Time-varying Environmental Betas and Latent Green Factors

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Abstract

We study whether the US stock market is pricing exposures to climate risks through the lenses of a latent linear factor model with time-varying betas estimable by the instrumented principal component analysis (IPCA) methodology of Kelly et al. (2019). In our specification, the factor loadings of the factors are allowed to be functions of both "financial" and environmental ("green") company-specific characteristics, such as ESG ratings and carbon intensity. We extend the original model of Kelly et al. (2019) to allow the presence of different sets of orthogonal factors whose loadings are driven by only one of the two types of characteristics. This methodological extension allows to interpret our factors as purely "green" or "financial" factors. Importantly, we are able to identify and estimate latent green factors from a large panel of stock returns without defining (and constructing) them ex-ante, as typically done in the climate finance literature. We identify one "green" factor which is important for the out-of-sample pricing of stocks in the Energy and Utilities sectors, above and beyond "financial" factors. This green factor is not relevant in explaining the time series variation and the average returns of the stocks in the other sectors, which are well explained by "financial" factors only.

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1 Introduction

In this work we address two questions related to the impact of climate and environmental risks on the returns of US equities. First, we study whether a separate risk factor driving the returns and associated to "environmental" characteristics exists on top of standard risk factors associated to commonly used "financial" characteristics, i.e. predictors of stock returns such as Size and Book-to-Market. Second, we want to assess the pricing ability of this this new environmental factor for the cross section of stock returns from which it is extracted.

Despite many recent works use observable environment-related factors, reviewed in Section 2, our approach is new in this context as we allow for this factor to be latent. The methodology we use and extend to answer the above questions is the instrumented principal component analysis (henceforth IPCA) proposed by Kelly et al. (2019): by starting from a large set of firm-level environmental and financial characteristics, we measure how they impact the exposure of returns to few latent factors, which we also estimate.

To separate environmental factor from financial factors, we propose a new constrained IPCA model where factors are allowed to depend either on green characteristics only, or on financial characteristics only.[1] This methodological innovation allows us to interpret the estimated factors as purely *green* or purely *financial* factors and then we can assess how each of the two sets of factors explains the time series variation and the average returns of all individual stocks, as measured by the the Predictive, Total and Pricing R^2s measures, respectively. Our methodological estimation allows to estimates the green factor in a way that is orthogonal to financial factors, implying that our green factor is associated to risks not related to "standard" financial factors.

ESG data are often used to create green factors or to describe the exposure of stocks to these factors. Nowadays there exist many competing ESG data providers, but often these data are not consistent among different sources as documented by Berg et al. (2020), Busch et al. (2020), and Avramov et al. (2021), Billio et al. (2020) among others. Starting from these recent studies, our maintained assumption is that each measurement of a

[1] In this work we define as environmental risks all that risks that may be associated to some environmental firm-level characteristics like ESG rating, emissions, etc. We define these characteristics and the factors associated to these characteristics as *green* to distinguish them from the *financial* characteristics like size, book-to-market, etc.

certain environmental characteristic is composed of relevant, and potentially common to other measures, information plus some noise. IPCA is based on the same premises: therefore, it allows to understand which linear combination of characteristics is most relevant to describe the loadings of companies' returns on the latent factors by filtering the noise and keeping only the common information in the different characteristics. Moreover, as the loadings in the IPCA model are allowed to depend on the company characteristics, we can identify the most relevant characteristics determining the loadings without selecting few of them ex-ante as typical done, for example, when applying Fama and French methodology (Fama and French (1993)). In the latter methodology risk factors are formed by sorting individual stocks on few predetermined characteristics like size and book-to-market, and taking long-short position on the wxtreme quantile portfolios. We just need to identify a set of potentially-interesting characteristics from which the methodology will find the most relevant ones. Finally, ESG characteristics are available for a few hundred of companies at the beginning of our sample in 2007, but in the last 5 years data providers cover thousands of listed companies. A final advantage of IPCA, is that it allows to handle easily the unbalanced nature of the large panels of returns of individual stocks and their green characteristics that we consider in our analysis. This issue is particular relevant when looking ESG characteristics as they are not available for many individual stocks.

To the best of our knowledge, only Lindsey et al. (2021) use the IPCA methodology alongside ESG data. The authors apply IPCA by using as instruments also ESG ratings in addition to financial characteristics. Their findings show that neither systemic risk nor alphas associated to ESG characteristics exist. There are three main differences between our work and their one: first, we are able to clearly separate the factors associated to green characteristics and financial characteristics, so we can better assess the contribution of the two sets of factors to explain the panel of individual stock returns. The second difference is the choice of the data, we are focusing more on the environmental risk and we have more granular environmental data while we ignore the only-social and only-governance dimension (they appear only in the ESG score). Third, we analyze the contribution of the environmental factor to the returns within each sectors. We find that environmental characteristics seem to matter only for a few sectors, namely Energy and Utilities. This result is still coherent with Lindsey et al. (2021)'s findings, since when we analyze all the entire stock universe, we do not find any relevant contribution of the environmental factor to the explain time-series variation and the average of stock returns. Furthermore, our analysis are both in-sample and out-of-sample, whereas Lindsey et al. (2021) perform only in-sample analysis.

Since IPCA factors are long-short portfolios, they are investable portfolios. In the last part of the paper, we assess how these factors perform if used as hedging portfolios against climate risk indexes as the ones proposed by Engle et al. (2020), Faccini et al. (2021), and Ardia et al. (2021). We find that our green factor works well to hedge the Internetional Summit index by Faccini et al. (2021), and in more general, IPCA factors work better than standard factors as Fama-French 5 factors and climate-narrative portfolios.

The rest of the paper is organized as follows: Section 2 contains the literature review. Section 3 presents the methodology and in Section 4 are described the data used. Section 5 contains the empirical results and their discussion. In section 6 we compare our factors with climate risk indexes already in the literature. Finally, Section 7 concludes, and presents avenues for future research that we are currently exploring. Figures and tables of results are collected in the appendixes at the end of the paper.

2 Literature Review

In this work we propose a new conditional factor model for individual stocks based on the instrumental principal component analysis (IPCA) developed by Kelly et al. (2019). We use as instrumental characteristics for the factor loadings also environmental characteristics from different ESG data providers to see if one (or more) "green" factor is priced in the cross sectional returns. We assume that this factor is latent and the exposure of stocks to this factor is driven by the level of some company characteristics. We use IPCA (i) to estimate the factor, and (ii) to test which subset of characteristics best explains the exposure to this green factor.

To the best of our knowledge, only Lindsey et al. (2021) use the IPCA methodology alongside ESG data. The authors apply IPCA by using as instruments ESG ratings in addition to the financial characteristics. Their findings show that neither systemic risk nor alphas associated to ESG characteristics exist. There are three main differences between our work and their one: first, we are able to clearly separate the factors associated to green characteristics and financial characteristics, so we can perfectly assess the contribution of the two sets of factors to the R^2. The second difference is the choice of the data, we are focusing more on the Environmental risk and we have more granular Environmental data while we ignore the only-social and only-governance dimension (they appear only in the ESG score). Third, we analyze the contribution of the Environmental factors to the R^2 within each sectors: we assess the model by using all the data at our disposal and then, for each sector, we assess the contribution of each factor to explain cross sectional variation of stock returns and average returns within the sector of interest. We find that environmental characteristics does not matter, but for a few sectors. This result is still coherent with Lindsey et al. (2021)'s findings, since when we analyze all the entire stock universe, we do not find any relevant contribution of the environmental factors to the R^2. Furthermore our analysis are both in-sample and out-of-sample, whereas Lindsey et al. (2021) perform only in-sample analysis.

In more general, environmental and climate finance, is a quite recent field of study. Indeed, starting with Nordhaus (1977), researchers have studied the interactions between climate change and the economy but only recently they have focused on the so called climate finance, see e.g. Giglio et al. (2020), by looking at whether and how climate risks are priced in different asset classes.

In the last years the number of academic works that study the impact of climate change and environmental risk in the asset pricing models has increased. Most of these works start by arbitrary choosing a greenness measure and use it either to build a factor as a long/short portfolio, and study if it is priced in the market, or use it directly as an explanatory variable for returns. Bolton and Kacperczyk (2020b) and Bolton and Kacperczyk (2020a) find that US stocks associated to high carbon emissions present higher returns and that investors are demanding compensation for being exposed to carbon risk. Similarly, Hsu et al. (2020), by constructing a long/short portfolio, find a pollution premium and suggest that it is attribute to environmental policy uncertainty. Görgen et al. (2020) estimate carbon risk through a zero-cost portfolio defined as brown minus green (BMG) using companies from all the world. Their greenness measure is defined as combination of factors from four comprehensive ESG databases. They do not find significant carbon risk premium.Alessi et al. (2020) define a factor on the level of firm emissions and environmental transparency. This factor is priced in the European market and the lower the greenness and the transparency, the higher the risk premium and then there exist a negative *greenium*. Chava (2014) and Trinks et al. (2021) show that companies with higher emissions have higher capital cost. Ilhan et al. (2020) find that climate policy uncertainty is priced in option market. They analyze the S&P500 constituents and they show that the cost for protecting against downside risk using options is higher for companies with high carbon intensity. In et al. (2019) create a long short portfolio carbon efficient minus inefficient and they find abnormal returns for the carbon efficient companies. Cheema-Fox et al. (2019) test several decarbonization strategies and find that the more aggressive ones - in terms of decarbonization - performs better in terms of alpha. Also Garvey et al. (2018) find that lower carbon intensity stocks present higher profitability and then higher expected returns. This is due to the lower exposure to the carbon regulation. Other interesting works are Monasterolo and De Angelis (2018) study carbon premium in the period after the Paris Agreement; Zerbib (2020) develops an asset pricing model taking into account ESG integration. The author finds the existence of a *taste* effect (the investors' preference for the green stocks) and an *exclusion* effect. These effects are varying over the different industries. Pastor et al. (2021b) and Pastor et al. (2021a) provide a theoretical analysis of financial market equilibrium when investors show preferences for ESG. They show that green assets have lower expected returns than brown, but green assets may have higher realized returns due to the investors' tastes for green assets. They also show that US green stocks outperform brown as climate concerns increase.

A different approach is used by Engle et al. (2020). The authors build through textual analysis of newspapers a climate news index that proxies climate change risk. Then they use a mimicking portfolio approach to build climate change hedge portfolios. They also suggest additional important directions for future work, such as more and better integration of data to measure firm-level climate risk exposures and the development of alternative definitions of the climate change risks. With this paper we will explore some of these directions since we are able to treat large amount of characteristics and the climate change risk factor is allowed to be latent and therefore not defined ex-ante. Textual analysis is used also by Sautner et al. (2020), who describe a new method to assess firm-level climate change exposure. They use a machine learning keyword discovery algorithm to captures exposures related to opportunity, physical, and regulatory shocks associated with climate change from the earning call conferences of 10000 companies. Hong et al. (2020) and Giglio et al. (2020) provide a comprehensive literature review about climate finance.

Our work has two major differences versus the prior literature on climate risks: first, we do not define ex-ante the factors, instead we treat them as unobservable and we estimate factors that best describe covariation among the return data. In this way we avoid measurement and specification errors. Measurement problem is a well known problem of ESG data, often used to build these "green" factors. With this approach we are able to purge these variables from noise. The second difference is that the IPCA betas (i.e. factor loadings) are estimated by defining them as a linear function of company characteristics. These characteristics are the instrument used to estimate time-varying conditional betas. Furthermore, IPCA methodology allows to control for a vast number of characteristics, fact that would be impossible to treat with standard approaches as Fama-MacBeth regression. In this way there is no the problem to choose a little set of characteristics ex-ante and it is possible to jointly analyze a large set of characteristics letting the model to choose the relevant characteristics. However, this approach permits also to control for observable factors and then we can test if (i) factors already identified by the literature describe well the relevant risks, or whether latent risk factors are still missing, and if (ii) the exposure to these factors are depending on characteristics.

3 Methodology

The IPCA methodology used in this paper has been originally proposed by Kelly et al. (2019), and consists in a conditional factor-pricing model that assumes a set of either latent or observable factors, and firm-level characteristics to be used as instrument for the unobservable (potentially) time-varying loadings. The model in their seminal paper can be summarized by the following equations:

$$\begin{gathered} r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1} \ , \\ \alpha_{i,t} = z'_{i,t}\Gamma_\alpha + \nu_{\alpha,i,t} \ , \qquad \beta_{i,t} = z'_{i,t}\Gamma_\beta + \nu_{\beta,i,t} \ , \end{gathered} \tag{1}$$

which holds for all the N assets over T periods in which they are observed. The excess return of asset i at date $t+1$ is denoted as $r_{i,t+1}$, and depends on K factors collected in the vector f_{t+1}. The factors may be either latent or observable. The loadings are time-varying and depend linearly on a set of observable characteristics $z_{i,t}$, which are observed at date t. The $L \times 1$ vector $z_{i,t}$ contains the $L-1$ characteristics of the company i at time t and a constant that captures the systemic risk that is common for all the stocks. As in Kelly et al. (2019) $z_{i,t}$ also include an additional characteristic that is constant over time and over all the companies ("constant" characteristic). If the characteristics provide noisy information, this methodology isolates the signal by linearly combining the characteristic in the loadings and averages out the noise. Any behavior of dynamic loadings that is orthogonal to the instruments falls into $\nu_{\beta,i,t}$ such that risk exposures may not be perfectly recognized observing the characteristics. The $L \times K$ matrix Γ_β maps the instruments to the loadings. Companies change over the years, and their exposure to risk and expected returns of their stocks are allowed to evolve accordingly.

The parametrization in (1) make the model more efficient in capturing the time varying exposure compared to the static beta estimated using rolling-windows. Additionaly, this method allows us to include in our analysis much more information since L may be very large. On the other hand, K has to be small to keep the model parsimonious. Since $K << L$ this specification reduces the dimensionality of the problem. Indeed, starting from a large set of characteristics that are instruments of a exposure to a risk, we can aggregate this large information in K factors and its loadings by keeping only the relevant signals without the noise.

The solution of IPCA can be approximated by applying PCA to the returns of L managed portfolios described in the following equation:

$$x_{t+1} = \frac{Z_t' r_{t+1}}{N_{t+1}} \,, \tag{2}$$

where $r_{t+1} = [r_{1,t+1}, ...r_{i,t+1}, r_{N_{t+1},t+1}]'$, is the N_{t+1}-dimension vector collecting the the returns of all assets at date $t+1$. The L-dimensional vector x_{t+1} contains the returns on the managed portfolios at time $t+1$. The $N \times L$ matrix Z_t contains all the N vectors $z_{i,t}$. The managed portfolios can be seen as portfolios with weights given by the (rescaled and re-centered) values of the characteristics. If the characteristics were constant over time, IPCA estimation and "classical" PCA on managed portfolio would coincide. In the IPCA procedure is imposed the normalization $\Gamma_\beta' \Gamma_\beta = \mathbb{I}_K$ and that the mean of each factor is non negative. These identifying restrictions are the standard in latent factor models and do not alter the fit and the economic content of the model.

3.1 Model specification

In our specification we assume that there exist two type of factors: financial and green. By assumption, financial (resp. green) factor loadings are driven only by financial (resp. green) characteristics, in this way the factors are easily interpretable. Our model specification is

$$r_{t+1} = Z_t^F \Gamma_\beta^F f_{t+1}^F + Z_t^G \Gamma_\beta^G f_{t+1}^G + \epsilon_{t+1} \ , \tag{3}$$

where Z_t^F (Z_t^L) is a matrix $N \times L^F$ ($N \times L^G$) containing all the L^F financial (L^G green) characteristics for the N companies at the time t; Γ_β^F (Γ_β^G) is a matrix $L^F \times K^F$ ($L^G \times K^G$) mapping the financial (green) characteristics into the loadings of the financial (green) factors: f_{t+1}^F (f_{t+1}^G). We also impose the cross-sectional orthogonality of green characteristics from financial characteristics at each dates (see section 4.1 for details) and, equally important, the time-series orthogonality of green and financial factors, that is $\mathbb{E}[f_{t+1}^F {f_{t+1}^G}'] = 0$. By using this specification we are able to keep the factors well separated and to interpret them as only-financial and only-green factor.

3.2 Model estimation

To simplify the exposition of this problem, and coherently with our empirical application, we analyze the case with only one green factor, $K^G = 1$. Equation (3) can be written as the original IPCA specification with a constrained Γ_β that we call $\tilde{\Gamma}_\beta$:

$$r_{t+1} = Z_t \tilde{\Gamma}_\beta f_{t+1} + \epsilon_{t+1} \ , \tag{4}$$

where we define the first 3 elements in the R.H.S. of the last equation as:

$$r_{t+1} = \underbrace{\begin{bmatrix} Z_t^F & Z_t^G \end{bmatrix}}_{=Z_t} \underbrace{\begin{bmatrix} \Gamma_\beta^F & \mathbf{0}_{L^F \times K^G} \\ \mathbf{0}_{L^G \times K^F} & \Gamma_\beta^G \end{bmatrix}}_{=\tilde{\Gamma}_\beta} \underbrace{\begin{bmatrix} f_{t+1}^F \\ f_{t+1}^G \end{bmatrix}}_{=f_{t+1}} + \epsilon_{t+1} \ . \tag{5}$$

We estimate Γ_β^F, Γ_β^G, f_t^F, and f_t^G for all t in the equations (3) with a recursive procedure. Our estimator is defined by the minimization of the sum squared errors under the restriction that set of financial factors is orthogonal to the set of green factors. Let this sum of squared errors be defined as:

$$h(\Gamma_\beta^F, \Gamma_\beta^G f) = \sum_{t=1}^{T-1} (r_{t+1} - Z_t \tilde{\Gamma}_\beta f_{t+1})'(r_{t+1} - Z_t \tilde{\Gamma}_\beta f_{t+1}) \tag{6}$$

where $\tilde{\Gamma}_\beta$, defined in (5), contains Γ_β^F and Γ_β^G and $f = [f_2, f_3, ...f_T]$, where $f_{t+1} = [f_{t+1}^F{}' f_{t+1}^G{}']'$. The constraint is

$$\sum_{t=1}^{T-1} f_{t+1}^F f_{t+1}^G{}' = \mathbf{0}_{K^F \times 1} \ , \tag{7}$$

where $\mathbf{0}_{K^F \times 1}$ is the K^F-dimension vector of zeros. The orthogonality within financial factors and within green factors is also imposed by pre-multiplying these by appropriate rotation matrices at the end of the estimation procedure, as in the estimation algorithm for IPCA proposed by Kelly et al. (2019). Nevertheless, the orthogonality between green and financial factors cannot be imposed in this (ex-post) way due the presence of the $\mathbf{0}$ constraints in matrix $\tilde{\Gamma}_\beta$, defined in (5). Therefore, the one in (7) is the only constraint we need in the Lagrangian associated to our estimation, which is:

$$\mathcal{L}(\Gamma_\beta^F, \Gamma_\beta^G f, \lambda) = h(\Gamma_\beta^F, \Gamma_\beta^G f) - \lambda' g(f) \tag{8}$$

where $h(\Gamma_\beta^F, \Gamma_\beta^G, f)$ is equation (6), $g(f)$ is equation (7), λ is a vector $K^F \times 1$ containing the Lagrangian multipliers.

The values of Γ_β^F, Γ_β^G, and f_{t+1} minimizing (8), satisfy the first order conditions

$$\frac{\partial \mathcal{L}}{\partial f_{t+1}} = 0 \Rightarrow \hat{f}_{t+1} = (\widehat{\tilde{\Gamma}}'_\beta Z_t' Z_t \widehat{\tilde{\Gamma}}_\beta - \Lambda)^{-1} \widehat{\tilde{\Gamma}}'_\beta Z_t' r_{t+1}, \quad \forall t \tag{9}$$

where Λ is the matrix $\begin{bmatrix} \mathbf{0}_{K^F \times K^F} & \lambda \\ \lambda' & \mathbf{0}_{K^G \times K^G} \end{bmatrix}$.

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0 \Rightarrow \sum_{t=1}^{T-1} f_{t+1}^F f_{t+1}^{G\,\prime} = \mathbf{0}_{K^F \times 1}, \tag{10}$$

$$\frac{\partial \mathcal{L}}{\partial \Gamma^F} = 0 \Rightarrow \text{vec}(\hat{\Gamma^F}'_\beta) = \left(\sum_{t=1}^{T-1} Z^{F\prime}_t Z_t^F \otimes \hat{f}_{t+1}^F \hat{f^F}'_{t+1} \right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t^F \otimes \hat{f^F}'_{t+1} \right]' \left(r_{t+1} - Z_t^G \hat{\Gamma^G}_\beta \hat{f}_{t+1}^G \right) \right), \tag{11}$$

and

$$\frac{\partial \mathcal{L}}{\partial \Gamma^G} = 0 \Rightarrow \text{vec}(\hat{\Gamma^G}'_\beta) = \left(\sum_{t=1}^{T-1} Z^{G\prime}_t Z_t^G \otimes \hat{f}_{t+1}^G \hat{f^G}'_{t+1} \right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t^G \otimes \hat{f^G}'_{t+1} \right]' \left(r_{t+1} - Z_t^F \hat{\Gamma^F}_\beta \hat{f}_{t+1}^F \right) \right). \tag{12}$$

We estimate the model by using alternating least squares and we describe the algorithm estimation in the Appendix B.1. As in the original IPCA, we impose that $\tilde{\Gamma}'_\beta \tilde{\Gamma}_\beta = \mathbb{I}_{K_F + K_G}$ and that the factors are orthogonal.

3.3 Performance Measures

To assess the goodness of our model to fit the model, we report three main statistical measures: the Total, Predictive and Pricing $R^{2\prime}$s (Kelly et al. (2019), Kelly et al. (2021)). The Total R^2 is the fraction of variance in stock returns described by exposure to the common factors:

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t} \left(r_{i,t+1} - \hat{\beta}'_{i,t} \hat{f}_{t+1} \right)^2}{\sum_{i,t} r_{i,t+1}^2}. \tag{13}$$

The Predictive R^2 is the fraction of variance in stock returns described by conditional expected returns coming from exposure to the common factors:

$$\text{Predictive } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - \hat{\beta}'_{i,t}\hat{\lambda}\right)^2}{\sum_{i,t} r_{i,t+1}^2}. \tag{14}$$

In contrast to the Total R^2, the Predictive R^2 represents the fraction of panel return variation explained by the model's conditional expected returns, $\hat{\beta}'_{i,t}\hat{\lambda}$. The parameter $\hat{\lambda}$ is a vector containing the average factor returns over time.

The Pricing error R^2 is the fraction of the squared unconditional mean returns that is described by the factors:

$$\text{Pricing } R^2 = 1 - \frac{\sum_n \left(\frac{1}{|\tau_i|}\sum_{t\in\tau_i} r_{i,t+1} - \hat{\beta}'_{i,t}\hat{f}_{t+1}\right)^2}{\sum_n \left(\frac{1}{|\tau_i|}\sum_{t\in\tau_i} r_{i,t+1}\right)^2}. \tag{15}$$

In contrast to the previous two R^2 measures, this focuses on whether the model's fitted values do a good job of explaining assets' average returns.

4 Data

To perform our ananlysis we have to build the $N \times L^F$ and $N \times L^G$ matrices Z_{t-1}^F and Z_{t-1}^G for each time t that contains all the stock-level characteristics at time $t-1$ and the matrix of dimension $T \times N$ containing all the returns. Returns are from Jul 2008 to May 2020, they are used monthly. Characteristics may be either monthly or yearly. In the case of yearly characteristics, we use them at year t to predict returns from July $t+1$ to June $t+2$ as in Freyberger et al. (2020). To select the financial characteristics we follow Langlois (2021). From Refinitive we select:

- Market capitalizations: we build monthly lagged market capitalizations by using the last available market capitalization during the previous month.
- Total assets (WC02999): represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets. It is yearly.
- Investment: We measure total asset growth on an annual basis.

- β: we estimate each month t and for each stock i the following regression of daily excess returns on a constant and the excess returns on market portfolio using daily data over the previous 12 months:

$$r_{i,t_d} - r_{f,t_d} = \alpha_{i,t} + \beta_{i,t} \left(r_{mkt,t_d} - r_{f,t_d} \right) + \epsilon_{i,t_d} \tag{16}$$

- Price To Book Value (PTBV): this is the share price divided by the book value per share. It is the inverse of book to market and it is annual.
- Dividend Yield (DY): it expresses the dividend per share as a percentage of the share price. It is monthly.
- Lagged monthly return: total return for month $t-1$.
- Momentum: Total return from month $t-12$ to month $t-2$.
- Idiosyncratic volatility: Volatility of the CAPM regression residuals ϵ_{i,t_d}, in Equation (16).
- ROE (WC08301).

To compute green characteristics we use both MSCI ESG IVA and Refrinitv ESG (ex Asset 4) datasets whereas financial-characteristics and returns are from Refinitiv. To select our asset universe we start by selecting all the US equity data in MSCI ESG IVA (4415 companies). The advantages of using this database is well described in Pastor et al. (2021a). MSCI covers more than other ESG rating providers and these rating are generated from corporate documents, media and governments data. The ratings are updated at least on annual basis. For these 4415 companies we use the following green characteristics from MSCI ESG IVA:

- IVA_COMPANY_RATING (ESG): A company's final ESG Rating. To arrive at a final letter rating, the weighted average of the key issue scores are aggregated and companies are ranked from best (AAA) to worst (CCC).
- ENVIRONMENTAL_PILLAR_SCORE (ENV): The Environmental Pillar Score represents the weighted average of all Key Issues that fall under the Environment Pillar.
- ENVIRONMENTAL_PILLAR_WEIGHT (w_ENV): The Environmental Pillar Weight represents the sum of the weights of all Key Issues that fall under the Environment

Pillar.

- CARBON_EMISSIONS_SCORE (EMISS): This key issue is relevant to those companies with significant carbon footprints. Companies that proactively invest in low-carbon technologies and increase the carbon efficiency of their facilities or score higher on this key issue. Companies that allow legal compliance to determine product strategy, focus exclusively on activities to influence policy setting, or rely heavily on exploiting differences in regulatory frameworks score lower. (Score: 0-10).

For these companies we download similar green-characteristics from Refinitiv:

- Refinitiv's Environment Pillar Score - ENSCORE (ENV): it is the weighted average relative rating of a company based on the reported environmental information and the resulting three environmental category scores.
- Refinitiv's ESG Combined Score - TRESCGS (ESG): it is an overall company score based on the reported information in the environmental, social and corporate governance pillars (ESG Score) with an ESG Controversies overlay.
- Emissions Score - TRESGENERS (EMISS): emission category score measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes.
- Carbon intensity (CI): CO2 Equivalent Emissions Total divided by revenues (ENERDP023 / Revenues). The level of carbon intensity may depend on the industry to which a company belongs to. For example companies within basic materials sector, on average, have higher carbon intensity than companies in IT sector by nature. Therefore, following Heston and Rouwenhorst (1994) and Langlois (2021), we decompose the carbon intensity characteristic into industry and adjusted component. For each month we run a cross-sectional regression of carbon intensity for stock i at time t, $CI_{i,t}$, using all available stocks,

$$CI_{i,t} = \kappa + \sum_{ind=1}^{N_{ind,t}-1} I_{ind,t} \mathbb{I}_{i \in ind} + v_{i,t} \tag{17}$$

In equation (17), κ is a constant, $I_{ind,t}$ is the coefficient for industry ind's effect at time t, $\mathbb{I}_{i \in ind}$ is an indicator variable equal to one if stock i is in industry ind, $v_{i,t}$ is the regression residual that capture the adjusted component of stock i, and $N_{ind,t}$ is the number of stocks at time t in the industry ind.

Out of 4415 companies, 2814 have at least for one period all the financial characteristics and green (Refinitv) characteristics, Figure 1; 2564 companies have financial characteristics and green (MSCI) characteristics, Figure 2. The characteristics start from 2007 whereas returns start in July 2008. All the green characteristics are yearly.

We present two specification of the model. In the first ($Refinitiv$) we use as instruments all the financial characteristics and the green characteristics provided by Refinitiv: 10 financial characteristics, 5 green characteristics and the constant. Therefore, the model has 16 instruments (there is also the constant). In the second specification ($MSCI$) we use MSCI green characteristics instead of the ones by Refinitiv but we add also carbon intensity from Refinitiv. In this case the model has 17 instruments.

We standardize the characteristics by computing the respective cross-sectional ranks and normalizing them in the [-0.5, 0.5] interval. The normalized characteristics are the new instruments used in the vectors $z_{i,t}$. By using this normalization, we ensures that we can compare the coefficients estimates of different characteristic components in IPCA model.

4.1 Orthogonalized green characteristics

The set of green characteristics may be correlated with financial characteristics. To be able to exactly identify the information embedded in the green characteristics we cross exactly on which characteristics the relevant information lays, we impose the cross-sectional orthogonalization of green characteristics from financial characteristics. We apply the following regression $L^G \times T$ times (for each date and each green characteristic):

$$z_t^{G_i} = \alpha_{G_i,t} + Z_t^F \beta G_i, t + \epsilon_t^{G_i}, \quad \forall t, \ \forall G_i \tag{18}$$

where $z_t^{G_i}$ is the N_t-dimension vector containing all the observation of the $i-th$ green characteristic at the time t for all the N_t companies, $\alpha_{G_i,t}$ is a constant, Z_t^F is the $N_t \times L^F$ matrix containing all the L^F financial characteristic at the time t for all the N_t companies. $\beta G_i, t$ is the L^F-dimension vector containing the loadings and $\epsilon_t^{G_i}$ are the residual of the regression. The residuals are the new $i-th$ green characteristic that is orthogonal to the financial characteristics by construction.

5 Results

In this section we present the results of the estimation of the IPCA model. We decide to use a 6-factor ($K^F = 5$ and $K^G = 1$) model with no Γ_α. This choice comes up after testing several specifications and the 5-financial factor unrestricted model is the model with the lowest number of factors that has a non-significant Γ_α. For this reason we opt in favor of a restricted 6-factor model: we keep a low number of factors but enough to kill the Γ_α. First we show the estimated latent factors, then we decompose the model to disentangle the contribution of green and financial factors to the R^2. We perform the analysis both in-sample and out-of-sample.

5.1 The financial factors

The first analysis is in-sample. We estimate the model by using two different set of characteristics: Refinitiv and MSCI. The $\tilde{\Gamma}_\beta$ matrix's columns describe how each characteristic maps into companies loadings on each factor. For each financial (green) factor we plot the correspondent Γ_β^F (Γ_β^G) columns. Figure 4 displays the first columns of Γ_β^F from Refinitiv specification. Loadings on the Financial Factor 1 are driven mainly from the constant, the beta, assets, and size. This suggest to interpret it as a mixture of market, size, and value factors. Indeed, the constant is the equally weighted portfolio, therefore all the asset universe is exposed to Factor 1. Furthermore, companies with higher beta are more exposed to this factor. The fact that small companies (low size characteristic) are positively exposed to this factor, suggest that there is a size component. In addition, companies with high value of assets and low size are positively exposed to this factor (value-factor). The correlation between Factor 1 and Fama-French (Fama and French (2015)) market factor is 66%, 57% with size factor, and 66% with value factor. Factor 2 (Figure 5) has a strong market component (58% of correlation). Indeed companies with high betas and high market capitalization are positively exposed to this factor. Exposure to Factor 3 (Figure 6) is mostly determined by idiosyncratic volatility. Finally, Factor 4 and 5 are a mixture of many characteristics. In Appendix H we show the financial factor loadings when MSCI green characteristics are used. The results are very similar to the ones with Refinitiv characteristics. We test the significance of financial characteristics by following the procedure described in Appendix B.2. We find that the constant, betas, size, and idiosyncratic volatility are characteristics whose contribute to the models (both the specification with green characteristics from Refinitiv and from MSCI) are statistically significant with a confidence level at 99% (Tabels 5 and 6).

5.2 The green factor

In Appendix I and Appendix J are displayed the Γ_β^G for the two specifications of the model. For both specifications, we observe that carbon intensity sector component is the main driver of the exposure to this factor.

Figure 14 suggests to interpret this factor as a green factor. Indeed, companies within sectors with low carbon intensity are positively exposed to this factor. Also for the green factor we test the significance of green characteristics by following the procedure described in Appendix B.2. We find that the industrial component of carbon intesity is the only characteristic statistically significant for both the specification with a confidence level at 99% (Tabels 8 and 7). Emissions score (that is different in the two specifications) is statistically significant only in the Refinitiv specification with a confidence level at 95%. Figure 14 and 17 show that Emissions score characteristic has different sign in the two specifications. Since they have opposite sign, this means that the information in Refinitiv and MSCI characteristics is not consistent. Indeed, there exist a large literature documenting the different informational content, and construction methodologies of ESG data form different providers, see e.g. Berg et al. (2020), Busch et al. (2020), and Avramov et al. (2021). Therefore, there is no reason why, a priori, the latent factor we estimate using portfolios sorted on Refinitiv Emissions score characteristic coincides with the facotrs estimated from portfolio sorted on Emissions score characteristic.

5.3 In-sample R^2

Tables 1-2 in the appendix display the in-sample Total, Predictive and Pricing $R^{2\prime}$s, defined as in Kelly et al. (2019) and Kelly et al. (2021). We start by computing the $R^{2\prime}$s including only the first financial factor, then we add to the model also the second financial factor and compute the new $R^{2\prime}$s. We keep adding factors until we include all the $K^F = 5$ financial factors. Then, we add the green factor. In the last column we display the R^2's of the complete model, which includes both the green and financial factors. The model is estimated on the entire universe of US stocks for which we observe returns and characteristics in a certain month, but we measure the R^2's for the different sectors since green characteristics may be relevant only for some of them. In the $Refinitiv$ specification, the Energy sector Total R^2 (Table 1) increases considerably from 39.1% to 41.3%. Also the Utilities sector Pricing R^2 increases substantially from 24.2% to 29.6%. Similar results are founded with the $MSCI$ specification (Table 2). The Energy Total R^2 increases from 42.4% to 44.8% and Utilities Pricing R^2 increases substantially from 31.6% to 37.9%.

5.4 Out-of-sample R^2

In this section we analyze the out-of-sample results. To construct out-of-sample fit measures, we follow Kelly et al. (2021). We use an expanding estimation window, with the first out-of-sample observation occurring 48 months after the start of our sample. Since the entire period is 2008.07-2020.05, the first window in which the model is estimated consists in the four years 2008.07-2012.06, implying the first out-of-sample prediction of is produced for July 2012 using data available up to June 2012. For each window we estimate IPCA model and denote the resulting $\hat{\Gamma^r}_{\beta,t}$. Then, following Equation (3), we calculate the out-of-sample realized factor return at time $t+1$. The out-of-sample total R^2 compares r_{t+1} to $Z_t\hat{\Gamma}_{\beta,t}\hat{f}_{t+1}$ whereas the out-of-sample predictive R^2 compares $r_t + 1$ to $Z_t\hat{\Gamma}_{\beta,t}\lambda_t$ where λ_t is the factor return mean over the estimation window.

Tables 3-4 in the appendix display the out-of-sample Total, Predictive and Pricing $R^{2\prime}$s, defined as in Kelly et al. (2019) and Kelly et al. (2021). We follow the same procedure as in the in-sample analysis: the model is estimated on the entire universe of US stocks for which we observe returns and characteristics in a certain month, but we measure the R^2's for the different sectors. We also disentangle the contribution to the R^2's of each single factor as in the previous analysis.

Looking at the out-of-sample R^2 of Table 3, we can compare the last column F1-G1 that includes both green and financial factors with the column F1-F5, which considers only the financial factors. The Total R^2 increases more for Energy sector (almost +2.5%) when the green factor is added to the pure financial ones and the Pricing R^2 increases more for Utilities sector (almost +6%).

These sectors are involved in the most polluting activities and therefore it is reasonable to think that green characteristics are more relevant to explain the time-series variation and the average of the (excess) returns of their stocks, as measured by the Total and Predictive R^2. Similar results are founded with the $MSCI$ specification (Table 4) only for the Energy sector.

5.5 Factor tangency portfolio

We analyze out-of-sample Sharpe ratios for the tangency portfolios built by using IPCA factors. We disentangle the contribution of financial and green factors to the Sharpe ratio of the tangency portfolio (that is the optimal mean-variance portfolio). We calculate out-of-sample factor returns following the same recursive estimation approach from Kelly et al. (2019). The tangency portfolio return for a set of factors is also constructed on a purely out-of-sample basis by using the mean and covariance matrix of estimated factors through t and tracking the post-formation $t+1$ return. We recall that, by construction, IPCA factors are weighted averages of the excess returns of individual assets. Therefore these factors are portfolios, implying that they are potentially investable assets (if we neglect transaction costs) to be consider in the mean-variance portfolio optimization problem for the creation of the "Tangency portfolio". See e.g. Kelly et al. (2019) for tangency portfolios constructed form IPCA factors, and Lettau and Pelger (2020) for tangency portfolios constructed using RP-PCA factors. Out-of-sample IPCA Sharpe ratios are displayed in Tables 10. In Table 10 the $k-th$ column, with k = 1; 2; ...; 5, we show the Sharpe ratio of the portfolio invested in the first $k-th$ financial factors. So the difference between the Sharpe ratio in column k^{th} and $(k-1)^{th}$ is to attribute by the fact we add the k^{th} factor. In the 6^{th} we add the green factor to the 5 financial factors. In the MSCI specification the financial factors do not completely span, in a mean-variance sense, the green factor, and that adding our green factor to the financial ones improves the investment opportunity set of investors. This does not happen within the Refinitiv specification.[2]

[2] Note that, following the similar analyses in Kelly et al. (2019) and Lettau and Pelger (2020), in our analysis we are not taking into account the transaction costs involved into the formation and replacing of our out-of-sample optimal portfolios, and implicitly we are not imposing any short-selling constraints. Taking these issues

6 Hedging Climate News

The factors estimated can be interpret as investable portfolios, indeed Equation (9) shows how IPCA factors are portfolio of assets where the weights for the K portfolios (factors) are in the $K \times N$ dimension matrix $(\widehat{\widehat{\Gamma}}'_\beta Z_t' Z_t \widehat{\widehat{\Gamma}}_\beta - \Lambda)^{-1} \widehat{\widehat{\Gamma}}'_\beta Z_t'$. Since our green factor is in theory an investible portfolio, in this section, we analyze how it can be used to hedge climate shocks. As climate shocks we use the AR(1) innovations to the different climate news series. We have the two series from Engle et al. (2020), Wall Street Journal Climate Change New Index (WSJ) and CH Negative Climate Change News Index (CHNEG); four series from Faccini et al. (2021), US Climate Policy, International Summits, Global Warming, and Natural Disaster; one serie from Ardia et al. (2021), MCCC[3]. Since the series from Faccini et al. (2021) and Ardia et al. (2021) are daily, we compute the 30-days average and then we filter it with the AR(1).

To assess if our factors can be used to hedge climate shocks, we build different mimicking portfolios by using six different sets of assets. Each set is composed by 6 portfolios. The first two sets are composed by our 6 IPCA factors respectively with MSCI and Refinitiv characteristics. We compare their hedging performance against other four sets of assets: (i) Fama-French 5 factors (FF5) plus a long-short portfolio based on the ESG scores of MSCI. (ii) FF5 plus a long-short portfolio based on the ESG scores of Refinitiv. (iii) FF5 plus a portfolio long in the Invesco Global Clean Energy ETF (Ticker: PBD) and short in the Energy Select Sector SPDR Fund (Ticker: XLE). This portfolio represents an environment-friendly minus standard energy portfolio (GEME) and it is used also in Alekseev et al. (2021). (iv) FF5 plus the Litterman's "stranded asset" portfolio used by Jung et al. (2021). This portfolio (SAP) consists of a long position in the stranded asset index: 30% in XLE and 70% in VanEck Vectors Coal ETF (Ticker: KOL), and a short position in SPDR S&P 500 ETF Trust (Ticker: SPY).

To compare the performances of the different sets of assets, for each set we build two mimicking portfolio: one containing only standard factors as our 5 financial factors or the

into account is on our future research agenda.

[3]https://sentometrics-research.com

FF5, the environmental-related factor

$$CC_t = f_t^{F'} \beta^F + \epsilon_t \ ,$$

and the other one containing the 5 standard factors plus the environmental-related factor

$$CC_t = f_t^{F'} \beta^F + f_t^G \beta^G + \epsilon_t \ .$$

CC_t is the value of the climate index at time t, f_t^F is a 5-dimension column-vectors containing the returns of the standard factors (either 5 IPCA financial factors or Fama-French 5 factors) at time t, β^F is the vector containing the weights of the standard factors in the mimicking portfolio, f_t^G is a scalar containing the return of a environmental-related factor and β^G is its corresponding weight in the mimicking portfolio. For each regression we collect the adjusted R^2 to measure: if the additional environmental-related factors are useful to hedge climate news and which set of assets hedges climate news best. Table 12 displays the adjusted-R^2 of the different mimicking portfolios (rows) for the different climate indexes (columns). Our factors seem to hedge well specially the indexes provided by Faccini et al. (2021) related to International Summits and Natural Disasters. Furthermore, the increment of the adjusted-R^2 when the green factor is added, shows that in the case of International Summits, most of the hedging power is coming from the green factors. Also Natural Disaster index and CHNEG index are hedged quite well but the marginal effects of our green factors are not so strong.

7 Conclusions

Our preliminary conclusions are threefold. First, also green characteristics matter for describing returns, but only for Energy and Utilities sectors. Second, industrial component of carbon intensity seems to count much more than the other characteristics. This is coherent with the fact that green characteristics are more relevant for some sectors. Third, our factors present a good hedging power specially for the climate change news index *International Summits.*

[**INCOMPLETE**]

Bibliography

Alekseev, G., S. Giglio, Q. Maingi, J. Selgrad, and J. Stroebel (2021): "A Quantity-Based Approach to Constructing Climate Risk Hedge Portfolios," *Working Paper*.

Alessi, L., E. Ossola, and R. Panzica (2020): "What greenium matters in the stock market? The role of greenhouse gas emissions and environmental disclosures," *Working paper*.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht (2021): "Climate change concerns and the performance of green versus brown stocks," *Working Paper*.

Avramov, D., S. Cheng, A. Lioui, and A. Tarelli (2021): "Sustainable Investingwith ESG Rating Uncertainty," *Journal Finacial Economics (forthcoming)*.

Berg, F., J. F. Kölbel, and R. Rigobon (2020): "Aggregate Confusion: The Divergence of ESG Ratings," *Working paper*.

Billio, M., M. Costola, I. Hristova, C. Latino, and L. Pelizzon (2020): "Inside the ESG Ratings: (Dis)agreement and Performance," *Working Paper*.

Bolton, P. and M. T. Kacperczyk (2020a): "Carbon Premium around the World," *Working Paper*.

——— (2020b): "Do Investors Care about Carbon Risk?" *Working Paper*.

Busch, T., M. Johnson, and T. Pioch (2020): "Corporate carbon performance data: Quo vadis?" *Journal of Industrial Ecology*, n/a.

Chava, S. (2014): "Environmental Externalities and Cost of Capital," *Management Science*, 60, 2223–2247.

Cheema-Fox, A., B. R. LaPerla, G. Serafeim, D. Turkington, and H. Wang (2019): "Decarbonization Factors," *Working Paper*.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel (2020): "Hedging Climate Change News," *The Review of Financial Studies*, 33, 1184–1216.

Faccini, R., R. Matin, and G. Skiadopoulos (2021): "Dissecting Climate Risks: Are they Reflected in Stock Prices?" *Working Paper.*

Fama, E. F. and K. R. French (1993): "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

——— (2015): "A five-factor asset pricing model," *Journal of Financial Economics*, 116, 1–22.

Freyberger, J., A. Neuhierl, and M. Weber (2020): "Dissecting Characteristics Nonparametrically," *The Review of Financial Studies*,.

Garvey, G. T., M. Iyer, and J. Nash (2018): "Carbon Footprint and Productivity: Does the "E" in ESG Capture Efficiency as Well as Environment?" *Journal of Investment Management.*

Giglio, S., B. T. Kelly, and J. Stroebel (2020): "Climate Finance," *Working paper.*

Görgen, M., A. Jacob, M. Nerlinger, R. Riordan, M. Rohleder, and M. Wilkens (2020): "Carbon Risk," *Working Paper.*

Heston, S. L. and K. Rouwenhorst (1994): "Does industrial structure explain the benefits of international diversification?" *Journal of Financial Economics*, 36, 3–27.

Hong, H., G. A. Karolyi, and J. A. Scheinkman (2020): "Climate Finance," *The Review of Financial Studies*, 33, 1011–1023.

Hsu, P.-H., K. Li, and C.-Y. Tsou (2020): "The Pollution Premium," *Working Paper.*

Ilhan, E., Z. Sautner, and G. Vilkov (2020): "Carbon Tail Risk," *The Review of Financial Studies*, hhaa071.

In, S. Y., K. Y. Park, and A. H. B. Monk (2019): "Is 'Being Green' Rewarded in the Market?: An Empirical Investigation of Decarbonization and Stock Returns," *Working Paper.*

Jung, H., R. F. Engle, and R. Berner (2021): "Climate Stress Testing," *Working Paper.*

Kelly, B. T., D. Palhares, and S. Pruitt (2021): "Modeling Corporate Bond Returns," *Journal of Finance (2021) forthcoming.*

Kelly, B. T., S. Pruitt, and Y. Su (2019): "Characteristics are covariances: A unified model of risk and return," *Journal of Financial Economics*, 134, 501–524.

Langlois, H. (2021): "What Matters in a Characteristic?" *Working Paper.*

Lettau, M. and M. Pelger (2020): "Factors That Fit the Time Series and Cross-Section of Stock Returns," *The Review of Financial Studies.*

Lindsey, L., S. Pruitt, and C. Shiller (2021): "The Cost of ESG Investing," *Working Paper.*

Monasterolo, I. and L. De Angelis (2018): "Blind to Carbon Risk? An Analysis of Stock Market's Reaction to the Paris Agreement," *Working Paper.*

Nordhaus, W. (1977): "Economic Growth and Climate: The Carbon Dioxide Problem," *American Economic Review*, 67, 341–46.

Pastor, L., R. F. Stambaugh, and L. A. Taylor (2021a): "Dissecting Green Returns," *Working Paper.*

——— (2021b): "Sustainable Investing in Equilibrium," *Journal of Financial Economics, Forthcoming.*

Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang (2020): "Firm-level Climate Change Exposure," *Working Paper.*

Trinks, A., G. Ibikunle, M. Mulder, and B. Scholtens (2021): "Carbon Intensity and the Cost of Equity Capital," *The Energy Journal.*

Zerbib, O. D. (2020): "A Sustainable Capital Asset Pricing Model (S-CAPM): Evidence from Green Investing and Sin Stock Exclusion," *Working Paper.*

Appendix A   Number of stocks per industry

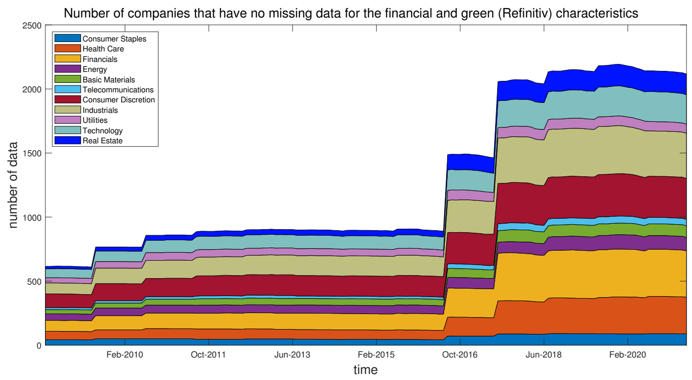

Figure 1: Number of companies that do not have missing data for the financial characteristics and the green (Refinitiv) characteristics. They are divided by industries

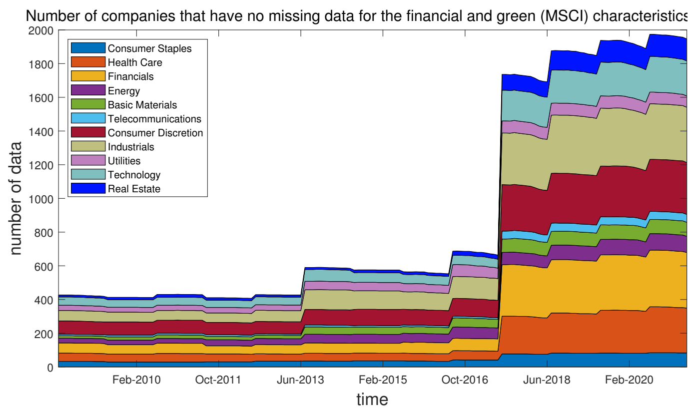

Figure 2: Number of companies that do not have missing data for the financial characteristics and the green (MSCI) characteristics. They are divided by industries

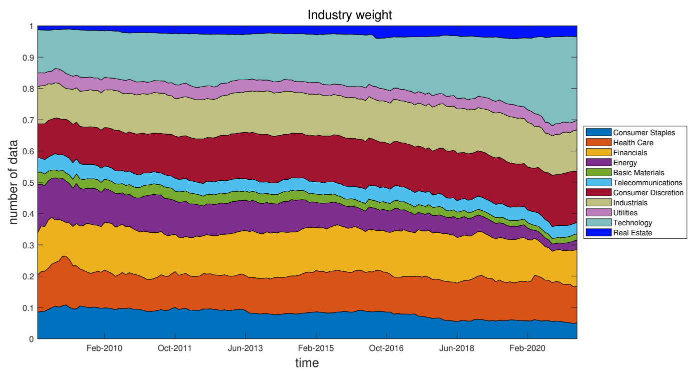

Figure 3: Distribution weighted by market capitalization of the industries

Appendix B Estimation and tests

B.1 Estimation

To estimate our constrained IPCA we use a similar recursive method to the one proposed in Kelly et al. (2019). The steps we follow are the following:

1. By using the original IPCA estimator, we compute Γ_β^F and Γ_β^G in Equations (19) and (20) to have $\tilde{\Gamma}_\beta^{(0)}$, the initial guess of $\tilde{\Gamma}_\beta$ that we need to start the numerical algorithm to solve the system of first order conditions.

$$r_{t+1} = Z_t^F \Gamma_\beta^F f_{t+1}^F + \epsilon_{t+1}^* \tag{19}$$

$$r_{t+1} = Z_t^G \Gamma_\beta^G f_{t+1}^G + \epsilon_{t+1}^{**} \tag{20}$$

2. With $\tilde{\Gamma}_\beta^{(0)}$, we compute $f_{t+1}^{(0)}$ for all the periods by using Equation (9) and Equation (10). We collect these values in the matrix $f^{(0)}$ with dimension $K \times T$.

3. With $f^{(0)}$ and $\Gamma_\beta^{G(0)}$ (resp. $\Gamma_\beta^{F(0)}$), we estimate $\Gamma_\beta^{F(1)}$ (resp. $\Gamma_\beta^{G(1)}$) by using Equation (11) (resp. (12)). With $\Gamma_\beta^{F(1)}$ and $\Gamma_\beta^{G(1)}$ we build $\tilde{\Gamma}_\beta^{(1)}$ [4].

4. We impose that $\tilde{\Gamma}_\beta^{(1)}$ is orthogonal:

   (a) we calculate the Cholesky factorization of both $\Gamma^{F(1)'}{}_\beta \Gamma^{F(1)}{}_\beta$ and $\Gamma^{G(1)'}{}_\beta \Gamma^{G(1)}{}_\beta$ and we call the upper triangular matrices U^F and U^G:

$$\Gamma^{F(1)'}{}_\beta \Gamma^{F(1)}{}_\beta = U^{F'} U^F$$

$$\Gamma^{G(1)'}{}_\beta \Gamma^{G(1)}{}_\beta = U^{G'} U^G$$

   (b) We apply the svd decomposition to $U^F f^{F(1)} f^{F(1)'} U^{F'}$ and $U^G f^{G(1)} f^{G(1)'} U^{G'}$:

$$U^F f^{F(1)} f^{F(1)'} U^{F'} = L^F S^F V^F$$

$$U^G f^{G(1)} f^{G(1)'} U^{G'} = L^G S^G V^G$$

[4] $\Gamma_\beta^{G(k)}$ and $\Gamma_\beta^{F(k)}$ are the submatrices of $\tilde{\Gamma}_\beta^{(k)}$, see Equation (**??**).

(c) We compute $\tilde{\Gamma}_{\beta}^{(1)}$ by using the rotation matrices of $\Gamma^{F(1)}{}_{\beta}$ and $\Gamma^{G(1)}{}_{\beta}$:

$$\tilde{\Gamma}_{\beta}^{(1)} = \begin{bmatrix} \Gamma^{F(1)}{}_{\beta} \times \left(U^F\right)^{-1} \times L^F & \mathbf{0}_{L^F \times K^G} \\ \mathbf{0}_{L^G \times K^F} & \Gamma^{G(1)}{}_{\beta} \times \left(U^G\right)^{-1} \times L^G \end{bmatrix}$$

and the matrix $f^{(1)}$

$$f^{(1)} = \begin{bmatrix} \left(L^F\right)^{-1} U^F f^F \\ \left(L^G\right)^{-1} U^G f^G \end{bmatrix}$$

5. We repeat the procedure from point 3 as many times until $f^{(k)} \simeq f^{(k+1)}$ and $\tilde{\Gamma}_{\beta}^{(k)} \simeq \tilde{\Gamma}_{\beta}^{(k+1)}$.

B.2 Testing instrument significance

For the test we apply the same procedure described in Kelly et al. (2019) by adapting it to our specification. We want to investigate whether a given instrument significantly contribute to β_t (defined as $Z_t \tilde{\Gamma}_{\beta}$ from Equation (1)) while simultaneously controlling for all other characteristics. Here, we show how to test a given instrument when it is a financial characteristic but, with the same methodology, we can test green instruments as well. To formulate the hypotheses, we partition the parameter matrix as

$$\Gamma_{\beta}^{F} = [\gamma_{\beta,1}, ..., \gamma_{\beta,L^F}]'$$

where $\gamma_{\beta,l}$ is a $K^F \times 1$ vector that maps the financial characteristic l to the loadings on the K^F financial factors. The characteristic in question that we want to test is the l^{th}. The hypothesis that we want to test are

$$\begin{aligned} H_0 :& \Gamma_{\beta}^{F} = [\gamma_{\beta,1}, ..., \gamma_{\beta,l-1}, \mathbf{0}_{K^F \times 1}, \gamma_{\beta,l+1}, ..., \gamma_{\beta,L^F}]' \\ H_1 :& \Gamma_{\beta}^{F} = [\gamma_{\beta,1}, ... \gamma_{\beta,L^F}]' \end{aligned}$$

Our Wald-type statistic in this case is

$$W_{\beta,l} = \gamma_{\beta,l}' \gamma_{\beta,l}.$$

Inference for this test is based on the same residual bootstrap described in Kelly et al. (2019). First we estimate the model as in Appendix B.1. Then we can rewrite the model as

$$x_{t+1} = Z_t^{F\prime} \left(r_{t+1} - Z_t^G \hat{\Gamma^G}_\beta \hat{f}_{t+1}^G \right) = Z_t^{F\prime} Z_t^F \Gamma_\beta^F f_{t+1}^F + Z_t^{F\prime} \epsilon_{t+1}.$$

By applying the same bootstrap procedure as in Kelly et al. (2019), we generate 10000 bootstrap samples under H_0 and for each sample we re-estimate the model and record the estimated test statistic

$$W_{\beta,l}^b = \gamma_{\beta,l}^{b\,\prime} \gamma_{\beta,l}^b.$$

Finally we draw inferences from the empirical null distribution by calculating a p-value as the fraction of bootstrapped $W_{\beta,l}^b$ statistics that exceed the value of $W_{\beta,l}$ from the actual data.

Appendix C In Sample R^2's, green characteristics from Refinitiv

	R^2	F1	F1-F2	F1-F3	F1-F4	F1-F5	F1-G1
Entire Asset Universe	Total	22.35	31.15	31.99	33.72	35.98	36.44
	Predictive	0.83	0.85	0.85	1.17	1.31	1.32
	Pricing	4.27	28.21	28.21	32.98	36.13	37.09
Consumer Staples	Total	11.2	13.58	14.51	16.44	21.63	21.52
	Predictive	0.31	0.32	0.31	0.6	0.85	0.78
	Pricing	-25.81	-32.77	-39.64	-41.08	-39.66	-39.37
Health Care	Total	5.92	13.59	13.9	18.34	19.95	20.11
	Predictive	0.61	0.63	0.62	1.09	1.3	1.28
	Pricing	1.35	19.17	18.64	24.31	24.82	26.27
Financials	Total	33.74	40.6	41.99	42.77	44.91	46.08
	Predictive	1.32	1.34	1.33	1.36	1.44	1.41
	Pricing	-16.48	30.66	34.69	35.86	42.48	39.51
Energy	Total	28.41	37.03	39.14	39.07	39.19	41.33
	Predictive	-0.05	-0.06	-0.06	-0.15	-0.4	-0.31
	Pricing	11.52	24.33	23.37	13.71	13	18.73
Basic Materials	Total	26.74	35.06	36.12	36.35	37.86	38.28
	Predictive	0.67	0.67	0.68	0.81	0.85	0.85
	Pricing	20.58	33.68	34.45	37.63	36.45	35.82
Telecommunications	Total	11.92	17.17	17.71	20.13	21.67	21.59
	Predictive	0.5	0.51	0.51	0.58	0.52	0.44
	Pricing	3.01	23.71	22.97	18.78	18.74	17.13
Consumer Discretion	Total	24.76	33.6	34.38	35.61	37.72	37.76
	Predictive	1	1.02	1.01	1.43	1.6	1.62
	Pricing	10.9	35.24	37.39	41.58	46.67	47.82
Industrials	Total	28.7	40.34	40.74	41.54	44.68	44.39
	Predictive	1.23	1.25	1.26	1.69	2.06	2.02
	Pricing	14.19	43.11	42.09	50.88	59.29	58.28
Utilities	Total	7.07	9.02	10.42	11.31	26.38	27.99
	Predictive	1.09	1.09	1.09	1.44	1.69	1.78
	Pricing	-17.85	5.62	5.49	10.82	24.22	29.15
Technology	Total	14.37	28.49	28.47	32.4	34.35	34.65
	Predictive	1.03	1.06	1.06	1.9	2.29	2.36
	Pricing	-0.28	35.24	34.23	49.47	54.4	55.65
Real Estate	Total	35.95	43.05	44.11	45.7	49.69	49.73
	Predictive	1.03	1.05	1.04	1.25	1.08	1.09
	Pricing	15.35	32.07	25.2	29.55	20.01	24.68

Table 1: This table shows the in-sample R^2 for the specification with 10 financial characteristics and 4 green characteristics from Refinitiv. The financial characteristics are the same used by Langlois (2021) built following Freyberger et al. (2020) and are: market capitalization, total assets, investment, β, book to market, dividend yield, lagged monthly return, momentum, idiosyncratic volatility, ROE. The green characteristics are: ESG rating, environmental score, emissions score and Carbon intensity (CO_2 emissions scope 1 and 2 normalized by revenues).

Appendix D In Sample R^2's, green characteristics from MSCI

	R^2	F1	F1-F2	F1-F3	F1-F4	F1-F5	F1-G1
	Total	18.68	32.37	33.22	35.63	37.74	38.25
Entire Asset Universe	Predictive	0.93	0.88	0.89	1.19	1.32	1.33
	Pricing	3.46	30.59	26.88	35.09	37.16	37.55
	Total	8.86	14.44	14.2	16.74	23.57	23.4
Consumer Staples	Predictive	0.5	0.47	0.49	0.86	1.13	1.11
	Pricing	-2.12	-10.33	-16.4	-19.84	-18.01	-20.59
	Total	5.08	13.11	13.09	18.4	19.9	20.08
Health Care	Predictive	0.55	0.51	0.52	0.94	1.17	1.16
	Pricing	3	17.55	14.05	19.67	20.05	20.77
	Total	29.97	42.54	44.35	44.98	46.83	48.16
Financials	Predictive	1.28	1.24	1.23	1.13	1.08	0.97
	Pricing	-21.89	36.56	31.63	33.11	37.97	34.37
	Total	23.6	39.16	41.31	42	42.42	44.79
Energy	Predictive	0.01	0.04	0.04	-0.08	-0.35	-0.23
	Pricing	18.53	33.45	30.24	24.21	23.57	28.14
	Total	23.29	37.7	38.75	39.02	40.39	40.48
Basic Materials	Predictive	0.93	0.89	0.91	1.1	1.15	1.12
	Pricing	21.07	48.69	46.91	57.35	59	54.9
	Total	9.86	16.84	16.72	20.57	22.16	22.69
Telecommunications	Predictive	0.55	0.54	0.54	0.55	0.54	0.43
	Pricing	-8.45	18.9	14.2	17.08	18.9	17.36
	Total	19.78	35.32	36.04	38.18	39.82	39.82
Consumer Discretion	Predictive	1.23	1.17	1.17	1.63	1.77	1.77
	Pricing	8.42	40.28	38.91	49.15	51.78	52.58
	Total	23.54	41.57	42.43	43.51	46.45	46.34
Industrials	Predictive	1.29	1.22	1.25	1.59	1.98	1.95
	Pricing	2.96	42.58	37.67	55.58	63.21	61.78
	Total	5.07	6.72	9.39	11.16	26.04	27.24
Utilities	Predictive	1.2	1.18	1.2	1.38	1.47	1.71
	Pricing	-34.32	7.66	-0.4	19.92	31.6	37.87
	Total	11.89	28.67	28.24	34.03	36.02	36.24
Technology	Predictive	1.17	1.06	1.1	2.03	2.54	2.63
	Pricing	-5.93	27.02	20.28	45.37	48.56	49.75
	Total	31.06	47.19	48.8	50.54	53.13	53.18
Real Estate	Predictive	1.16	1.11	1.1	1.26	1.12	1.17
	Pricing	19.37	38.86	30.73	35.13	25.74	31.22

Table 2: This table shows the in-sample R^2 for the specification with 10 financial characteristics and 5 green characteristics. The financial characteristics are from Refinitiv and are the same used by Langlois (2021) built following Freyberger et al. (2020) and are: market capitalization, total assets, investment, β, book to market, dividend yield, lagged monthly return, momentum, idiosyncratic volatility, ROE. The green characteristics are 4 from MSCI ESG IVA and 1 from Refinitiv: ESG rating, environmental score, emissions score and Carbon intensity (CO_2 emissions scope 1 and 2 normalized by revenues).

Appendix E Out of Sample R^2's, green characteristics from Refinitiv

	R^2	F1	F1-F2	F1-F3	F1-F4	F1-F5	F1-G1
	Total	18.51	27.72	29.24	31.02	32.81	33.27
Entire Asset Universe	Predictive	0.76	0.41	0.25	0.72	1.07	1.08
	Pricing	-28.83	-2.25	-3.55	13.87	17.63	18.7
	Total	8.57	10.74	12.34	14.29	18.78	18.63
Consumer Staples	Predictive	0.12	-0.05	-0.3	0.03	0.23	0.14
	Pricing	-95.36	-105.63	-112.07	-106.29	-101.99	-100.74
	Total	4.03	11.13	13.95	16.83	17.64	17.86
Health Care	Predictive	0.58	0.24	0.18	0.85	1.14	1.13
	Pricing	-18.74	0.52	0.74	16.57	19.71	20.29
	Total	34.54	43.64	43.92	44.41	47.48	48.95
Financials	Predictive	1.62	1.13	0.91	0.85	1.39	1.36
	Pricing	0.03	36.75	30.13	48.31	55.26	54.59
	Total	27.63	35.17	37.49	37.88	37.54	39.76
Energy	Predictive	-0.26	-0.21	-0.58	-0.46	-0.58	-0.5
	Pricing	7.67	10.51	3.63	-7.33	-9.69	-3.16
	Total	22.65	30.39	31.21	32.54	33.09	33.47
Basic Materials	Predictive	0.26	0.11	-0.1	0.15	0.48	0.45
	Pricing	-22.41	-0.55	3.85	17.46	20.79	20.77
	Total	9.16	11.89	13.66	15.5	17.3	17.72
Telecommunications	Predictive	0.8	0.54	0.46	0.78	0.92	0.86
	Pricing	-23.39	-4.52	-4.22	0.54	0.02	-0.98
	Total	19.32	29.64	31.15	32.87	34.36	34.36
Consumer Discretion	Predictive	0.91	0.55	0.39	0.98	1.28	1.29
	Pricing	-42.31	-2.7	-0.02	27.69	32.81	33.18
	Total	23.28	36.97	37.23	38.62	40.95	40.58
Industrials	Predictive	1.21	0.6	0.45	0.86	1.81	1.75
	Pricing	-40.74	-0.54	-3.46	21.42	30.85	29.27
	Total	7.22	5.54	7.14	8.63	24.02	22.45
Utilities	Predictive	1.33	1.06	0.93	1.48	1.88	1.95
	Pricing	-71.85	-39.13	-46.35	-14.6	4.2	9.87
	Total	9.19	22.48	23.83	27.91	29.5	29.84
Technology	Predictive	1.13	0.49	0.48	1.54	2.24	2.36
	Pricing	-67.18	-16.19	-17.06	19.63	24.93	26.71
	Total	29.66	38.99	40.51	41.47	45.98	46.06
Real Estate	Predictive	0.65	0.53	0.42	0.78	0.43	0.45
	Pricing	19.09	30.5	25.42	30.04	24.2	27.46

Table 3: This table shows the out-of-sample R^2 for the specification with 10 financial characteristics and 4 green characteristics from Refinitiv. The financial characteristics are the same used by Langlois (2021) built following Freyberger et al. (2020) and are: market capitalization, total assets, investment, β, book to market, dividend yield, lagged monthly return, momentum, idiosyncratic volatility, ROE. The green characteristics are: ESG rating, environmental score, emissions score and Carbon intensity (CO_2 emissions scope 1 and 2 normalized by revenues). The out-of-sample estimation is performed with expanding window over the period 2007.01 - 2019.12. The first estimation window consists in the first 4 years of the sample.

Appendix F Out of Sample R^2's, green characteristics from MSCI

	R^2	F1	F1-F2	F1-F3	F1-F4	F1-F5	F1-G1
Entire Asset Universe	Total	15.42	30.52	31.08	33.88	35.57	36.05
	Predictive	0.82	0.39	0.28	0.92	1.03	1.03
	Pricing	-15.62	13.16	8.01	20.8	21.61	22.19
Consumer Staples	Total	7.57	13.11	12.93	16.43	21.67	21.74
	Predictive	0.59	0.34	0.09	0.67	0.63	0.63
	Pricing	1.99	-0.06	-6.33	-7.54	-6.48	-5.3
Health Care	Total	3.76	12	12.11	18.01	18.47	18.69
	Predictive	0.53	0.22	0.13	0.81	1.01	1.03
	Pricing	-19.54	-2.12	-6.98	2.32	2.41	2.73
Financials	Total	30.3	44.84	46.09	46.35	49.83	51.65
	Predictive	1.45	0.92	0.65	0.8	0.79	0.69
	Pricing	13.94	49.56	41.4	51.34	53.31	53.38
Energy	Total	22.39	38.86	40.35	40.84	40.75	43.12
	Predictive	-0.16	-0.45	-0.48	-0.36	-0.52	-0.44
	Pricing	10.75	18.93	13.96	3.69	2.88	6.44
Basic Materials	Total	19.98	35.55	36.23	36.78	37.69	37.8
	Predictive	0.59	0.15	0.02	0.5	0.57	0.52
	Pricing	-41.58	9.24	4.98	21.44	23.94	22.36
Telecommunications	Total	8.22	13.68	13.62	17.92	19.32	19.86
	Predictive	0.63	0.39	0.41	0.59	0.63	0.52
	Pricing	-28.95	-2.71	-10.47	-8.6	-7.88	-8.47
Consumer Discretion	Total	15.33	33.53	34.4	36.56	37.63	37.51
	Predictive	1.09	0.63	0.56	1.39	1.44	1.44
	Pricing	-16.69	26.74	25.46	44.07	44.64	44.76
Industrials	Total	18.15	39.43	39.76	41.26	43.41	43.24
	Predictive	1.2	0.62	0.47	1.29	1.71	1.66
	Pricing	-33.8	18.19	10.75	39.85	44.78	43.45
Utilities	Total	5.02	3.5	4.56	7.33	24.79	23.83
	Predictive	1.36	1.11	0.91	1.42	1.35	1.59
	Pricing	-77.68	-30.66	-42.85	-2.17	15.13	18.15
Technology	Total	7.89	24.94	24	31.45	32.75	32.88
	Predictive	1.1	0.52	0.42	1.79	2.3	2.41
	Pricing	-50.52	-8.6	-16.54	19.2	19.85	20.45
Real Estate	Total	26.03	45.43	46.45	48.12	51.66	51.56
	Predictive	0.91	0.55	0.49	0.97	0.47	0.49
	Pricing	41.64	47.05	40.31	38.97	35.89	38.65

Table 4: This table shows the out-of-sample R^2 for the specification with 10 financial characteristics and 5 green characteristics. The financial characteristics are from Refinitiv and are the same used by Langlois (2021) built following Freyberger et al. (2020). The green characteristics are 4 from MSCI ESG IVA and 1 from ESG Refinitiv (Asset 4). The financial characteristics are: market capitalization, total assets, investment, β, book to market, dividend yield, lagged monthly return, momentum, idiosyncratic volatility, ROE. The green characteristics are: ESG rating, environmental score, environmental weight, emissions score. In addition we add Carbon intensity (CO_2 emissions scope 1 and 2 normalized by revenues) from ESG Refinitiv (Asset 4). The out-of-sample estimation is performed with expanding window over the period 2007.01 - 2019.12. The first estimation window consists in the first 4 years of the sample.

Appendix G Γ_β^F coefficient estimates using Refinitiv green characteristics

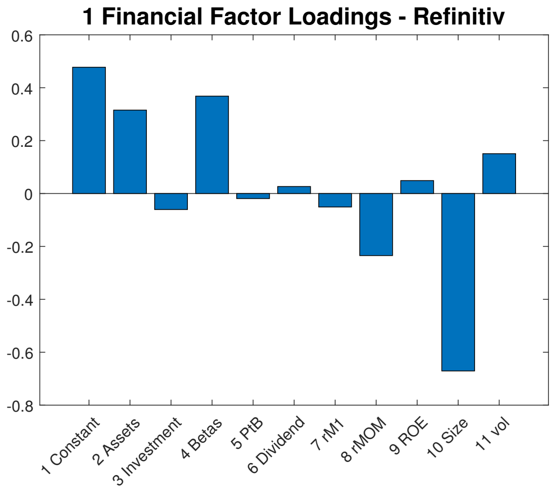

Figure 4

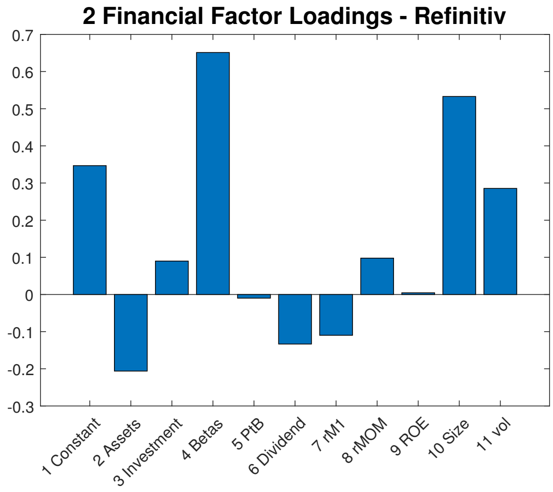

Figure 5

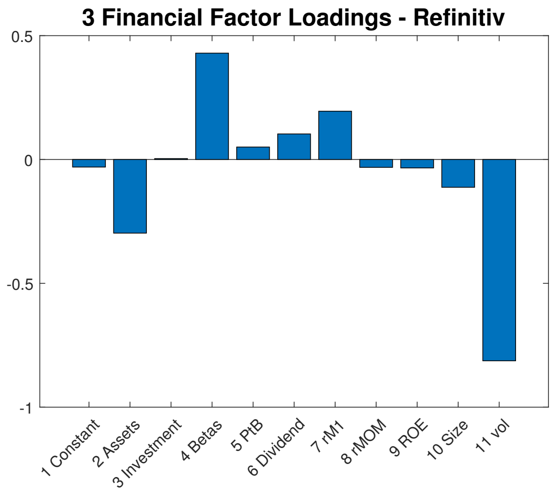

Figure 6

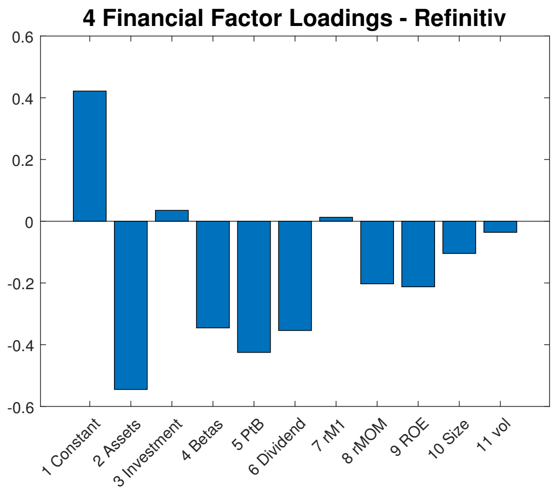

Figure 7

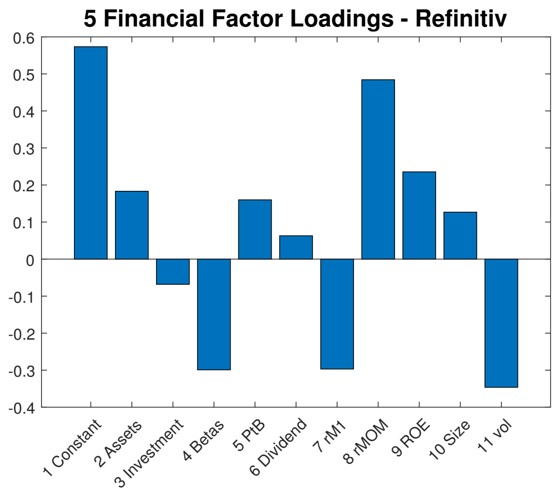

Figure 8

	F1	F2	F3	F4	F5	$p-$value	
Constant	0.48	0.35	-0.03	0.42	0.57	0	***
Assets	0.32	-0.21	-0.3	-0.55	0.18	0	***
Investment	-0.06	0.09	0	0.04	-0.07	0.32	
Betas	0.37	0.65	0.43	-0.35	-0.3	0	***
PtB	-0.02	-0.01	0.05	-0.42	0.16	0.041	**
Dividend	0.03	-0.13	0.1	-0.35	0.06	0.106	
rM1	-0.05	-0.11	0.19	0.01	-0.3	0.123	
rMOM	-0.23	0.1	-0.03	-0.2	0.48	0.106	
ROE	0.05	0	-0.03	-0.21	0.24	0.07	*
Size	-0.67	0.53	-0.11	-0.1	0.13	0	***
vol	0.15	0.29	-0.81	-0.04	-0.35	0	***

Table 5: Γ_β^F matrix from Refinitiv specification and $p-$values for testing the significance of any characteristic to contribute to the model, while simultaneously controlling for all other characteristics

Appendix H Γ_β^F coefficient estimates using MSCI green characteristics

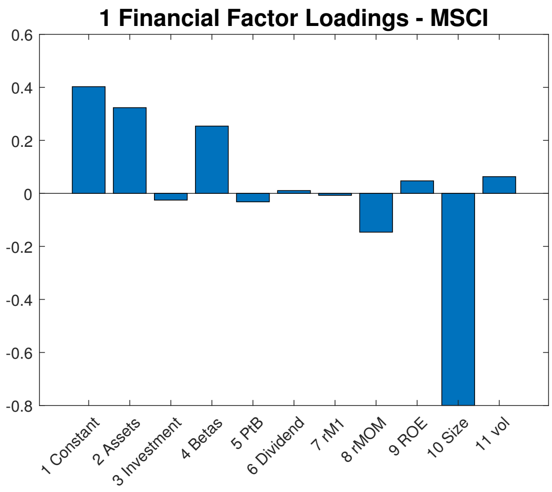

Figure 9

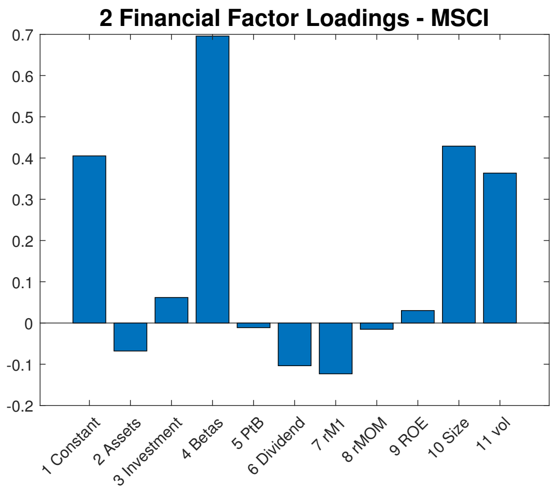

Figure 10

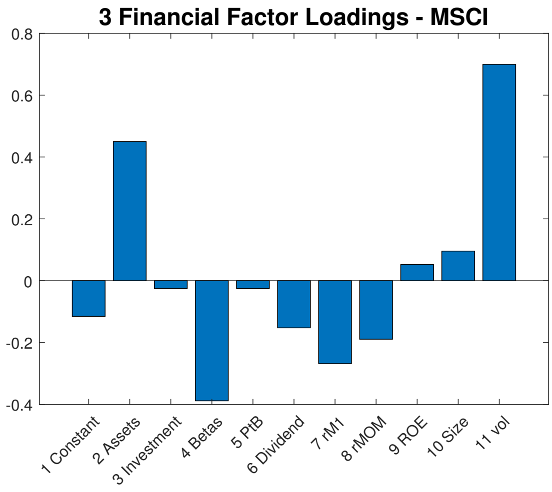

Figure 11

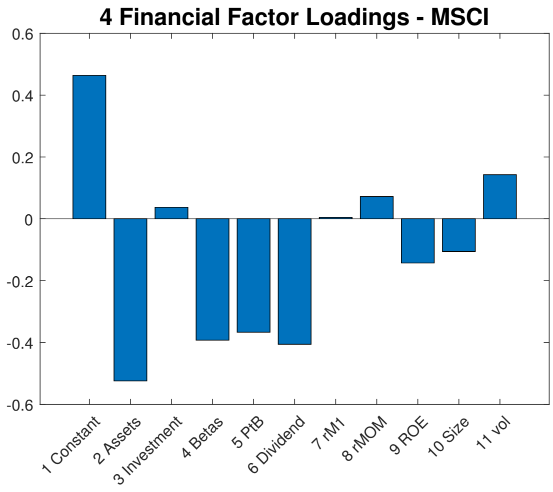

Figure 12

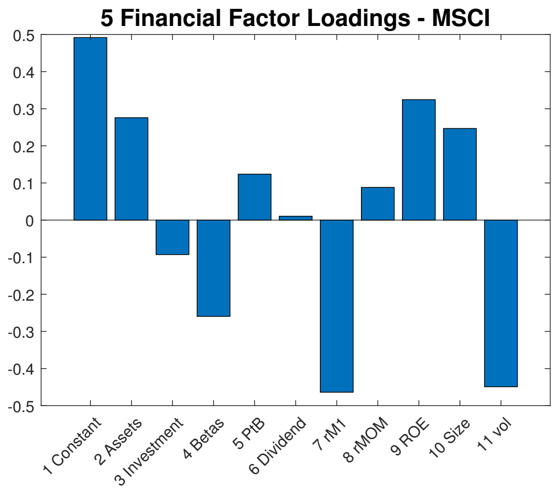

Figure 13

	F1	F2	F3	F4	F5	$p-$value	
Constant	0.41	0.4	-0.1	0.47	0.47	0	***
Assets	0.32	-0.07	0.37	-0.51	0.23	0.015	**
Investment	-0.03	0.05	-0.04	0.05	-0.1	0.301	
Betas	0.24	0.7	-0.4	-0.37	-0.27	0	***
PtB	-0.02	0.01	0	-0.37	0.13	0.104	
Dividend	0.01	-0.08	-0.08	-0.44	0.08	0.071	*
rM1	-0.01	-0.14	-0.29	0.01	-0.5	0.002	***
rMOM	-0.15	-0.01	-0.16	0.07	0.07	0.529	
ROE	0.05	0.04	0.07	-0.16	0.36	0.027	**
Size	-0.8	0.42	0.08	-0.08	0.22	0	***
vol	0.07	0.36	0.75	0.12	-0.43	0	***

Table 6: Γ_β^F matrix from MSCI specification and $p-$values for testing the significance of any characteristic to contribute to the model, while simultaneously controlling for all other characteristics

Appendix I Γ_β^G coefficient and cumulative returns of the Green Factor estimated using Refinitiv green characteristics

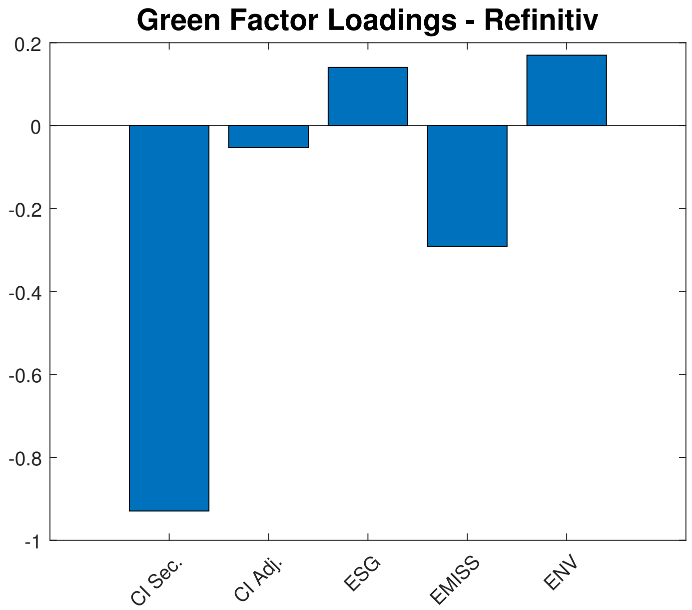

Figure 14: XXX

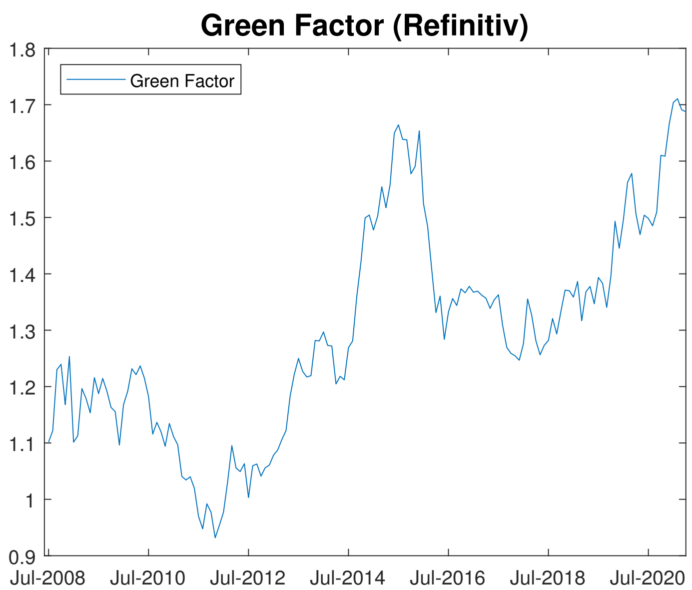

Figure 15: XXX

	G1	$p-$value	
CI Sec.	-0.93	0	***
CI Adj.	-0.05	0.479	
ESG	0.14	0.136	
EMISS	-0.29	0.050	**
ENV	0.17	0.363	

Table 7: Γ_β^G matrix from MSCI specification and $p-$values for testing the significance of any characteristic to contribute to the model, while simultaneously controlling for all other characteristics

Appendix J Γ_β^G coefficient and cumulative returns of the Green Factor estimated using MSCI green characteristics

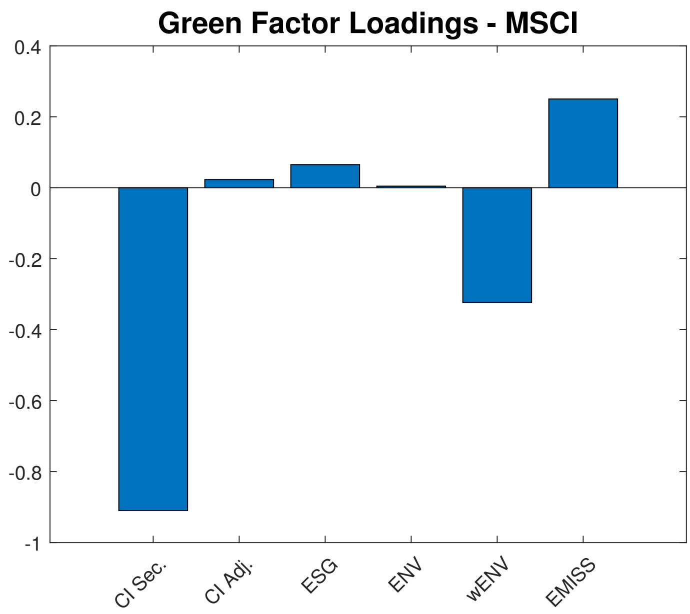

Figure 16: XXX

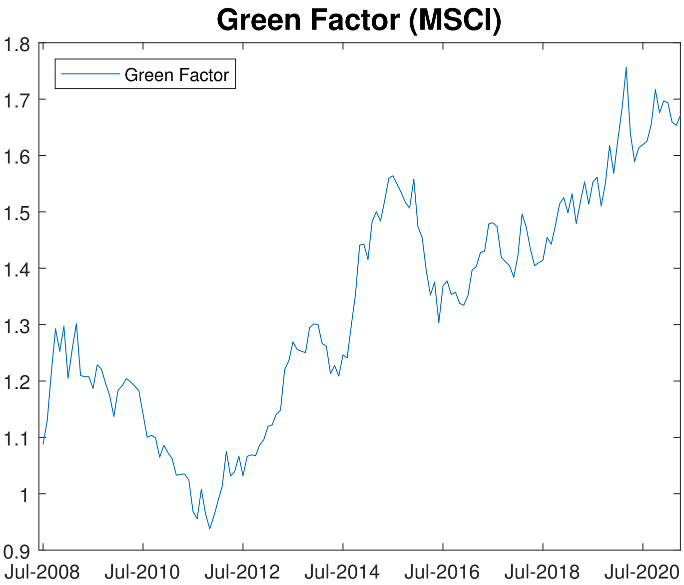

Figure 17: XXX

	G1	$p-$value	
CI Sec	-0.91	0	***
CI Adj	0.02	0.818	
ESG	0.07	0.461	
ENV	0	0.973	
wENV	-0.32	0.562	
EMISS	0.25	0.171	

Table 8: Γ_{β}^{G} matrix from MSCI specification and $p-$values for testing the significance of any characteristic to contribute to the model, while simultaneously controlling for all other characteristics

Appendix K Factors correlations

	A4 F1	A4 F2	A4 F3	A4 F4	A4 F5	A4 G1	M F1	M F2	M F3	M F4	M F5	M G1	Mkt-RF	SMB	HML	RMW	CMA
A4 F1	1	0	0	-0.03	-0.03	-0.01	0.94	0.23	-0.06	-0.1	0.06	0	0.66	0.57	0.66	-0.16	0.26
A4 F2		1	0	0	0	0	-0.15	0.93	0.11	0.11	-0.09	0	0.58	0.28	-0.15	-0.3	-0.41
A4 F3			1	0	0	0	0.04	-0.09	0.84	-0.29	-0.06	0.03	-0.03	0	-0.04	0.12	-0.06
A4 F4				1	-0.08	-0.04	0.04	-0.1	0.1	0.84	-0.16	-0.01	0	0.18	-0.47	-0.18	-0.25
A4 F5					1	-0.03	-0.09	0.06	0.23	0.11	0.89	-0.1	0.37	-0.14	0.05	0.17	0.06
A4 G1						1	-0.05	0.03	0.04	-0.02	-0.04	0.91	0	0.12	0.17	-0.3	-0.1
M F1							1	0	0	-0.03	-0.04	-0.02	0.51	0.51	0.61	-0.16	0.31
M F2								1	0	0	0	0	0.72	0.36	0.07	-0.28	0.31
M F3									1	0	-0.01	0	0.08	0.03	-0.05	0.04	-0.08
M F4										1	-0.08	-0.04	0.09	0.15	-0.4	-0.21	-0.19
M F5											1	-0.05	0.34	-0.17	0.08	0.24	0.09
M G1												1	-0.01	0.06	0.14	-0.28	-0.07
Mkt-RF													1	0.43	0.32	-0.2	-0.09
SMB														1	0.4	-0.37	0.1
HML															1	-0.09	0.47
RMW																1	0.04
CMA																	1

Table 9: Correlation matrix between the 6 latent factors of the two different specifications (Refinitv:A4, MSCI:M) and the Fama-French 5 factors

Appendix L Out-of-sample Sharpe ratio of the maximum Sharpe ratio portfolio

	F1	F1-F2	F1-F3	F1-F4	F1-F5	F1-F5 + G1
MSCI	-0.17	-0.68	-0.73	0.62	1.29	1.34
Refinitiv	0.01	-0.41	-0.62	0.23	1.14	1.14

Table 10: This table shows the annualized Sharpe ratio of the out-of-sample maximum Sharpe ratio portfolio that can be obtained by an optimal linear combination of of the factors which are ultimately portfolio of individual stocks. Column $i-th$, with $i = 1, 2, ..., 6$, shows the Sharpe ratio obtained by using only the first $i-th$ factors; the first 5 are financial factors, whereas the $6-th$ is the green factor. We perform this analysis both for the Refinitiv and MSCI specifications.

	F1	F2	F3	F4	F5	G1
			Out-of-sample			
MSCI	-0.17	-1.05	-0.27	1.15	0.97	0.52
Refinitiv	0.01	-0.64	-0.07	0.72	0.94	0.51
			In-sample			
MSCI	0.42	0.04	0.06	0.90	1.10	0.56
Refinitiv	0.35	0.02	0.04	1.08	0.93	0.40

Table 11: This table shows the annualized Sharpe rations of our IPCA factors computed both in-sample and out-of-sample.

Appendix M R^2 Hedging Climate risk

	Engle et al.		Faccini, Matin, Skiadopoulos				Ardia et al.
	WSJ	CHNEG	US ClimPolicy	IntSummit	GlobWarm	NatDis	MCCC
			IPCA Factors				
Financial factors *MSCI*	0.009	0.085	-0.017	0.004	0.072	0.096	**0.065**
Financial and green factors *MSCI*	0.003	**0.101**	-0.023	**0.108**	**0.074**	**0.099**	0.058
Financial factors *Refinitiv*	**0.013**	0.045	-0.018	-0.013	0.065	0.078	0.03
Financial and green factors *Refinitiv*	0.01	0.066	-0.025	**0.098**	0.068	**0.095**	0.022
			Observable Factors				
Fama-French 5	-0.005	0.012	0.03	0.025	-0.004	-0.023	-0.017
Fama-French 5 + Ref ESG	-0.014	0.004	0.026	0.018	-0.005	-0.008	-0.022
Fama-French 5 + MSCI ESG	-0.012	0.022	0.032	0.02	0.01	-0.028	-0.024
Fama-French 5 +GEME	-0.014	0.026	0.026	0.023	-0.008	-0.03	-0.026
Fama-French 5 + SAP	-0.013	0.013	0.023	0.018	-0.009	-0.004	-0.026
			FF5 + IPCA Green factors				
Fama-French 5 + green *MSCI* factor	0.001	0.02	0.03	**0.116**	0.001	-0.025	-0.023
Fama-French 5 + green *Refinitiv* factor	0.008	0.024	0.026	**0.115**	0.003	-0.012	-0.021

Table 12: This table shows the total adjusted R^2 of the regressions of the factors (rows) on the climate risk indexes in the literature (columns). In bold the highest numbers for each index. These are full-saple regressions.