), 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). Conversely, many papers show that ESG stocks have higher returns than other stocks including Edmans (2011), In et al. (2020), Görgen et al. (2020) and Hong et al. (2019).

[3] Shleifer (1986) shows that index inclusions are associated with positive realized returns due to buying pressure by index funds. Other papers investigating the impact of non-fundamental demand shocks on asset prices include Coval and Stafford (2007), Frazzini and Lamont (2008), Parker et al. (2020), Ben-David et al. (2020), Hartzmark and Solomon (2021), Pavlova and Sikorskaya (2022), Schmickler and Tremacoldi-Rossi (2022)

mand curves from data on portfolio holdings and links the estimated demand coefficients to equilibrium asset prices and returns.[4] I propose identifying the demand elasticities from investors' trades, that is changes in their portfolios, as opposed to their portfolio holdings in levels. This alleviates the endogeneity concern of slow-moving unobservable variables (such as investment mandates) that drive investors' holdings in the cross-section and are correlated with prices. I furthermore introduce stock-specific demand elasticities that capture investors' differential willingness to trade ESG versus non-ESG stocks. In a related paper, Berk and van Binsbergen (2022) calibrate the demand elasticity with respect to ESG stocks in a frictionless CAPM world. They argue that the equilibrium impact of ESG investing is negligible because the high return correlation between ESG and non-ESG stocks makes them close substitutes. Therefore, inducing other investors to hold non-ESG stocks requires little price concessions in equilibrium.[5] I directly estimate demand elasticities from trade data and find that the market's quarterly elasticity of substitution between ESG and non-ESG stocks is low. Thus - at least in the short term - investors require large price concessions to accommodate ESG flows leading to high realized returns in recent years. Due to the short sample period, it is difficult to draw definite conclusions about long-run price impact and *expected* ESG returns. Instead, I show that the distortion in *realized* ESG returns due to ESG flows is large. Therefore, investors should treat the realized returns of ESG funds with caution as they may not be indicative of high expected returns. However, the framework is not confined to investigating ESG returns and could be applied to alternative settings such as technology returns during the 'dotcom boom' or the underperformance of value strategies over the past decade.

The remainder of this paper is structured as follows. Section 2 describes the data. In Section 3, I measure ESG and construct a representative ESG portfolio. In Section 4, I measure flows into the ESG portfolio. Section 5 describes the structural identification of elasticities from data on institutional trades. Section 6 uses the model to quantify the impact of ESG flows on ESG returns. Section 7 provides robustness tests and applications. Section 8 concludes.

[4]See e.g. Koijen et al. (2022), Noh and Oh (2022), Han et al. (2021), Bretscher et al. (2020), Jiang et al. (2020), van der Beck and Jaunin (2021), Haddad et al. (2021), Huebner (2023), Darmouni et al. (2022).

[5]Petajisto (2009), on the other hand, 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 potentially overestimates investors' short-term elasticity of substitution between stocks.

2 Data

A Prices and Fundamentals

Stock price data on common ordinary shares (share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ (exchange codes 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, investment, momentum and industry affiliation.[6] 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 biotech, firearms, oil, military, and cement companies. 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 revealed preference measure using portfolio tilts of ESG mutual funds (see next section). As a robustness check, I also use readily available ESG Scores from MSCI.

B Holdings and Flows

In the US, institutional investment managers who have discretion over \$100 million or more in designated 13F securities must report their respective holdings via quarterly SEC 13F filings. I obtain institution-level and mutual fund holdings from Thomson's Institutional Holdings Database (s34 file) and CRSPs Mutual Fund database respectively. The holdings data are subsequently merged with characteristics data from CRSP and Compustat. 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. Institution-level and mutual fund portfolio weights $w^i_{t,n} = \frac{Q^i_{t,n} P_{t,n}}{A^i_t}$ are constructed as the dollar holdings in each stock (price times shares held) divided by their assets under management A^i_t. An institution's assets under management are given by the sum of its dollar holdings. Monthly data on mutual funds' holdings, net returns, and total net assets (TNA), as well as other fund-specific characteristics, are obtained from the CRSP survivorship-bias-free mutual fund database. I restrict the sample to domestic equity mutual funds and ETFs

[6] See KY (2019) for further details on the construction of the stock-specific characteristics.

and compute flows as $f_t^i = \frac{TNA_t^i - TNA_{t-1}^i(1+r_t^i)}{TNA_{t-1}^i}$ where r_t^i is the monthly fund return between $t-1$ and t as reported by CRSP.

3 Identifying ESG Stocks

A The Representative ESG Portfolio

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 384 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. I then match the ESG funds with their quarterly stock holdings using Thomson's Mutual Fund Holdings Database (s12 file). I construct the representative ESG portfolio $w_{t,n}^{ESG}$ as the aggregate portfolio held by the sample of ESG mutual funds. The weight of stock n at quarter t in the representative ESG portfolio is given by the ESG funds' total dollar holdings divided by their aggregate assets under management.[7] Table 1 provides summary statistics on the sample of ESG funds and their aggregate portfolio.

[Table 1 about here.]

From 2012 to 2022, the number of labeled ESG funds increased from 50 to 211 and their total assets under management grew from \$20 to \$140 billion. The ESG portfolio's 'Active Share' - the deviation from the aggregate mutual fund portfolio - is around 65%. 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 robust to different subsets of ESG funds. Using the ESG portfolio, I construct a revealed-preference measure $\tau_{t,n}$ of investors' ESG tastes for a stock given by

$$\tau_{t,n} = w_{t,n}^{ESG} - w_{t,n}^{MF} \tag{1}$$

where $w_{t,n}^{MF}$ denotes the aggregate portfolio held by all mutual funds, not just ESG funds.

[7] Formally, 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 portfolio is then given by $w_{t,n}^{ESG} = \frac{P_{t,n} Q_{t,n}^{ESG}}{\sum_{n=1}^{N} P_{t,n} Q_{t,n}^{ESG}}$. 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.

I henceforth refer to the aggregate mutual fund portfolio as the market portfolio.[8] Stocks with a higher $\tau_{t,n}$ are perceived to be more sustainable as they are overweighted by ESG investors. 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 label stocks with $\tau_{t,n} > 0$ as ESG stocks and stocks with $\tau_{t,n} < 0$ as other (non-ESG) stocks. Formally, the label is captured by the indicator variable $\mathbb{1}_n^{ESG}$ equal to 1 if a stock is an ESG stock. This revealed-preference measure is available for all stocks at a quarterly frequency over a large time horizon.[9] 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. Appendix B provides detailed summary statistics on the sample of ESG funds, the representative ESG portfolio, as well as robustness checks to the identification of the ESG label. In particular, I show that $\tau_{t,n}$ is significantly related to commonly used sustainability metrics and is robust to different subsets of ESG funds used.

B Realized ESG Returns

From 2012 to 2022, ESG stocks had higher returns than non-ESG stocks. Panel b) of Table 1 reports the alphas of the long-short ESG portfolio $\tau_t = w_t^{ESG} - w_t^{MF}$.[10] 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 all positive. In particular, despite the short sample period from 2017 to 2022, the long-short ESG portfolio had a significant four-factor alpha of 1.04%. This suggests that the representative ESG investor has been *rewarded* instead of *penalized* for investing according to her ESG preferences. The weights in the long-short ESG portfolio can

[8] Empirically $w_{t,n}^{MF}$ is extremely close to the market equity-weighted portfolio so that defining $\tau_{t,n}$ in excess of market weights leaves all results of the paper unchanged.

[9] The ESG label varies over time when ESG funds change from underweighting to overweighting a stock (or vice versa). Here, I omit the t subscript for notational simplicity.

[10] These portfolio denote N-vectors with elements equal to $w_{t,n}^{ESG}$, $w_{t,n}^{MF}$, and $\tau_{t,n}$ respectively. They are not necessarily tradeable as funds usually delay their SEC report by up to 45 days. Furthermore, the returns may not be 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.

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. Note that despite the apparent outperformance of the ESG portfolio, the goal of this paper is not to add to the debate about whether or why ESG investing has higher or lower *expected* returns in equilibrium. Given the short sample period for which ESG measures are available, it is difficult to draw meaningful conclusions about expected returns. This paper tries to answer the question of how, ceteris paribus, the cross-section of *realized* returns has been affected by flows into the ESG portfolio. Independent of the sign or significance of the observed realized ESG returns, is the distortion in realized returns due to ESG flows quantitatively important?

4 Measuring ESG Flows

Total flows in the ESG portfolio are difficult to observe. According to Morningstar, labeled ESG mutual funds held \$350 billion in total assets in 2021, which was less than 1% of the total \$37 trillion held by all ETFs and Mutual funds in the US.[11] However, this does not include the (unobservable) ESG tilts of other mutual funds and large institutions such as investment advisors, pension funds, banks and insurance companies. Therefore, the flows from labeled ESG mutual funds only represent a small subset of total ESG flows. 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 ESG stocks and underweights non-ESG 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^i_{t+1} are 0, but the manager buys some ESG stocks and sells some non-ESG stocks. In the aggregated 13F holdings, these trades only show up as active trades, even though they are purely flow-driven.

In order to address this issue, I use 13F filings to estimate each institution's ESG share, $\theta^{i,ESG}_t$. The ESG share measures the fraction of an investor's assets that are allocated to the ESG portfolio in quarter t, controlling for tilts towards other characteristics-managed portfolios. Here, I briefly outline the main procedure. Technical details are delegated to Appendix C. At each quarter t, I project an institution's portfolio $w^i_{t,n}$ onto the ESG

[11] See Morningstar's 2021 Sustainable Funds U.S. Landscape Report. The assets of labeled ESG funds from the previous section are of the same order of magnitude.

portfolio $w_{t,n}^{ESG}$, controlling for a set of S managed portfolios $w_{t,n}^{s}$,

$$w_{t,n}^{i} = \theta_t^{i,ESG} w_{t,n}^{ESG} + \sum_{s \in S} \theta_t^{i,s} w_{t,n}^{s} + a_{t,n}^{i} \tag{2}$$

The managed portfolios include the market portfolio, the equal-weighted portfolio, and value, growth, momentum, profitability, and technology portfolios. The total ESG flow can then be computed as the sum of institution-specific ESG flows

$$F_{t+1}^{ESG} = \sum_{i=1}^{I} A_{t+1}^{i,ESG} - A_t^{i,ESG}(1 + R_{t+1}^{ESG}) \tag{3}$$

where $A_t^{i,ESG} = \theta_t^{i,ESG} A_t^i$ 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 ESG flows relies on equity holdings only and therefore only captures intensive flows, i.e. flows *between* equity investors with different tilts towards the ESG portfolio. It does not capture extensive flows, i.e. flows to the ESG portfolio that come from outside of the stock market. With granular data on institutional holdings across asset classes including cash, one could measure both intensive and extensive ESG flows. Extensive flows would affect both aggregate stock market returns and ESG returns. As the focus of this paper lies on the *excess* returns of ESG stocks (over non-ESG stocks), intensive ESG flows are the appropriate measure of ESG demand. Lastly, note that this measure only captures the ESG demand by 13F institutions. Smaller institutions, households, and other non-13F investors are not captured. While the sum of all investors must hold the market portfolio, this does not necessarily imply that the ESG flow across all investors (not just 13F institutions) is zero. Investors hold different subsets of stocks and (2) is controlling for alternative portfolio tilts such as momentum, growth, or technology. Therefore, the ESG tilt $\theta_t^{i,ESG}$ by one investor can be offset by e.g. the value tilt of another investor. 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 \$2.5 trillion as of 2022. In comparison, total cumulative flows into labeled ESG mutual funds amount to only \$140 billion. While the quarterly correlation between the two is relatively high (ρ=33%), the difference in magnitudes underlines the importance of accounting for the ESG tilts of large institutions that do not carry an explicit ESG label.

Lastly, the correlation between ESG flows F_{t+1}^{ESG} and ESG returns is 34%. While this correlation is by no means causal evidence for flow-driven price pressure, it is nevertheless high. Notably, PST (2022) find that their GMB return is not significantly correlated with flows into labeled ESG mutual funds. 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 depends on how the ratings are used to construct portfolio weights. Thus ESG flows may not directly target the GMB portfolio. In Appendix C, I replicate their empirical specification and provide further evidence on the importance of computing the suitable flow into the object of interest.

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.

5 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. 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. There are I investors indexed by $i = 1, ..., I$ that hold a subset $N_t^i \subseteq N$ of all stocks. $Q_t^i \in \mathbb{R}^{N^i}$ denotes the vector of shares held by i at t. Because of the normalization, Q_t^i are equal to ownership shares such that $\sum_{i=1}^{I} Q_{t,n}^i = 1$. The optimal portfolio $Q_t^i = g^i(P_t, V_t)$ is a function $g^i(\cdot)$ 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 ESG scores, assets under management, interest rates, fundamentals, or investment constraints). Lowercase letters denote logs (if not otherwise specified) and one-period changes in variables are denoted by $\Delta x_t = x_t - x_{t-1}$. I denote the identity matrix as $\mathbf{I}$ and a vector of ones as $\mathbf{1}$.

An investor's elasticity of demand with respect to the price, henceforth elasticity of demand, is defined as the negative percentage change in holdings when the price of a stock increases by 1 %. Formally,

$$\zeta^i_{t,n} = -\frac{\partial Q^i_{t,n}/Q^i_{t,n}}{\partial P_{t,n}/P_{t,n}}. \tag{4}$$

Similarly, the cross-elasticity of demand is given by $\zeta^i_{t,nm} = -\frac{\partial Q^i_{t,n}/Q^i_{t,n}}{\partial P_{t,m}/P_{t,m}}$ and measures how much of n investor i sells when m's price increases by 1%.[12]

The stock-specific and cross elasticities can be stacked in an $N^i_t \times N^i_t$ elasticity matrix ζ^i_t for every investor. The aggregate elasticity of demand is defined as the ownership-weighted sum of the investor-specific elasticity matrices,

$$\zeta_t = \sum_{i=1}^{I} \mathrm{diag}(Q^i_t)\zeta^i_t \tag{5}$$

with elements equal to $\zeta_{t,nm} = \sum_{i=1}^{I} Q^i_{t,n}\zeta^i_{t,nm}$.[13] Stocks that are primarily held by passive index funds (with $\zeta^i_t = 0$) 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 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 ESG 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 a demand shock $\Delta d_t \in \mathbb{R}^N$. Equilibrium prices adjust in order to accommodate the demand shock resulting in realized log returns $\Delta p_t \in \mathbb{R}^N$. A first-order approximation to the equilibrium realized return is given by

$$\Delta p_t = \mathcal{M}_t \Delta d_t + \epsilon_t \tag{6}$$

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

[13]Recall, that shares outstanding are normalized to 1. Therefore $\sum_{i=1}^{I} \mathrm{diag}(Q^i_t)$ is equal to the identity matrix.

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

$$\mathcal{M}_t = \zeta_t^{-1}. \tag{7}$$

See Appendix A for a proof. ϵ_t captures other sources of return variation such as factor exposures or fundamental news and may be correlated with the ESG demand shock Δd_t. This is a first-order approximation to the realized returns following demand shocks for a large class of models (including e.g. the CAPM or Demand System Approach to Asset Pricing). However, as the focus of this paper is purely empirical, equation (6) 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 ESG 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 ESG stocks primarily by substituting towards non-ESG industries, the relative price impact of ESG investing may be negligible. In order to bolster intuition, consider the following simplified example.

Example. There are two stocks, an ESG stock g and a non-ESG stock b with a market equity of 1, 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 a net-zero ESG flow in g and b equal to \$1 and -\$1 respectively. The flow-driven price pressure (6), 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 equity of g and b after the demand shock is given by $\frac{2}{\zeta_g+\zeta_{g,b}}$.[14] First, the greater the stock-specific elasticity (i.e. the more willing the investor is to sell ESG and buy non-ESG shares) the smaller the price impact. Second, the greater the cross-elasticity (i.e investors' substitution towards non-ESG stocks as a result of the price increase of the ESG stock) the smaller the equilibrium price impact. The equilibrium impact of ESG investing, therefore, depends on i) how willing the arbitrageurs are to provide ESG shares and ii) which stocks they substitute towards. As outlined below, the matrix $\mathcal{M}_t$, which

[14]To see this, note that the log return on ESG and non-ESG stocks is given by $\begin{bmatrix} \zeta_g & -\zeta_{g,b} \\ -\zeta_{g,b} & \zeta_g \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$. Multiplying by market equity (which is equal to 1) approximates the change in dollar terms. The difference in market equity between the ESG and the non-ESG stock after the flow is therefore given by $\begin{bmatrix} 1 & -1 \end{bmatrix} \begin{bmatrix} \zeta_g & -\zeta_{g,b} \\ -\zeta_{g,b} & \zeta_g \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \frac{2(\zeta_g-\zeta_{g,b})}{\zeta_g^2-\zeta_{g,b}^2} = \frac{2}{\zeta_g+\zeta_{g,b}}$.

links demand shocks and realized returns, can be obtained structurally from data on investors' trades.[15]

C Estimating Elasticities from Trades

I define institutions' trades as $\Delta q^i_{t,n} = \log Q^i_{t,n} - \log Q^i_{t-1,n} \approx \Delta Q^i_{t,n}/Q^i_{t-1,n}$. Thus $\Delta q^i_{t,n}$ 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 (4). Up to a first order, an investor's demand curve can be identified from a linear regression of trades $\Delta q^i_{t,n}$ onto log returns $\Delta p_{t,n}$.

$$\Delta q^i_{t,n} = \beta^i \Delta p_{t,n} + d^i_{t,n} \tag{8}$$

where $-\beta^i$ is a reduced-form approximation of an investor's average stock-specific elasticity ζ^i_n. Demand shifters such as fundamental news, flows, or unobserved (latent) demand shocks are denoted by $d^i_{t,n}$. Holding portfolio weights constant, (8) implies homogeneous demand elasticities across all stocks for a given investor. As in the 2-stock example above, (8) assumes that investors' elasticities with respect to ESG and non-ESG stocks are the same. In order to capture a potential difference in the willingness to trade ESG versus non-ESG stocks ($\zeta_g \neq \zeta_b$), I let β^i vary across stocks. In particular, I parameterize β^i_n as a linear function of a stock's ESG label, $\beta^i_n = b^i + b^i_{ESG}\mathbb{1}^{ESG}_n$. Thus b^i_{ESG} captures the difference in elasticities between ESG and non-ESG stocks. This adds an interaction term to (8) and yields the following linear specification:

$$\Delta q^i_{t,n} = \underbrace{b^i \Delta p_{t,n} + b^i_{ESG}(\mathbb{1}^{ESG}_n \Delta p_{t,n})}_{\beta^i_n \Delta p_{t,n}} + d^i_{t,n}. \tag{9}$$

Note, that the linear specifications (8) and (9) only yield scalar regression coefficients, β^i and β^i_n, for every investor. Estimating the full elasticity matrix ζ^i including cross-elasticities requires additional structural assumptions. In Appendix D, I show that under a logit demand function, β^i_n and portfolio weights $w^i_t \in \mathbb{R}^N$ are sufficient to pin down the whole elasticity matrix as $\zeta^i = -B^i\mathbf{I} + (\mathbf{I} + B^i)\mathbf{1}(w^i_t)'$ where B^i is a diagonal matrix containing the stock-specific coefficients β^i_n. When β^i is constant across stocks (as in 8),

[15] In Appendix D, I outline the benefits of the structural identification over reduced-form regressions.

then $B^i = \beta^i \mathbf{I}$.[16] Appendix D provides further technical details and examples.

D Trades versus Holdings

The reduced-form specification (9) essentially corresponds to a first difference estimator of the logit demand specification in KY (2019) and estimates demand parameters from investors' *trades* as opposed to their portfolio *holdings* in levels. Identification from portfolio holdings implies high price elasticities for investors tilting towards cheaper (controlling for fundamental value) stocks in the cross-section. The cross-sectional identification in levels therefore does not contain an explicit time horizon and likely captures long-run elasticities. The coefficients identified from trades capture quarterly elasticities, i.e. the quarterly change in demand resulting from changes in prices. As this paper is about the quarterly price impact of ESG demand shocks, the first difference estimator is a more suitable specification for estimating investor demand. Lastly, institutional portfolios are to a large extent driven by (unobservable) investment mandates, which are captured by the error term in the demand estimation. Any unobservable determinant of the cross-sectional portfolio choice that is correlated with prices leads to biased elasticities. The first-difference estimator has the advantage of eliminating time-invariant drivers of cross-sectional portfolio holdings that are potentially correlated with prices. Appendix D provides a simple simulation that compares the two estimators in a controlled setting.

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.[17] 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. Flow-driven trades by mutual funds

[16]Note, that because a stock's ESG label $\mathbb{1}_n^{ESG}$ may vary over time, the parameterized elasticity β_n^i, B^i, and ζ^i are also time-varying. I omit the time subscript for notational simplicity but account for this variation in the estimation.

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

provide exogenous cross-sectional variation in demand under the (strong) assumption that the flows are not driven by the funds' underlying fundamentals. To address these concerns, one could construct surprise flows by orthogonalizing the cross-section of fund flows with respect to the funds' underlying holdings and characteristics.[18] 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 trades. Let $D_{t,n}$ denote stock n's dividends per share paid in quarter t. For every investor 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 D, I show that mutual funds tend to proportionally reinvest aggregate dividend payouts in their existing portfolios. 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 from n's own dividend announcement, I follow Schmickler and Tremacoldi-Rossi (2022) and construct $DIT_{t,n}^{-i}$ using dividend flows from all other stocks excluding n.[19] Having constructed investor-specific instruments, the elasticities can be obtained in a simple two-stage least squares procedure by using $DIT_{t,n}^{-i}$ as an instrument for $\Delta p_{t,n}$ in the investor-specific elasticity estimation (8) and (9). The significant relationship between flow-driven trades 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 reinvested dividends are significantly related to contemporaneous stock returns at an annual frequency. Table 2 reports the

[18]See e.g. Huebner (2023). In a similar spirit, Schmickler (2020) constructs high-frequency flow shocks to address contemporaneous return chasing in mutual fund flows.

[19]Formally, $DIT_{t,n}^{-i} = \sum_{j \in MF, j \neq i} df_{t,-n}^j Q_{t-1,n}^j$ where $df_{t,-n}^j = \sum_{m \neq n} D_{t,m} Q_{t,m}^j / A_t^j$. I furthermore exclude outlier dividend flows that exceed the 95th percentile across all institution-quarter pairs.

relevance of the investor-specific instrument. Dividend-induced trading is significantly related to quarterly returns with a first-stage F-statistic of 13. Appendix D provides further details on the identification and robustness checks.

F The Multiplier Matrix

I estimate elasticities over the panel of quarterly trades from 2010 to 2022. I pool investors by their institutional type and active share and include quarter fixed effects, log book equity, market beta, and investment as controls. Table 2 reports the estimated coefficients for all investors, both for the homogeneous specification (8) and the parameterization (9). The first row reports the estimates for a pooled regression across all investors. The pooled β is -1.73, which implies that on average institutions sell 1.73% of their holdings in a stock when the price increases by 1%.[20] The remaining rows report the elasticities obtained in a pooled estimation within institutional types. There is great heterogeneity in the estimated elasticities β^i across types.[21] β^i is lower for large passive investment advisors such as Blackrock, Fidelity and Vanguard. Mutual funds are the most elastic investor group with a β^i of -2.4.[22] Investment advisors' elasticity furthermore increases monotonically in their active share.

[Table 2 about here.]

The second column reports the estimates of the parameterization of β^j as a linear function of the ESG label. The estimates reveal that almost all investors are less elastic with respect to ESG stocks than non-ESG stocks. On average, investors' demand for ESG stocks is over 10% less responsive to price changes than the demand for non-ESG stocks. This suggests that ESG stocks are potentially more affected by non-fundamental demand shocks as investors are less willing to aggressively trade against mispriced ESG stocks. While the different elasticity for ESG versus non-ESG has important quantitative implications for the price impact of ESG flows, a deeper investigation of the sources of inelastic ESG demand is outside the scope of this paper.

[20] Note that β only approximates the structural stock-specific elasticity, which is given by $\zeta^i_{t,n} = -\beta + (1+\beta)w^i_{t,n}$. Empirically $w^i_{t,n}$ is small, so that $\zeta^i_{t,n} \approx \beta \quad \forall \quad n,t$. However, when aggregating demand shocks (e.g. across all ESG stocks) these spillover effects are potentially important. See Section 6 for further details.

[21] Because ownership shares vary across stocks, investor-specific elasticities lead to non-trivial heterogeneity in the stock-specific price impact that could not be captured using the pooled estimate.

[22] 'Other' 13F institutions have a higher, albeit insignificant, point estimate. However, over the limited subset of stocks traded by this group of institutions, the instrument is weak. Setting their elasticity equal to the pooled estimate leaves all results of the paper unchanged.

Having estimated the investor-specific demand coefficients, we are now in the position to construct the multiplier matrix $\mathcal{M}_t \in \mathbb{R}^{N \times N}$ as given by the inverse of the aggregate (ownership-weighted) elasticity. To this end, recall that $\mathcal{M}_t = \left(\sum_{i=1}^{I} \text{diag}(Q)\zeta^i\right)^{-1}$ where $\zeta^i = -B^i + (\mathbf{I} + B^i)\mathbf{1}(w_t^i)'$. While 13F institutions hold a large fraction of the shares outstanding for the majority of stocks, a structural estimate of the multiplier matrix requires the elasticity and ownership of *all* investors, not just 13F investors. I, therefore, assume that the remaining shares not held by 13F investors are held by a residual investor with an elasticity equal to the pooled estimate.[23] In the following, I omit the time t subscript for notational simplicity. The diagonal elements of $\mathcal{M}_t$ are the stock-specific multiplier effects. The off-diagonal elements are the spillover effects to other stocks. Table 3 summarizes the elements of the multiplier matrix. The first row reports the price impact of buying 1% of each ESG stock on ESG and non-ESG stocks respectively. Note, that this is equivalent to the realized return due to a 1% inflow in the aggregate portfolio of all ESG stocks. The second row reports the price impact of buying 1% of each non-ESG stock.

[Table 3 about here.]

The average stock-specific multiplier among ESG stocks is around 0.75, implying that (on average) a 1% increase in the demand for an ESG stock leads to a 0.75% increase in the price of that stock. Furthermore, the increased ESG demand has positive spillover effects on non-ESG stocks, whose prices increase by 0.18% on average. Thus cross-substitution between ESG and non-ESG stocks does not undo the relative price effect. Lastly, as institutions are less elastic with respect to ESG than non-ESG stocks, buying non-ESG stocks has a smaller effect on prices than buying ESG stocks.

G The ESG Flow Multiplier

What is the impact on aggregate valuations, if investors reallocate \$1 from the market portfolio towards the ESG portfolio? I define the ESG flow multiplier as the increase in the aggregate market value of ESG stocks in excess of non-ESG stocks that results

[23] KY (2019) explicitly estimate the elasticity of the residual investor (the household sector). When estimating the elasticity from trades, the residual investor's β is insignificant and positive. This would imply upward-sloping demand curves for stocks with small institutional ownership. In order to avoid this mechanical effect of data coverage on the stock-specific multiplier, I instead apply the pooled estimate of -1.66 to the residual investor.

from this reallocation.[24] Note, that the net flow from this reallocation is 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. As the focus of this paper lies on the *excess* returns of ESG stocks (over non-ESG stocks), net-zero flows are the appropriate way of modeling the ESG multiplier.

Panel (b) of Table 3 reports the average ESG flow multiplier. The ESG flow multiplier is 0.7 with a standard error of 0.04. Thus, withdrawing \$1 from the market portfolio and investing it in the ESG portfolio leads to an increase in ESG stocks' market value of around \$0.7 relative to non-ESG stocks. This is the key channel through which continued capital flows into ESG firms can lead to high realized returns. The impact can be decomposed into a \$0.37 increase in the value of ESG stocks and a \$0.32 decrease in the value of non-ESG stocks. As investors' demand is less elastic with respect to ESG stocks, buying ESG stocks has a larger effect on relative valuations than selling non-ESG stocks.

6 The 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 Counterfactual ESG Returns in the Absence of Flows

The ESG flow multiplier captures the price impact of a hypothetical \$1 flow. Paired with the large ESG flows of \$2.5 trillion, this suggests that the flow-driven demand for ESG stocks has potentially large aggregate pricing implications. In order to quantify the return distortion from total ESG flows, F_{t+1}^{ESG}, I conduct a simple simulation. I simulate counterfactual realized ESG returns if the ESG flows were instead reinvested in the aggregate mutual fund portfolio. Figure 2 plots the cumulative returns of the ESG portfolio along with the counterfactual ESG return without price pressure from total ESG flows. In the absence of ESG flows, the representative ESG investor would have not outperformed the market portfolio in recent years.

[Figure 2 about here.]

[24]Formally, a \$1 ESG flow translates into stock-specific demand shocks given by $\Delta d_{t+1,n}^{ESG} = (w_{t,n}^{ESG} - w_{t,n}^{MF})/P_{t,n}$. Equation (6) then implies, that the equilibrium change in prices $\Delta P_{t+1}^{ESG} \in \mathbb{R}^N$ due to ESG flows is simply $\Delta P_{t+1}^{ESG} = \text{diag}(P_t)\mathcal{M}_t \Delta d_{t+1,n}^{ESG}$. The ESG flow multiplier is the total impact on ESG stocks relative to non-ESG stocks: $\sum_n \mathbb{1}_n^{ESG} \Delta P_{t+1,n}^{ESG} - \sum_n (1 - \mathbb{1}_n^{ESG}) \Delta P_{t+1,n}^{ESG}$.

Table 4 reports average ESG returns, flow-driven ESG returns, and counterfactual ESG returns in the absence of flow-driven price pressure.

[Table 4 about here.]

The first row reports the empirically observed ESG return. The second row reports the flow-driven ESG return, i.e. the realized ESG return that can be attributed to the price impact from ESG flows. From 2017 to 2022, the annual flow-driven ESG return was 2.07%. This impact remains statistically significant controlling for common risk factors, the returns to the technology industry, as well as PST's (2022) Green Factor. The results emphasize the sizeable gap between realized and expected returns from ESG investing that is driven by total ESG flows. The bottom panel reports the counterfactual ESG returns observed in the absence of ESG flows. In the absence of total ESG flows, the ESG portfolio has an insignificant annualized CAPM alpha of -0.86. 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. The last row reports the counterfactual ESG returns without price pressure from flows to labeled ESG mutual funds. The raw return and alphas drop by merely 30 basis points. The impact of flows from specifically labeled sustainable funds is therefore small. Thus, when assessing the impact of ESG investing, it is important to account for the ESG tilts by all institutions, including investment advisors, banks, pension funds, and insurance companies.

B Evidence from the Cross-Section

The structural model above implies that ESG flows have a large impact on aggregate 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 ESG and non-ESG firms ($\mathcal{M}_t$), and a considerable deviation of the ESG portfolio from the market portfolio (τ_t). However, if flow-driven purchases by institutions drive aggregate ESG returns, they should also affect the cross-section of ESG returns. In other words, ESG stocks that experience higher ESG demand should exhibit higher realized returns in the cross-section. This allows for a reduced-form test of the structural estimates. To this end, I construct ESG demand for individual stocks by aggregating the flow-driven trades of all labeled ESG mutual funds. Formally,

$$\Delta d_{t+1,n}^{ESG} = \frac{\sum_{i \in I^{ESG}} Q_{t,n}^i f_{t+1}^i}{S^{ESG}}, \tag{12}$$

where I^{ESG} is the subset of labeled ESG mutual funds. If ESG flows affect the cross-section of stock returns, then $\Delta d_{t+1,n}^{ESG}$ should be significantly related to the cross-section of stock returns. Furthermore, because $Q_{t,n}^i$ are ownership shares, $\Delta d_{t+1,n}^{ESG}$ can be interpreted as an ESG demand shock in percent relative to shares outstanding. Under the assumption that the flow-driven demand *among* ESG funds is orthogonal to fundamentals, a regression of quarterly stock returns onto the flow-driven trades by ESG funds should uncover the average stock-specific ESG multiplier. However, flows into labeled ESG mutual funds only represent a small subset of total ESG flows. Therefore, a regression onto raw flow-driven trades would overstate the true multiplier. I consequently scale the flow-driven trades by the average asset share of labeled ESG funds S^{ESG} relative to the total ESG assets.[25]

Table 5 reports the estimated multiplier from a panel regression of quarterly stock returns onto $\Delta d_{t+1,n}^{ESG}$ from 2012 to 2022.

[Table 5 about here.]

The flow-driven trades of ESG mutual funds have a significant effect on the cross-section of ESG returns. The reduced-form coefficient is 0.25 for the OLS regression (1) and 0.44 for the value-weighted regression (2). When ESG funds purchase 1% of the shares outstanding of a stock because of inflows this translates on average into a realized return of 0.44%. The reduced-form estimate is very close to the average stock-specific multiplier obtained from the structural model equal to 0.53.[26] This is strong evidence in favor of the overall magnitude of the demand elasticities obtained from trade data. On average, the ESG multiplier obtained from institutional trades correctly maps the cross-section of ESG demand shocks into the realized return space.[27]

[25]Formally, the asset share of labeled ESG funds is given by as $S_t^{ESG} = \frac{\sum_{i \in I^{ESG}} A_t^i}{\sum_i A_t^{i,ESG}}$, where $\sum_i A_t^{i,ESG}$ are total ESG assets under management as identified in the previous section. As the asset share of labeled ESG funds is relatively stable through time, I use the time series average $S^{ESG} = \bar{S}_t^{ESG}$.

[26]The average stock-specific multiplier is given by the diagonal elements of $\mathcal{M}_t$ averaged across all stocks and quarters, i.e. $\frac{1}{NT} \sum_n \sum_t \mathcal{M}_{t,n}$.

[27]Berk and van Binsbergen (2022) run a similar cross-sectional regression of stock returns onto ESG demand shocks. They 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. In Appendix E I show that few ESG funds follow the 4 Good Index resulting in small demand shocks upon inclusion.

7 Robustness Tests and Applications

A Fossil Fuel Divestment Multiplier

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 fossil stocks and invests it in the value-weighted portfolio of all other (non-fossil fuel) stocks. Panel (a) of Figure 3 plots the impact of the divestment strategy on the aggregate market value of fossil fuel and ESG companies.

[Figure 3 about here.]

Every dollar withdrawn from the fossil fuel industry reduces its aggregate market capitalization by \$0.5. These estimates suggest that divestment strategies can have a large effect on stock prices and therefore firms' cost of capital. Even though ESG stocks are not directly affected by the divestment strategy, their aggregate value is indirectly affected via spillover effects. Substituting away from fossil fuel companies increases the market value of ESG stocks by around \$0.2.

B The ESG Flow Multiplier over Time

The ESG flow multiplier is driven by two components: First, flows play a stronger role in cross-sectionally inelastic markets with a low elasticity of substitution between ESG stocks and other stocks. Intuitively, if price inelastic investors are the main shareholders of ESG stocks (i.e. they have a high ownership $Q^i_{t,n}$), then prices have to adjust a lot in order to induce them to accommodate the ESG flows by substituting towards non-ESG stocks. 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 prices regardless of the multiplier effect $\mathcal{M}_t$. Panel (b) of Figure 3 plots the ESG flow multiplier over time. In recent years, the multiplier has declined from 0.75 to 0.6. The decline in the ESG multiplier is directly related to the decline in the active share of the ESG portfolio in recent years (see Table 1). As the ESG portfolio moves closer to the market portfolio, ESG flows lead to smaller demand shocks and therefore a smaller price impact.[28]

[28]Note, that as more money is flowing into ESG funds, the ESG and the market portfolio converge *mechanically*. In the limit, all money is invested in ESG funds and the ESG portfolio coincides with

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 targeted toward inelastic stocks.[29] A fund's ability to affect ESG firms' cost of capital is limited, if it overweights stocks that are held by elastic investors and by investors who respond by substituting towards non-ESG stocks. ESG stocks that are associated with a high multiplier are best suited for impact investing as flows induce large realized returns and hence a lower cost of capital. Table 6 reports the impact of a \$1 flow from the market portfolio towards the largest ESG mutual funds averaged over the past 5 years.

[Table 6 about here.]

There is great heterogeneity in the funds' impact on ESG stocks. A \$1 flow to the Calvert Social Investment Fund boosts the aggregate value of ESG stocks by \$0.38. By tilting towards more inelastic ESG stocks, the iShares MSCI USA ESG Select ETF achieves the same price impact with a 10% lower active share. In contrast, the same flow towards the Vanguard ESG US Stock ETF raises the value of ESG stocks by only \$0.07. Note, that while there is no objective measure of a stock's *true* sustainability, all of the displayed funds tilt away from fossil fuel and sin stocks and thereby negatively affect their market values. There is nevertheless considerable heterogeneity in funds' impact on these stocks. For example, a dollar flow into the TIAA Social Choice Fund is ten times less effective in lowering the market value of fossil fuel stocks than the same dollar flowing into the Vanguard FTSE Social Index Fund.

Asset managers use different sustainability metrics, which often diverge substantially (see Berg et al. 2019, 2021). On the other hand, funds differ strongly in their deviation from the market portfolio. Many labeled ESG funds deviate very little from market weights and hence primarily serve as a way for investors to feel good about themselves without having a material impact on valuations. Overall, Table 6 emphasizes that while sustainable flows do impact firms' realized returns and therefore their cost of capital, the choice of the appropriate fund is crucial to affect change in the preferred direction.

the market portfolio. Using the modeling framework by Koijen et al. (2022) one could decompose the convergence of the two portfolios into a green-washing and a price impact channel.

[29]Formally, fund i's impact is given by $\text{diag}(P_t)\mathcal{M}_t\Delta d^i_{t+1}$ where $\Delta d^i_{t+1,n} = (w^i_{t,n} - w^{MF}_{t,n})/P_{t,n}$ is the stock-specific demand shock from reallocating one dollar from the aggregate mutual fund portfolio to fund i.

8 Concluding Remarks

This paper investigates the extent to which the realized returns from ESG investing are owed to price pressure arising from ESG flows. Flow-driven price pressure is the product of the ESG portfolios' deviation from the market 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 market value of ESG stocks by $0.6 relative to non-ESG stocks. Further, ESG funds would have likely underperformed the market in the absence of flow-driven price pressure on ESG 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 ESG funds that invest in cross-sectionally inelastic stocks considerably increase the stock price of the firms in the funds' portfolios, thereby lowering the cost of capital.

The large impact of flows on realized ESG returns has important consequences for *expected* ESG returns going forward. Assessing the extent to which *expected* returns are affected by demand pressures is non-trivial as it depends on the *expected* flows into ESG funds. If ESG funds continue to receive inflows then the prices of ESG firms will further increase causing positive realized returns in the future. The reduction in short-term expected returns due to flow-induced price pressure is therefore small. If, however, ESG inflows unexpectedly revert, realized future ESG returns may be strongly negative. The question, of whether ESG funds will receive outflows in the future strongly depends on whether ESG flows are performance- or taste-based. At least some flows to ESG funds are likely driven by past performance rather than *true* shifts in ESG preferences. Even if none of the flows to ESG funds are performance-driven, ESG preferences fluctuate over time and may well decline during bad economic times. Importantly, *expected* ESG returns going forward also depend on the transitory versus permanent nature of *past* demand shocks. Van der Beck (2022) shows, that investors become more elastic in the long run. The impact of demand shocks on equilibrium prices therefore partly reverts over time. In other words, over a longer horizon, investors are more willing to accommodate ESG flows. As ESG funds move closer to the market portfolio, this effect may outweigh the price impact of continued ESG flows. Investigating the implications of demand shocks, elasticities, and arbitrage in a dynamic context is an important avenue for further research.

Lastly, the purpose of impact investing goes beyond (temporarily) boosting the stock prices of ESG companies. Do sustainable firms capitalize on the rise of ESG investing by issuing new shares at elevated prices and investing in sustainable projects? Investigating the *real* effects of flow-driven price pressure by providing an explicit link between demand-based asset pricing and corporate finance opens up an exciting research agenda.

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Figure 1: **Total ESG Flow**

The figure plots the total institutional ESG flow from 2012 to 2022. I compute the ESG tilt $\theta_t^{i,ESG}$ of each 13F institution to infer their ESG assets under management $A_t^{i,ESG} = \theta_t^{i,ESG} A_t^i$. Total ESG flows are given by the return-adjusted change in ESG assets under management, summed across all institutions. Formally, $F_{t+1}^{ESG} = \sum_{i=1}^{I} A_{t+1}^{i,ESG} - A_t^{i,ESG}(1 + R_{t+1}^{ESG})$. The dotted line plots the ESG flow when only controlling for exposures to the market and equal-weighted portfolio in the estimation of $\theta_t^{i,ESG}$.

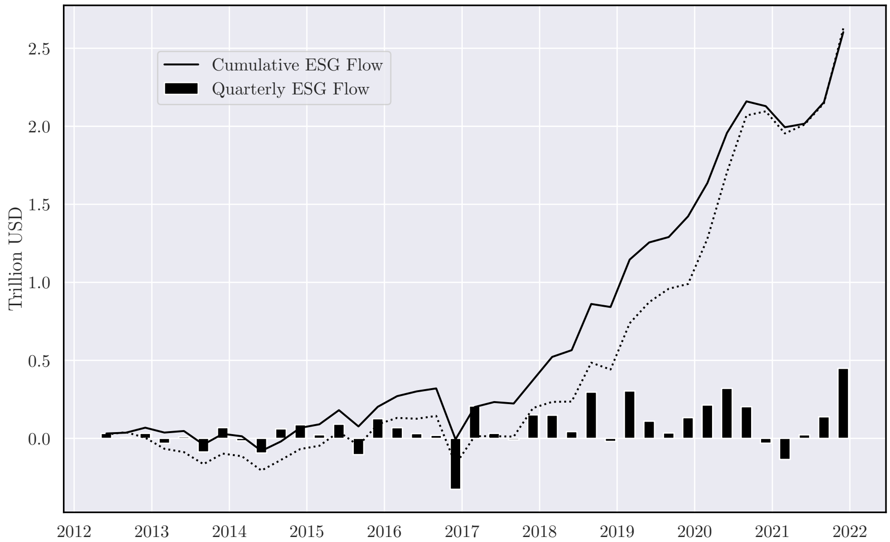


Figure 2: **Cumulative ESG Returns without Flow-Driven Price Pressure**
The figure plots the cumulative return to the ESG portfolio w_t^{ESG}, the market portfolio w_t^{MF}, and the cumulative ESG return in the absence of price pressure from total ESG flows F_{t+1}^{ESG}. The portfolios are rebalanced quarterly based on the funds' SEC filings.

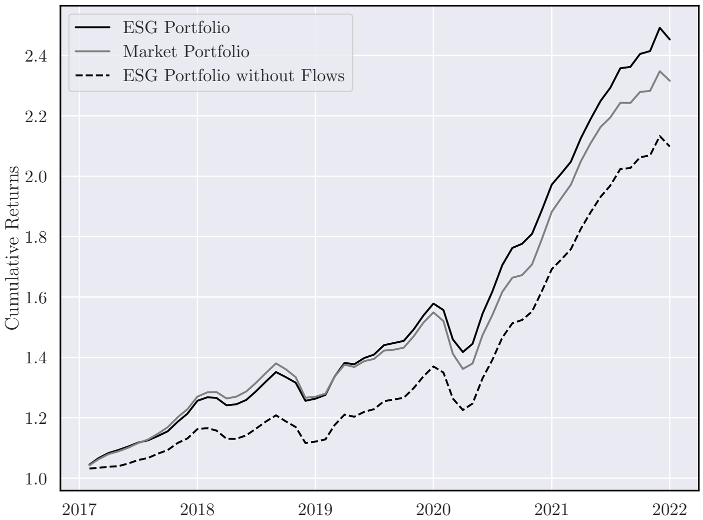
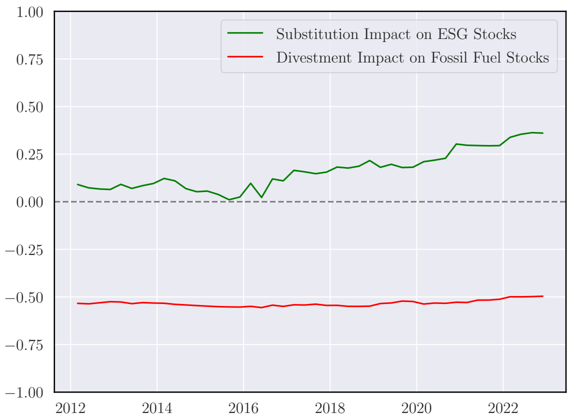


Figure 3: **ESG Flow Multiplier over Time**
The figure plots the multiplier of ESG investing. Panel (a) plots the impact of a divestment strategy that divests $1 from a value-weighted portfolio of all fossil fuel stocks and reinvests the dollar in a value-weighted portfolio of all non-fossil fuel stocks. The red line shows the direct impact on the market value of fossil fuel stocks. The green line shows the indirect spillover effects on ESG stocks. Panel (b) reports the impact of a $1 ESG flow on the aggregate market value of both ESG stocks (green line) and non-ESG stocks (red line). The ESG flow multiplier is the excess impact, i.e. the difference between the two.

(a) Fossil-Fuel Divestment Multiplier



(b) ESG Flow Multiplier

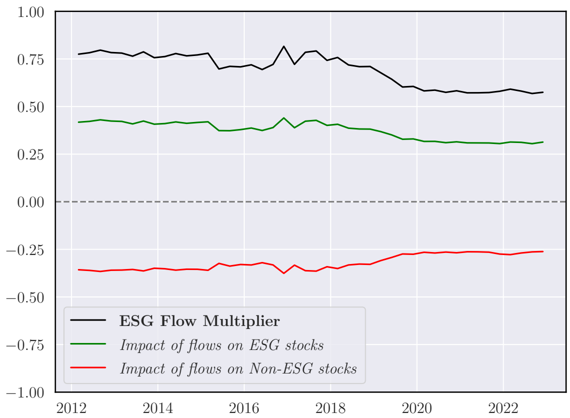


Table 1: **ESG Summary Statistics**

Panel a) reports summary statistics describing the sample of ESG funds and their aggregate portfolio w_t^{ESG}. I report yearly averages of quarterly variables. Average AUM and total AUM across all ESG funds are in \$ billions. Active share is defined as $\frac{1}{2}\sum_n |w_{t,n}^{ESG} - w_{t,n}^{MF}|$ 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. Panel b) reports annualized alphas of the long-short ESG portfolio $\tau_t = w_t^{ESG} - w_t^{MF}$. The portfolios are rebalanced quarterly based on the funds' SEC filings. Alphas are computed with respect to the CAPM, and the Carhart four-factor model (CH4). Newey-West t-statistics with 12 lags are reported in parentheses.

(a) ESG Funds

Year	# Funds	Avg. AUM	Total AUM	Active Share
2012	50	0.39	19.63	0.69
2014	48	0.52	24.96	0.68
2016	55	0.39	21.63	0.67
2018	98	0.38	37.53	0.62
2020	125	0.56	71.47	0.55
2022	211	0.66	138.74	0.59

(b) ESG Portfolio Returns

	α (CAPM)	α (CH4)
2012-2022	0.57	0.31
	(0.87)	(0.80)
2017-2022	1.75	1.04
	(1.88)	(2.31)

Table 2: **Demand Curves by Institution 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 institutions belonging to a certain type, such that one demand curve is estimated per institution type j. Formally, the estimation equation is given by

$$\text{Homogeneous Elasticities: } \Delta q^j_{t,n} = \beta^j \Delta p_{t,n} + Controls + \epsilon^j_{t,n}$$
$$\text{ESG-specific Elasticities: } \Delta q^j_{t,n} = b^j \Delta p_{t,n} + b^j_{ESG}(\mathbb{1}^{ESG}_n \Delta p_{t,n}) + Controls + \epsilon^j_{t,n}$$

where dividend-induced trades ($DIT^{-j}_{t,n}$) are used as an instrument for $\Delta p_{t,n}$. The control variables log book equity, investment, market beta, quarter fixed effects, as well as the error term capture the demand shifter $d^j_{t,n}$. Institutional types are denoted by $j = 1, ..., J$ and include investment advisors, mutual funds, banks, pension funds, and insurance companies. Standard errors (in parentheses) are clustered at the stock-quarter level.

			Parameterization							
	β^j		b^j		b^j_{ESG}		1st Stage F-stat.	Quarter FE	Controls	Obs.
Pooled All	-1.73	(0.48)	-1.79	(0.50)	0.22	(0.12)	13.33	Yes	Yes	22,403,487
Pooled by Type										
Investment advisors										
High Active Share	-1.45	(0.44)	-1.60	(0.50)	0.30	(0.12)	11.29	Yes	Yes	3,230,579
Medium Active Share	-1.34	(0.42)	-1.41	(0.45)	0.19	(0.10)	11.13	Yes	Yes	4,160,093
Low Active Share	-0.60	(0.19)	-0.62	(0.20)	0.06	(0.04)	13.22	Yes	Yes	5,141,911
Mutual funds	-2.40	(0.68)	-2.47	(0.73)	0.12	(0.16)	13.27	Yes	Yes	3,293,855
Banks	-1.31	(0.31)	-1.33	(0.31)	0.07	(0.09)	21.52	Yes	Yes	2,503,984
Pension funds	-1.96	(0.71)	-1.99	(0.74)	0.10	(0.16)	7.87	Yes	Yes	1,280,101
Insurance companies	-0.70	(0.31)	-0.68	(0.32)	-0.11	(0.07)	8.03	Yes	Yes	953,894
Other 13F Institutions	-9.40	(55.27)	-7.25	(31.09)	1.28	(5.44)	0.03	Yes	Yes	1,728,189

Table 3: **Flow Multipliers**

Panel (a) summarizes the elements of the $N \times N$ multiplier matrix as of the first quarter of 2021. I aggregate the results by ESG and non-ESG stocks. The first (second) row reports the value-weighted average returns when buying 1% of each ESG (non-ESG) stock. Standard deviations across ESG and non-ESG returns are value-weighted. Panel (b) reports the average ESG flow multiplier from 2012 to 2022, i.e. the change in the aggregate value of ESG relative to non-ESG stocks due to a \$ 1 reallocation from w_t^{MF} to w_t^{ESG}. Newey-West standard errors with 12 lags are reported in parentheses.

(a) The Multiplier Matrix

	ESG Stocks	Non-ESG Stocks
Buy 1% of all ESG Stocks		
Price Impact (%)	0.75	0.18
Std. Deviation (%)	0.015	0.012
Buy 1% of all Non-ESG Stocks		
Price Impact (%)	0.15	0.69
Std. Deviation (%)	0.010	0.020

(b) ESG Flow Multiplier

	Impact of \$1 ESG Flow
ESG Stocks (\$)	0.37
	(0.020)
Non-ESG Stocks (\$)	-0.32
	(0.017)
ESG Flow Multiplier (\$)	0.69
	(0.037)

Table 4: **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) labeled ESG mutual fund flows and ii) total ESG flows. I report raw returns and alphas with respect to the CAPM, and the Carhart four-factor model (CH4). The last column controls for PST's Green Factor (G) and the returns of the technology industry (T). Newey-West t-statistics with 12 lags are reported in parentheses.

	Return	α (CAPM)	α (CH4)	α (CH4 +G+T)
True ESG Returns empirically observed				
	1.44	1.75	1.04	1.24
	(1.69)	(1.88)	(2.31)	(2.43)
Flow-Driven ESG Returns from total ESG flows				
	2.07	1.99	1.90	2.47
	(2.54)	(2.54)	(2.57)	(2.63)
1. Counterfactual Returns without total ESG flows				
	-0.63	-0.25	-0.86	-1.22
	(-0.51)	(-0.19)	(-0.77)	(-0.87)
2. Counterfactual Returns without labeled ESG flows				
	1.42	1.73	1.02	1.22
	(1.67)	(1.86)	(2.28)	(2.41)

Table 5: **ESG Flows in the Cross-Section**

The table reports the slope coefficient of a panel regression of quarterly stock returns $\Delta p_{t,n}$ from 2012 to 2022 onto flow-driven demand by ESG funds $\Delta d_{t,n}^{ESG}$.

$$\Delta p_{t,n} = \alpha_t + \beta \Delta d_{t,n}^{ESG} + Controls + \epsilon_{t,n}$$

(1) reports the OLS coefficient. (2) reports the WLS coefficient with weights proportional to lagged market equity. The rightmost column reports the stock-specific multiplier from the structural model diag($\mathcal{M}_t$) averaged across stocks and quarters. The control variables include investment, log book equity, log market equity, and market beta. Standard errors (in parentheses) are double-clustered by stock and year-quarter.

	Regression Multiplier		
	(1)	(2)	Structural Multiplier
$\Delta d_{n,t}^{ESG}$	0.253	0.442	0.532
	(0.068)	(0.116)	(0.001)
Controls	Yes	Yes	
FE	Yes	Yes	
R^2	0.002	0.004	
Obs.	53460	53460	

Table 6: **Flow Impact at the Fund Level**

The table reports the impact of a \$1 flow towards a sample of the largest ESG mutual funds and ETFs in the US. I compute the impact at every quarter and then average across quarters from 2012 to 2022. I report the impact on ESG stocks (with $\tau_{t,n} > 0$), as well as fossil fuel and sin stocks. The second column reports the funds' active deviation from the aggregate mutual fund portfolio $\frac{1}{2}\sum_n |w^i_{t,n} - w^{MF}_{t,n}|$.

		Impact of 1\$ Flow onto...		
	Active Share	Green Stocks	Fossil Fuel Stocks	Sin Stocks
TIAA-CREF Funds: Social Choice Equity Fund	0.560	0.207	0.002	-0.006
Calvert Social Investment Fund	0.820	0.379	-0.016	-0.007
Vanguard FTSE Social Index Fund	0.428	0.096	-0.008	-0.007
iShares MSCI USA ESG Select ETF	0.715	0.279	-0.006	-0.007
iShares FTSE KLD 400 Social Index Fund	0.600	0.193	-0.003	-0.007
Brown Advisory Winslow Sustainability Fund	0.873	0.315	-0.016	-0.007
iShares MSCI USA ESG Optimized ETF	0.354	0.122	-0.003	-0.003
Vanguard ESG US Stock ETF	0.195	0.071	-0.012	-0.003
Xtrackers MSCI USA ESG Leaders ETF	0.569	0.255	-0.005	-0.004
iShares ESG MSCI USA Leaders ETF	0.567	0.253	-0.005	-0.003

Appendix A Proofs

A.1 Proof of Equation (6)

I omit the subscript t for expositional simplicity. The market clearing condition implies that $\sum_{i=1}^{I} Q^i = Q^*$ where $Q^i = g^i(P, V)$ and Q^* is aggregate supply, which is normalized to a vector of ones. Recall that price elasticities and cross-elasticities are defined as $\zeta_n^i = -\frac{\partial Q^i(n)}{\partial P(n)} \frac{P(n)}{Q^i(n)}$ and $\zeta_{n,m}^i = -\frac{\partial Q^i(n)}{\partial P(m)} \frac{P(m)}{Q^i(n)}$ respectively. In matrix form, the elasticity matrix is therefore given by $\zeta^i = -\text{diag}(Q^i)^{-1} \frac{\partial Q^i}{\partial P} \text{diag}(P)$. I also define the elasticity in absolute terms (instead of percentages) as $\tilde{\zeta}^i = -\frac{\partial Q^i}{\partial P}$. We want to approximate the effects of an exogenous shock ΔV on equilibrium prices P. For example, ΔV can be interpreted as a change in ESG scores resulting in a change of demand, or capital flows towards ESG funds resulting in flow-driven trades. Differentiating both sides of the market clearing condition with respect to V yields

$$\frac{\partial Q^*}{\partial V} = \sum_{i=1}^{I} \frac{\partial Q^i}{\partial V} + \frac{\partial Q^i}{\partial P} \frac{\partial P}{\partial V} \tag{13}$$

Shares outstanding are normalized to 1. Therefore $\frac{\partial Q^*}{\partial V} = 0$. Rewriting (13) in terms of elasticities yields

$$0 = \sum_{i=1}^{I} \frac{\partial Q^i}{\partial V} - \tilde{\zeta}^i \frac{\partial P}{\partial V} \tag{14}$$

Now we can solve for $\frac{\partial P}{\partial V}$:

$$\frac{\partial P}{\partial V} = \left(\sum_{i=1}^{I} \tilde{\zeta}^i \right)^{-1} \sum_{i=1}^{I} \frac{\partial Q^i}{\partial V} \tag{15}$$

Let $\Delta d = \sum_{i=1}^{I} \frac{\partial Q^i}{\partial V} \Delta V$ be the first order approximation to the aggregate demand shock caused by the exogenous shock ΔV, measured as a fraction of shares outstanding. For example, changes in the Co2 emissions of a company lead investors to increase their non-pecuniary preferences for the stock causing an ESG demand shock Δd. A first order approximation to the equilibrium increase in prices is given by

$$\Delta P = \left(\sum_{i=1}^{I} \tilde{\zeta}^i \right)^{-1} \Delta d \tag{16}$$

When elasticities ζ^i are defined in percentages (as in the main text), we can write the equilibrium price change as

$$\Delta p = \left(\sum_{i=1}^{I} \text{diag}(Q^i)\zeta^i \right)^{-1} \Delta d. \tag{17}$$

where $\Delta p = \text{diag}(P)^{-1}\Delta P$.

Appendix B Measuring ESG

B.1 ESG Mutual Funds

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 the following 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 larger. For brevity, this list excludes all keywords that are not actually used in funds' names. Panel a) of Table B.7 plots the 30 largest ESG funds and their assets under management as of 2022. Panel b) reports summary statistics on the sample of ESG funds and their aggregate portfolio. From 2012 to 2022 the average ESG fund held around 180 stocks in its portfolio. While the average assets have remained relatively stable at around \$400-600 million, the number of labeled ESG funds has more than quadrupled from 50 to 211. The fifth column reports the total number of ESG name changes in a given year. Out of the sample of ESG funds, 45 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, ESG funds received around 2-3% higher quarterly inflows than other funds. Section B.3 provides an in-depth analysis of ESG flows controlling for fund characteristics, performance, and portfolio holdings. The three rightmost columns report summary statistics on the representative ESG portfolio w_t^{ESG}. Total assets grew from \$20 to \$140 billion. At the same time, the fraction of ESG funds that track an ESG index has also steadily increased to over 50%.

Table B.7: **ESG Mutual Funds Summary Statistics**
Panel a) reports the largest 20 ESG funds and their assets under management (in $ billion) identified by the list of sustainability keywords as of 2022. Panel b) reports summary statistics describing the sample of ESG funds. The first 5 columns report statistics at the fund level. The last 3 columns report statistics for the aggregated portfolio of all ESG funds w_t^{ESG}. I report yearly averages of quarterly variables. Avg. AUM and Total AUM are in $ billions. The active share is computed as

(a) Largest 20 ESG Funds

Fund Name	Assets	Fund Name	Assets
Vanguard FTSE Social Index Fund	14.27	iShares MSCI KLD 400 Social ETF	3.55
iShares ESG Aware MSCI USA ETF	14.24	Xtrackers MSCI USA ESG Leaders Equity ETF	3.27
Brown Advisory Sustainable Growth Fund	6.78	iShares MSCI USA ESG Select ETF	3.26
Calvert Equity Fund	6.65	iShares ESG MSCI USA Leaders ETF	3.17
Vanguard ESG US Stock ETF	6.14	Catholic Responsible Investments Equity Index	3.04
Social Choice Equity Fund	5.79	Calvert Small Cap Fund	2.87
Putnam Sustainable Leaders Fund	5.12	Impax Sustainable Allocation Fund	2.23
US Sustainability Core 1 Portfolio	5.10	Fidelity US Sustainability Index Fund	2.18
Sustainable Equity Fund	4.19	Calvert US Large-Cap Value Responsible Index Fund	1.71
Calvert US Large-Cap Core Responsible Index Fund	4.18	Nuveen ESG Large-Cap Value ETF	1.57

(b) ESG Summary Statistics

	ESG Fund-Level Statistics					Aggregate Statistics on w_t^{ESG}		
Year	# Funds	Avg. # Stocks	Avg. AUM ($ Billion)	Excess Flows (%)	# Name Changes	Total AUM ($ Billion)	% Indexed AUM	Active Share
2012	50	172	0.39	-0.74	0	19.63	0.18	0.69
2013	47	141	0.46	-1.74	0	22.12	0.19	0.69
2014	48	140	0.52	-1.77	0	24.96	0.23	0.68
2015	52	151	0.45	0.03	0	23.46	0.29	0.68
2016	55	176	0.39	2.90	4	21.63	0.32	0.67
2017	81	182	0.35	2.34	4	28.28	0.24	0.65
2018	98	181	0.38	1.13	9	37.53	0.26	0.62
2019	108	188	0.42	2.38	5	45.89	0.35	0.60
2020	125	207	0.56	2.46	9	71.47	0.47	0.55
2021	160	199	0.79	2.10	6	127.13	0.56	0.56
2022	211	189	0.66	0.63	10	138.74	0.58	0.59

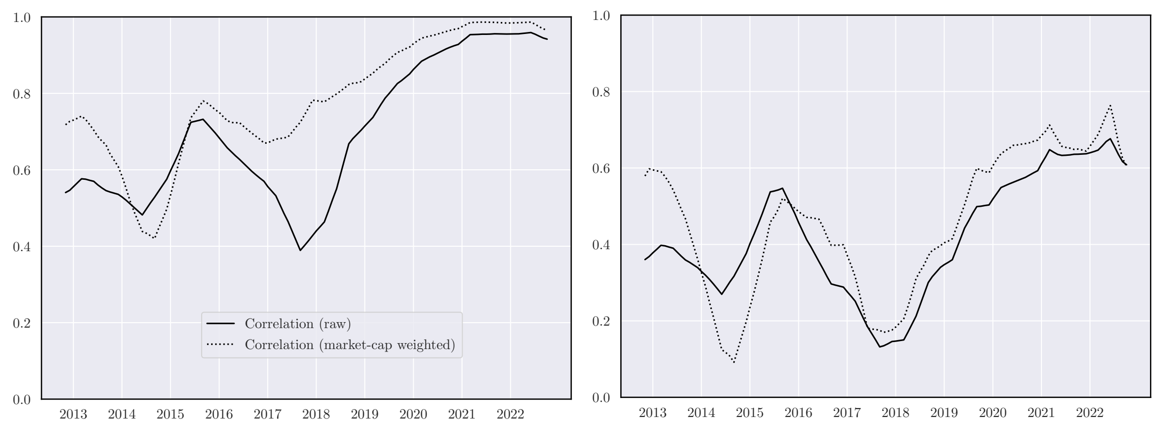
B.2 Robustness of the ESG portfolio

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 representative 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 into 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 ESG 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}.[30] Figure B.4 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 value-weighted correlations.

Figure B.4: **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}. I compute both equal-weighted and value-weighted correlations and plot 12-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 driven by 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%. Value-weighted correlations are slightly higher implying that there is stronger agreement among ESG funds for larger stocks.

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

B.3 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 $\mathbb{1}^i_{ESG,t}$ 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 $\mathbb{1}^i_{ESG,t}$ controlling for lagged flows, fund size, fund performance, portfolio tilts and factor exposures. Panel (a) of Table B.8 reports the estimated coefficient on the ESG dummy across different specifications.

Table B.8: **ESG Labels and Flows**
The table reports the results to panel regressions of quarterly flows onto ESG indicators from 2012 to 2022. The first column reports the coefficient on $\mathbb{1}^i_{ESG,t}$, which is equal to one if fund i has an ESG keyword in its name as of time t. The second column includes an indicator variable ($\mathbb{1}^i_{ESG}$) equal to one, if fund i is an ESG fund at some point in the sample. The third column includes an indicator variable ($\mathbb{1}^i_{\text{Name Change}}$) equal to one, if the fund changed its name at some point during in the sample. In all specifications I control for the funds' log assets under management, CAPM alpha, flows lagged up to 4 quarters, and portfolio-level characteristic scores for value, size and ESG. Standard errors are double-clustered by fund and year-quarter.

	Quarterly Flow f^i_t		
	(1)	(2)	(3)
$\mathbb{1}^i_{ESG,t}$	0.020	0.035	0.024
	(0.006)	(0.007)	(0.006)
$\mathbb{1}^i_{ESG}$		-0.016	
		(0.005)	
Name Change^i			-0.024
			(0.004)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
R^2	0.06	0.06	0.06
Observations	130465	130465	130465

The estimates reveal that having an ESG keyword in the title leads to 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. Nevertheless, it is possible that ESG funds differ from other funds along some dimensions not captured by directly observable fund characteristics and portfolio tilts. To address remaining endogeneity concerns, I use funds' name changes as exogenous variation in

ESG titles. As mentioned in the main text, 45 out of the 384 identified ESG funds have changed their name at some point between 2012 and 2022 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. To this end, I construct a dummy variable $\mathbb{1}^i_{ESG}$ equal to 1 if the fund had an ESG keyword in the title at some point between 2010 and 2020. Controlling for $\mathbb{1}^i_{ESG}$ effectively turns the coefficient on $\mathbb{1}^i_{ESG,t}$ into a difference-in-differences estimate. Any flow heterogeneity from having an ESG keyword in the title that is driven by some unobservable fund-level fixed effect is captured by $\mathbb{1}^i_{ESG}$, such that $\mathbb{1}^i_{ESG,t}$ captures the pure effect of the name change. Note, that if there are no name changes in the sample $\mathbb{1}^i_{ESG,t}$ and $\mathbb{1}^i_{ESG}$ are perfectly collinear. Despite having very few name changes in the sample, the coefficient on the name change indicator $\mathbb{1}^i_{ESG,t}$ remains statistically significant and slightly increases to 3.4%. Thus changing the fund's name to include an ESG keyword boosts quarterly flows by 3.4%. Note, that the coefficient on $\mathbb{1}^i_{ESG}$ is significantly negative. This suggests that 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. The last column controls for $\mathbb{1}^i_{\text{Name Change}}$, which is a dummy variable equal to 1 if the fund changed its name at some point during the sample.

B.4 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 emissions 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 commonly used ESG scores. To this end, I estimate two regressions. The first is a panel OLS regression of $\tau_{t,n}$ onto different ESG scores. The second is a probit regression of the ESG dummy $\mathbb{1}_{t,n}^{ESG}$ onto the same set of ESG scores. As sustainability characteristics, I use MSCI ESG Scores a Vanguard 4 Good dummy equal to 1, if the stock is in the Vanguard 4 good index. I furthermore control for log market equity, market beta, log book equity and investment in both specifications. Table B.9 reports the results.

Table B.9: **ESG Tastes and Sustainability Characteristics**
The first panel reports the result to a pooled OLS regression including quarter fixed effects of $\tau_{t,n}$ onto different sustainability characteristics. t-Statistics are computed using double-clustered standard errors at the stock and year-quarter level. The second panel reports the results to a pooled probit regression of the ESG dummy $\mathbb{1}_{t,n}^{ESG}$ onto the same set of sustainability characteristics. The control variables in all specifications are log market equity, market beta, log book equity, and investment, as well as quarter fixed effects.

	Sustainability Characteristics					
	ESG Score	Vanguard 4 Good Index	Controls	Quarter FE	R^2	N
Panel Regression $\tau_{t,n}$						
Coefficient	0.13	0.58	Yes	Yes	0.07	221566
t-Stat.	(5.84)	(6.41)				
Probit Regression $\mathbb{1}_{\tau>0}$						
Coefficient	0.28	0.66	Yes	Yes	0.14	221566
t-Stat.	(77.20)	(67.22)				

The coefficients the ESG scores are all statistically significant with the right sign. The ESG portfolio tilts towards stocks with high MSCI scores as well as stocks that are in the Vanguard 4 Good Index. This is strong evidence, that ESG funds (on average) do tilt towards widely used ESG scores. 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 C Measuring ESG Flows

C.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 labeled ESG mutual funds from Section 3 amount to roughly \$140 billion as of 2022. However, the flows into labeled ESG do not include the (unobservable) ESG tilts of other mutual funds, 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 instead of flow-driven trades $Q_t^i f_{t+1}^i$. I therefore 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 institution-quarter pair, I am projecting the portfolio weights onto the ESG portfolio $w_{t,n}^{ESG}$ and a set of S managed portfolios (or individual funds):

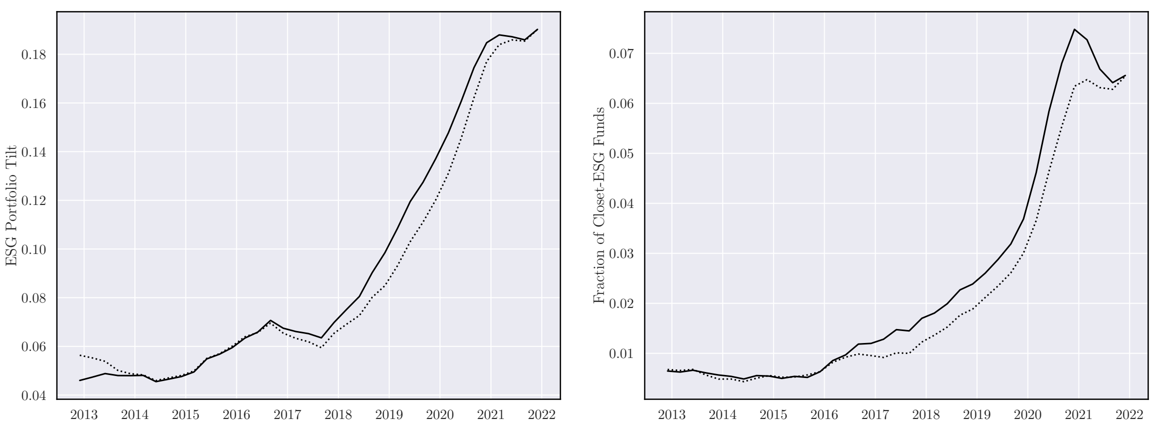
$$\begin{aligned} \min_{\{\theta_t^s\}_{s=1}^S} \quad & ||w_{t,n} - \sum_{s \in \{S, ESG\}} \theta_t^s w_{t,n}^s||_2 \\ \text{s.t.} \quad & -1 \leq \theta_t^s \leq 2 \quad \forall s \in \{S, ESG\}. \end{aligned} \tag{18}$$

Thus θ_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 equity-weighted portfolio $w_{t,n}^{Mkt} = P_{t,n} / \sum_{n \in N^i} P_{t,n}$, the ESG portfolio $w_{t,n}^{ESG}$, a value-weighted portfolio of stocks in the technology industry, and characteristics-managed portfolios based on cross-sectional momentum, value, profitability, investment and market beta ranks. (18) can also be interpreted as 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 $a_{t,n} = w_{t,n} - \sum_{s=1}^S \theta_t^s w_{t,n}^s$ 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 zero-investment long-short 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 $\frac{1}{2} \sum_{n \in N^i} |a_{t,n}|$. 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 $\sum_{s=1}^S \theta_t^s = 1$. The coefficients θ_t^s can therefore be interpreted as the wealth shares of the individual funds w_t^s within the management company i. Figure C.5 summarizes the ESG tilt across 13F investors. Panel (a) plots the average ESG tilt across all 13F institutions from 2012 to 2022. The average ESG tilt θ_t^{ESG} steadily grew from 6 to 19% in the past 10 years.

Figure C.5: **ESG Tilts across 13F Investors**
Panel (a) plots the average ESG tilt $\bar{\theta}_t^{ESG} = \frac{1}{I}\sum_{i=1}^I \theta_t^{i,ESG}$ across all 13F institutions. Panel (b) plots the fraction of Closet-ESG investors. Closet-ESG investors are defined as investors with an ESG-share of over 50%. The dotted lines report values obtained when controlling for only the market and the equal-weighted portfolio in the estimation of $\theta_t^{i,ESG}$.

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



Using the investor-specific ESG tilts $\theta_t^{i,ESG}$ and their total assets under management A_t^i, we can compute the total ESG assets held by investor i as $A_t^{i,ESG} = A_t^i \theta_t^{i,ESG}$. 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,

$$F_{t+1}^{i,ESG} = A_{t+1}^{i,ESG} - A_t^{i,ESG}(1 + R_{t+1}^{ESG}) \tag{19}$$

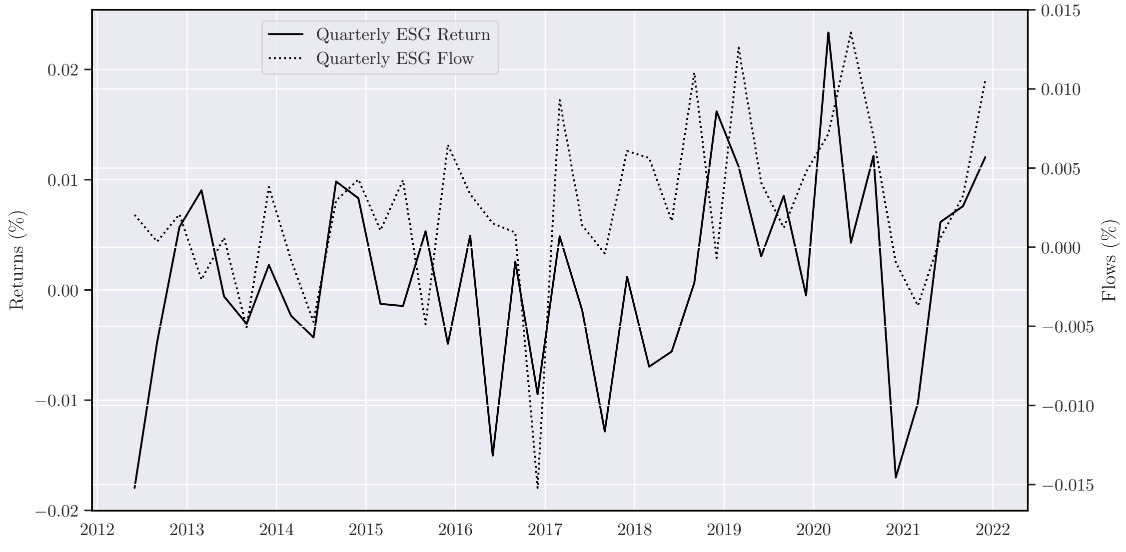
where R_{t+1}^{ESG} is the return on the ESG portfolio. Note that empirically, this return may differ across investors because 13F institutions hold different subsets of stocks $N^i \subseteq N$.

Summing across all investors yields the total flow by 13F investors in the ESG portfolio. Lastly, note that the ESG tilt θ_t^{ESG} allows distinguishing 13F investors by their tilt towards ESG stocks. I define 'Closet-ESG' investors as 13F institutions that hold over 50% of their assets in the ESG portfolio (i.e. $\theta_t^{ESG} > 0.5$). Panel (b) plots the fraction of Closet-ESG funds. Between 2017 and 2022, the total fraction of Closet-ESG funds grew from 1 to 7%. Lastly, the average ESG tilt, the fraction of Closet-ESG funds, and the corresponding total flows to the ESG portfolio are largely unaffected by controlling for tilt towards alternative characteristics-managed portfolios.

C.2 ESG Flows and Returns: Reduced-Form Evidence

The structural approach presented in this paper allows for circumventing the issue that flows and returns are jointly endogenous. Within the model, ESG flows have a large impact on ESG returns. If ESG returns are truly flow-driven, then aggregate ESG flows should be correlated to realized ESG returns. Figure C.6 plots the quarterly flow into the ESG portfolio along with the excess return on the ESG portfolio.

Figure C.6: **Aggregate ESG Flows and Returns**
The figure plots the quarterly return on the ESG portfolio τ_t against the quarterly total ESG flow F_{t+1}^{ESG} measured in percent relative to the CRSP total stock market capitalization.



The correlation between quarterly ESG flows and returns is 34%. Notably, PST (2022) find that ESG returns and flows into labeled ESG mutual funds are not significantly correlated. Table C.10 reports the results of OLS regressions of returns onto flows in the style of PST (2022).

Table C.10: **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 returns to the long-short portfolio τ_t as a measure for ESG returns, the second set of columns uses quarterly GMB factor returns of PST (2022). Specification (1) uses the total ESG flow estimated from institutional holdings scaled by total CRSP stock market capitalization. Specification (2) uses the flow into labeled ESG mutual funds scaled by their lagged assets. In specification (3), I instrument for the flow into labeled ESG mutual funds by its lag F_{t-1}^{ESG} as in PST (2022). The first stage t-Statistic is 6.99. I only report IV results for labeled ESG mutual fund flows, as the relevance condition does not hold for total ESG flows. Robust standard errors are reported in parentheses.

	ESG Return τ_t			GMB Factor Returns (PST, 2022)		
	(1)	(2)	(3)	(1)	(2)	(3)
const	-0.0	0.0	0.02	0.02	0.0	0.02
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Total ESG Flow	0.58			0.0		
	(0.18)			(0.16)		
ESG Mutual Fund Flow		0.06			0.05	
		(0.04)			(0.05)	
IV (lagged Flow)			0.8			0.27
			(0.85)			(0.27)
R^2	0.12	0.07	-	0.0	0.6	-
Observations	35	35	35	35	34	34

I first regress ESG returns on the total ESG flow and the flow to labeled ESG mutual funds separately. Total ESG flows are significantly related to ESG returns with an R^2 of 12%. Note that simple regressions of 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 depends 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}).

Appendix D Details on the Estimation and Identification

D.1 Structural versus Reduced-Form Estimation

Before diving into estimating elasticities from trade 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 ESG stocks Δd_t from e.g. a stock's inclusion in an ESG index as in Berk and van Binsbergen (2022).[31] The shocks could be used to directly estimate the multiplier using (6) as a linear regression. Nevertheless, there are three distinct benefits of the structural approach. First, it gives insights into the underlying investor-specific determinants of the flow multiplier. Second, one can obtain cross-elasticities, stock-specific elasticities and time-varying effects even if we estimate a scalar elasticity for every investor. Because the ownership $Q^i_{t,n}$ varies across stocks and time, ownership-weighted sums across elasticities $\sum_{i=1}^{I} \operatorname{diag}(Q^i_{t,n})\zeta^i$ vary across stocks and time. Third, one can use a large cross-section of trade 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 for example 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.

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

D.2 Two-Stage Least Squares Procedure

Institutional trades measured via Δq^i_t are relatively noisy and contain large outliers. Furthermore, for individual institutions, there are often not sufficiently many observations to obtain demand coefficients with reasonable statistical precision. I, therefore, pool investors by their institutional type into six groups given by mutual funds, banks, pension funds, insurance companies, and investment advisors denoted by $j = 1, ..., J$. I furthermore split investment advisors into activeness terciles based on their active share, which measures an institution's deviation from holding a (passive) value-weighted portfolio. I then estimate the group-specific demand curves using pooled Two-Stage Least Squares. I pool the trades $\Delta q^i_{t,n}$ over stocks, quarters, and all institutions belonging to a group j. Formally, the two-stage estimation is given by

$$\begin{aligned}
&\text{1st Stage:} \quad \Delta p_{t,n} = \psi DIT^{-j}_{t,n} + Controls + \epsilon_{t,n} \\
&\text{2nd Stage (Homogenous Elast.):} \quad \Delta q^j_{t,n} = \beta^j \Delta \hat{p}^j_{t,n} + Controls + \epsilon^j_{t,n} \\
&\text{2nd Stage (Parameterization):} \quad \Delta q^j_{t,n} = b^j \hat{p}^j_{t,n} + b^j_{ESG}(\mathbb{1}^{ESG}_n \hat{p}^j_{t,n}) + Controls + \epsilon^j_{t,n}
\end{aligned}$$

where $\Delta \hat{p}^j_t$ denotes the fitted value from regressing returns onto $DIT^{-j}_{t,n}$, the dividend induced trades by all 13F institutions excluding the institutions belonging to group j. For example, the instrument for banks is the dividend-induced trading from all institutions except banks. The second stage regression of trades Δq^j_t onto the instrumented return $\Delta \hat{p}^j_t$ allows identifying the group-specific demand elasticities ζ^j_t. The control variables include log book equity, investment, market beta, and quarter fixed effects. To remove the influence of outliers I winsorize trades at the 95% level. I then merge the group-specific elasticities to the respective institutions from each group. The construction of the multiplier matrix requires elasticity estimates for all shares outstanding. To all shares held by smaller unlabelled institutions, as well as the remaining shares outstanding not held by 13F institutions, I am applying the pooled elasticity across all 13F institutions. While the investor-specific instrument is only marginally relevant for some investor groups (see Table 2), the second-stage elasticities estimates are all of the same order of magnitude. This alleviates potential concerns about a relative bias from weak instruments. The strongest instrument is obtained when excluding mutual funds from total dividend-induced trading. This is owed to the fact that most mutual funds are tracking a total return index and therefore automatically reinvest dividends in the dividend-paying stock, as opposed to distributing them across their other positions. If we exclude mutual funds in the construction of $DIT^{-i}_{t,n}$, the estimated elasticities remain quantitatively unchanged.

D.3 Dividend Reinvestments

Do institutions reinvest total dividend payouts in their existing portfolio? I assess the extent to which institutions invest a stock's dividend payout in all other stocks within their portfolios. Let $\Delta s^i_{t,n} = \text{Shares}^{i,adj.}_{t,n}/\text{Shares}^i_{t-1,n} - 1$ denote the split-adjusted percentage change in shares held between two quarters.[32] If institutions reinvest dividend payouts across their entire portfolio, then $\Delta s^i_{t,n}$ should be significantly related to the dividend flow from all *other* stocks $df^i_{t,-n}$. I test this in a pooled regression given by

$$\Delta s^i_{t,n} = \alpha_{t,n} + \beta df^i_{t,-n} + \epsilon^i_{t,n}$$

Table D.11 reports the coefficient estimates across different specifications. I exclude large trades that exceed 100% of previous holdings, i.e. $\Delta s^i_{t,n} < 1$, and only consider meaningful positions beyond 0.1% of total assets, i.e. $w^i_{t-1,n} > 0.001$.

Table D.11: **Dividend Reinvestments**
The table reports the estimated coefficients from the pooled regression of 13F trades $s^i_{t,n}$ onto dividend flows from other stocks $df^i_{t,-n}$ and a constant. I control for stock-quarter fixed effects in all specifications. Standard errors (in parentheses) are double-clustered at the stock and fund-quarter level.

	Quarterly trades $\Delta q^i_{t,n}$	
	(1)	(2)
Dividend Flow $df^i_{t,-n}$	8.279	1.101
	(0.330)	(0.514)
Stock×Quarter FE	Yes	Yes
Institution FE	No	Yes
R^2	0.001	0.000
Observations	10025375	10025375

The dividend-scaling coefficient θ is significantly positive. Thus, on average institutions reinvest their dividend payouts across all other stocks in their portfolios. When including institution fixed effects, the estimated reinvestment coefficient is 1.1. This implies that, when institutions receive a 1% dividend inflow, they proportionally scale up

[32]To provide maximal comparability with Lou (2012), I use this alternative definition of institutional trades. Empirically $s^i_{t,n}$ is close to $\Delta q^i_{t,n}$ with a correlation of 95%.

their existing holdings in all stocks by roughly the same percentage.

D.4 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:

$$\log \delta^i_{t,n} = (1 + \beta^i_n) \log P_{t,n} + \varepsilon^i_{t,n} \tag{20}$$

where $\delta^i_{t,n} = w^i_{t,n}/w^i_{t,0}$ is the portfolio weight relative to the weight in an outside asset $w^i_{t,0}$ and $\varepsilon^i_{t,n}$ includes a constant, observable characteristics, and a residual.[33] Here, I let β^i_n vary across stocks. Constant coefficients are a special case of this more general specification. The portfolio constraint that $\sum_{n \in N^i} w^i_{t,n} = 1 - w^i_{t,0}$ implies that

$$w_{t,n} = \frac{\delta^i_{t,n}}{1 + \sum_{m=1}^{N} \delta^i_{t,m}}. \tag{21}$$

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 $\log \delta^i_{t,n} = \log Q^i_{t,n} + \log P^i_{t,n} - \log w^i_{t,0} A^i_t$. Rearranging and taking first differences yields[34]

$$\Delta q^i_{t,n} = \beta^i_n \Delta p_{t,n} + d^i_{t,n} \tag{22}$$

where $d^i_{t,n} = \Delta \log(w^i_{t,0} A^i_t) + \Delta \varepsilon^i_{t,n}$. A first-order approximation of investor's demand elasticity is given by the scalar regression coefficient $-\frac{\Delta q^i_{t,n}}{\Delta p_{t,n}} = -\beta^i_n$. However, this measure of elasticity does not ensure that the investor's portfolio weights add up to 1, (or alternatively: that her assets A^i_t remain unchanged). In order to ensure that the budget constraint holds we need to plug the estimated coefficient into (21). To this end, note that $\log w^i_{t,n} = \log Q^i_{t,n} + \log P^i_{t,n} - \log A^i_t$. Differentiating and rearranging yields the following

[33] For the empirical application, I follow KY (2019) and construct the outside asset as all foreign stocks, real estate investment trusts and stocks with missing characteristics or returns.

[34] KY (2019) actually propose re-estimating (20) over the cross-section of portfolio weights every quarter t resulting in time-varying coefficients $\beta^i_{t,n}$. 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.

stock-specific elasticity

$$-\frac{\partial \log Q^i_{t,n}}{\partial \log P_{t,n}} = -\beta^i_n + \underbrace{w^i_{t,n}(1+\beta^i_{t,n})}_{\text{Portfolio Constraint}}. \tag{23}$$

The elasticity is given by $-\beta^i_{t,n}$ plus a correction term, which ensures that portfolio weights add up to 1.[35] Precisely because of the portfolio constraint, price changes have spillover effects to other stocks. Cross-elasticities are given by

$$-\frac{\partial \log Q^i_{t,n}}{\partial \log P_{t,m}} = w^i_{m,t}(1+\beta^i_m). \tag{24}$$

Thus cross-elasticities are not directly estimated. They emerge from the portfolio constraint and are determined by the structural assumption of logit demand.[36] We can stack the elasticities into an elasticity matrix $-\frac{\partial \log Q^i_t}{\partial \log P'_t} \in \mathbb{R}^{N\times N}$ given by

$$-\frac{\partial \log Q^i_t}{\partial \log P'_t} = -B^i + (\mathbf{I} + B^i)\mathbf{1}(w^i_t)' \tag{25}$$

where $B^i \in \mathbb{R}^{N\times N}$ is a diagonal matrix with elements β^i_n. When the estimated coefficient is constant across stocks and quarters, then $\beta^i_n = \beta^i\mathbf{I}$ and the elasticity matrix simplifies to $-\frac{\partial \log Q^i_t}{\partial \log P'_t} = -\mathbf{I}\beta^i + (1+\beta^i)\mathbf{1}(w^i_t)'$. Thus the logit framework allows transforming the simple scalar regression coefficient $\beta^i_{t,n}$ into a demand-elasticity matrix that accounts for spillover effects across the entire cross-section of holdings.

D.5 Simulation

In order to better understand the difference between identifying elasticities from portfolio holdings versus trades, consider the following simulation. Investor i enters the market in 2018 with \$1 billion dollars under management and equally distributes her assets across the 500 largest stocks in the US, i.e. she starts with an equal-weighted portfolio. The vector of purchased shares (as reported in her 13F filing) is given by $\theta_n = 1\text{billion} * \frac{1}{500*P_{2018n}}$ where P_{2018n} are the market prices as of 2018. She never trades and therefore

[35] 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 the price of n and we have to make a downward adjustment to the elasticity to satisfy the portfolio constraint.

[36] 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 $w^i_{m,t}$.

holds the shares purchased in 2018 until the end of the sample. Her portfolio can be described as

$$\log Q^i_{t,n} = \log \theta_n + \varepsilon_{t,n}. \tag{26}$$

where $\varepsilon_{t,n}$ are iid liquidity trades or reporting errors in the holdings data. θ_n can be interpreted as an unobservable investment mandate. As she does not trade, her demand is perfectly inelastic, i.e. $\zeta^i_t = 0$. I compute θ_n as of 2018 and then simulate her portfolio path until 2021.[37] Elasticity estimates in levels will be unbiased as long as θ_n and $P_{t,n}$ are cross-sectionally uncorrelated. Here, θ_n is negatively correlated to market prices, which should lead to a downward bias in β^i_t, i.e. an upward bias in the elasticity $\zeta^i_t \approx -\beta^i_t$.[38] In other words, the estimation in levels will produce elasticity estimates that are too high. In first differences, however, the unobservable investment mandate (and hence the omitted variable bias) is removed as $\Delta q^i_t = \Delta\varepsilon_{t,n}$. Table D.12 reports the estimated coefficients from the simulation. The first column reports the investor's true elasticity, which is 0. The estimation in levels produces a strong and significant upward bias in the elasticity estimates. Estimating elasticities in first differences (i.e. using trades) eliminates the bias by removing the influence of the latent investment mandate.

Table D.12: **Elasticity Simulation.**
The table reports the estimated elasticities from simulated portfolio data. I simulate the portfolio of an investor that enters the market in 2018 with an equal-weighted portfolio across the largest 500 stocks and (up to iid liquidity trades $\varepsilon_{t,n}$) never trades thereafter. Thus her portfolio is given by $\log Q^i_{t,n} = \log \theta_n + \varepsilon_{t,n}$ where $\theta_n = \frac{1\text{billion}}{500 * P_{2018,n}}$ and $\varepsilon_{t,n} \sim \mathcal{N}(\mu_Q, \sigma^2_{\log Q_{2018}})$ where μ_Q and σ^2_Q are the cross-sectional sample mean and standard deviation of $\log Q^i_{2018}$. I simulate her portfolio from 2018 until 2021 and estimate demand every quarter. I report the average coefficient over time along with its standard error.

	True ζ^i	Estimates β^i: Levels ($\log Q^i_t$)	Estimates β^i: Changes (Δq^i_t)
Average	0	-0.92***	-0.01
Std. Error	-	(0.016)	(0.024)

[37] I use $\varepsilon_{t,n} \sim \mathcal{N}_t(\mu_Q, \sigma^2_{\log Q_{2018}})$ where μ_Q and σ^2_Q are the cross-sectional sample mean and standard deviation of $\log Q^i_{2018}$.

[38] More formally, $\log \theta_n = \log(\frac{1\text{billion}}{500}) - \log P_{2018,n}$ is negatively related to the market prices of 2018. Because the cross-section of prices in subsequent years is positively correlated to the prices of 2018, $\text{Cov}_t(\log\theta_n, \log P_{t,n}) < 0$. In a univariate regression of $\log Q^i_{t,n}$ onto $\log P_{t,n}$ the bias in the estimate is given by $\frac{\text{Cov}_t(\log\theta_n, \log P_{t,n})}{\text{Var}_t(\log P_{t,n})}$. The point estimate is therefore biased downward which implies an overestimation of the elasticity.

The simple simulation emphasizes the importance of accounting for unobservable investment mandates or portfolio tilts. The direction of the bias is driven by the correlation of the mandate with market prices. E.g. if the investor cross-sectionally tilts towards tech stocks (which are more expensive controlling for fundamental value) the elasticity estimates from levels will be biased downward. Constructing exogenous variation in prices potentially mitigates these concerns. Section 3E in the main text addresses this issue in more detail and provides an instrument for $\Delta p_{t,n}$ to cleanly identify ζ^i using how investors trade as opposed to what they hold.

D.6 Details on the Flow Simulation

Let Δp_{t+1}^{ESG} denote vector of price pressures (expressed in dollars) resulting from $\$X$ flow from the market portfolio towards the ESG portfolio. Equation (6) implies that

$$\Delta p_{t+1}^{ESG}(\$X) = \mathcal{M}_t \Delta d_{t+1}^{ESG}(\$X).$$

where $\Delta d_{t+1}^{ESG}(\$X) = \frac{w_t^{ESG} - w_t^{MF}}{P_{t,n}} * \$X$ is the fraction of stock n's shares outstanding purchased due to a $\$X$ dollar reallocation from the market portfolio to the ESG portfolio. Note, that true (empirically observed) realized returns of the ESG portfolio are given by $R_{t+1}^{ESG} = \sum_n \tau_{t,n} \Delta p_{t+1,n} = \tau_t' r_{t+1}$. The structurally implied price pressure from a $\$X$ ESG flow is given by

$$\text{Pressure}_{t+1}^{ESG}(\$X) = \sum_{n=1}^{N} \tau_{t,n}(e^{\Delta p_{t+1,n}^{ESG}(\$X)} - 1)$$

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

$$\tilde{R}_{t+1}^{ESG}(\$X) = R_{t+1}^{ESG} - \text{Pressure}_{t+1}^{ESG}(\$X).$$

Appendix E ESG Index Inclusion

A well-known ESG index is the FTSE USA 4 Good Index (henceforth 4G Index). The stocks in the 4G Index are a strict subset of the stocks in the FTSE USA 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. 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 4 Good (4G) Index large enough to generate meaningful demand shocks based on its reconstitution?

To further investigate this, I construct mutual fund demand $\Delta q^{MF}_{t,n}$ as the change in ownership by mutual funds for every stock n and quarter t. Table E.13 reports regressions in the style of Berk and van Binsbergen (2022). $\Delta I^{4G}_{t,n}$ is a variable equal to 1 in the quarter of inclusion in the 4G Index, -1 in the quarter of exclusion, and 0 otherwise. $\Delta I_{t,n}$ is defined equivalently but for the FTSE USA Index. I first regress mutual fund demand onto $\Delta I^{4G}_{t,n}$ and $\Delta I_{t,n}$ including the controls used in Berk and van Binsbergen (2022).[39] Additions to the FTSE USA Index are associated with a significant increase in total mutual fund ownership of 3.2 percent. Additions to the 4G Index, however, have no effect on mutual fund demand. This suggests that the 4G Index is not sufficiently widely followed such that reconstitutions cause meaningful shocks to index investor demand. In line with this result, quarterly stock returns (column 3) are not significantly related to 4G Index reconstitutions.

Table E.13: **How much money is following the FTSE 4 Good Index?**
The table reports panel regressions of quarterly mutual fund demand $\Delta q^{MF}_{t,n}$ and returns $\Delta p_{t,n}$ from 2012 to 2022 onto index inclusion indicators in the style of Berk and van Binsbergen (2022). $\Delta I^{4G}_{t,n}$ is equal to 1 in the quarter of inclusion in the FTSE 4 Good Index, -1 in the quarter of exclusion, and 0 otherwise. $\Delta I_{t,n}$ is defined equivalently, but for the FTSE USA index. $\mathbb{1}^{\text{ESG-Demand}}_{n,t}$ is a dummy equal to 1 if the aggregate change in ownership by ESG funds has the same sign as $\Delta I^{4G}_{t,n}$. The control variables include dummy variables equal to 1 in all quarters after inclusion in the 4G Index and the FTSE USA Index respectively, as well as the raw $\mathbb{1}_{\text{ESG-Demand}}$. Standard errors (in parentheses) are double-clustered by stock and year-quarter.

	Mutual Fund Demand $\Delta q^{MF}_{t,n}$		Quarterly Returns $\Delta p_{t,n}$	
	(1)	(2)	(3)	(4)
$\Delta I_{n,t}$	0.029	0.029	0.021	0.022
	(0.005)	(0.005)	(0.015)	(0.015)
$\Delta I^{4G}_{n,t}$	-0.002	-0.008	-0.034	-0.044
	(0.006)	(0.006)	(0.034)	(0.048)
$\Delta I^{4G}_{n,t} \times \mathbb{1}^{\text{ESG-Demand}}_{n,t}$		0.022		0.064
		(0.008)		(0.047)
Controls	Yes	Yes	Yes	Yes
R^2	0.092	0.093	0.004	0.004
Observations	139696	139696	139696	139696

[39] Because additions and deletions are encoded as 1 and -1 respectively, I refer to all index reconstitutions as additions. As mutual fund holdings are only available quarterly, I run the regression at a quarterly frequency. While I do not have exact data on the FTSE constituents, I approximate them using the holdings of the Vanguard Total Stock Market ETF and the Vanguard FTSE Social Index Fund.

In order to identify relevant (i.e. widely followed) reconstitution events, I use ownership changes of labeled ESG mutual funds that track an ESG index. In only 44% of all reconstitutions, the aggregate change in ownership by index-tracking ESG mutual funds has the same sign as the reconstitution.[40] I interact the 4G index reconstitutions with a dummy variable, $\mathbb{1}_{n,t}^{\text{ESG-Demand}}$, equal to 1 if the demand by ESG index trackers has the same sign as the reconstitution. Conditional on ESG index funds following the reconstitution, aggregate mutual fund ownership increases significantly by 2.3% during 4G Index reconstitutions. The conditional reconstitutions are also associated with a large (albeit insignificant) increase in stock prices of 5%. This suggests that ESG index inclusion may have an effect on prices, as long as ESG funds actually purchase the stock when it is included. Furthermore, the implied price impact is roughly 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 $2.2 - 0.8 = 1.4\%$ demand shock by mutual funds and experience $6.4 - 4.4 = 2\%$ higher returns, which implies an ESG demand multiplier of $\frac{2}{1.4} = 1.43$. Note, that $\mathbb{1}_{n,t}^{\text{ESG-Demand}}$ measures the demand by index-tracking ESG funds and should therefore not contain contemporaneous return-chasing behavior. Nevertheless, endogeneity concerns remain because index trackers often focus on the largest or most liquid stocks within the index, which may precisely be the ones that had high returns.

[40]From 2012 to 2022 and using quarterly data, I obtain 572 reconstitution events of the 4G index, conditional on the stock already being in the FTSE USA Index. For 252/572=44% out of these events, the aggregate ownership change of ESG index trackers has the same sign as the reconstitution.

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