Time-varying Environmental Betas and Latent Green Factors*

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PRELIMINARY VERSION

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 an extension of the instrumented principal component analysis (IPCA) of Kelly, Pruitt, and Su (2019). In our specification, the factor loadings 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 IPCA model to allow for the presence of different sets of orthogonal factors whose loadings are driven by only one of the two types of characteristics. Our extension allows (i) 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, (ii) to interpret our factors as purely "green" or "financial" factors. 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, which suffice to explain the cross section of stock returns of the stocks in the other sectors.

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1 Introduction

In this work we address two issues related to the impact of climate and environmental risks on the returns of US equities. First, we study whether a separate risk factor associated to "environmental" characteristics exists in addition to standard risk factors associated to a large set of commonly used "financial" characteristics, predictors of stock returns (such as size and book-to-market to name a few) as studied in the recent papers by Chen and Zimmermann (2022) and Freyberger, Neuhierl, and Weber (2020). Second, we want to assess the pricing ability of this new environmental factor for the cross section of stock returns. 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.

A growing number of works, reviewed in our Section 2, study observable (i.e. pre-specified by econometrician) environmental risk factors. Our approach is new in this context as we allow for this factor to be latent. In particular we answer the above questions by extending the instrumented principal component analysis (henceforth IPCA) originally proposed by Kelly et al. (2019): by starting from a large set of firm-level financial and environmental characteristics (i.e. the instruments in this methodology), we measure how they affect the exposure of returns to few latent factors, which we are able to estimate.

To separate the environmental and financial factors, we propose a new constrained IPCA model where each type of factors is allowed to depend either on green characteristics only, or on financial characteristics only. This methodological innovation allows us to interpret the factors as purely green or purely financial, and to assess how each of the two types of factors explains the variability and the premia of individual stocks, as measured by the Total, Predictive, and Pricing R^2s defined by Kelly et al. (2019) and in our Section 3.3. By construction, our methodology allows to estimate the green factors which are orthogonal to financial factors, implying that the only green factor we estimated in our empirical analysis is not (linearly) related to "standard" financial factors.

ESG data are often used to create green factors or to describe the exposure of stocks to these factors, see e.g Pastor, Stambaugh, and Taylor (2021a), Engle, Giglio, Kelly, Lee, and Stroebel (2020), Litterman (2015), and Alessi, Ossola, and Panzica (2020). It is also known that ESG data from different providers are not consistent among each other, as documented by Berg, Kölbel, and Rigobon (2020), Busch, Johnson, and Pioch (2020), and Avramov, Cheng, Lioui, and Tarelli (2021). Compatible with these studies, our maintained assumption is that each environmental characteristics can be decomposed into some relevant environmental information common to other characteristics and some idiosyncratic noise. Notably, IPCA is based on the same premises, and therefore, it allows to understand which 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 information common to different characteristics.

Moreover, as the loadings in the IPCA model are allowed to depend on company characteristics, the methodology lets the data tell us which is the most relevant ones determining the factors 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 extreme quantile portfolios. In this way we select the characteristics ex-ante, and then we build the factors based on the selected characteristics.

Another drawback of using ESG data, is that these 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. An 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 at ESG characteristics as they are not available for many individual stocks.

To the best of our knowledge, only Lindsey, Pruitt, and Shiller (2021) use the IPCA methodology alongside ESG data. The authors apply IPCA by using as instruments some ESG ratings in addition to financial characteristics. Remarkably, they cannot find either systemic risks, or alphas, associated to ESG characteristics. There are three main differences between our work and theirs: first, our methodology allows us to clearly separate the factors associated to green characteristics and financial characteristics, as our factor loadings are either one of the two groups, while the way they run IPCA, does not impose these restrictions. This implies we can better assess the contribution of the two sets of factors in explaining the individual stock returns. The second difference is the choice of the data, we are focusing mainly on the environmental risk and have more granular environmental data. Third, by analysing the contribution of our environmental factor to the returns within each sectors, we find that environmental characteristics matter for the Energy and Utilities sectors. This result is still coherent with Lindsey et al. (2021)'s findings, since when we analyse the entire stock universe, we do not find any relevant contribution of the green factor in explainining 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 by construction investable portfolios, we also assess how these factors perform when used to build hedging portfolios of the climate risk indexes of Engle et al. (2020), Faccini, Matin, and Skiadopoulos (2021), and Ardia, Bluteau, Boudt, and Inghelbrecht (2021). We find that our green factor works well for to hedge the International Summit index by Faccini et al. (2021), and more generally, IPCA factors provide better hedging compared to Fama-French 5 factors and climate-narrative portfolios.

The rest of the paper is organised as follows: Section 2 provides the literature review. Section 3 presents the methodology and Section 4 the data used. Section 5 contains the empirical results and their discussion. In Section 6 we present the results of hedging portfolio of climate risk indexes. Finally, Section 7 concludes, and presents avenues for future research that we are currently exploring. The appendix includes figures, tables, the estimation procedures of the model and tests.

2 Literature Review

Environmental and climate finance, has gained traction in academic literature recently (see the review studies Hong, Karolyi, and Scheinkman (2020) and Giglio, Kelly, and Stroebel (2020): they provide a comprehensive literature review about climate finance). 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. The number of academic works studying climate change and environmental risk in asset pricing has increased. Te majority of these works start by arbitrary choosing a firm-level measure that proxies the environmental/climate risk exposure of the companies and use it either to build a factor as a long/short portfolio, and study if it is priced in the market (e.g. Pastor, Stambaugh, and Taylor (2021b), Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2020), Hsu, Li, and Tsou (2020) among others), or use it directly as an explanatory variable for the cross-section of returns (e.g. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2020) among others). Often these works find completely opposite results, depending on the choice of the greenness measure. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2020) find that US and international stocks, respectively, associated to high carbon emissions have 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 by using toxic emission intensity, 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 international companies. Their greenness measure is defined as combination of factors from four comprehensive ESG databases and 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, Ibikunle, Mulder, and Scholtens (2021) show that companies with higher emissions have higher capital cost. Ilhan, Sautner, and Vilkov (2020) find that climate policy uncertainty is priced in option market. They analyse 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, Park, and Monk (2019) create a long short portfolio carbon efficient minus inefficient and they find abnormal returns for the carbon efficient companies. Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang (2019) test several decarbonisation strategies and find that the more aggressive ones - in terms of decarbonization - performs better in terms of alpha. Also Garvey, Iyer, and Nash (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.

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. Zerbib (2020) develops an asset pricing model taking into account ESG integration and finds evidence of the coexistence of a *taste* effect (the investors' preference for the green stocks) and an *exclusion* effect. These effects are varying over the different industries. Monasterolo and De Angelis (2018) study carbon premium in the period after the Paris Agreement.

A different approach is used by Engle et al. (2020). The authors build a climate news index that proxies climate change risk by using textual analysis on newspapers articles and build mimicking portfolios of the climate change index. Similarly Faccini et al. (2021), Ardia et al. (2021), Apel, Betzer, and Scherer (2021), and Bua, Kapp, Ramella, and Rognone (2022) use textual analysis to extract climate factors, on different data news sources. Textual analysis is used also by Sautner, van Lent, Vilkov, and Zhang (2020), who describe a new method to assess firm-level climate change exposure. They use a machine learning keyword discovery algorithm to captures exposures to climate change from the earning call conferences of 10000 companies. Alekseev, Giglio, Maingi, Selgrad, and Stroebel (2021) propose a new methodology to build hedging climate change portfolios by looking at the trading behaviour of mutual funds when the fund adviser is exposed to local extreme weather events to predict how investors react when local extreme weather events occur. Jung, Engle, and Berner (2021) develop a stress testing procedure to test the resilience of financial institute to climate risks. Choi, Gao, and Jiang (2020) find that in financial markets, stocks of carbon-intensive firms underperform firms with low carbon emissions in abnormally warm weather. Retail investors (not institutional investors) sell carbon-intensive firms in such weather, and return patterns are unlikely to be driven by changes in fundamentals. Krueger, Sautner, and Starks (2020) measures the importance of climate risks among institutional investors.

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. In this work we use as instrumental characteristics for the factor loadings also environmental characteristics from different ESG data providers to assess if one "green" factor is priced in the cross-section of equity returns. 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 but, as mentioned in our introduction, our paper differs in the methodology and in the data used from their paper. With this approach we are able to purge these variables from idiosyncratic 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 allows to include a vast number of characteristics in the empirical analysis, which would be impossible in standard Fama-MacBeth regression or portfolio construction sorted on characteristics. In fact, the methodology allows the data to choose the characteristics for factor construction. 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. further details regarding IPCA model are in Kelly et al. (2019), and its asymptotic properties in Kelly, Pruitt, and Su (2020).

3 Methodology

The IPCA methodology used in this paper has been originally proposed by Kelly et al. (2019) and Kelly et al. (2020). They consider a conditional factor-pricing model with latent factors and firm-level characteristics are used as instruments to infer the unobservable (potentially) time-varying loadings. Their model can be summarized by the following system of equations:

$$r_{i,t+1} = \alpha_{i,t} + \beta_{i,t} f_{t+1} + \epsilon_{i,t+1} \ ,$$
$$\alpha_{i,t} = z'_{i,t}\Gamma_\alpha + \nu_{\alpha,i,t} \ , \qquad \beta_{i,t} = z'_{i,t}\Gamma_\beta + \nu_{\beta,i,t} \ , \tag{3.1}$$

which hold for each asset $i = 1, ..., N_t$ over all periods $t = 0, ..., T-1$ in which N_{t+1} assets are observed[1]. 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 one constant that captures the systemic risk that is common over time for all the stocks. Any behavior of dynamic

[1]The number of assets is allowed to change over time, and therefore N is indexed by t

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, it does not change over time and is constant for all companies. However, companies change over the years, and their exposure to risk and expected returns of their stocks are allowed to evolve accordingly; this feature is allowed since characteristics may change over time and, consequently, also the loadings.

The parametrization in (3.1) makes the model more efficient in capturing the time varying exposure compared to the static beta estimated using rolling-windows, which involves the estimation of $N_t \times K$ loadings in each window ending at time t. Therefore, this method also allows to include a relative large number of characteristics L, but in order to keep the model parsimonious, L, has to be smaller than N and t. As in our factor model the number of factors also needs to be small to keep the model parsimonious, in particular we must have $K << L$. Indeed, starting from a large set of L characteristics which are instruments of exposures to risk factors, the model aggregates this information in K factors, and their loadings by keeping only the relevant signals from characteristics and implicitly averaging out the noise.

In the case characteristics are constant over time, the solution of IPCA can be obtained by applying PCA to the returns of L managed portfolios by sorting stocks on characteristics. If the characteristics are not constant over time, IPCA estimation can only be approximated by "classical" PCA on managed portfolios (which is actually the starting point of the IPCA estimation procedure).

The L-dimensional vector x_{t+1} contains the returns of managed portfolios at time $t+1$ defined by the following equation:

$$x_{t+1} = \frac{Z_t' r_{t+1}}{N_{t+1}} , \tag{3.2}$$

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 returns of all assets. N_{t+1} is the number of non missing stock observations, and the $N_{t+1} \times L$ matrix $Z_t = [z'_{1,t}, ...z'_{i,t}, ...z'_{i,N_{t+1}}]$ contains all the N_{t+1} vectors of characteristics, $z_{i,t}$. The managed portfolios are portfolios with weights given by the values of the characteristics[2]. Two identification restrictions are

[2]Following Kelly et al. (2019), characteristics are cross-sectionally ranked, demeaned, and scaled (except the constant) to live in the [-0,5; 0,5] interval

imposed in the IPCA procedure, namely: $\Gamma'_\beta\Gamma_\beta = \mathbb{I}_K$ and the positivity of the mean of the estimated factors. 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 types of factors: "financial" and "green". We define financial (resp. green) factor loadings as driven only by financial (resp. green) characteristics, in this way the factors are easily interpretable. Our model specification is

$$r_{t+1} = \underbrace{Z_t^F\Gamma_\alpha^F + Z_t^G\Gamma_\alpha^G}_{\alpha_t} + \underbrace{Z_t^F\Gamma_\beta^F f_{t+1}^F + Z_t^G\Gamma_\beta^G f_{t+1}^G}_{\beta_t f_{t+1}} + \epsilon_{t+1} \ , \tag{3.3}$$

where Z_t^F (Z_t^L) is a matrix $N_{t+1} \times L^F$ ($N_{t+1} \times L^G$) containing all the L^F financial (L^G green) characteristics for the N_{t+1} 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). Γ_α^F and Γ_α^G are the two vectors mapping the financial and green characteristics into the α_t, in this way we are able to assess the contribution of the two sets of characteristics to the α_t. In order to keep the factors well separated and to interpret them as only-financial and only-green factors, we also impose the cross-sectional orthogonality of green characteristics from financial characteristics at each dates (see Section 4.1 for details) and the time-series orthogonality of green and financial factors, that is $\mathbb{E}[f_{t+1}^F f_{t+1}^G{}'] = 0$.

3.2 Model estimation

To simplify the exposition of this problem, and coherently with our empirical application, we analyze the case with $K_G = 1$ green factor only. Then, equation (3.3) can be written as the original IPCA specification with zero constraints in matrix Γ_β which we rename $\tilde{\Gamma}_\beta$:

$$r_{t+1} = Z_t\Gamma_\alpha + Z_t\tilde{\Gamma}_\beta f_{t+1} + \epsilon_{t+1} \ , \tag{3.4}$$

where we define the elements in the r.h.s. of the last equation as:

$$r_{t+1} = \underbrace{\begin{bmatrix} Z_t^F & Z_t^G \end{bmatrix}}_{=Z_t} \cdot \underbrace{\begin{bmatrix} \Gamma_\alpha^F \\ \Gamma_\alpha^G \end{bmatrix}}_{=\Gamma_\alpha} + \underbrace{\begin{bmatrix} Z_t^F & Z_t^G \end{bmatrix}}_{=Z_t} \cdot \underbrace{\begin{bmatrix} \Gamma_\beta^F & \mathbf{0}_{L^F \times K^G} \\ \mathbf{0}_{L^G \times K^F} & \Gamma_\beta^G \end{bmatrix}}_{=\tilde{\Gamma}_\beta} \cdot \underbrace{\begin{bmatrix} f_{t+1}^F \\ f_{t+1}^G \end{bmatrix}}_{=f_{t+1}} + \epsilon_{t+1} \ , \tag{3.5}$$

where $\mathbf{0}_{q_1 \times q_2}$ is the generic $q_1 \times q_2$ matrix of zeros. Taking inspiration from the estimation procedure of the original IPCA model, we propose a recursive procedure to estimate Γ_β^F, Γ_β^G, Γ_α, f_t^F, and f_t^G for all t in the equations (3.3). Our estimator $\{\hat{\Gamma}_\beta^F, \hat{\Gamma}_\beta^G, \hat{\Gamma}_\alpha, \hat{f}\}$ defined as the set of values $\{\Gamma_\beta^F, \Gamma_\beta^G, \Gamma_\alpha, f\}$ which minimize the sum squared errors $h(\Gamma_\beta^F, \Gamma_\beta^G, \Gamma_\alpha, f)$, defined as:

$$h(\Gamma_\beta^F, \Gamma_\beta^G, \Gamma_\alpha, f) := \sum_{t=1}^{T-1} (r_{t+1} - Z_t\Gamma_\alpha - Z_t\tilde{\Gamma}_\beta f_{t+1})'(r_{t+1} - Z_t\Gamma_\alpha - Z_t\tilde{\Gamma}_\beta f_{t+1}) \tag{3.6}$$

where $\tilde{\Gamma}_\beta$ defined in (A.4) contains both Γ_β^F and Γ_β^G, moreover $f = [f_2, f_3, ...f_T]$, where $f_{t+1} = [f_{t+1}^{F\prime} f_{t+1}^{G\prime}]'$, and we impose the constraint that

$$\sum_{t=1}^{T-1} f_{t+1}^F f_{t+1}^{G\prime} = \mathbf{0}_{K^F \times 1} \ . \tag{3.7}$$

Importantly, the orthogonality within financial factors and within green factors is imposed by pre-multiplying these by appropriate rotation matrices at the end of the estimation procedure, similarly to 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 zero constraints in matrix $\tilde{\Gamma}_\beta$. Therefore, the one in (A.6) is the only constraint we explicitly need in the Lagrangian associated to our estimation procedure, which is:

$$\mathcal{L}(\Gamma_\beta^F, \Gamma_\beta^G f, \Gamma_\alpha, \lambda) = h(\Gamma_\beta^F, \Gamma_\beta^G, \Gamma_\alpha, f) - \lambda' g(f) \ , \tag{3.8}$$

where $g(f) = \sum_{t=1}^{T-1} f_{t+1}^F f_{t+1}^{G\prime}$, and λ is the K^F-dimensional vector of the Lagrange multipliers.

The values of Γ_β^F, Γ_β^G, Γ_α, and f_{t+1} minimizing (3.8), satisfy the first order conditions

$$\frac{\partial \mathcal{L}}{\partial f_{t+1}} = 0 \Rightarrow \hat{f}_{t+1} = (\widehat{\tilde{\Gamma}}'_\beta Z_t' Z_t \widehat{\tilde{\Gamma}}_\beta - \Lambda)^{-1} \widehat{\tilde{\Gamma}}'_\beta Z_t'(r_{t+1} - Z_t \widehat{\Gamma}_\alpha), \qquad \text{for all } t \tag{3.9}$$

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

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0 \Rightarrow \sum_{t=1}^{T-1} f_{t+1}^F f_{t+1}^{G\prime} = \mathbf{0}_{K^F \times 1}, \tag{3.10}$$

$$\frac{\partial \mathcal{L}}{\partial \Gamma_\beta^F} = 0 \Rightarrow \text{vec}(\hat{\Gamma}_\beta^{F\prime}) = \left(\sum_{t=1}^{T-1} Z^{F\prime}{}_t Z_t^F \otimes \hat{f}_{t+1}^F \hat{f}_{t+1}^{F\prime} \right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t^F \otimes \hat{f}_{t+1}^{F\prime} \right]' \left(r_{t+1} - Z_t \hat{\Gamma}_\alpha - Z_t^G \hat{\Gamma}_\beta^G \hat{f}_{t+1}^G \right) \right), \tag{3.11}$$

and

$$\frac{\partial \mathcal{L}}{\partial \Gamma_\beta^G} = 0 \Rightarrow \text{vec}(\hat{\Gamma}_\beta^{G\prime}) = \left(\sum_{t=1}^{T-1} Z^{G\prime}{}_t Z_t^G \otimes \hat{f}_{t+1}^G \hat{f}_{t+1}^{G\prime} \right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z_t^G \otimes \hat{f}_{t+1}^{G\prime} \right]' \left(r_{t+1} - Z_t \hat{\Gamma}_\alpha - Z_t^F \hat{\Gamma}_\beta^F \hat{f}_{t+1}^F \right) \right). \tag{3.12}$$

$$\frac{\partial \mathcal{L}}{\partial \Gamma_\alpha} = 0 \Rightarrow \text{vec}(\hat{\Gamma}_\alpha) = \left(\sum_{t=1}^{T-1} Z'{}_t Z_t \otimes 1 \right)^{-1} \left(\sum_{t=1}^{T-1} [Z_t \otimes 1]' \left(r_{t+1} - Z_t \hat{\tilde{\Gamma}}_\beta \right) \right) \tag{3.13}$$

In the Appendix A.1 we show all the steps to solve the restricted model by using the alternating least squares. The restricted model, i.e. $\Gamma_\alpha = 0$, is the model in which this asset pricing restriction is imposed and the factors are assumed to be the only sources of explanation of premia. 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. The estimation procedure can be easily extended to control also for observable factors f_{obs}, as described in Appendix A.1.1.

3.3 Performance Measures

To assess the ability of our model to fit the data, we report three goodness of fit measures introduced by Kelly et al. (2019): the Total, Predictive and Pricing $R^{2\prime}$s (Kelly et al. (2019)). In order to define the three measures we need to define $\hat{\beta}_{i,t} := z_{i,t} \widehat{\tilde{\Gamma}}_\beta$

1. The Total R^2 is the fraction of variance in stock returns explained by the time-varying exposure to the common factors:

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - \hat{\beta}_{i,t}\hat{f}_{t+1}\right)^2}{\sum_{i,t} r_{i,t+1}^2}. \tag{3.14}$$

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

$$\text{Predictive } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - \hat{\beta}_{i,t}\hat{\lambda}\right)^2}{\sum_{i,t} r_{i,t+1}^2}. \tag{3.15}$$

   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.

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

$$\text{Pricing } R^2 = 1 - \frac{\sum_{n}\left(\frac{1}{|\tau_i|}\sum_{t\in\tau_i} r_{i,t+1} - \hat{\beta}_{i,t}\hat{f}_{t+1}\right)^2}{\sum_{n}\left(\frac{1}{|\tau_i|}\sum_{t\in\tau_i} r_{i,t+1}\right)^2}\ , \tag{3.16}$$

   The notation τ_i recognizes that each asset has a different set of time indices for which it is observed, and $|\tau_i|$ denotes the number of elements in this set. 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, i.e. estimated risk premia. This measure is similar to a re-scaled version of a GRS statistic Shanken, Gibbons, and Ross (1989) premultiplied by -1, so that values near to zero (resp. one) indicate large (resp. small) mispricing, that is "alpha", implied by the factor model for the test assets.

4 Data

To perform our ananlysis we build the $N_t \times L^F$ and $N_t \times L^G$ matrices Z_{t-1}^F and Z_{t-1}^G for each time t that contain all the financial and green characteristics respectively, and the N_t-dimension vector containing all the returns at the time t. We use monthly returns from Jul 2008 to Apr 2021 and characteristics are observed with either monthly or annual frequency. 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 Refinitiv we select:

1. Market capitalization (monthly): we build monthly lagged market capitalizations by using the last available market capitalization during the previous month;

2. Total assets (annual): represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets;

3. Investment(annual): We measure total asset growth on an annual basis;

4. β(monthly): 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:

$$r_{i,t_d} - r_{f,t_d} = \alpha_{i,t} + \beta_{i,t} \left(r_{mkt,t_d} - r_{f,t_d} \right) + \epsilon_{i,t_d} \tag{4.17}$$

5. Price To Book Value (annual): this is the share price divided by the book value per share and it is the inverse of book to market ratio;

6. Dividend Yield (monthly): it expresses the dividend per share as a percentage of the share price;

7. Lagged monthly return (monthly): total return at month t - 1;

8. Momentum (monthly): Total return from month t - 12 to month t - 2;

9. Idiosyncratic volatility (monthly): Volatility of the CAPM regression residuals ϵ_{i,t_d}, in equation (4.17);

10. ROE (annual).[3]

Green characteristics are computed using both MSCI ESG IVA and Refrinitv ESG (ex Asset 4) datasets whereas financial-characteristics and returns are from Refinitiv. In order to determine our test assets we start by selecting all the US equities available in in MSCI ESG IVA that have at least an ESG score (4415 companies). The advantages of using this database is well described in Pastor et al. (2021a). In particular 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[4]:

1. 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);

2. ENVIRONMENTAL_PILLAR_SCORE (ENV): the Environmental Pillar Score represents the weighted average of all Key Issues that fall under the Environment Pillar.

3. 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;

4. 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[5]:

1. 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;

[3] Refinitiv code of total assets: WC02999; Price to Book: PTBV; ROE: WC08301; Dividend Yield: DY

[4] The definitions of the characteristics are from a dictionary provided by MSCI alongside MSCI ESG IVA data

[5] The definitions of the characteristics are from Refinitiv

2. 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;

3. Emissions Score - TRESGENERS (EMISS): emission category score measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes;

4. 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 the original idea Heston and Rouwenhorst (1994) and more recently 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,

$$CI_{i,t} = \kappa + \sum_{ind=1}^{N_{ind,t}-1} I_{ind,t} \mathbb{I}_{i \in ind} + v_{i,t} \tag{4.18}$$

In equation (4.18), 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 both financial and green Refinitv characteristics, see Figure B.1a; 2564 companies have both financial and green MSCI characteristics, see Figure B.1b. The characteristics start from 2007 whereas returns start in July 2008. All the green characteristics are available on annual frequency.

We present two specification of the model. In the first ("Refiniti") 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.

Similarly to Kelly et al. (2019). 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 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):

$$z_t^{G_i} = \alpha_{G_i,t} + Z_t^F \beta_{G_i,t} + \epsilon_t^{G_i}, \qquad \forall t, \qquad \forall G_i \tag{4.19}$$

where $z_t^{G_i}$ is the N_{t+1}-dimension vector containing all the observation of the i-th green characteristic at the time t for all the N_{t+1} companies, $\alpha_{G_i,t}$ is a constant, Z_t^F is the $N_{t+1} \times L^F$ matrix containing all the L^F financial characteristic at the time t for all the N_{t+1} 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. In our main specification We use a six factors model with no Γ_α where we include $K^F = 5$ financial factors and $K^G = 1$ green factor. The choice of 5 financial factors is compatible with Kelly et al. (2019) who consider only financial characteristics in their model. First we show the estimated latent factors, then we study the contribution of green and financial factors, respectively, to the R^2's defined in Section 3.3. Importantly, we perform the analysis both in-sample and out-of-sample as described in detail below.

5.1 The financial factors

We start with the in-sample analysis where the model parameters are estimated only once using the entire sample of observations from July 2008 to Apr 2021. We re-estimate the model twice by keeping always the same financial characteristics but by changing the source of green characteristics, namely "Refinitiv" and "MSCI". The $\tilde{\Gamma}_\beta$ matrix's columns describe how each characteristic maps into companies loadings on each factor. For each financial (resp. green) factor we plot the correspondent Γ_β^F (resp. Γ_β^G) columns. Figure C.1a 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 C.1b) 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 C.1c) is mostly determined by idiosyncratic volatility. Finally, Factor 4 and 5 (Figures C.1d and C.1e) are a mixture of many characteristics. In Appendix C.1.2 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 A.2. We find that the constant, betas, size, and idiosyncratic volatility are characteristics whose contribution to the models (both the specification with green characteristics from Refinitiv and from MSCI) are statistically significant with a confidence level at 99% (Tabels C.1f and C.2f).

5.2 The green factor

In Appendix C.2 and Appendix C.2.2 are displayed the Γ_β^G for the two specifications of the model. For both of them, we observe that carbon intensity sector component is the main driver of the exposure to this factor. Figure C.3 suggests to interpret this factor as a green factor: 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 A.2. We find that the industrial component of carbon intensity is the only characteristic statistically significant for both the specification with a confidence level at 99% (Tables C.1 and C.2). The green factor extracted by using MSCI (resp. Refinitiv) characteristics presents an excess annual return of 5.6% (resp. 4.8%), annual standard deviation 10.1% (resp. 12.1%), and Sharpe ratio 0.55 (resp. 0.40).

We compare our green factors with the "stranded asset" portfolio proposed by Litterman,[6] and built as in Jung et al. (2021).[7] We represent the cumulative returns of both our green factors and stranded asset portfolio in Figure C.5. Stranded assets have suffered from unanticipated or premature write-downs, devaluation or conversion to liabilities. In recent years, the academic literature and the industry are debating regarding the issue of stranded assets due to environmental factors, such as climate change and society's attitudes towards it. This portfolio (stranded asset portfolio) consists of a short position in the stranded asset index: 30% in Energy Select Sector SPDR ETF (ticker: XLE) and 70% in VanEck Vectors Coal ETF (ticker: KOL), and a long position in SPDR S&P 500 ETF Trust (ticker: SPY). The correlation of the MSCI (resp. Refinitiv) green factor and the stranded asset portfolio is 41% (resp. 37%). A possible explanation is that the two portfolios (IPCA factor and stranded asset portfolio) are exposed to a common source of risk. It is interesting to note that the two methodologies are different, as Litterman chooses the composition of the portfolio a priori, whereas we are agnostic and let the data inform the construction of the portfolio. In particular Litterman sells a brown portfolio and invests the proceeds in the market (the S&P 500). On the other hand, our method is agnostic in identifying green and brown stocks, and creates a long/short portfolio. It is likely the two portfolios contain different stocks exposed to the same factor: a common green priced factor.[8] Theoretical models that justify the presence of a green factor can be found in Pastor et al. (2021b) and Avramov, Lioui, Liu, and Tarelli (2022).

[6]See `http://www.intentionalendowments.org/selling_stranded_assets_profit_protection_and_prosperity`

[7]We thank Prof. Riccardo Rebonato and researchers at ERCII for this valuable suggestion.

[8]We are currently analysing this by comparing the composition of the IPCA green factors and the composition of the stranded asset portfolio.

5.3 In-sample R^2

Tables C.5 and C.6 display the in-sample Total, Predictive and Pricing $R^{2\prime}$s, defined in section 3.3. 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 particularly relevant for some of them. In the "Refinitiv" specification, the Energy sector Total R^2 (Table C.5) increases considerably from 39.1% to 41.3%. Also the Utilities sector Pricing R^2 increases from 24.2% to 29.6%. Similar results are founded with the "MSCI" specification (Table C.6). 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

To construct out-of-sample fit measures, we follow Kelly, Palhares, and Pruitt (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 2008.07-2021.04, 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 ending in month t, we estimate IPCA model and denote the resulting estimates as $\hat{\hat{\Gamma}}_{\beta,t}$. 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 $Z_t\hat{\hat{\Gamma}}_{\beta,t}\hat{f}_{t+1}$ whereas the out-of-sample predictive R^2 compares $r_t + 1$ to $Z_t\hat{\hat{\Gamma}}_{\beta,t}\lambda_t$ where λ_t is the factor return mean over the estimation window.

Tables C.7 and C.8 display the out-of-sample Total, Predictive and Pricing $R^{2\prime}$s. 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 C.7, we can compare the last column F1:F5+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 C.8) 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 recall that, by construction, IPCA factors are weighted averages of the excess returns of managed portfolios (with weights proportional to the columns of $\hat{\hat{\Gamma}}_{\beta,t}$) and therefore, also of individual stocks (with weights proportional to the columns of $Z_t\hat{\hat{\Gamma}}_{\beta,t}$).[9] 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.

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), section 4.4. 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. Out-of-sample IPCA Sharpe ratios are displayed in Tables C.9. In Table C.9 the k-th column, with k going from 1 to 5, we show the Sharpe ratio of the portfolio invested in the first k-th financial factors. Therefore, the difference between the Sharpe ratios in column k and $k-1$ is due to the addition of the k-th factor. In the six column we add the green factor to the five financial factors. In the MSCI specification the financial factors do not completely span, in a mean-variance sense, the green

[9]More precisely, from equation (A.8) we can clearly see that, when $\Gamma_\alpha = 0$, IPCA factors $\hat{f}_{t+1}$ are returns of portfolios of individual stocks, where the weights for the k-th factor are given by the k-th row of the $K \times N$ matrix $(\hat{\hat{\Gamma}}'_\beta Z_t' Z_t \hat{\hat{\Gamma}}_\beta - \Lambda)^{-1}\hat{\hat{\Gamma}}'_\beta Z_t'$.

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.[10]

6 Hedging Climate News

Since our green factors are investible portfolios, we analyze how they can be used to hedge climate risks. Following the literature, we define climate risks shocks as the innovations of an AR(1) model fitted to the different climate news series. We consider a) the two series from Engle et al. (2020), namely the Wall Street Journal Climate Change New Index (WSJ) and the Negative Climate Change News Index (CHNEG); b) four series from Faccini et al. (2021), US Climate Policy, International Summits, Global Warming, and Natural Disaster; c) one serie from Ardia et al. (2021), thet use climate change-related news published by major U.S. newspapers (MCCC).[11]

Inspired by the analysis in Engle et al. (2020), in order to assess whether our factors are useful to hedge climate shocks, we build different mimicking portfolios by using six different sets of assets. Each set is composed by six portfolios. The first two sets are composed by our six 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.[12] (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), and described above.

To compare the performances of the different sets of assets, for each set we build two mimicking

[10]Note that, similarly to Kelly et al. (2019) and Lettau and Pelger (2020), in the formation of the out-of-sample optimal portfolio, we do not take into account the transaction costs, and we do not impose any short-selling constraints. Taking these issues into account is on our future research agenda.

[11]The series from Engle et al. (2020), Faccini et al. (2021), and Ardia et al. (2021) are available here, here, and here, respectively. Series from Faccini et al. (2021), and Ardia et al. (2021) are available with daily frequency, therefore we compute the 30-days average.

[12]Fama-French 5 factors are available here.

portfolios: one containing only standard factors as our 5 financial factors or the FF5,

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

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 assess i) if the additional environmental-related factors are useful to hedge climate news, and ii) which assets hedge climate news best. Table C.10 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 strong.

7 Conclusions [INCOMPLETE]

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* and it is quite correlated with the Litterman's stranded asset portfolio.

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Appendix

A.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 (A.1) and (A.2) 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.

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

$$r_{t+1} = Z_t^G \Gamma_\beta^G f_{t+1}^G + \epsilon_{t+1}^{**} \tag{A.2}$$

2. With $\tilde{\Gamma}_\beta^{(0)}$, we compute $f_{t+1}^{(0)}$ for all the periods by using equation (A.8) and equation (A.9). 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 (A.10) (resp. (A.11)). With $\Gamma_\beta^{F(1)}$ and $\Gamma_\beta^{G(1)}$ we build $\tilde{\Gamma}_\beta^{(1)}$ [13].

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 $U^G f^{G(1)} {f^{G(1)}}' {U^G}'$:

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

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

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

(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 $\tilde{\Gamma}_\beta^{(k)} \simeq \tilde{\Gamma}_\beta^{(k+1)}$.

A.1.1 Estimation with observable factors

The IPCA model with observable factors f_{obs} is:

$$r_{t+1} = Z_t \Gamma_\delta f_{obs,t+1} + Z_t \tilde{\Gamma}_\beta f_{t+1} + \epsilon_{t+1} \; . \tag{A.3}$$

It is possible to include among the observable factors the all-ones vector to control also for the α: in this case the Γ_α is the column of Γ_δ associated to the all-ones vector. In the case $f_{obs,t+1} = 1$ for all periods t, Γ_δ coincides with Γ_α and, therefore, the following estimation procedure, can be sees as an alternative procedure to estimate Γ_α. We rewrite (A.3) as:

$$r_{t+1} = \underbrace{\begin{bmatrix} Z_t^F & Z_t^G \end{bmatrix}}_{=Z_t} \cdot \underbrace{\begin{bmatrix} \Gamma_\delta^F \\ \Gamma_\delta^G \end{bmatrix}}_{=\tilde{\Gamma}_\delta} \cdot f_{obs,t+1} + \underbrace{\begin{bmatrix} Z_t^F & Z_t^G \end{bmatrix}}_{=Z_t} \cdot \underbrace{\begin{bmatrix} \Gamma_\beta^F & \mathbf{0}_{L^F \times K^G} \\ \mathbf{0}_{L^G \times K^F} & \Gamma_\beta^G \end{bmatrix}}_{=\tilde{\Gamma}_\beta} \cdot \underbrace{\begin{bmatrix} f_{t+1}^F \\ f_{t+1}^G \end{bmatrix}}_{=f_{t+1}} + \epsilon_{t+1} \; . \tag{A.4}$$

Our estimator $\{\hat{\Gamma}_\beta^F, \hat{\Gamma}_\beta^G, \hat{\Gamma}_\delta, \hat{f}\}$ defined as the set of values $\{\Gamma_\beta^F, \Gamma_\beta^G, \Gamma_\delta, f\}$ which minimize:

$$h(\Gamma_\beta^F, \Gamma_\beta^G, f) := \sum_{t=1}^{T-1} (r_{t+1} - Z_t \Gamma_\delta f_{obs,t+1} - Z_t \tilde{\Gamma}_\beta f_{t+1})' (r_{t+1} - Z_t \Gamma_\delta f_{obs,t+1} - Z_t \tilde{\Gamma}_\beta f_{t+1}) \; . \tag{A.5}$$

We impose the constraint that

$$\sum_{t=1}^{T-1} f^F_{t+1} f^{G\prime}_{t+1} = \mathbf{0}_{K^F\times 1} \; . \tag{A.6}$$

The Lagrangian associated to our estimation procedure is:

$$\mathcal{L}(\Gamma^F_\beta, \Gamma^G_\beta f, \Gamma_\delta, \lambda) = h(\Gamma^F_\beta, \Gamma^G_\beta, \Gamma_\delta, f) - \lambda' g(f) \; , \tag{A.7}$$

where $g(f) = \sum_{t=1}^{T-1} f^F_{t+1} f^{G\prime}_{t+1}$, and λ is the K^F-dimensional vector of the Lagrange multipliers.

The values of Γ^F_β, Γ^G_β, Γ_δ, and f_{t+1} minimizing (A.7), satisfy the first order conditions

$$\frac{\partial \mathcal{L}}{\partial f_{t+1}} = 0 \Rightarrow \hat{f}_{t+1} = (\widehat{\hat{\Gamma}}'_\beta Z'_t Z_t \widehat{\hat{\Gamma}}_\beta - \Lambda)^{-1} \widehat{\hat{\Gamma}}'_\beta Z'_t (r_{t+1} - Z_t \widehat{\Gamma}_\delta f_{obs,t}), \qquad \text{for all } t \tag{A.8}$$

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

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0 \Rightarrow \sum_{t=1}^{T-1} f^F_{t+1} f^{G\prime}_{t+1} = \mathbf{0}_{K^F\times 1}, \tag{A.9}$$

We define $\hat{f}^{F\&O}_{t+1} = [f^F_{t+1}, f_{obs,t+1}]'$ (resp. $\hat{f}^{G\&O}_{t+1} = [f^G_{t+1}, f_{obs,t+1}]'$) the vector containing the returns of the K_F (resp. K_G) financial factors and the K_O observable factors at the time $t+1$.

Similarly we define $\Gamma^{F\&O}_\beta$ (resp. $\Gamma^{G\&O}_\beta$) the $L_F \times (K_F + K_O)$ matrix containing the matrices Γ^F_β and Γ^F_δ (resp. Γ^G_β and Γ^G_δ)

$$\frac{\partial \mathcal{L}}{\partial \Gamma^{F\&O}_\beta} = 0 \Rightarrow \mathrm{vec}(\hat{\Gamma}^{F\&O\prime}_\beta) = \left(\sum_{t=1}^{T-1} Z^{F\prime}{}_t Z^F_t \otimes \hat{f}^{F\&O}_{t+1} \hat{f}^{F\&O\prime}_{t+1} \right)^{-1} \left(\sum_{t=1}^{T-1} \left[Z^F_t \otimes \hat{f}^{F\&O\prime}_{t+1} \right]' \left(r_{t+1} - Z^G_t \hat{\Gamma}^{G\&O}_\beta \hat{f}^{G\&O}_{t+1} \right) \right), \tag{A.10}$$

and

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

A.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 (3.1)) 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 A.1. Then we can rewrite the model as

$$x_{t+1} = Z_t^{F'}\left(r_{t+1} - Z_t^G \hat{\Gamma^G}_\beta \hat{f}_{t+1}^G\right) = Z_t^{F'} Z_t^F \Gamma_\beta^F f_{t+1}^F + Z_t^{F'}\epsilon_{t+1}.$$

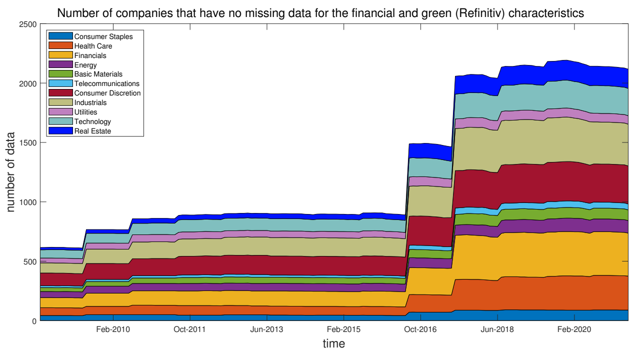
By applying the same bootstrap procedure as in Kelly et al. (2019), we generate 10000 bootstrap samples under H_0 and for each sample we re-estimate the model and record the estimated test statistic

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

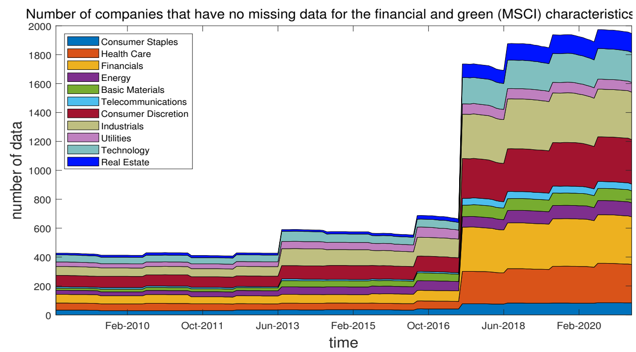
Finally we draw inferences from the empirical null distribution by calculating a p-value as the fraction of bootstrapped $W_{\beta,l}^b$ statistics that exceed the value of $W_{\beta,l}$ from the actual data.

B.1 Descriptive Analysis

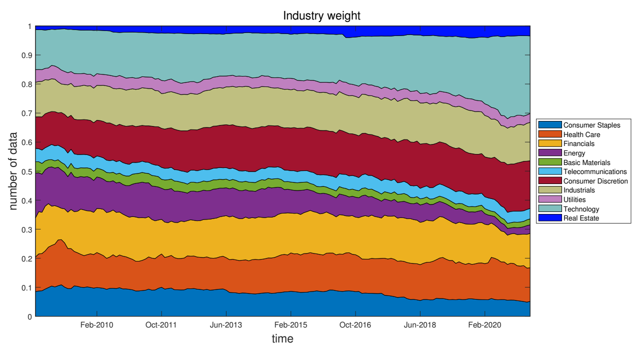
Figure B.1: Number of stocks for each industry in our sample and market capitalization weight of each industry



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



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



(c) Distribution weighted by market capitalization of the industries

B.2 Characteristics correlation

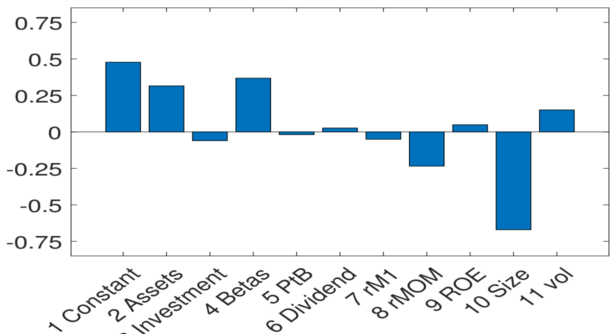
Table B.1: This table shows the characteristics' time-average cross-sectional correlation. Characteristics are ranked but not orthogonalized yet.

	Assets	Investment	Betas	PtB	Dividend	rM1	rMOM	ROE	Size	Idio vol	CI sec (A4)	CI adj (A4)	ESG (A4)	EMISS (A4)	ENV (A4)	ESG (MSCI)	ENV (MSCI)	wENV (MSCI)	EMISS (MSCI)
Assets	1	-0.03	-0.08	0.4	0.34	0	-0.03	0.02	0.67	-0.34	-0.11	0.16	0.36	0.45	0.4	0.12	0.15	-0.03	0.31
Investment	-0.03	1	0.01	0.02	-0.14	0	-0.02	0.21	0.13	0.01	-0.04	-0.03	-0.08	-0.11	-0.11	0.01	-0.01	-0.08	-0.03
Betas	-0.08	0.01	1	-0.01	-0.28	-0.01	-0.08	-0.21	-0.2	0.52	-0.07	-0.01	-0.14	-0.13	-0.13	-0.08	-0.09	-0.04	-0.15
PtB	0.4	0.02	-0.01	1	0.14	-0.02	-0.08	-0.16	0.14	-0.17	0.04	0.02	0.07	0.1	0.07	-0.03	-0.06	0.07	-0.01
Dividend	0.34	-0.14	-0.28	0.14	1	-0.03	-0.07	0.15	0.17	-0.41	0.14	0.08	0.27	0.29	0.28	0.04	0.03	0.21	0.12
rM1	0	0	-0.01	-0.02	-0.03	1	0.25	0.01	0.06	-0.03	-0.02	0	0	0	0	0	0.01	-0.02	0.01
rMOM	-0.03	-0.02	-0.08	-0.08	-0.07	0.25	1	0.04	0.22	-0.19	-0.03	-0.01	0.01	-0.01	0	0.02	0.05	-0.04	0.06
ROE	0.02	0.21	-0.21	-0.16	0.15	0.01	0.04	1	0.31	-0.33	0.02	-0.09	0.19	0.15	0.18	0.12	0.1	-0.04	0.17
Size	0.67	0.13	-0.2	0.14	0.17	0.06	0.22	0.31	1	-0.46	-0.08	0.06	0.39	0.45	0.44	0.21	0.26	-0.07	0.36
Idio vol	-0.34	0.01	0.52	-0.17	-0.41	-0.03	-0.19	-0.33	-0.46	1	0	-0.04	-0.28	-0.26	-0.25	-0.13	-0.15	-0.02	-0.24
CI sec (A4)	-0.11	-0.04	-0.07	0.04	0.14	-0.02	-0.03	0.02	-0.08	0	1	-0.4	0.03	0.17	0.19	-0.04	-0.1	0.62	-0.22
CI adj (A4)	0.16	-0.03	-0.01	0.02	0.08	0	-0.01	-0.09	0.06	-0.04	-0.4	1	0.06	0.07	0.05	-0.04	-0.03	-0.04	0.02
ESG (A4)	0.36	-0.08	-0.14	0.07	0.27	0	0.01	0.19	0.39	-0.28	0.03	0.06	1	0.68	0.73	0.36	0.27	0.06	0.39
EMISS (A4)	0.45	-0.11	-0.13	0.1	0.29	0	-0.01	0.15	0.45	-0.26	0.17	0.07	0.68	1	0.9	0.29	0.28	0.22	0.39
ENV (A4)	0.4	-0.11	-0.13	0.07	0.28	0	0	0.18	0.44	-0.25	0.19	0.05	0.73	0.9	1	0.31	0.29	0.26	0.39
ESG (MSCI)	0.12	0.01	-0.08	-0.03	0.04	0	0.02	0.12	0.21	-0.13	-0.04	-0.04	0.36	0.29	0.31	1	0.49	-0.05	0.39
ENV (MSCI)	0.15	-0.01	-0.09	-0.06	0.03	0.01	0.05	0.1	0.26	-0.15	-0.1	-0.03	0.27	0.28	0.29	0.49	1	-0.17	0.46
wENV (MSCI)	-0.03	-0.08	-0.04	0.07	0.21	-0.02	-0.04	-0.04	-0.07	-0.02	0.62	-0.04	0.06	0.22	0.26	-0.05	-0.17	1	-0.18
EMISS (MSCI)	0.31	-0.03	-0.15	-0.01	0.12	0.01	0.06	0.17	0.36	-0.24	-0.22	0.02	0.39	0.39	0.39	0.39	0.46	-0.18	1

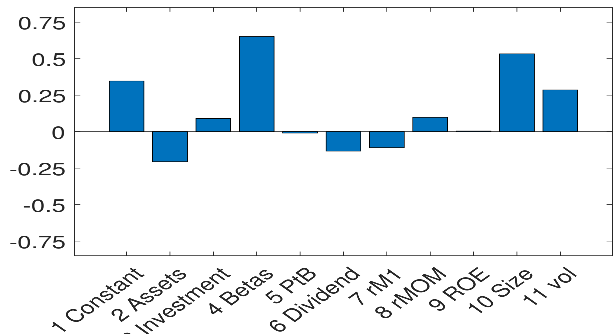
C.1 Empirical Results

C.1.1 Financial factors loadings (Γ_β^F) composition from the “Refinitiv” specification

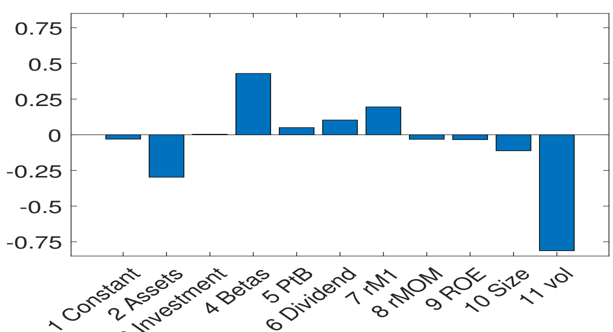
Figure C.1: Γ_β^F coefficient estimates from the “Refinitiv” specification with $K_F = 5$ financial factors and $K_G = 1$ green factor and tests



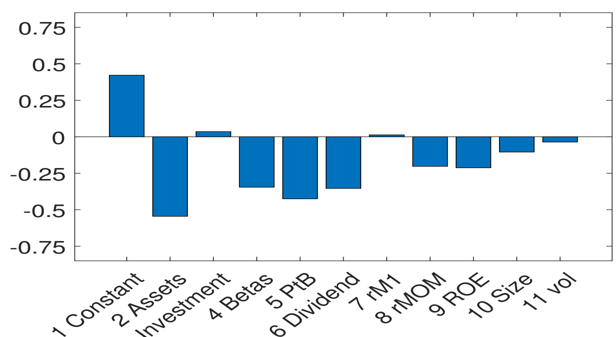
(a) First column of Γ_β^F



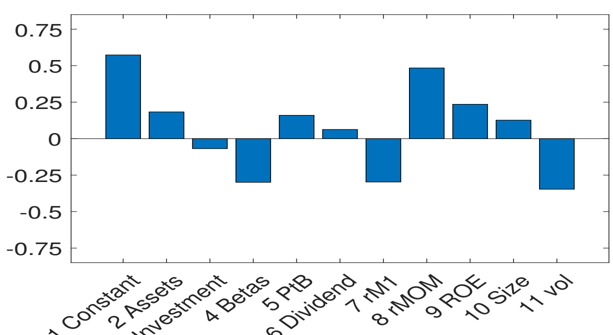
(b) Second column of Γ_β^F



(c) Third column of Γ_β^F



(d) Fourth column of Γ_β^F



(e) Fifth column of Γ_β^F

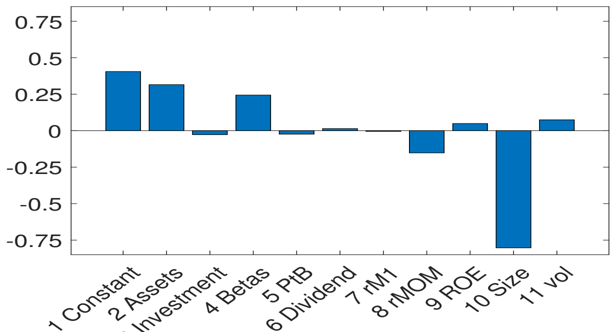
	F1	F2	F3	F4	F5	$p-$value	
Constant	0.48	0.35	-0.03	0.42	0.57	0	***
Assets	0.32	-0.21	-0.3	-0.55	0.18	0	***
Investment	-0.06	0.09	0	0.04	-0.07	0.32	
Betas	0.37	0.65	0.43	-0.35	-0.3	0	***
PtB	-0.02	-0.01	0.05	-0.42	0.16	0.041	**
Dividend	0.03	-0.13	0.1	-0.35	0.06	0.106	
rM1	-0.05	-0.11	0.19	0.01	-0.3	0.123	
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	***

(f) Γ_β^F and p-values

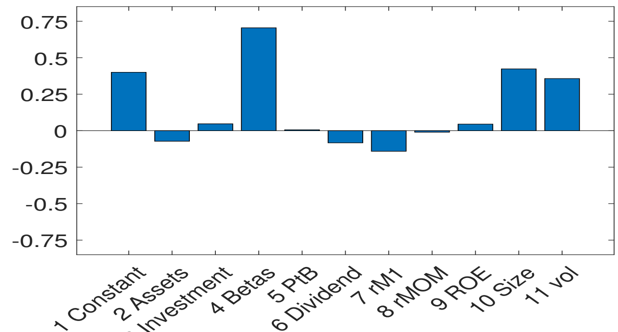
For each of the financial factors the figure displays the loadings composition: the columns of the estimated Γ_β^F coefficient matrix. Last panel displays the Γ_β^F matrix and the p-values for testing each characteristic under the null hypothesis that the characteristic do not contribute significantly to the loadings, while simultaneously controlling for all other characteristics. The test is described in Appendix A.2

C.1.2 Financial factors loadings (Γ_β^F) composition from the "MSCI" specification

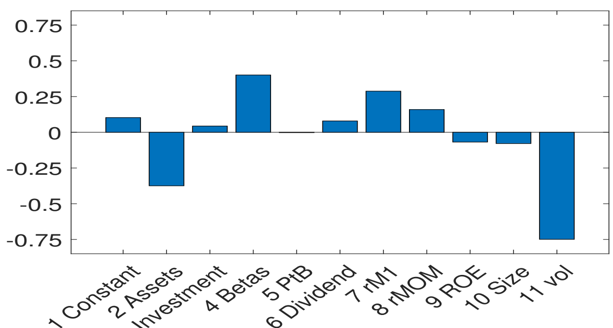
Figure C.2: Γ_β^F coefficient estimates from the "MSCI" specification with $K_F = 5$ financial factors and $K_G = 1$ green factor and tests



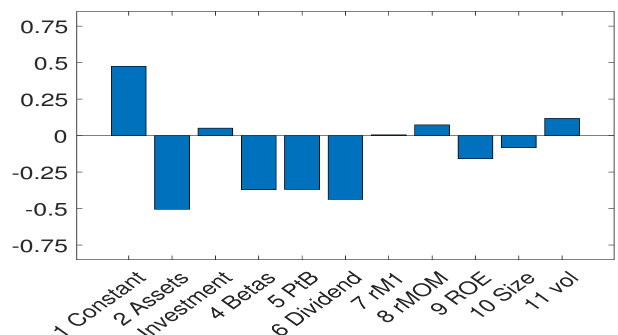
(a) First column of Γ_β^F



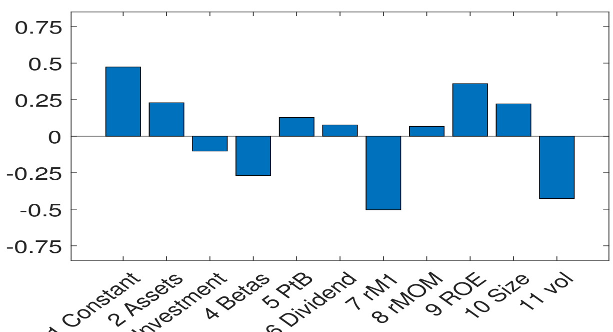
(b) Second column of Γ_β^F



(c) Third column of Γ_β^F



(d) Fourth column of Γ_β^F



(e) Fifth column of Γ_β^F

	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	***

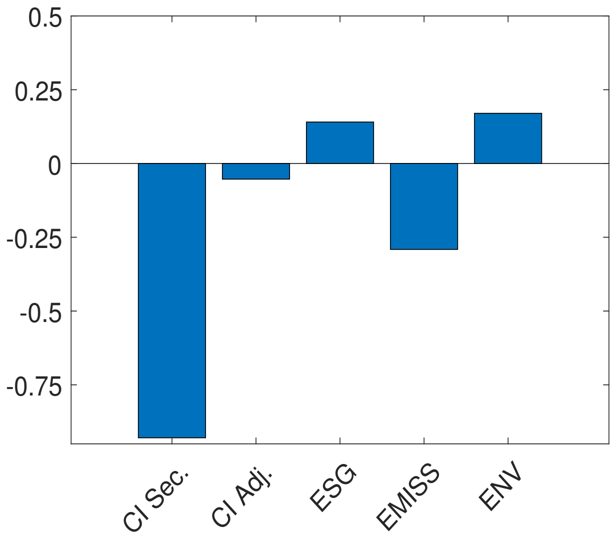
(f) Γ_β^F and p-values

For each of the financial factors the figure displays the loadings composition: the columns of the estimated Γ_β^F coefficient matrix. Last panel displays the Γ_β^F matrix and the p-values for testing each characteristic under the null hypothesis that the characteristic do not contribute significantly to the loadings, while simultaneously controlling for all other characteristics. The test is described in Appendix A.2

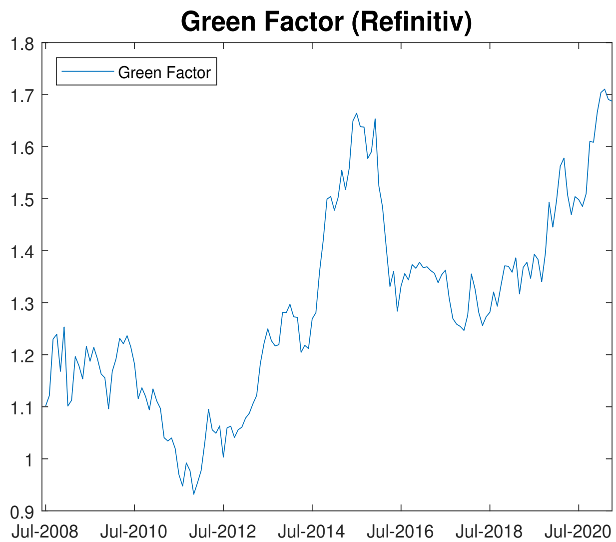
C.2 Green factor loadings (Γ_β^G) and cumulative returns

C.2.1 "Refinitiv" Specification

Figure C.3: Green factor loadings composition and cumulative returns of the green factor



(a) Γ_β^G estimated by using green characteristics from Refinitiv



(b) Cumulative returns of the green factor estimated by using green characteristics from Refinitiv

The figure displays the Γ_β^G from the specification "Refinitiv". These values can are proportional to weights of a portfolio composed by the managed portfolios that replicates the green factor. The table in Panel (b) displays the values Γ_β^G and the $p-$values: the sectorial carbon intensity and the emissions score are the only two characteristics whose contribution to the green factor loadings is statistically significant

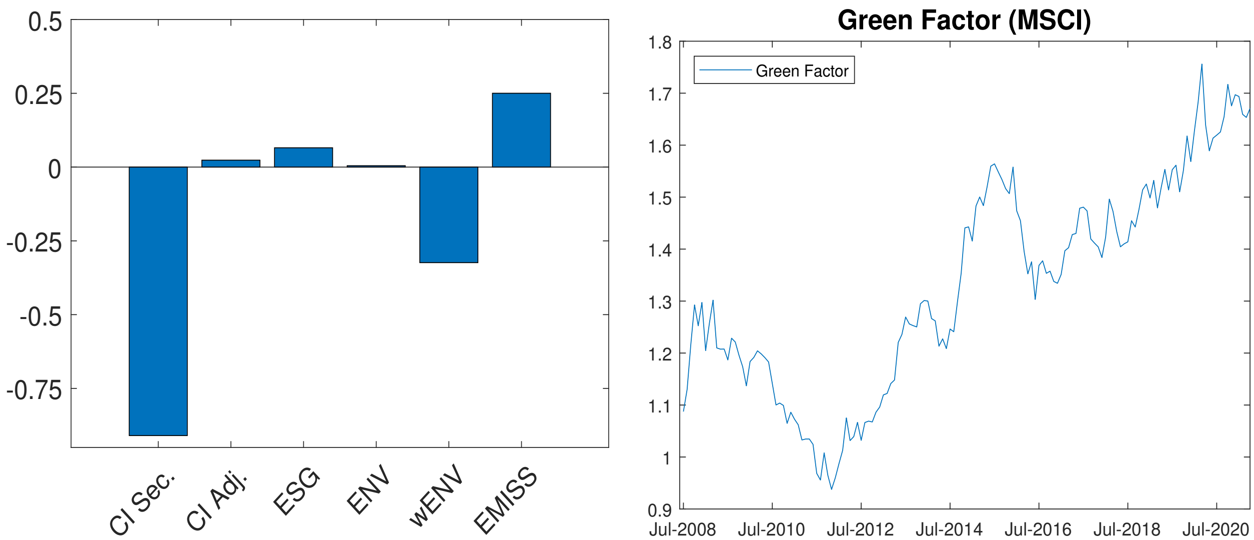
Table C.1: Γ_β^G matrix from "Refinitiv" specification and $p-$values for testing the significance of any characteristic to contribute to the model, while simultaneously controlling for all other characteristics

	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	

The table displays the values Γ_β^G and the $p-$values: the sectorial carbon intensity and the emissions score are the only two characteristics whose contribution to the green factor loadings is statistically significant

C.2.2 "MSCI" Specification

Figure C.4: Green factor loadings composition and cumulative returns of the green factor



(a) Γ_{β}^{G} estimated by using green characteristics from Refinitiv

(b) Cumulative returns of the green factor estimated by using green characteristics from Refinitiv

The figure displays the Γ_{β}^{G} from the specification "MSCI". These values are proportional to weights of a portfolio (composed by green managed portfolios) that replicates the green factor displayed in panel (b)

Table C.2: 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

	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	

The table displays the values Γ_{β}^{G} and the $p-$values: the sectorial carbon intensity is the only characteristics whose contribution to the green factor loadings is statistically significant

C.3 IPCA green factors and Stranded Asset Portfolio

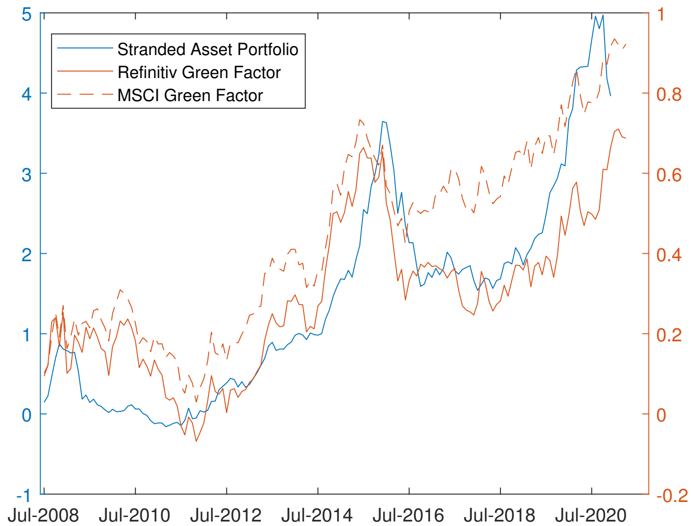


Figure C.5: Comparison between IPCA green factors and Stranded Asset Portfolio

C.4 Factor correlations and Sharpe ratios

	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 C.3: Correlation matrix between the 6 latent factors of the two different specifications (Refinitv:A4, MSCI:M) and the Fama-French 5 factors

	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 C.4: This table shows the annualized Sharpe rations of our IPCA factors computed both in-sample and out-of-sample.

C.5 Total, Pricing, and Predictive R^2's

C.5.1 In Sample R^2's, green characteristics from Refinitiv

	R^2	F1	F1-F2	F1-F3	F1-F4	F1-F5	F1-G1
	Total	22.35	31.15	31.99	33.72	35.98	36.44
Entire Asset Universe	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
	Total	11.2	13.58	14.51	16.44	21.63	21.52
Consumer Staples	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
	Total	5.92	13.59	13.9	18.34	19.95	20.11
Health Care	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
	Total	33.74	40.6	41.99	42.77	44.91	46.08
Financials	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
	Total	28.41	37.03	39.14	39.07	39.19	41.33
Energy	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
	Total	26.74	35.06	36.12	36.35	37.86	38.28
Basic Materials	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
	Total	11.92	17.17	17.71	20.13	21.67	21.59
Telecommunications	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
	Total	24.76	33.6	34.38	35.61	37.72	37.76
Consumer Discretion	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
	Total	28.7	40.34	40.74	41.54	44.68	44.39
Industrials	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
	Total	7.07	9.02	10.42	11.31	26.38	27.99
Utilities	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
	Total	14.37	28.49	28.47	32.4	34.35	34.65
Technology	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
	Total	35.95	43.05	44.11	45.7	49.69	49.73
Real Estate	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 C.5: 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) divided in the two components, namely sectorial and adjusted.

C.5.2 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 C.6: 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) divided in the two components, namely sectorial and adjusted carbon intensity.

C.5.3 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 C.7: This table shows the out-of-sample R^2 for the specification with 10 financial characteristics and 5 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 from ESG Refinitiv - Asset 4) divided in the two components, namely sectorial and adjusted carbon intensity. 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.

C.5.4 Out of Sample R^2's, green characteristics from MSCI

	R^2	F1	F1-F2	F1-F3	F1-F4	F1-F5	F1-G1
	Total	15.42	30.52	31.08	33.88	35.57	36.05
Entire Asset Universe	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
	Total	7.57	13.11	12.93	16.43	21.67	21.74
Consumer Staples	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
	Total	3.76	12	12.11	18.01	18.47	18.69
Health Care	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
	Total	30.3	44.84	46.09	46.35	49.83	51.65
Financials	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
	Total	22.39	38.86	40.35	40.84	40.75	43.12
Energy	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
	Total	19.98	35.55	36.23	36.78	37.69	37.8
Basic Materials	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
	Total	8.22	13.68	13.62	17.92	19.32	19.86
Telecommunications	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
	Total	15.33	33.53	34.4	36.56	37.63	37.51
Consumer Discretion	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
	Total	18.15	39.43	39.76	41.26	43.41	43.24
Industrials	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
	Total	5.02	3.5	4.56	7.33	24.79	23.83
Utilities	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
	Total	7.89	24.94	24	31.45	32.75	32.88
Technology	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
	Total	26.03	45.43	46.45	48.12	51.66	51.56
Real Estate	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 C.8: 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) divided in the two components, namely sectorial and adjusted carbon intensity. 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.

C.6 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 C.9: 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.

C.7 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 C.10: 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-sample regressions.