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Green Risk in Europe

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Green risk in Europe[1,2]

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Abstract

Climate change poses serious economic, financial, and social challenges to humanity, and green transition policies are now actively implemented in many industrialized countries. Whether financial markets price climate risks is critical to ensuring that the necessary funding flows into environmentally sound projects and that stranded assets risk is adequately managed. In this paper, we assess climate risks for the European stock market within the context of Alessi et al. (2023) greenness and transparency factor. We show that measures of returns spreads of green vs. brown investment might reflect climate risks and assets' exposition to systematic macro-financial risk factors. These latter factors should be filtered out to measure climate risks accurately. We show that climate risks are priced in the European stock market by focusing on aggregate, industry, and company-level data. We propose a market-based green rating procedure, which might be of particular interest to evaluate non-transparent and non-disclosing companies for which ESG information is unavailable. We illustrate its implementation using a sample of over 800 non-transparent firms.

Keywords: Climate risk, environmental disclosure, macro-finance interface, unconditional factor models, asset pricing, European Union.

JEL Classification: G01; G11; G12; Q54.

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1. Introduction

Eight years after the seminal speech by Mark Carney, at the time Governor of the Bank of England and Chairman of the Financial Stability Board, the "tragedy of the horizon" seems not to have been broken (Carney, 2015). Green transition costs are high and materialize in the short term; the benefits are uncertain and occur only in the long run. It is challenging for governments to implement policies with a long-term horizon against the pressures of the carbon-oil lobby, the urge of shareholder power for (very) short-term profits, and the difficulties in generating and spreading public awareness about climate risks, namely because climate change may be perceived as a century-away problem. It has been tough to adjust government and political intentions to the needs imposed by combating climate risks.

However, climate risks have reached wider public visibility as a result, in part, of the 2015 Paris Agreement. The Paris Agreement contains three key and interconnected objectives: 1) containment of the rise in the earth's average temperature below +1.5°C; 2) strengthening the capacity to adapt and promote development with low (or zero) GHG emissions; 3) making financial flows compatible with these objectives.

Climate change raises two main challenges: mitigation and adaptation. Mitigation concerns the containment of greenhouse gas (GHG) emissions. Mitigation generates transition risks due to abrupt or unanticipated changes in policies and regulations, consumers' and investors' behavior, and technological innovations. If not appropriately managed, the transition risks will lead to stranded assets, financial and output losses, and adverse effects on income distribution worldwide. Adaptation involves adjusting the economic and financial systems and human societies to make them resilient to climate change's physical risk. The changing intensity and frequency of extreme weather episodes - droughts, floods, and hurricanes - and the increasing likelihood of crossing tipping points concerning, among others, natural oscillations, sea level, ice sheets, global thermohaline circulation, rainforests, melting permafrost, and epidemics are the main determinants of climate change physical risks. According to climatology scientific literature, sizable economic, financial, and human life losses will result from materializing physical risks should mitigation fail to contain GHG emissions going forward.

However, there is a sharp contrast between the views of economists and climatologists on these matters (Keen et al., 2022). The economists that have contributed to IPCC reports and are most influential in this narrowly researched field in economics (e.g., Nordhaus and co-authors) typically predict that damages from global warming will be as low as 2% of global GDP for a 3ºC rise in global average surface temperature. The problem is that the financial services industry and pension funds have relied chiefly on advice and scenarios generated by economists, not climatologists. Hence, asset prices may not reflect the dangerously rising climate risks (Trust et al., 2023).

Given the significant investments required in facing climate change due to transition and physical risks, assessing to what extent financial markets are already pricing these risks is most important. Aligning financial market activity with policy and regulation interventions is necessary to foster an orderly transition to a carbon-free economy. For instance, within the European Green Deal strategy, the EU Taxonomy (EU, 2020) provides firms, investors, and policymakers with detailed criteria to assess the environmental sustainability of economic activities concerning climate change mitigation and adaptation, among other sustainability objectives. Directing funding and investments towards sustainable projects and activities should make the EU more resilient against climate and environmental shocks. Ideally, the Taxonomy should enhance the security and protection of investors from greenwashing, help companies along the green transition, and help shift investments where their "green" or "sustainability" return is highest. It will also impose company costs regarding strategy changes, reporting, and disclosure. Assessing how the market is pricing firms' activities along their green transition path is crucial to evaluate the impact of the transparency and disclosure requirements imposed by the Sustainable Finance Disclosure Regulation (SFDR) and the Taxonomy Regulation in directing financial investments toward products that are, or at least are classified as, environmentally sustainable.

This assessment falls within the set of research objectives of sustainable finance (see, e.g., the review by Hong et al., 2020; Giglio et al., 2020; Venturini, 2022; Campiglio et al., 2023). From an asset pricing perspective, many studies seek to explain the cross-sectional pattern of stock returns based on systematic risk factors such as size and book-to-market or firm-specific risks augmented by a climate change or environmental risk factor. Pástor et al. (2021), Gorgen et al. (2020), and Hsu et al. (2023), among others, introduce an arbitrary firm-level measure as a proxy of the environmental/climate risk exposure of the companies and use it to build a factor as a long/short portfolio and study its pricing in the market. Among others, Bolton and Kacperczyk (2021, 2022) use the firm-level measure as an explanatory variable for the cross-section of returns. Another strand of asset pricing literature assesses 'climate sentiment' measures constructed using textual and narrative analysis on climate change news from newspapers, Reuters, and Twitter (see, e.g., Ardia et al., 2020; Engle et al., 2020; Faccini et al., 2023; Santi, 2023). The available results are contrasting, chiefly depending on the choice of the greenness measure (Chini and Rubin, 2022). For instance, Bolton and Kacperczyk (2021, 2022) and Bansal et al. (2021) provide evidence that climate change is priced in the market, showing that higher CO_2-emitter firms have higher returns and that global temperature variations at low frequency negatively impact global stock markets, respectively. These findings are consistent with a carbon premium: stocks facing higher climate transition risk, i.e., brown stocks, should require a higher expected return. Investors in brown stocks should require compensation, i.e., a carbon premium, for the higher risks they are exposed to, for instance, associated with future regulatory interventions, shifting consumer and investor preferences, and technological change, which likely will turn these assets into stranded assets.

On the other hand, and following the same logic, green stocks should command lower expected returns if they are a hedge against climate risks. A higher (lower) expected return also eventually entails a higher (lower) realized return, leading to a positive brown vs. green stock premium. Yet, due to an increase in the demand for green stocks, caused, for instance, by a shift in investor preferences and regulatory measures and the rigidity of its supply, green stocks' realized returns could outperform brown stocks' returns even if they have a lower expected return (Pástor et al., 2021). This theoretical context provides some rationale for various studies documenting the overperformance of green over brown stocks. For instance, Bauer et al. (2023) reported the existence of a positive green vs. brown stock premium for the US and most G7 countries since 2012, yet a sign of inversion since 2022, following the energy crisis triggered by Russia's war in Ukraine. Previous similar evidence is provided by In et al. (2019) and Pástor (2022) for the US. In this context, Alessi et al. (2021) find a priced European 'greenness and transparency' systematic factor based on companies' GHG emissions and the quality of their environmental disclosures. In a time-invariant setting, Alessi et al. (2021) find a negative *greenium*, i.e., a negative risk premium linked to firms' carbon emissions and environmental transparency, indicating that investors might prefer a hedging strategy to reduce their exposure to climate risk. Alessi et al. (2023) extend their previous results by studying the evolution of the *greenium*. Investors in the European equity market seem to prefer a hedging strategy when economic shifts toward low carbon become more credible, for example, after the Paris Agreement, the first global climate strike, and the announcement of the EU Green Deal. In line with this stream of literature, Gimeno and González (2022) propose a green factor (i.e., GMP, Green companies Minus Polluters) based on companies' carbon footprints. Their methodology for building a green factor is close to Alessi et al. (2021) and Gorgen et al. (2020). They show investors prefer companies with lower carbon footprints, driving higher prices of greener stocks. Conflicting empirical results, however, also follow from the choice of the greenness measure. For instance, greenness can be measured by the level, intensity, or growth rate of CO_2 emissions or the E score of ESG ratings, which, in turn, might change according to the rating agency. For instance, Bolton and Kacperczyk (2021, 2022) find a carbon premium for the emissions levels. On the other hand, In et al. (2019) and Bauer et al. (2023) find a green premium for portfolios sorted on emission intensities, and Pástor et al. (2022) for portfolios sorted on E-scores. The sensitivity of the results also depends on the sample size and statistical procedures implemented (Bauer et al., 2023). Finally, Rebonato (2023) shows that mispricing of climate risk is the most likely explanation for failing to identify a robust and significant climate risk premium.

Considering the above findings, we first investigate the information content of the greenness and transparency portfolio proposed by Alessi et al. (2023) and then exploit it within an asset pricing context to provide a complementary, market-based tool for companies' green rating. In this respect, ESG ratings are criticized for failing to be compiled on quality data. For instance, ESG data are self-reported by the rated companies and not audited, leaving the door open for companies to distort their information disclosure to inflate their ESG rating artificially. Other biases might be associated with company size, geographic location, and industry sector. For instance, larger companies might have more resources than small firms to invest in improving their ESG scoring, leading to a size bias; European firms are subject to stricter disclosure regulations than US firms, generating a geographic bias. Finally, while data are normalized by industry, they might fail to factor in company-specific risks. This failure might cause a biased rating for a company based on its sector rather than its company-specific risk.

Moreover, ratings tend to differ according to rating agencies due to divergence in attributes, weight and aggregation functions, and indicators in measurement in ESG ratings. A market-based measure could improve upon all the above-listed shortcomings but still be subject to errors in measuring green investment performance or transition/green risk. While market awareness of green risk is rising over time (Baiardi and Morana, 2021), it is unclear how univocal and accurate its pricing is. Hence, this paper proposes a market-based tool based on accurate green risk modeling, yielding complementary information to standard

ESG ratings and improving existing approaches to rate non-transparent or non-disclosing companies.

Moreover, as argued by Trust et al. (2023), it is worrisome that "economic models used to underpin climate-change scenario analysis in financial services, leading to the publication of implausible results in the Task Force on Climate-related Financial Disclosure (TCFD) reporting, show benign, or even positive, economic outcomes in a hot-house world". If, as documented, institutional investors have been guided in their long-term portfolio allocation by such scenarios, why should short-term investors worry about climate risks?

Our findings suggest that standard measures of green/brown investment performance contain information that goes well beyond what could have been attributed to the pricing of climate risks, and, therefore, a more accurate measurement of climate risks should be found. These findings are consistent with evidence for other well-known risk factors, such as Fama-French (Morana, 2014; 2022). We propose constructing a green factor or measure independent of macroeconomic and financial information, i.e., a 'filtered green factor', obtained from the Alessi et al. (2023) greenness and transparency portfolio, depurated by financial and business cycle components. Using our filtered green factor, we find evidence that climate risks are priced in the European stock market. We find that, empirically, green investments have been a hedge over business and financial cycle developments and that restrictive economic policies negatively impact its yield. Moreover, increasing environmental concerns and physical risks are hedged in the stock market; the rising investor's environmental concern, following EU policy provisions such as the launch of the Green Deal and possibly also because of the COVID-19 pandemic, has led to higher performance of green vs. brown stocks. Finally, our sectorial analysis shows climate risks are negatively priced in typically brown sectors. We find a conditional association between a green-risk company beta and the green score of Alessi et al. (2023). Our market-based tool exploits this linkage to rate non-transparent and non-disclosing firms.

The paper is as follows. Section 2 discusses the construction of the Alessi et al. (2023) greenness and transparency factor. Section 3 presents the data, and Section 4 investigates the information content of the greenness and transparency factor, introduces its filtered version, and assesses its connection with climate concerns and physical risk. Sections 5 and 6 assess the pricing of climate risks in the European stock market, focusing on industry and company-level data. Section 6 also discusses the market-based strategy for rating non-transparent and non-disclosing firms. Finally, Section 7 concludes. We place the details on the dataset and the methodology for building portfolios in the online Supplementary Material (SM). Additional tables and figures for robustness checks are also available in the SM.

2. Theoretical setting

Alessi et al. (2021, 2023) propose a greenness and transparency factor (GR), a *green* factor for short, i.e., a portfolio that hedges against climate risk by going long on greener and more transparent stocks and short on high carbon/brown assets. Following Alessi et al. (2023), we identify greener and more transparent companies based on the indicator defined as a weighted average of two firms' characteristics: the inverse of the company ranking in terms of greenhouse gas (GHG) emission intensity *K*, and the company ranking based on the environmental score (E-score) *E*. For instance, for year *y*, company *i*, this indicator is $G_{i,y} = \gamma K_{i,y} + (1-\gamma)E_{i,y}$, with $\gamma \in [0,1]$. GR sets $\gamma = 0.5$.

Focusing on the distribution's tails, we select the top 20% of European firms ranked in greenness and transparency, i.e., the "greenest and most transparent" companies. Then, we build three value-weighted portfolios formed on size: a green portfolio of small firms ($r_{g,s}$); a green portfolio of medium-sized firms ($r_{g,m}$); and a green portfolio of large firms ($r_{g,l}$). Concerning "high-carbon"/brown companies, we select those firms that do not disclose environmental information and are active in high-carbon sectors (see the Climate-Policy-Relevant Sectors classification in Battiston et al., 2017). Also, for high-carbon firms, we build three value-weighted portfolios formed on size: a high-carbon portfolio including small, medium, and large firms, respectively ($r_{hc,s}, r_{hs,m}$, and $r_{hc,l}$). The monthly *t* greenness and transparency excess return GR_t is defined as follows:

$$\mathrm{GR}_t = \frac{1}{3}\left(r_{g,s,t} + r_{g,m,t} + r_{g,l,t}\right) - \frac{1}{3}\left(r_{hc,s,t} + r_{hc,m,t} + r_{hc,l,t}\right). \quad (1)$$

GR_t yields the difference between the average return on the three green portfolios and the average return on the three brown portfolios. Considering (1) as the market return on a portfolio hedging strategy is somewhat misleading. Such a strategy would provide systematic gains from "pure arbitrage" as zero investor's wealth is invested in such a strategy. Moreover, whether such trading activities are feasible or even available in the stock markets without huge trading costs and elevated operational risks is questionable. Yet, it is possible that time variation in GR_t reveals the kind of shocks and risks that drive green vs. brown stock returns. With this interpretation in mind, we carry out our empirical analysis.

To study the sources of systematic risk in the excess return of the greenness and transparency stocks, we follow Morana (2021, 2022) and decompose GR_t as follows,

$$\mathrm{GR}_t = f_{g_T,t} + f_{g_C,t} + \mathrm{GRF}_t, \tag{2}$$

where $f_{g_T,t}$ is the medium to long-term or trend component, $f_{g_C,t}$ corresponds to the short-term or cyclical component, and GRF_t measures the residual component. The decomposition is implemented through an OLS PC-regression for GR_t, by conditioning on some relevant euro area macro-financial factors. The factors used in this study are obtained by Morana (2022) from a large macro-financial dataset for the euro area. They subsume medium to long-term and short-term euro area macro-financial stylized facts. They are grounded on acknowledging two sources of systematic economic fluctuations: financial and business cycles. The financial cycle is of relatively low frequency, with a periodicity longer than ten years, i.e., between fifteen to twenty years on average in advanced countries since the 1980s. The business cycle is of relatively higher frequency, with a periodicity shorter than ten years (see Borio, 2014; Borio et al., 2019; Beaudry et al., 2020). In this context, medium to long-term fluctuations in economic time series are associated with the financial cycle and the concurrent long swings in economic activity. In contrast, short-term fluctuations are associated with the business cycle (and other more volatile episodes). The implementation of this decomposition relies on standard regression analysis and general-to-specific model reduction. Morana (2022) implements the decomposition using a two-step procedure based on sequential univariate decompositions and principal components analysis. The decomposition in Eq. (2) is then performed as the third and final step.

3. The data

We compute the stocks' greenness and transparency excess return GR defined in Eq. (1) over 3,607 European stocks traded in the leading European stock-exchange markets. The dataset does not include financial firms and penny stocks (see Appendix A of the SM for a comprehensive description of the data involved in the analysis and the methodology applied to portfolio formation, respectively). The sample begins in January 2006 and ends in August 2022. Figure 1 Panel A shows the monthly excess returns of the greenness and transparency stocks; Panel B displays its year-on-year excess returns. In contrast, Panel C shows the cumulative monthly excess returns. The light grey shaded areas correspond to periods of financial distress, while the dark grey shaded areas highlight recessions, as defined according to the EABCN chronology. According to EABCN chronology, since January 1999, three recessions occurred in the Euro Area, the first from March 2008 through June 2009 (included), the second from June 2011 through March 2013 (included), and the third from March 2020 through September 2020 (included). Following Morana (2021), we identify three periods of financial distress: the dot-com bubble (April 2000 through March 2003), the subprime financial crises (August 2007 through June 2009), and the Euro Area sovereign debt crisis (October 2009 through August 2012). Since February 2022, Russia's invasion of Ukraine has brought economic and financial distress to Europe and the World. Finally, in the plots, we highlight two relevant European climate-related events: the Paris Agreement (December 2015) and the launch of the European Green Deal (December 2019).

As shown in Figure 1, green and transparency excess returns were mainly negative during the first third of the sample investigated. However, green stocks outperformed brown stocks during crisis periods, i.e., during most of the Great Recession and the Euro Area sovereign debt crisis, yet not during the pandemic recession. This finding is most clear from the year-on-year and cumulative monthly green and transparency stocks excess returns displayed in Panels B and C, respectively. A decrease in the range of excess returns variation from the end of the Euro Area sovereign debt crisis recession through the beginning of the pandemic recession is also clear-cut from Figure 1, Panel A.

As shown in Figure 1, Panel C, a pure arbitrage portfolio, going long in green stocks and short in brown stocks with the sum of weights equal to zero, would have been profitable from mid-2012 until mid-2016. However, considering the fifteen years included in the analysis, the excess returns are (mean-reverting to) zero, of course, without considering the transaction costs and operational risks involved in implementing such a portfolio strategy (if feasible). Our findings contrast with other available empirical evidence from In et al. (2019), Pástor et al. (2022), and Bauer et al. (2023), where, however, the green factor is constructed using different procedures and not focused on the Euro Area stocks. Concerning Europe, Bauer et al. (2023) show contrasting evidence, with persistent overperformance of green vs. brown stocks in Germany, France, and the UK since 2010, but the other way around for Italy.

To further investigate the properties of the green and brown portfolios included in the calculation of GR, we conduct a mean-variance portfolio analysis. Figure 2 Panel A shows the efficient frontier built using six portfolios, i.e., three greener (and more transparent) and three high-carbon portfolios. The portfolios are reported concerning their level of risk and return. Considering the large stocks, we observe a slightly higher return for the high-carbon portfolio, albeit with a higher risk (variance) than the large green portfolio. Concerning the medium-sized portfolios, green stocks show a higher return than the medium-sized brown stocks, however, with higher risk (variance). Finally, small stocks' returns are the lowest, and their risks are the highest; however, in this case, small green stocks dominate small brown stocks individually as they have higher returns and lower risk. The minimum-variance portfolio (MVP) has the following composition without restrictions on the signs of the portfolio weights: green stocks: large 130%; medium -89%; small 21%; brown stocks: large 21.3%; medium 3%; small 14%. Not surprisingly, the MVP is mainly composed of large stocks, both green and brown, overweighting green large stocks, which is partially compensated with a negative position in medium green stocks. To understand the weight of the small brown portfolio in the MVP, we must consider that its return has the lowest correlation with the return on the large green portfolio, contributing to the reduction of portfolio variance through the diversification effect. For higher return-risk efficient portfolios, the small brown portfolio largely drops out of the efficient portfolios.

Figure 2 Panel B shows the return on the MVP over the sample period. The lowest risk-efficient investment provided a steady accumulation in monthly returns, contrasting with zero mean-reverting results on the GR (arbitrage) portfolio. This supports our interpretation of the meaning of that measure of excess returns.

3.1 The filtered greenness and transparency excess returns

Our excess return decomposition aims to shed light on the conflicting evidence on the pricing of climate risks in the literature. We employ the Morana (2022) eight Euro Area macro-financial stylized facts/common factors to decompose GR. These macro-financial factors are obtained from a dataset of twenty-eight monthly seasonally adjusted economic and financial variables for the Euro Area-19 from January 1999 to August 2022. See Morana (2022) for details concerning their derivation. These factors capture empirical regularities that marked the first twenty years of the Euro area. Morana (2022) identifies these as the financial cycle ($\hat{\mathbf{f}}_{\mathbf{n}_1}$), the demand ($\hat{\mathbf{f}}_{\mathbf{a}_i}$) and supply side ($-\hat{\mathbf{f}}_{\mathbf{a}_2}$) business cycle components, the globalization supply trend ($-\hat{\mathbf{f}}_{\mathbf{n}_2}$), medium-term fiscal ($-\hat{\mathbf{f}}_{\mathbf{n}_3}$) and monetary ($\hat{\mathbf{f}}_{\mathbf{n}_4}$) policies, and short-term financial factors ($\hat{\mathbf{f}}_{\mathbf{a}_3}$, $\hat{\mathbf{f}}_{\mathbf{a}_4}$). Given the scope of the paper, we focus on the stylized facts most informative to account for the green and transparency stocks excess returns variability, as it will become apparent from the empirical results. The common macro-financial factors data is available to researchers upon request.

The relevant estimated common factors are plotted in Figure 3 from January 1999 through August 2022. In particular, the top plot displays the financial cycle ($\hat{\mathbf{f}}_{\mathbf{n}_1}$), followed by the fiscal and monetary policy components ($-\hat{\mathbf{f}}_{\mathbf{n}_3}$, $\hat{\mathbf{f}}_{\mathbf{n}_4}$) and the supply-side business cycle factor ($-\hat{\mathbf{f}}_{\mathbf{a}_2}$); finally, the bottom plot shows the short-term financial factor ($\hat{\mathbf{f}}_{\mathbf{a}_3}$). Given the scope of the analysis, we focus our comments on the shorter sample of January 2007-August 2022. Figure 2, Panel A shows that almost two boom-bust financial phases occurred in the Euro Area since the early 2000s. The peak of the first cycle is in early 2005. Its trough is about two years long, between the end of the Great Recession and the early phase of the recession of the Euro Area sovereign debt crisis (June 2009-October 2011). The second financial cycle might have already peaked in December 2020. Still, no evidence of the winding down of the cycle can be found as of August 2022 (this indicator is closely associated with housing price measures). In Figure 2, Panel B shows that fiscal policy was countercyclical during all three recessionary episodes in the sample, yet at a much lower extent during the recession of the Euro Area sovereign debt crisis (an $-\hat{\mathbf{f}}_{\mathbf{n}_3}$ increase corresponds to a fiscal expansion). Figure 2, Panel C, shows a change in the ECB's monetary policy stance, marked by the Euro Area sovereign debt crisis. A relatively looser second regime sets in smoothly (yet not monotonically) since the late phase of the Great Recession, leading to the relevant policy rate (deposit facility rate) reaching negative nominal values and, eventually, the launch of various Asset Purchase Programs (i.e., QE policy). ECB's monetary policy response was countercyclical during all the crisis episodes in the sample (a $\hat{\mathbf{f}}_{\mathbf{n}_4}$ decrease corresponds to monetary policy loosening). Figure 2, Panel D, shows that supply-side cyclical developments have contributed to the depth of all recessionary episodes in the sample. The contribution was particularly sizable during the

Great Recession. Following Russia's invasion of Ukraine, a new supply-side recessionary impulse can be noted since early 2022 (this factor strongly comove with the stock market). Finally, Figure 2, Panel E, points to weakening overall conditions since the inception of the subprime financial crisis through the early phase of the Euro area sovereign debt crisis, and then again during the pandemic recession and since Russia's war in Ukraine began (an $\hat{\mathbf{f}}_{\mathbf{a}_3}$ increase is associated with weakening financial conditions; it is closely connected with the Fama-French European value factor). See Morana (2022) for complete details.

4. Decomposition of the green and transparency stocks' excess return

As we aim to disentangle the contribution of the various macro-financial factors to the performance of the green and transparency excess returns, we employ its year-on-year measure to match the observation frequency of the macro-financial data. The year-on-year frequency is also best suited for this purpose, as the smoothing it entails allows controlling for erratic fluctuations, which are unlikely to be determined by economic forces, which, on the other hand, can be expected to affect its underlying evolution. Moreover, as Jagannathan et al. (2012) pointed out, using year-on-year data does not affect the validity of unconditional asset pricing models. Jagannathan et al. (2012) show that the consumption-based asset pricing model (CCAPM) also holds when investors review their decisions infrequently, and not only at every point in time as assumed by the standard theory, allowing the use of low-frequency data in asset pricing.

Following Morana (2022), we implement the decomposition by an OLS regression of the year-on-year green and transparency stocks excess return GR on the complete set of eight common macro-financial factors, i.e.,

$$GR_t = \mu_{f_g} + \sum_{i=1}^{4} \beta_i \hat{f}_{\mathbf{n}_i,t} + \sum_{i=1}^{4} \beta_i \hat{f}_{\mathbf{a}_i,t} + \varepsilon_t, \tag{3}$$

where ε_t is a zero-mean stochastic disturbance. We report the results in the first two columns of Table 1. In column one, we report the results for the unrestricted regression with HACSE standard errors in round brackets. In the second column, we report the results of the restricted regression obtained from the omission of the statistically non-significant terms (5% level). As shown in Table 1, the reduction omits three regressors: the globalization supply-side trend $-\hat{\mathbf{f}}_{\mathbf{n}_2}$, the demand-side business cycle component $\hat{\mathbf{f}}_{\mathbf{a}_i}$, and the short-term financial factor $\hat{\mathbf{f}}_{\mathbf{a}_4}$. Despite the omissions, the proportion of accounted variance by the regression is virtually unchanged, i.e., over 60% for both the unrestricted and restricted regression. Notice that the instability of the estimates is due to the near orthogonality of the common factors. For this reason, the variance decomposition is obtained upon rescaling.

As shown in Table 1, the five retained regressors provide information on the performance of the excess returns of the green and transparency stocks since 2007. Concerning its trend developments, the financial cycle accounts for about 7% of the excess returns variance, and the fiscal and monetary policy components for about 11% and 22%, respectively. Concerning short-term developments, the business cycle supply-side component and the short-term financial factor account for about 14% and 9% of the variance, respectively. Hence, trend and cyclical developments account for 40% and 23% of the variance of the excess returns of the green and transparency portfolios; 37% is left unaccounted by the systematic macro-financial components.

The sign of the estimated parameters also conveys relevant information. According to the estimated negative signs, we can conclude that green and transparency stocks have been a hedge over the financial cycle, therefore hedging medium-term developments in the housing market and general financial distress. Moreover, it has been a hedge during the business cycle, hedging adverse stock market developments. Also, green and transparency stocks have been a hedge against weakening short-term financial conditions, moving countercyclically to the Fama-French value factor and comoving with the real estate in this context. Finally, restrictive monetary policy negatively impacts excess returns. In contrast, it is positively affected by a fiscal expansion, consistent with its hedging property over the business cycle and the countercyclical use of monetary and fiscal policy in the Euro area in the sample investigated.

In light of the auxiliary regression results and the information content of the estimated common factors, consistent with (2), GR is decomposed into three components: trend ($f_{g_T,t}$), cyclical ($f_{g_C,t}$), and residual (GRF_t) return. According to the results of the PC-regression analysis, we then have

$$f_{g_T,t} \equiv E\left[GR_t | \hat{f}_{n_1,t}, -\hat{f}_{n_3,t}, \hat{f}_{n_4,t}\right] = \hat{\mu}_{GR} + \hat{\beta}_1 \hat{f}_{n_1,t} + \hat{\beta}_2\left(-\hat{f}_{n_3,t}\right) + \hat{\beta}_3 \hat{f}_{n_4,t}, \qquad (4)$$

the trend or medium to long-term return component measures the expected GR excess return conditional to the macro-financial information set subsumed by its financial cycle ($\hat{\mathbf{f}}_{\mathbf{n}_1}$) and the fiscal and monetary policy factors ($-\hat{\mathbf{f}}_{\mathbf{n}_3}, \hat{\mathbf{f}}_{\mathbf{n}_4}$).

Moreover,

$$f_{g_C,t} \equiv E\left[(GR_t - \hat{\mu}_{GR})| - \hat{f}_{a_2,t}, \hat{f}_{a_3,t}\right] = \hat{\beta}_4\left(-\hat{f}_{a_2,t}\right) + \hat{\beta}_5 \hat{f}_{a_3,t}, \tag{5}$$

the cyclical or short-term return component measures the expected (demeaned) GR excess return conditional to the macro-financial information set subsumed by the supply-side/market return ($-\hat{\mathbf{f}}_{\mathbf{a}_2}$) and other short-term financial ($\hat{\mathbf{f}}_{\mathbf{a}_3}$) components.

Finally,

$$\begin{aligned} GRF_t &\equiv GR_t - E\left[GR_t | \hat{f}_{n_1,t}, -\hat{f}_{n_3,t}, \hat{f}_{n_4,t}, -\hat{f}_{a_2,t}, \hat{f}_{a_3,t}\right] \\ &\equiv GR_t - f_{g_T,t} - f_{g_C,t} \end{aligned} \tag{6}$$

the residual component measures the unexpected GR excess return, given the information set composed of the common macro-financial factors.

Morana (2022) points out that the macro-financial factors are orthogonal within each set by construction but not necessarily across sets. Sample correlations show that $f_{g_T,t}$ and $f_{g_C,t}$ are nearly orthogonal, as the correlation coefficient is -0.13 and not statistically different from zero at the 1% level. This result extends across sets' components due to their within-set orthogonality.

Figure 4 plots the historical decomposition of the greenness and transparency stocks' excess returns into their trend, cyclical, and residual components. In Figure 5, we further report the decomposition of the trend and cyclical components in their sub-components.

As shown in Figure 4 Panel A, *green and transparency* stocks' returns outperformed *brown* stocks during most of the Great Recession and most of the Euro Area sovereign debt crisis. However, it underperformed during the pandemic recession. Green and transparency stocks have been overperforming brown stocks again since mid-2021, throughout Russia's invasion of Ukraine (up to 2022:8, the end of our sample). Moreover, a trend decline in green and transparency stocks' excess returns can be noted since the recovery from the Euro Area sovereign debt crisis recession in early 2013 through mid-2017, followed by a recovery lasting through mid-2021. Trend underperformance of green and transparency stocks can be observed from mid-2015 through the end of 2020. As shown in Figure 5, Panel A, the downward trend is mainly determined by its exposition to the financial cycle and the fiscal stance, as the loose monetary policy regime set in since the later phase of the Great Recession has yielded a partially offsetting contribution.

Figure 4 Panel B shows that green and transparency stocks' overperformance during the Great Recession was primarily cyclical and driven by supply-side cyclical factors (Figure 5, Panel B). Largely cyclical is also green and transparency stocks underperformance during the COVID-19 crisis, determined by worsening short-term supply-side and financial conditions. Most recent developments point to some cyclical supply-side offsetting of the stable, downward trend in green and transparency stocks' excess returns.

GR, and therefore GRF, crucially depends on the Alessi et al. (2023) greenness and transparency indicator $G_{i,y} = \gamma K_{i,y} + (1-\gamma)E_{i,y}$, with $\gamma \in [0,1]$, computed setting $\gamma = 0.5$. For robustness, we repeat the decomposition analysis using the two limiting cases $\gamma = 0, 1$, yielding the alternative unfiltered (filtered) factors GR^0 (GRF^0) and GR^1 (GRF^1), respectively. As shown in Table 1, the decomposition results are strongly robust regarding selected specifications, retaining the same regressors, which also show the same signs. Moreover, we implement the decomposition for other available portfolio-based measures of green risk, such as Gimeno and González (2022) for the Euro Area and Bauer et al. (2023) for various European countries. As shown in the SM, Table C0, the results are robust also to the green risk measure employed, highlighting the importance of business cycle and economic policy factors and making the case for filtering portfolio-based measures of green risk relevant in general. A detailed discussion is reported in Appendix B in the SM.

4.1 Green factor and green risk in Europe

GRF is (linearly) unrelated to trend and cyclical macro-financial determinants by construction. As shown in Figure 4 Panel C, GRF appears to have contributed to overperformance during the Euro Area sovereign debt crisis and most of the recovery from the pandemic recession. An opposite contribution can be noted since Russia invaded Ukraine in 2022. This result is consistent with the energy market disruption brought about by the war and the increased uncertainty about the pace of the green transition. On average, the residual year-on-year return component is -0.05% from January 2007 through November 2015, -0.04% from December 2015 through November 2019, and 0.16% from December 2019 through August 2022. The increase in the green factor is consistent with the upward trend detected in raw returns displayed in Figure 1, suggesting that there is some market reward for green investment since the end of the pandemic crisis, which has, however, been eroding since the current geopolitical crisis began.

GRF should provide a more accurate measure of green risk, having been purged from other sources of systematic risk. In this Section, we further dig into the information content of GRF by assessing its interconnection with measures of climate change concern and physical risk. Our measure of climate concern is obtained through Google Trends and is based on the total searches of the words "climate change" worldwide (CC). An increase in the CC indicator means increased searches about climate change, which we associate with increased climate change concerns. The measure of physical risk is the European Extreme Events Climate Index (E3CI). The index is based on seven components yielding information on cold and heat stresses, droughts, heavy precipitations, intense winds, hail-leading conditions, and forest fires. It is available country-by-country from https://e3ci.dataclime.com/. An increase in the index points to higher overall physical risk stemming from extreme weather occurrences. For data coherence, one-year lagged moving averages (MA-12) are computed for CC and E3CI indexes. Concerning E3CI, we compute European aggregates for the fifteen countries whose stock markets are considered in the study, i.e., Belgium, Austria, Switzerland, Italy, Germany, Denmark, Spain, Finland, Ireland, Sweden, Netherlands, Norway, United Kingdom, France, Portugal, using Principal Components Analysis. The results are reported in Table 2, Panel A. The first four principal components account for over 80% of the total variance in both cases. The first PC accounts for 51% of the total variance and loads with negative weight on all the country indicators, yielding a common European measure (PC_1). The other PCs account for 15%, 12%, and 7.5% of the total variance. Based on the eigenvectors, they yield information on Southern vs. Northern Europe excess risk (PC_2), Atlantic vs. Continental excess risk (PC_3), and periphery vs. core Europe excess risk (PC_4), respectively.

The benchmark OLS regression is

$$GRF_t = \alpha_0 + \alpha_1 PA_t + \alpha_2 GD_t + \sum_{i=1}^{5} \beta_i x_{i,t} + \sum_{i=1}^{5} \gamma_i \left(x_{i,t} \times PA_t \right) + \sum_{i=1}^{5} \delta_i \left(x_{i,t} \times GD_t \right) + \varepsilon_t . \qquad (7)$$

where PA is a step dummy taking a unitary value following the Paris Agreement in December 2015, i.e., since January 2016, GD is a step dummy taking a unitary value following the launch of the European Green Deal in December 2019, i.e., since January

2020, and zero elsewhere, the regressors $x_i = CC, -PC_1, ..., PC_4$, and ε_i is a zero-mean stochastic disturbance. HACSE standard errors are computed to ensure valid inference. The European Green Deal dummy also covers the COVID-19 pandemic and might convey nonunivocal information.

The regression results are reported in Table 2, Panel B. In addition to results for GRF, we report results for GRF^0 and GRF^1 for robustness. We report the starting profligate specification in (7) and the final parsimonious model obtained for each filtered factor by excluding the non-significant regressors. For instance, for GRF, the estimated starting regression is reported in column 1, while the final parsimonious regression is reported in column 2. As our sample ends in August 2022, we do not include an additional dummy variable to account for Russia's invasion of Ukraine in February 2022.

As shown in Table 2, Panel B, columns 2, 4, and 6, the connection between the filtered green factor and the measure of climate concern and physical risk is clear-cut in all cases, strongest for GRF^1 and GRF where the adjusted coefficient of determination for the final regression is about 0.5, while lower and about 0.25 for GRF^0. This interesting finding suggests that the stock market might process information related to a firm's carbon emissions more extensively, as the signal might be more univocal than ESG rating, which is subject to various types of arbitrariness concerning information disclosures by firms and assessment by rating agencies. Concerning our benchmark measure GRF, the "Paris Agreement" and "Green Deal/COVID-19" dummy variables are statistically significant, not only when interacting with the other regressors. A lower-than-average green factor characterizes 2016-2021, while a higher-than-average green factor can be detected for the last period in the sample. Higher investors' climate concerns following the Paris Agreement might have led them initially to choose green investments as a hedge against transition risk. At the same time, the deepening of environmental awareness following the launch of the European Green Deal Strategy (or resulting from the COVID-19 pandemic) might have boosted demand for green stocks, thereby providing a basis for their excess returns. This interpretation is consistent with the switching sign of the Google trends-based climate concern index, turning to be positively priced following the Paris Agreement and then negatively priced again (and more sizably so) over the last sample period. Consistent with the rising environmental concern is the finding that our core measure of physical risk ($-PC_1$) is negatively and significantly priced only over the last period in the sample, pointing to hedging market behavior toward (environmental) physical risk. The periphery vs. core Europe excess risk (PC_4) measure is also negatively priced over the last sample period. This measure and the Southern vs. Northern Europe excess risk (PC_2) measure show some changing patterns over time but are significant over the whole sample at various extents (apart from PC_2 in the last sample period).

Overall, the findings suggest that increasing environmental concern and physical risk is hedged in the stock market; the rising investor's environmental concern, following EU policy provisions such as the launch of the Green Deal and possibly also because of the COVID-19 pandemic, has led to high demand and overperformance of green vs. brown stocks. As with the other findings, this core result is robust to the measure of the green factor employed (see the results for the GRF^0 and GRF^1 regressions).

5. Industry portfolio analysis and the idiosyncratic green risk

We develop a multifactor asset pricing analysis of the value-weighted industry portfolios based on the European statistical classification of economic activities (NACE) at division levels.[1] We include 2,252 assets with available monthly observations of returns and NACE division in the analysis. Table 3 reports the number of assets for each industry portfolio. By construction, we omit sectors "Financial and insurance activities " (K) and "Real estate activities" (L). We exclude from the analysis the companies for which the NACE division is not available and the NACE divisions for which no companies are included. The most populated industry is "Manufacturing" (C), a broad, highly heterogeneous industry, including manufacturing food products, tobacco products, chemical and pharmaceutical products, and basic metals.

For each division k and month t in year y we build the following value-weighted portfolio:

$$r_t^{\mathrm{k}} = \sum_{i \in k} w_{i,t} I_{i,t} r_{i,t}, \text{ where } w_{i,t} = \frac{I_{i,t}^{mc} mc_{i,t}}{\sum_t I_{i,t}^{mc} mc_{i,t}},$$

where $mc_{i,t}$ is the monthly market capitalization (see Appendix A.2 in the SM for details), and $I_{i,t}$ is an indicator function such that $I_{i,t} = 1$ if the return of asset i is observed at date t, and 0 otherwise. Then, we perform multifactor asset pricing analysis using time-series regressions for the industry portfolios on the five-factor model by Fama and French (2015),

[1] See https://ec.europa.eu/eurostat/web/products-eurostat-news/w/WDN-20230210-1, for details.

the four-factor model by Carhart (1997), the three-factor model by Fama and French (1993), all augmented by the green factor GRF. For instance, the augmented five-factor Fama-French time-series regression specification for the generic industry stock index i is

$$r_{i,t} = \alpha_i + \beta_{i,1}MKT_t + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}RMW_t + \beta_{i,5}CMA_t + \beta_{i,6}GRF_t + \varepsilon_{i,t}, \quad (8)$$

where MKT_t is the market factor return, SMB_t the small minus big factor return, $HML_t$the value portfolio return, RMW_t the robust minus weak factor return, CMA_t the conservative minus aggressive factor return, GRF_t the filtered green factor return, and $\varepsilon_{i,t}$ a zero-mean idiosyncratic disturbance.

Table 4 shows the pairwise correlation between the regressors included in the analysis. The Fama-French (MKT SMB, RMW, CMA) and momentum (MOM) factors are strongly correlated.

Different from the unfiltered green factor (GR), which also is mildly and significantly correlated with the other risk factors (apart from MKT), the filtered green factor (GRF) is statistically significant and uncorrelated with all the variables, except with the market (MKT) and profitability (RMW) factors. GRF is, however, only weakly correlated with MKT and RMW (15%). For completeness, we also report the correlation with the filtered green factors computed using $\gamma = 0, 1$ (GRF^0, GRF^1). As expected, these factors are highly correlated with GRF and have a similar correlation structure of GRF with the Fama-French and momentum factors. The factor GRF^0, including only the E-score information, is not statistically significantly correlated with the Fama-French and momentum factors. Instead, GRF^1, including only emission intensity as environmental information, is statistically significantly correlated with the market and profitability factors. These results are consistent with the view that measures of excess performance of green vs. brown stocks might also account for other sources of systematic risk, which need to be filtered out to extract a climate risk measure.

Table 5 reports the results of the industry OLS regression analysis. The estimates collected are robust for heteroskedasticity and autocorrelation. From the results for the augmented five-factor Fama-French model, reported in Table 5 Panel A, the green factor GRF is negatively priced in agriculture (A), electricity, gas, steam, and air conditioning supply (D), water supply (E), mining and quarrying (B). Still, it is only statistically significant for sector B (mining and quarrying). Thus, a positive green factor implies a reduction in the portfolio performance of industries mostly related to environmental issues. However, these results are not statistically significant, suggesting an underpricing of climate risks. The sign results are confirmed across the linear models for the augmented Carhart and the three-factor Fama-French models (see Table 5, Panels B and C); however, the negative pricing of GRF is statistically significant in these models, including, in addition to mining (B), also agriculture (A), electricity, gas, steam, and air conditioning supply (D), and transportation (H). A negative sign is estimated for water supply (E) and construction (F). Interestingly, a puzzling negative and significant sign can be found for the information and communication (J) sector. On the other hand, in the augmented Fama-French five-factor model, GRF is positively priced in divisions I, M, and R, corresponding to "Accommodation and food services activities", "Professional, scientific and technical activities" and "Arts, entertainment and recreation", respectively. The linkage is, however, statistically significant only for the professional and scientific activities sector. Put together, these results suggest some pricing of climate risks, at least in some industries. Coincidence or not, Nordhaus and co-authors' estimates of climate change damages list as severely impacted sectors: farms, forestry, and fisheries and moderately affected sectors: construction, energy and utilities, water and sanitary. By assumption, they consider that the bulk of economic activities in the USA will not be impacted by climate change because most are performed indoors (and thereby protected by air conditioning), namely industrial activities except construction (see Trust, 2023). Of course, evidence that climate risks are being priced in European stock markets does not allow us to conclude that the pricing is efficient in accurately reflecting all known scientific information about transition and physical risks.

For comparison, in Table C1 in the SM, we provide the regression analysis results on industry portfolios by estimating augmented models, including the green factor GR. Concerning the augmented Fama-French five-factor and Carhart models, we find similar results to those obtained using GRF and stronger evidence of negative pricing of the green factor in the sectors where the environmental concern is highest (A, B, D, E, and C), but also a puzzling negative impact for the human health sector (Q) in addition to the information and communication sector (J). Finally, Tables C2 and C3 in the SM provide the regression analysis for the green factors GRF^0 and GRF^1. The results confirm the negatively signed loadings in the sectors most exposed and linked to environmental issues.

6. Individual stocks analysis

In this Section, we further assess individual stock market responses to climate risks within an unconditional five Fama-French factors model, which we augment to include the filtered green factor GRF (Subsection 6.1). We construct a market-based green scoring tool that can be calculated when the 'greenness and transparency' indicator is not disclosed or is unavailable (Subsection 6.2).

6.1 Idiosyncratic green risk

The results in this Section complement the sectorial analysis. The specification for the generic stock i is as in (8). We report summary results in Figure 6. We show box plots for the estimated loadings on the filtered green factor GRF industry-by-industry. For robustness analysis, the exercise is also performed for the non-filtered green factor GR and the filtered and unfiltered green factors obtained in the two limiting cases discussed in Subsection 4.1, i.e., by setting $\gamma = 0, 1$.

As shown in Figure 6, the median $\hat{\beta}_{6,i}$ estimate is negative for agriculture (A), mining and quarrying (B), and the electricity, gas, steam, and air conditioning supply (D) industry, confirming the results for the industry portfolios reported in Table 5. Indeed, the median exposition to the green factor is negative in the sectors most exposed and linked to environmental issues. On the opposite, the NACE divisions M and R, corresponding to "Professional, scientific and technical activities" and "Arts, entertainment and recreation", respectively, take on median positive values of the loadings, confirming the positive and significant result gathered for the industry portfolios in Table 5. The distribution of loadings for the "Manufacturing" (C) division, i.e., the most populated division, is symmetric around zero. This result also aligns with the estimates gathered for the industry portfolios.

6.2 A market-based rating tool

We then further explore the linkage between the time average of the rescaled greenness and the transparency indicator proposed by Alessi et al. (2023) for the generic stock i and its estimated loading on the filtered green factor GRF, i.e., $\hat{\beta}_{6,i}$. Figure 7 provides the distributions of the average indicator by grouping companies at the industry level.

Suppose climate risks are priced in the stock market. In that case, we can set up a market-based green scoring tool that can be calculated when the 'greenness and transparency' indicator is not disclosed or is unavailable. For instance, we have 2,252 stocks in our usable sample, but only 1,385 correspond to transparent firms, i.e., provide the information necessary to compute $\overline{G}_i$. An approximate score for these 867 non-transparent firms can be obtained through our market-based tool exploiting their estimated loading on the filtered green factor GRF.

The procedure requires the estimation of the following auxiliary OLS regression.

$$\overline{G}_i = \sum_{j=1}^{n} g_j I_{j,i} + \sum_{j=1}^{n} b_j I_{j,i} \hat{\beta}_{6,i} + \varepsilon_i , \tag{8}$$

where i is the index referring to the available transparent stocks ($i = 1,...,N$), j is the sectorial index ($j = 1,...,n$), $I_{j,i}$ is a dummy variable taking value equal to one if stock i belongs to sector j and zero otherwise, and g_j, b_j are parameters. In the analysis, we omit those sectors for which we have less than twenty stocks, i.e., agriculture (A), water supply (E), education (P), and other service activities (S), as reported in Table 3. Hence, in our empirical implementation, the number of industries is n = 12, and the number of usable stocks is $N = 1,367$. We report the results of the estimated regression in Table 6. For efficiency reasons, we also report the results of restricted OLS estimation obtained from the imposition of equality restrictions across the parameters of the unrestricted model based on numerical congruity. For robustness, we report the results obtained using the $\hat{\beta}_{i,6}$ coefficient from asset pricing regressions using the alternative green factors GRF^0 and GRF^1. We also report results obtained from the unfiltered green factors GR, GR^0, and GR^1 in Table C4 in the SM for robustness and to assess the comparative performance of the different filtering approaches. We have three disjoint models where the same dependent variable, i.e., the average score $\overline{G}_i$, is regressed on other $\hat{\beta}_{i,6}$ coefficient series, corresponding to the regressors GRF, GRF^1, and GRF^0 used alternatively. We can also estimate a single joint model within the classical model averaging approach proposed by Morana (2015). Our context is discussed in Subsection 3.2.1 in Morana (2015). For instance, for the filtered factor case, we have the following three disjoint models:

$$
\begin{aligned}
\bar{G}_i &= \sum\nolimits_{j=1}^{n} g_j I_{j,i} + \sum\nolimits_{j=1}^{n} b_j I_{j,i}\hat{\beta}_{6,i} + \varepsilon_i \\
\bar{G}_i &= \sum\nolimits_{j=1}^{n} g_{j,1} I_{j,i} + \sum\nolimits_{j=1}^{n} b_{j,1} I_{j,i}\hat{\beta}_{6,\gamma=1,i} + \varepsilon_{i,1} \\
\bar{G}_i &= \sum\nolimits_{j=1}^{n} g_{j,0} I_{j,i} + \sum\nolimits_{j=1}^{n} b_{j,0} I_{j,i}\hat{\beta}_{6,\gamma=0,i} + \varepsilon_{i,0}
\end{aligned}
\tag{8}
$$

and the corresponding stacked model

$$
\bar{G}_i^* = \sum\nolimits_{j=1}^{n} g_j I_{i,j}^* + \sum\nolimits_{j=1}^{n} b_j I_{i,j}^* \hat{\beta}_{i,6}^* + \varepsilon_i^* \tag{9}
$$

where $\bar{G}_i^*$ is the generic entry in the stacked vector $\bar{\mathbf{G}}^* = \mathbf{i}_3 \otimes \bar{\mathbf{G}}$ and $\bar{\mathbf{G}} = \left[\bar{G}_1 \quad \bar{G}_2 \quad \dots \quad \bar{G}_N\right]'$, $\mathbf{i}_3 = (1 \quad 1 \quad 1)'$; $I_{i,j}^*$ is the generic entry in the stacked vector $\mathbf{I}_j^* = \mathbf{i}_3 \otimes \mathbf{I}_j$ and $\mathbf{I}_j = \left[I_{j,1} \quad I_{j,2} \quad \dots \quad I_{j,N}\right]'$; $\hat{\beta}_{6,i}^*$ is the generic entry in the stacked vector $\hat{\boldsymbol{\beta}}_6^* = \left(\hat{\boldsymbol{\beta}}_6' \quad \hat{\boldsymbol{\beta}}_{6,\gamma=1}' \quad \hat{\boldsymbol{\beta}}_{6,\gamma=0}'\right)'$, and $\hat{\boldsymbol{\beta}}_6 = \left[\hat{\beta}_{6,1}^* \quad \hat{\beta}_{6,2}^* \quad \dots \quad \hat{\beta}_{6,N}^*\right]'$,

$\hat{\boldsymbol{\beta}}_{6,\gamma=1} = \left[\hat{\beta}_{6,\gamma=1,1}^* \quad \hat{\beta}_{6,\gamma=1,2}^* \quad \dots \quad \hat{\beta}_{6,\gamma=1,N}^*\right]'$, $\hat{\boldsymbol{\beta}}_{6,\gamma=0} = \left[\hat{\beta}_{6,\gamma=0,1}^* \quad \hat{\beta}_{6,\gamma=0,2}^* \quad \dots \quad \hat{\beta}_{6,\gamma=0,N}^*\right]'$.

The estimated parameters from the stacked model are equivalent to a weighted average of the parameter estimates obtained from the various candidate models, where the optimal weights are implicitly computed ex-ante according to the MSE metric and are proportional to the relative variation of the regressors. By exploiting all the available information on the various candidate sets of variables and relying on more degrees of freedom, the procedure should lead to more accurate, robust, and (relatively) more efficient estimation. We have also implemented the model averaging method for the parameters obtained from the unfiltered green factors (see Table C4 in the SM).

We report the results in Table 6. In columns one, three, five, and seven, we report the results for the disjoint regression involving the filtered green factors GRF, GRF^1, GRF^0, and for the stacked model, respectively. We report the same results for the restricted regressions in columns two, four, six, and eight. Restricted models are obtained by imposing equality restrictions across the model's parameters based on similar estimated magnitudes. Restricted models deliver more efficient estimates.

As shown in Table 6, significant industry effects point to average lower scores for traditionally brown sectors such as mining (B), energy supply (D), and transportation (H), but also for accommodation (I), human health (Q), and entertainment (R). Relatively higher scores are measured for manufacturing (C), construction (F), information and communication (J), professional/scientific activity (M), and administrative services (N). These findings are robust across all models. The linkage between the average green score and the $\hat{\beta}_{i,6}$ coefficient series is highly robust across models concerning its sign. In this respect, the link is positive for the relatively brown sectors such as mining (B), construction (F), and transport (H), but also for automotive sale and repair (G), and negative for the service sectors accommodation (I), human health (Q), entertainment (R), information and communication (I), professional/scientific activity (J), and administrative services (N). These linkages are significant at the usual level (5%) for the restricted models, while only industry effects are generally significant for the unrestricted disjoint models.

The pattern detected is coherent with the average magnitude of the estimated $\hat{\beta}_{6,i}$ coefficient series and the average indicator reported in Figure 7. Focusing on the Mining and quarrying industry, i.e., the most exposed and linked to environmental issues, we observe that the estimated g_B takes a value that approximates the median of the average indicator in Figure 6. Furthermore, we also observe that the estimates of b_B is positive and significant for the restricted model, implying, on average, a smaller value of the greenness and transparency factor since the median $\hat{\beta}_{6,i}$ value is negative for individual stocks in this sector.

The restricted models are all valid, based on the likelihood-ratio test and the comparison of the BIC information criterion for the unrestricted and restricted models. The restricted models are never rejected (5% level), and their BIC is always sizably smaller than the unrestricted models. The coefficient of determination is also unaffected by the imposition of the restrictions despite being very low in all cases. Moreover, the comparison with the models for the unfiltered green factors reported in the SM confirms that filtering impacts the estimated magnitudes of the b_j parameters, pointing to the importance of accurately measuring the exposition of the various stocks to green risk.

Despite the low coefficient of determination, the pattern detected is clear-cut and potentially exploitable to compute an implied average green score G for the non-transparent companies. For exemplification purposes, we have used the estimates reported in column one in Table 6 to calculate the implied green score G for the 855 non-transparent firms in our sample of interest. The results are reported in Figures 7 and 8, where we compare the average green score for the 1,367 transparent companies in our sample with the estimated average green score for the non-transparent companies. Not surprisingly, the estimated average green scores show smaller variability than the actual scores, particularly for those sectors for which the linkage measured by the auxiliary regression is weaker, such as manufacturing. This sector is very diverse, collecting many different types of activities. We conclude that the implied green rating procedure we propose in this paper would benefit from a finer sectorial grouping of companies.

7. Conclusions

Within the European Green Deal strategy, the EU Taxonomy (EU, 2020) provides firms, investors, and policymakers with detailed criteria to assess the environmental sustainability of economic activities. Therefore, financial markets must give accurate signals for investors to direct funding and investments toward sustainable projects and activities. A *greener* capital allocation would make the EU more resilient against climate and environmental shocks, aligning economic activity with policy and regulatory interventions. All those are necessary conditions to foster an orderly transition to a carbon-free economy.

Whether EU financial markets are pricing green transition risk is a critical issue. The related climate finance literature is rapidly growing, and conflicting evidence has emerged concerning the hedging properties of green investment and the pricing of green risk. Divergence in empirical results critically arises from the choice of the greenness measure, which is far from being univocally defined. This paper employs the Alessi et al. (2023) greenness and transparency factor. A green factor can be constructed within the Fama-French tradition of multifactor risk measures. The empirical evidence shows that it might capture climate risks. This paper further investigates its information content and tentative hedging properties of green investments.

We follow Morana (2021, 2022) and decompose the green factor into a trend, cyclical, and residual component orthogonal to the former two. We find that stocks' exposition to macro-financial systematic risk accounts for the first two parts. The residual part, i.e., the filtered green factor, should provide a more accurate measure of green risk than the excess return of green stocks vs. brown stocks. Within an unconditional multifactor asset pricing model context, we find evidence that green risk is priced in the European stock market. At the aggregate level, we find that since 2007, green investments have allowed hedging over the business and financial cycle developments. We also find that the filtered green factor reflects both climate concerns and physical risk. These risks are hedged in the European stock market at a higher extent since the launch of the European Green Deal strategy. At the industry level, climate risks are negatively priced in the typically high carbon/brown sectors. At the firm level, we find a conditional association between a green-risk company beta and the green score of Alessi et al. (2023). Based on this conditional linkage, we propose a regression method to compute a market-based implied measure for the green score for non-transparent and non-disclosing firms for which ESG or carbon intensity measures are unavailable. The application to over 800 non-transparent European companies illustrates its viability and the conditions under which it might work best.

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Table 1: Green factor return decomposition regressions

	GR	GR	GR^0	GR^0	GR^1	GR^1
$\hat{f}_{n_1}$	-4.336 (2.240)	**-3.997** (1.548)	**-5.763** (1.589)	**-5.477** (1.071)	-3.638 (2.494)	**-4.762** (1.665)
$-\hat{f}_{n_2}$	0.632 (2.072)	-	0.037 (1.343)	-	-0.535 (2.231)	-
$-\hat{f}_{n_3}$	4.471 (3.869)	**4.834** (1.761)	**2.818** (2.490)	**3.737** (1.461)	**8.433** (4.230)	**5.675** (2.237)
$\hat{f}_{n_4}$	**-6.995** (1.474)	**-6.920** (1.243)	**-6.445** (0.867)	**-6.411** (0.794)	**-6.742** (1.625)	**-7.106** (1.519)
$\hat{f}_{a_1}$	0.478 (1.302)	-	**1.747** (0.889)	**2.074** (0.663)	1.685 (1.318)	-
$-\hat{f}_{a_2}$	**-5.667** (0.968)	**-5.576** (0.914)	**-5.264** (0.642)	**-5.490** (0.614)	**-3.854** (0.980)	**-3.531** (1.040)
$\hat{f}_{a_3}$	**-4.714** (1.189)	**-4.500** (1.250	**-7.071** (0.894)	**-7.452** (0.845)	-0.760 (1.380)	-
$\hat{f}_{a_4}$	-0.126 (1.087)	-	1.343 (0.906)	-	1.659 (0.931)	-
μ_{f_g}	-4.093 (2.358)	**-3.791** (1.279)	-5.889 (1.646)	-5.582 (1.001)	-0.081 (1.605)	-1.191 (1.600)
R^2	**0.632**	**0.626**	**0.768**	**0.758**	**0.568**	**0.548**
$\overline{R}^2$	**0.615**	**0.616**	**0.757**	**0.750**	**0.549**	**0.538**
Var %	**GR**	**GR**	GR^0	GR^0	GR^1	GR^1
$\hat{f}_{n_1}$	0.08	0.07	0.15	0.13	0.05	0.11
$-\hat{f}_{n_2}$	0.00	0.00	0.00	-	0.00	-
$-\hat{f}_{n_3}$	0.09	0.11	0.04	0.06	0.27	0.15
$\hat{f}_{n_4}$	0.22	0.22	0.19	0.18	0.17	0.23
$\hat{f}_{a_1}$	0.00	0.00	0.01	0.02	0.01	-
$-\hat{f}_{a_2}$	0.14	0.14	0.13	0.13	0.06	0.06
$\hat{f}_{a_3}$	0.10	0.09	0.23	0.24	0.00	-
$\hat{f}_{a_4}$	0.00	0.00	0.01	-	0.01	-

The Table reports the results of the estimated PC regressions for the monthly year-on-year green and transparency factor on selected Morana (2022) common macro-financial factors. Figures in round brackets refer to Newey-West consistent SE. The estimated parameters in bold are significant at the 5% level. The (adjusted) coefficient of determination is denoted as ($\overline{R}^2$) R^2. The Table also reports the % green factor variance accounted for by any of the selected common factors (Var %). The estimation sample is 2007:1-2022:8. GR is the benchmark Alessi et al. (2023) green factor; GR^0 and GR^1 are the green factors for the two limiting cases, where $\gamma = 0$ and $\gamma = 1$, respectively.

Table 2, Panel A: Principal components analysis of E3CI country measures

Eigenvalues				Eigenvectors				
	EV	**% VAR**	**% CUM**		**PC1**	**PC2**	**PC3**	**PC4**
PC1	7.70	51.33	51.33	**BE**	-0.226	-0.025	-0.026	-0.273
PC2	2.23	14.87	66.20	**AT**	-0.243	0.071	0.473	-0.014
PC3	1.81	12.04	78.24	**CH**	-0.286	0.196	-0.276	-0.078
PC4	1.13	7.50	85.74	**IT**	-0.234	0.410	0.012	0.095
PC5	0.70	4.66	90.40	**DK**	-0.323	-0.155	-0.100	0.049
PC6	0.40	2.67	93.07	**DE**	-0.266	-0.031	-0.196	-0.459
PC7	0.27	1.78	94.85	**ES**	-0.207	0.478	-0.028	0.189
PC8	0.22	1.46	96.31	**FI**	-0.255	-0.292	-0.220	0.291
PC9	0.15	0.98	97.29	**IE**	-0.236	-0.190	0.460	0.071
PC10	0.13	0.89	98.18	**SE**	-0.282	-0.276	-0.083	0.304
PC11	0.11	0.71	98.89	**NE**	-0.275	0.088	-0.393	-0.239
PC12	0.06	0.40	99.29	**NO**	-0.240	-0.353	-0.117	0.367
PC13	0.05	0.34	99.62	**UK**	-0.256	-0.095	0.441	-0.257
PC14	0.04	0.24	99.86	**FR**	-0.333	0.019	0.109	-0.207
PC15	0.02	0.14	100.00	**PT**	-0.160	0.442	0.091	0.422

Table 2, Panel B: Filtered green factor return regressions on CC and E3CI

	GRF	**GRF**	**GRF^0**	**GRF^0**	**GRF^1**	**GRF^1**
α_0	11.11 (5.695)	**12.04** (5.757)	1.634 (4.203)	0.337 (0.809)	-2.161 (6.137)	-0.268 (1.043)
α_1	**-26.84** (7.738)	**-20.81** (8.001)	-5.003 (6.098)	-	-14.99 (8.260)	-
α_2	**54.70** (8.825)	**49.23** (8.904)	**29.26** (6.098)	**20.61** (6.692)	**55.22** (8.131)	**37.75** (6.001)
β_1	**-1.927** (0.944)	**-2.068** (0.831)	-0.517 (0.666)	-	0.185 (0.992)	-
β_2	0.179 (1.199)	-	-0.932 (1.196)	-	-0.461 (1.231)	-
β_3	2.606 (1.999)	**4.094** (1.095)	2.031 (1.222)	**2.143** (0.752)	**5.452** (2.261)	**5.525** (1.029)
β_4	5.667 (4.877)	-	1.620 (4.307)	-	1.263 (6.364)	-
β_5	**-3.396** (1.634)	**-3.932** (1.086)	-1.881 (1.149)	-1.426 (0.796)	-3.246 (1.815)	**-3.087** (1.224)
γ_1	**4.208** (1.146)	**3.090** (1.068)	1.108 (0.826)	-	**2.465** (1.245)	-
γ_2	2.263 (1.446)	-	**3.873** (1.485)	**2.654** (0.590)	**4.475** (1.497)	**2.091** (0.725)
γ_3	-3.656 (2.035)	**-3.241** (1.185)	-2.430 (1.375)	**-1.829** (0.895)	**-7.453** (2.354)	**-4.535** (1.070)
γ_4	3.900 (5.620)	-	**10.40** (5.082)	**9.613** (1.964)	11.02 (7.161)	-
γ_5	**0.820** (0.263)	**0.965** (0.176)	**0.666** (0.191)	**0.580** (0.166)	**0.744** (0.267)	**0.611** (0.259)
δ_1	**-5.167** (0.948)	**-4.024** (0.849)	**-2.839** (0.847)	**-1.741** (0.534)	**-4.759** (1.043)	**-2.189** (0.475)
δ_2	**-5.652** (1.562)	**-2.933** (0.872)	**-4.752** (1.595)	**-4.129** (1.354)	**-10.303** (1.278)	**-6.248** (1.037)
δ_3	-2.774 (3.460)	-	3.370 (3.360)	-	4.043 (2.485)	-
δ_4	**-8.774** (4.218)	-	**-10.613** (3.949)	**-9.102** (3.250)	**-8.834** (3.954)	-
δ_5	**-7.247** (2.783)	**-8.578** (2.777)	-5.721 (3.187)	-5.001 (3.223)	**-7.754** (2.164)	**-7.350** (2.834)
R^2	**0.500**	**0.465**	**0.319**	**0.300**	**0.532**	**0.502**
$\bar{R}^2$	**0.450**	**0.432**	**0.251**	**0.256**	**0.485**	**0.477**

Panel A reports the results of the principal components (PCs) analysis conducted on the E3CI country for the relevant countries in our sample. EV denotes the estimated eigenvalues, while % VAR is the proportion of total variance accounted by each associated PC, and % CUM is the cumulative percentage of variance. The sample countries are Belgium (BE), Austria (AT), Switzerland (CH), Italy (IT), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), Ireland (IE), Sweden (SE), Netherlands (NE), Norway (NO), United Kingdom (UK), France (FR), Portugal (PT). Panel B reports the results of the estimated regressions for the filtered green factors GRF, GRF^0, and GRF^1 on the climate concern and physical risk measures. Figures in round brackets refer to Newey-West consistent SE. The estimated parameters in bold are significant at the 5% level. The (adjusted) coefficient of determination is denoted as ($\overline{R}^2$) R^2 .

Table 3: Distribution at NACE division levels of individuals stocks			
NACE Division	**Title**	**# companies**	**# transparent companies**
A	Agriculture, forestry and fishing	11	8
B	Mining and quarrying	92	40
C	Manufacturing	1004	659
D	Electricity, gas, steam and air conditioning supply	58	41
E	Water supply; sewerage, waste management and remediation activities	15	9
F	Construction	79	54
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	156	110
H	Transportation and storage	89	64
I	Accommodation and food service activities	44	28
J	Information and communication	363	186
K	Financial and insurance activities	0	0
L	Real estate activities	0	0
M	Professional, scientific, and technical activities	183	82
N	Administrative and support service activities	75	50
O	Public administration and defense; compulsory social security	0	0
P	Education	1	0
Q	Human health and social work activities	38	23
R	Arts, entertainment and recreation	43	30
S	Other service activities	1	1
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0	0
U	Activities of extraterritorial organisations and bodies	0	0
-	NaN NACE	449	270

The table reports the distribution by NACE divisions of individual stocks with available monthly observations of returns. Furthermore, the table reports the number of transparent companies, i.e., the companies for which the average greenness and transparency indicator is available.

Table 4, Panel B: Correlation matrix across the observable factors										
	MKT	**SMB**	**HML**	**RMW**	**CMA**	**WML**	**GR**	**GRF**	**GRF^0**	**GRF^1**
MKT	1.000	0.199	0.213	-0.260	-0.298	-0.398	-0.057	0.150	0.074	0.147
SMB	*0.006*	1.000	0.366	0.661	0.471	0.288	0.170	-0.051	-0.004	0.016
HML	*0.003*	*0.000*	1.000	0.228	0.747	0.019	0.423	-0.072	0.016	-0.052
RMW	*0.000*	*0.000*	*0.002*	1.000	0.656	0.538	0.455	0.159	0.077	0.235
CMA	*0.000*	*0.000*	*0.000*	*0.000*	1.000	0.461	0.548	-0.060	-0.025	-0.060
WML	*0.000*	*0.000*	*0.796*	*0.000*	*0.000*	1.000	0.208	0.012	-0.077	-0.009
GR	*0.435*	*0.019*	*0.000*	*0.000*	*0.000*	*0.004*	1.000	0.612	0.434	0.519
GRF	*0.040*	*0.489*	*0.324*	*0.030*	*0.414*	*0.865*	*0.000*	1.000	0.709	0.839
GRF^0	*0.311*	*0.960*	*0.825*	*0.294*	*0.735*	*0.295*	*0.000*	*0.000*	1.000	0.553
GRF^1	*0.043*	*0.830*	*0.478*	*0.001*	*0.416*	*0.901*	*0.000*	*0.000*	*0.000*	1.000

In the upper triangular part, the table reports Pearson's correlation coefficients between all pairs of variables. In the lower triangular part, the p-values (in *italics)* for the test of zero correlation for each pair of variables. The variables included are the five Fama-French factors (MKT, SMB, HML, RMW, CMA), the momentum (WML), the green factor (GR), the filtered green factor (GRF), and the filtered alternative green factors computed by fixing $\gamma = 0,1$ (GRF^0, GRF^1).

Table 5, Panel A: Augmented five-factor Fama-French model on industry portfolios							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**12.025**	4.914	**6.676**	**5.161**	-3.171	1.888	1.576
	(2.656)	(3.977)	(0.479)	(1.668)	(1.970)	(2.011)	(2.344)
MKT	**0.507**	**0.825**	**0.872**	**0.617**	**1.146**	**1.527**	**1.370**
	(0.185)	(0.213)	(0.035)	(0.103)	(0.118)	(0.119)	(0.111)
SMB	0.263	**-1.386**	**-0.373**	**-0.916**	**-0.895**	**0.464**	0.290
	(0.296)	(0.456)	(0.067)	(0.181)	(0.269)	(0.222)	(0.210)
HML	**1.144**	**1.896**	-0.134	**0.450**	0.218	**-1.058**	**-1.267**
	(0.387)	(0.398)	(0.075)	(0.208)	(0.247)	(0.219)	(0.235)
RMW	-0.037	0.625	**-0.290**	-0.214	**0.659**	**-0.933**	**-0.755**
	(0.288)	(0.594)	(0.063)	(0.226)	(0.282)	(0.189)	(0.264)
CMA	**-1.897**	**-2.877**	-0.151	**-0.773**	**-0.822**	**0.731**	**0.885**
	(0.512)	(0.594)	(0.098)	(0.287)	(0.356)	(0.337)	(0.304)
GRF	-0.385	**-0.877**	0.036	-0.341	-0.220	-0.022	0.101
	(0.225)	(0.303)	(0.044)	(0.205)	(0.225)	(0.196)	(0.211)
R^2	**0.753**	**0.749**	**0.978**	**0.827**	**0.788**	**0.892**	**0.838**
$\overline{R}^2$	**0.745**	**0.740**	**0.978**	**0.822**	**0.781**	**0.888**	**0.833**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	**6.474**	3.304	**3.600**	**6.771**	**2.330**	**5.072**	**10.183**
	(1.190)	(1.866)	(0.891)	(1.470)	(1.180)	(1.634)	(1.502)
MKT	**1.070**	**1.338**	**0.995**	**0.944**	**1.303**	**0.813**	**0.759**
	(0.088)	(0.112)	(0.053)	(0.083)	(0.089)	(0.120)	(0.102)
SMB	0.072	-0.299	**-0.337**	**0.348**	0.281	0.117	**1.245**
	(0.145)	(0.224)	(0.121)	(0.118)	(0.174)	(0.266)	(0.225)
HML	0.144	-0.390	**-0.684**	**-0.663**	**-0.603**	**-1.190**	**-0.487**
	(0.173)	(0.268)	(0.109)	(0.165)	(0.208)	(0.244)	(0.238)
RMW	**-0.663**	**-0.731**	**-0.482**	**-0.783**	**-0.874**	**-0.559**	**-0.815**
	(0.128)	(0.250)	(0.112)	(0.195)	(0.206)	(0.213)	(0.187)
CMA	-0.406	**1.028**	**0.443**	0.338	**0.639**	**0.683**	**-0.798**
	(0.233)	(0.361)	(0.151)	(0.244)	(0.277)	(0.288)	(0.301)
GRF	0.037	0.336	**-0.232**	**0.308**	-0.012	-0.072	0.311
	(0.091)	(0.218)	(0.010)	(0.154)	(0.160)	(0.183)	(0.178)
R^2	**0.940**	**0.809**	**0.927**	**0.890**	**0.907**	**0.717**	**0.901**
$\overline{R}^2$	**0.938**	**0.802**	**0.925**	**0.886**	**0.904**	**0.708**	**0.897**

Table 5, Panel B: Augmented Carhart model on industry portfolios							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**11.501**	7.000	**5.722**	1.558	**-3.832**	1.556	3.463
	(2.913)	(3.826)	(0.697)	(2.032)	(1.860)	(1.883)	(2.347)
MKT	**1.016**	**1.428**	**0.971**	**0.985**	**1.340**	**1.417**	**1.112**
	(0.150)	(0.220)	(0.033)	(0.082)	(0.107)	(0.078)	(0.128)
SMB	-0.233	**-1.562**	**-0.635**	**-1.457**	**-0.760**	0.089	0.199
	(0.230)	(0.406)	(0.050)	(0.154)	(0.179)	(0.188)	(0.164)
HML	**-0.311**	-0.259	**-0.272**	-0.152	**-0.356**	**-0.575**	**-0.656**
	(0.141)	(0.242)	(0.027)	(0.105)	(0.161)	(0.133)	(0.134)
WML	**-0.423**	**-0.565**	**-0.095**	0.046	**0.205**	**-0.273**	**-0.355**
	(0.114)	(0.221)	(0.036)	(0.124)	(0.072)	(0.096)	(0.113)
GRF	**-0.585**	**-0.906**	-0.088	**-0.560**	-0.109	-0.247	-0.006
	(0.199)	(0.395)	(0.052)	(0.212)	(0.214)	(0.214)	(0.177)
R^2	**0.690**	**0.708**	**0.966**	**0.786**	**0.779**	**0.879**	**0.850**
$\overline{R}^2$	**0.681**	**0.699**	**0.965**	**0.780**	**0.773**	**0.876**	**0.845**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	3.390	3.248	**2.328**	**4.910**	2.396	2.082	**7.093**
	(1.778)	(1.716)	(0.933)	(0.955)	(1.280)	(1.631)	(2.364)
MKT	**1.351**	**1.127**	**0.970**	**0.991**	**1.196**	**0.806**	**1.152**
	(0.065)	(0.072)	(0.046)	(0.076)	(0.074)	(0.065)	(0.095)
SMB	**-0.601**	**-0.475**	**-0.590**	-0.138	-0.057	-0.240	0.395
	(0.126)	(0.170)	(0.091)	(0.123)	(0.115)	(0.166)	(0.174)
HML	**-0.216**	0.337	**-0.383**	**-0.466**	-0.186	**-0.708**	**-1.160**
	(0.070)	(0.251)	(0.075)	(0.060)	(0.150)	(0.119)	(0.105)
WML	-0.146	**-0.125**	-0.022	**-0.146**	**-0.303**	**0.160**	**-0.318**
	(0.096)	(0.059)	(0.049)	(0.064)	(0.053)	(0.054)	(0.158)
GRF	**-0.274**	0.206	**-0.367**	0.058	-0.219	-0.247	-0.083
	(0.129)	(0.216)	(0.114)	(0.176)	(0.156)	(0.168)	(0.229)
R^2	**0.897**	**0.784**	**0.907**	**0.851**	**0.890**	**0.700**	**0.835**
$\overline{R}^2$	**0.894**	**0.779**	**0.905**	**0.847**	**0.897**	**0.692**	**0.831**

Table 5, Panel C: Augmented three-factor Fama-French model on industry portfolios							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**7.027**	1.033	**4.719**	2.046	-1.669	-1.330	-0.285
	(2.496)	(3.322)	(0.593)	(1.557)	(1.963)	(1.682)	(2.045)
MKT	**1.210**	**1.686**	**1.014**	**0.964**	**1.247**	**1.542**	**1.275**
	(0.123)	(0.164)	(0.034)	(0.072)	(0.107)	(0.076)	(0.121)
SMB	**-0.534**	**-1.963**	**-0.702**	**-1.424**	**-0.615**	-0.106	-0.054
	(0.239)	(0.363)	(0.049)	(0.132)	(0.173)	(0.176)	(0.148)
HML	**-0.303**	-0.248	**-0.270**	-0.153	**-0.360**	**-0.570**	**-0.649**
	(0.140)	(0.247)	(0.032)	(0.106)	(0.167)	(0.130)	(0.149)
GRF	**-0.686**	**-1.040**	-0.111	**-0.549**	-0.060	-0.312	-0.090
	(0.223)	(0.431)	(0.058)	(0.215)	(0.208)	(0.209)	(0.166)
R^2	**0.639**	**0.667**	**0.961**	**0.785**	**0.766**	**0.861**	**0.810**
$\overline{R}^2$	**0.631**	**0.660**	**0.960**	**0.780**	**0.761**	**0.858**	**0.806**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	1.848	1.931	**2.100**	**3.372**	-0.803	**3.762**	**3.737**
	(1.254)	(1.728)	(0.847)	(1.289)	(1.501)	(1.768)	(1.434)
MKT	**1.418**	**1.184**	**0.979**	**1.057**	**1.334**	**0.733**	**1.297**
	(0.061)	(0.068)	(0.038)	(0.063)	(0.083)	(0.071)	(0.104)
SMB	**-0.705**	**-0.564**	**-0.606**	**-0.241**	**-0.272**	-0.126	0.169
	(0.110)	(0.182)	(0.083)	(0.114)	(0.130)	(0.170)	(0.159)
HML	**-0.213**	0.339	**-0.382**	**-0.463**	-0.180	**-0.711**	**-1.154**
	(0.075)	(0.255)	(0.075)	(0.061)	(0.160)	(0.117)	(0.117)
GRF	**-0.308**	0.176	**-0.372**	0.023	-0.291	-0.209	-0.159
	(0.127)	(0.207)	(0.109)	(0.165)	(0.148)	(0.166)	(0.245)
R^2	**0.891**	**0.780**	**0.907**	**0.841**	**0.871**	**0.683**	**0.809**
$\overline{R}^2$	**0.888**	**0.775**	**0.905**	**0.837**	**0.868**	**0.676**	**0.804**

The Table reports estimates of the augmented five-factor Fama-French model (Panel A), the Carhart model (Panel B), and three-factor Fama-French model (Panel C) from time-series regressions. HACSE standard errors are reported in square brackets. The estimated parameters in bold are significant at the 5% level. The (adjusted) coefficient of determination values is ($\overline{R}^2$) R^2.

Table 6: Green score unrestricted and restricted (*) auxiliary regressions, filtered green factors								
	GRF	GRF*	GRF^{1}	GRF^{1*}	GRF^{0}	GRF^{0*}	GRF^{ALL}	GRF^{ALL*}
gB	**44.656**	**45.834**	**44.856**	**45.759**	**45.517**	**45.871**	**44.947**	**45.847**
	(1.765)	(0.621)	(2.103)	(0.624)	(2.227)	(0.624)	(1.104)	(0.356)
gC	**51.191**	**51.007**	**51.204**	**51.018**	**51.208**	**51.049**	**51.199**	**51.040**
	(0.387)	(0.283)	(0.388)	(0.286)	(0.383)	(0.281)	(0.222)	(0.163)
gD	**47.376**	**45.834**	**47.421**	**45.759**	**47.467**	**45.871**	**47.414**	**45.847**
	(1.250)	(0.621)	(1.291)	(0.624)	(1.260)	(0.624)	(0.700)	(0.356)
gF	**51.397**	**51.007**	**51.436**	**51.018**	**51.548**	**51.049**	**51.465**	**51.040**
	(1.201)	(0.283)	(1.224)	(0.286)	(1.251)	(0.281)	(0.685)	(0.163)
gG	**52.145**	**51.007**	**52.205**	52.205	**52.093**	**51.049**	**52.139**	**51.040**
	(0.927)	(0.283)	(0.935)	(0.935)	(0.928)	(0.281)	(0.530)	(0.163)
gH	**45.890**	**45.834**	**45.770**	**45.759**	**45.839**	**45.871**	**45.837**	**45.847**
	(1.368)	(0.621)	(1.392)	(0.624)	(1.383)	(0.624)	(0.778)	(0.356)
gI	**46.881**	**45.834**	**46.752**	**45.759**	**46.105**	**45.871**	**46.559**	**45.847**
	(2.277)	(0.621)	(1.392)	(0.624)	(1.383)	(0.624)	(0.779)	(0.356)
gJ	**50.490**	**51.007**	**50.491**	**51.018**	**50.537**	**51.049**	**50.505**	**51.040**
	(0.652)	(0.283)	(0.649)	(0.286)	(0.641)	(0.281)	(0.370)	(0.163)
gM	**50.012**	**51.007**	**50.064**	**51.018**	**50.041**	**51.049**	**50.039**	**51.040**
	(1.053)	(0.283)	(1.050)	(0.286)	(1.038)	(0.281)	(0.593)	(0.163)
gN	**49.253**	**51.007**	**49.189**	**51.018**	**49.577**	**51.049**	**49.379**	**51.040**
	(1.199)	(0.283)	(1.145)	(0.286)	(1.198)	(0.281)	(0.669)	(0.163)
gQ	**44.645**	**45.834**	**44.637**	**45.759**	**44.876**	**45.871**	**44.687**	**45.847**
	(1.882)	(0.621)	(1.932)	(0.624)	(1.272)	(0.624)	(1.058)	(0.356)
gR	**45.400**	**45.834**	**45.345**	**45.759**	**45.040**	**45.871**	**45.316**	**45.847**
	(1.223)	(0.621)	(1.188)	(0.624)	(1.206)	(0.624)	(0.662)	(0.356)
bB	1.648	**1.658**	2.281	**2.328**	1.709	**1.787**	1.752	**1.589**
	(2.025)	(0.609)	(2.676)	(1.215)	(1.857)	(0.645)	(1.066)	(0.308)
bC	-0.311	-0.255	-0.071	-0.210	-0.250	-0.314	-0.222	-0.231
	(0.383)	(0.356)	(0.447)	(0.389)	(0.412)	(0.335)	(0.236)	(0.235)
bD	-2.644	-3.133	-2.304	-3.087	-2.415	-3.275	**-2.483**	**-3.141**
	(1.612)	(1.718)	(1.536)	(1.952)	(1.976)	(2.083)	(0.874)	(0.969)
bF	1.619	**1.658**	1.991	2.328	1.530	**1.787**	**1.669**	**1.589**
	(1.183)	(0.609	(1.515)	(1.215)	(1.352)	(0.645)	(0.687)	(0.308)
bG	0.878	**0.905**	0.926	**1.278**	0.572	0.314	0.799	**0.724**
	(0.769)	(0.383)	(0.844)	(0.465)	(0.856)	(0.335)	(0.460)	(0.259)
bH	0.774	**0.905**	1.108	**1.278**	0.260	0.314	0.656	**0.724**
	(1.111)	(0.383)	(1.335)	(0.465)	(1.164)	(0.335)	(0.651)	(0.259)
bI	-1.704	**-1.658**	-1.892	**-1.278**	-1.185	-0.919	-1.596	**-1.589**
	(1.871)	(0.609)	(2.268)	(0.465)	(2.464)	(0.5654)	(1.059)	(0.308)
bJ	-0.739	**-0.905**	-0.630	-0.210	-0.778	-0.919	-0.721	**-0.724**
	(0.721)	(0.383)	(0.948)	(0.389)	(0.666)	(0.5654)	(0.429)	(0.259)
bM	-1.051	**-0.905**	-1.332	**-1.278**	-1.761	**-1.787**	**-1.332**	**-1.589**
	(0.905)	(0.383)	(0.956)	(0.465)	(1.057)	(0.645)	(0.538)	(0.308)
bN	0.153	0.255	0.334	0.210	-0.824	-0.919	-0.145	**-0.724**
	(1.380)	(0.356)	(1.370)	(0.389)	(1.151)	(0.5654)	(0.712)	(0.259)
bQ	-0.159	-0.255	-0.162	-0.210	-1.714	**-1.787**	-0.521	**-0.724**
	(1.424)	(0.356)	(2.236)	(0.389)	(3.496)	(0.645)	(1.097)	(0.259)
bR	-1.235	**-0.905**	-1.686	**-1.278**	-0.241	-0.314	-1.088	**-1.589**
	(0.942)	(0.383)	(0.977)	(0.465)	(1.168)	(0.335)	(0.565)	(0.308)
R^2	0.062	0.056	0.061	0.057	0.059	0.055	0.060	0.055
$\bar{R}^2$	0.046	0.053	0.045	0.054	0.043	0.051	0.055	0.054
SBC	4.601	4.511	4.603	4.511	4.604	4.513	4.525	4.493
p-val	-	0.957	-	0.928	-	0.984	-	0.088
N	1367	1367	1366	1366	1367	1367	4100	4100

The table reports the estimated coefficients from the auxiliary regressions of the average green score for the transparent companies on the green factor company beta from the augmented five-factor Fama-French model. Heteroskedasticity-robust standard errors are reported in brackets. The results in columns one, three, five, and seven refer to the case where the filtered green factors **GRF**, **GRF^1**, and **GRF^0**, are used in the *unrestricted* asset pricing regressions; column seven reports the results from the joint model. Columns two, four, six, and eight refer to the case of restricted regressions (*). Figures in bold are significant at the 5% level. R^2 ($\overline{R}^2$) is the (adjusted) coefficient of determination, SBC the Bayes-Schwarz information criterion, p-val the p-value of the Likelihood-ratio test for the restricted (Panel B) versus the unrestricted (Panel A) models, and N is the sample size. See Table 2 for details about the sectors investigated (A, B, C, D, F, G, H, I, J, M, N, Q, R).

Figure 1: The Alessi et al. (2023) greenness and transparency factor GR

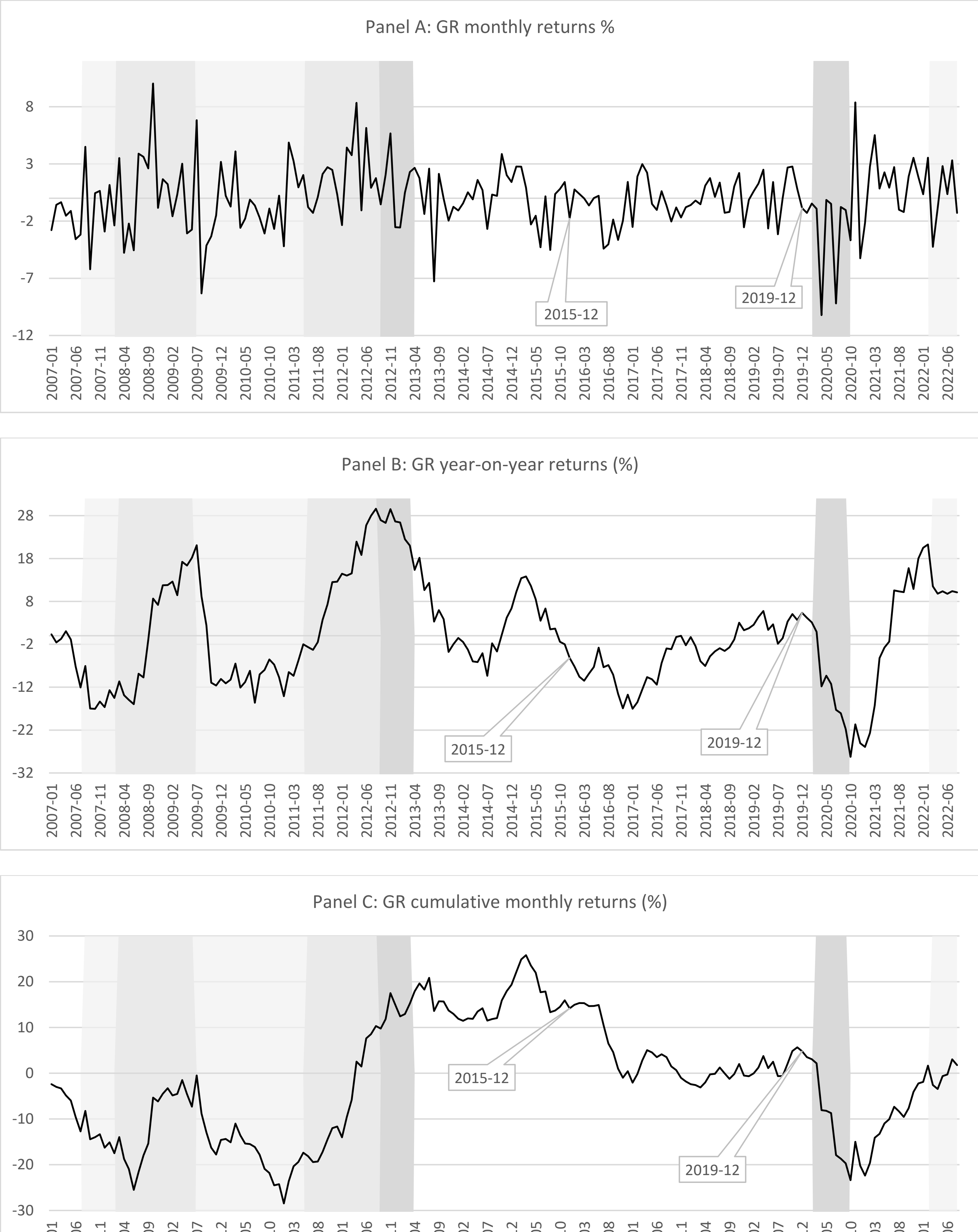
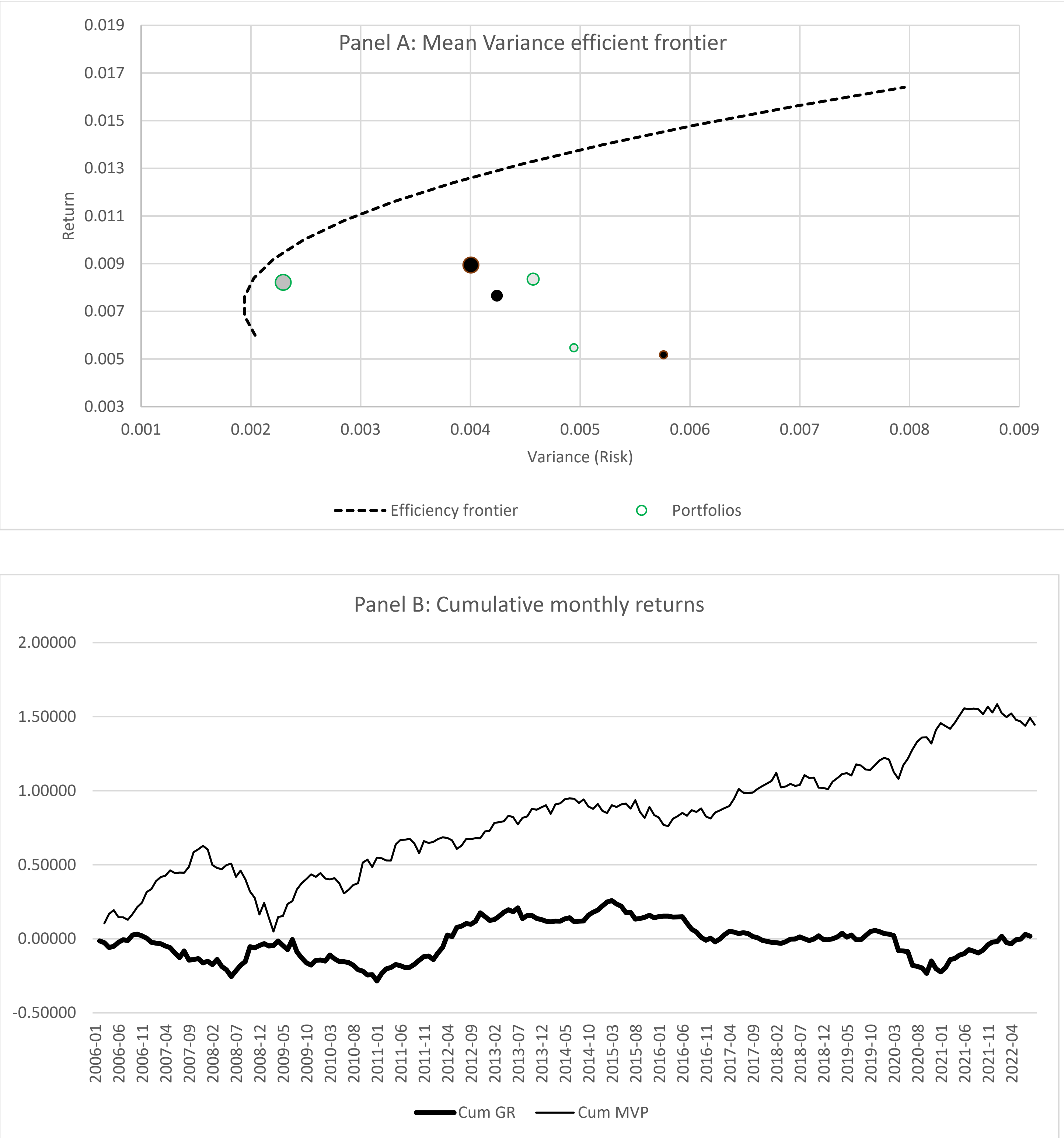


Figure 2: Mean-variance efficient frontier for the 3 green and transparent and 3 high-carbon portfolios.



Panel A shows 3 green portfolios (large, medium, and small gray dots) and 3 brown portfolios (large, medium, and small black dots). The efficiency frontier is calculated for combinations of the 6 portfolios that maximize the portfolio return for a given level of risk measured by the resulting portfolio variance. Panel B shows the cumulative monthly log returns for the Mean-Variance efficient portfolio (MVP) and Alessi et al. (2023) greenness and transparency factor (GR).

Figure 3: Morana (2022) Euro area macro-financial factors

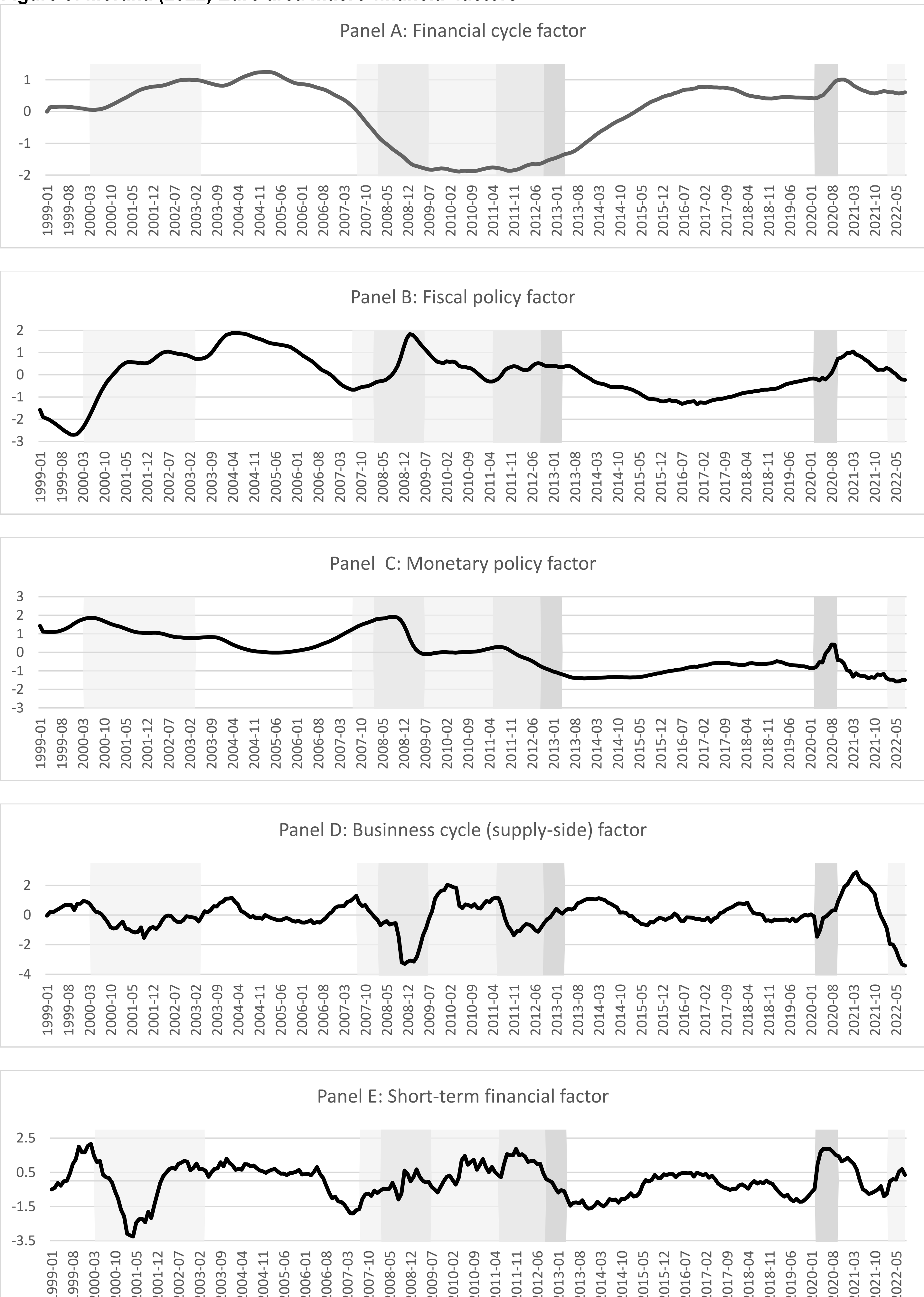


Figure 4: Greenness and transparency portfolio factor decomposition in trend (Panel A), cyclical (Panel B), and residual (Panel C) components

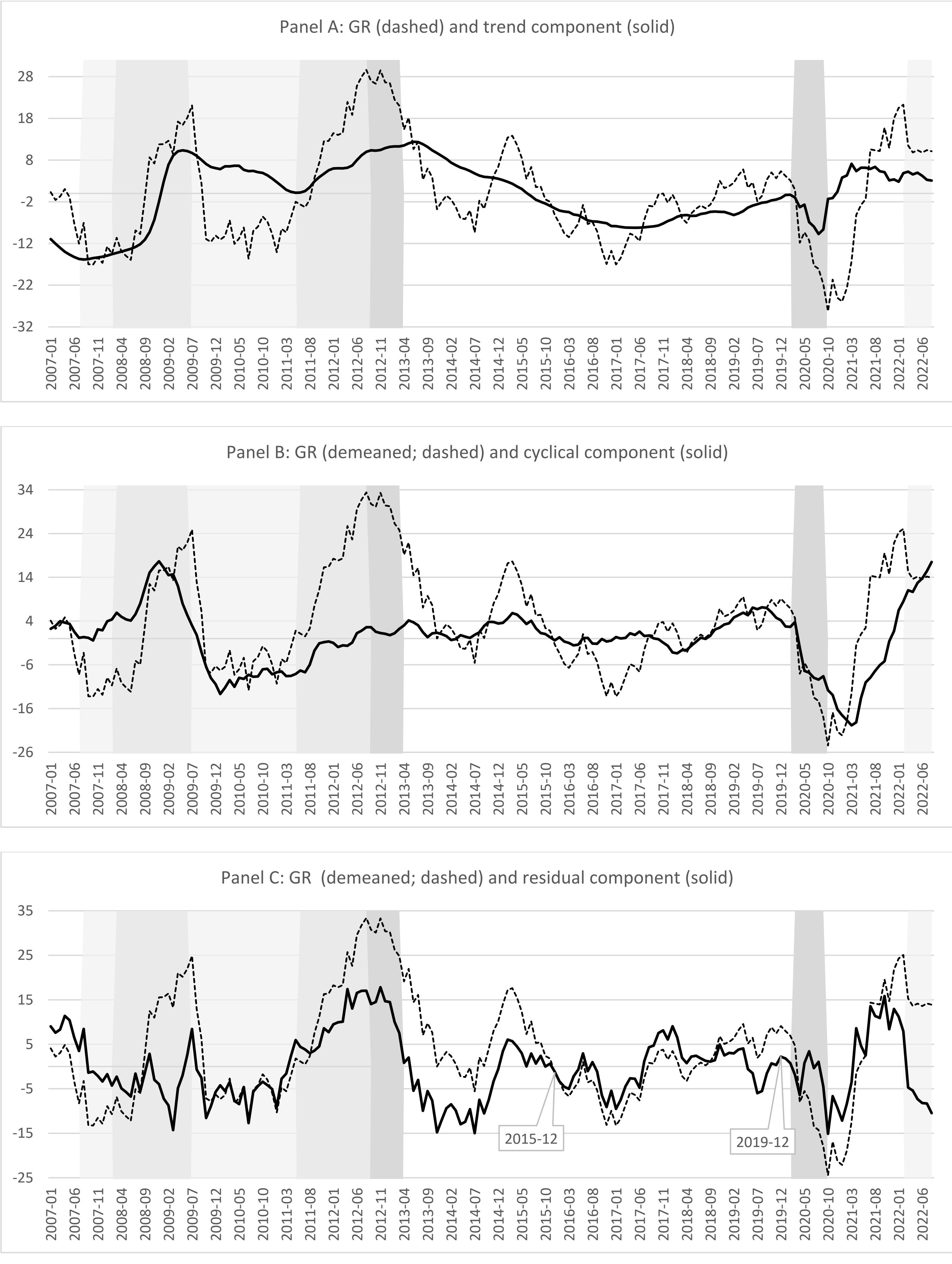
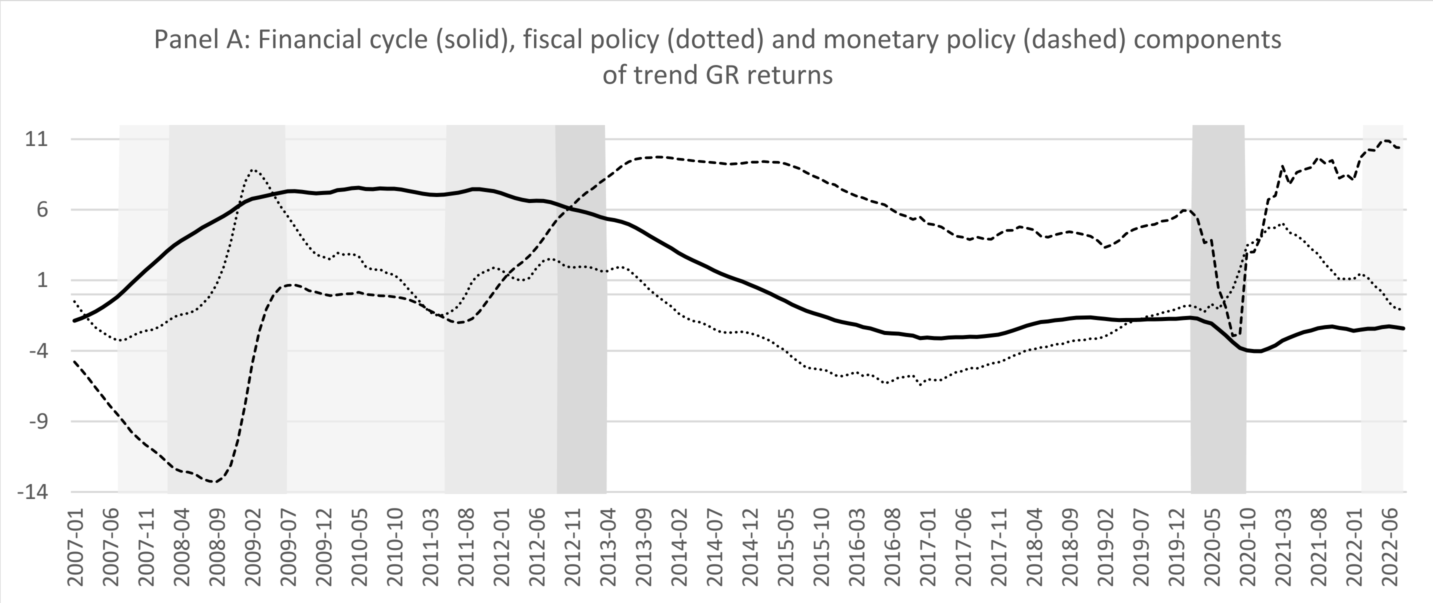


Figure 5: Trend and cyclical greenness and transparency factor decompositions (net of mean level)



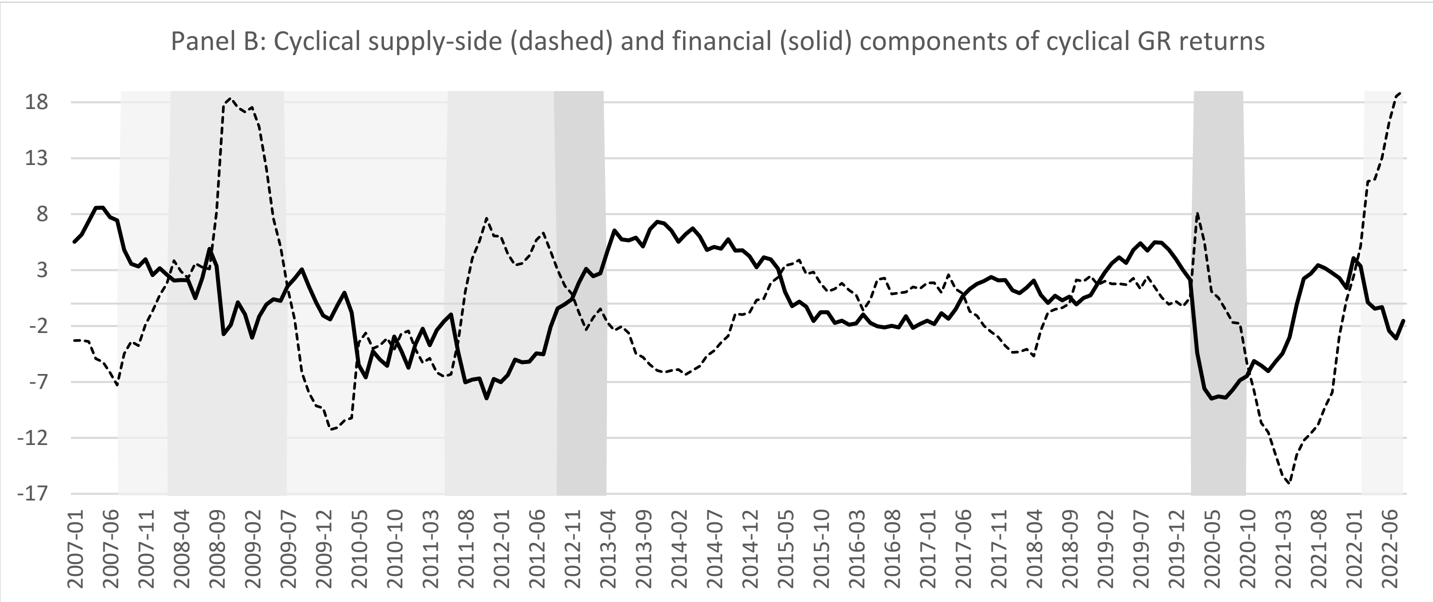
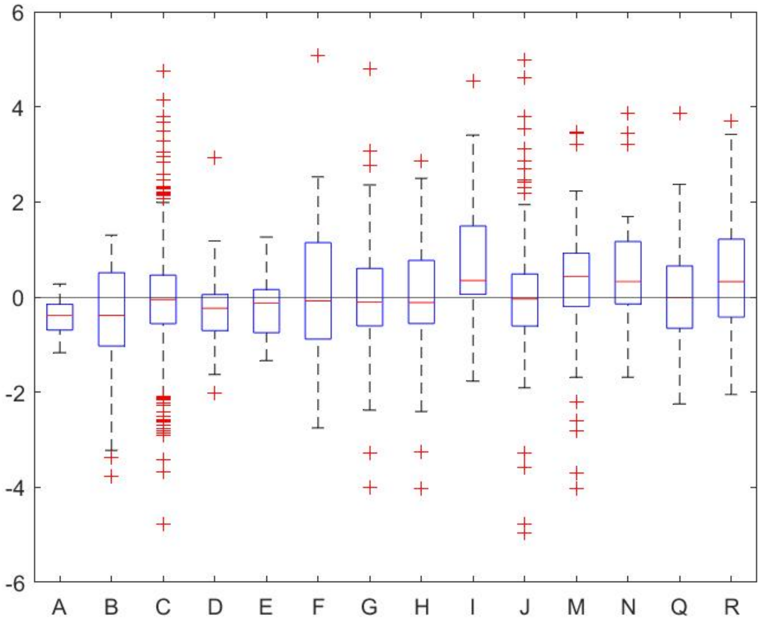
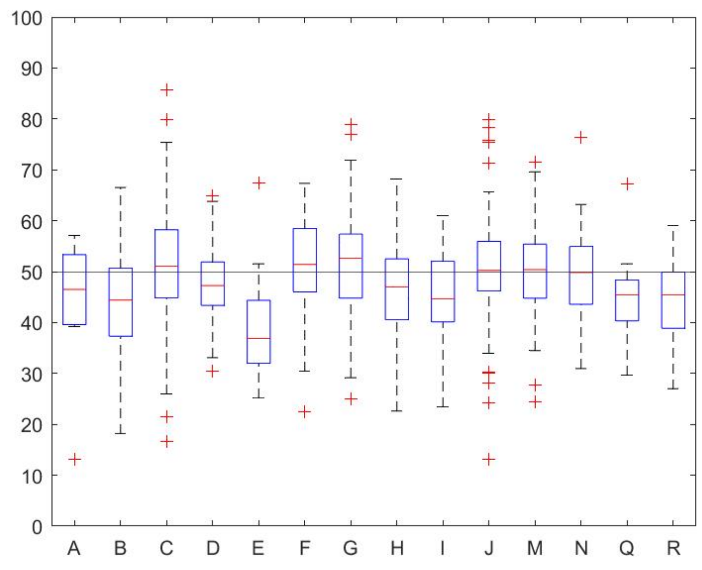


Figure 6: Distribution at the industry level of estimated loadings for the greenness and transparency filtered factor GRF



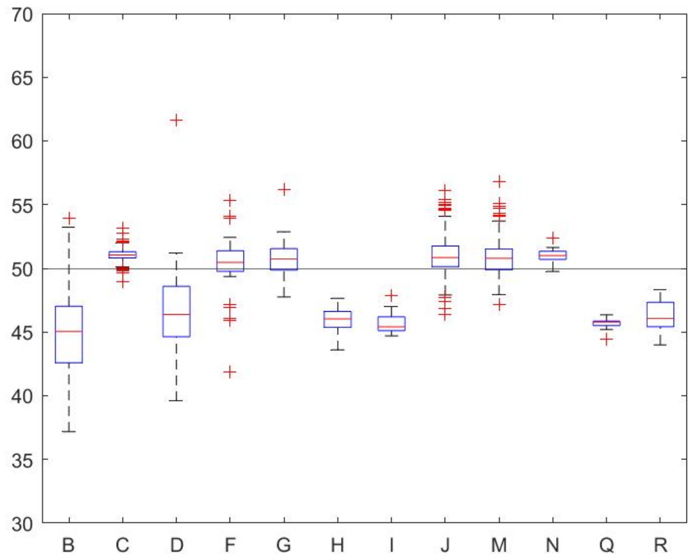
The figure shows the box plots of the estimated loadings for the filtered greenness and transparency factor GRF at the industry level. The estimates are computed from the augmented five-factor Fama-French model. Assets are grouped by the NACE division.

Figure 7: Distribution at the industry level of the average re-scaled greenness and transparency indicator $\overline{G}_i$



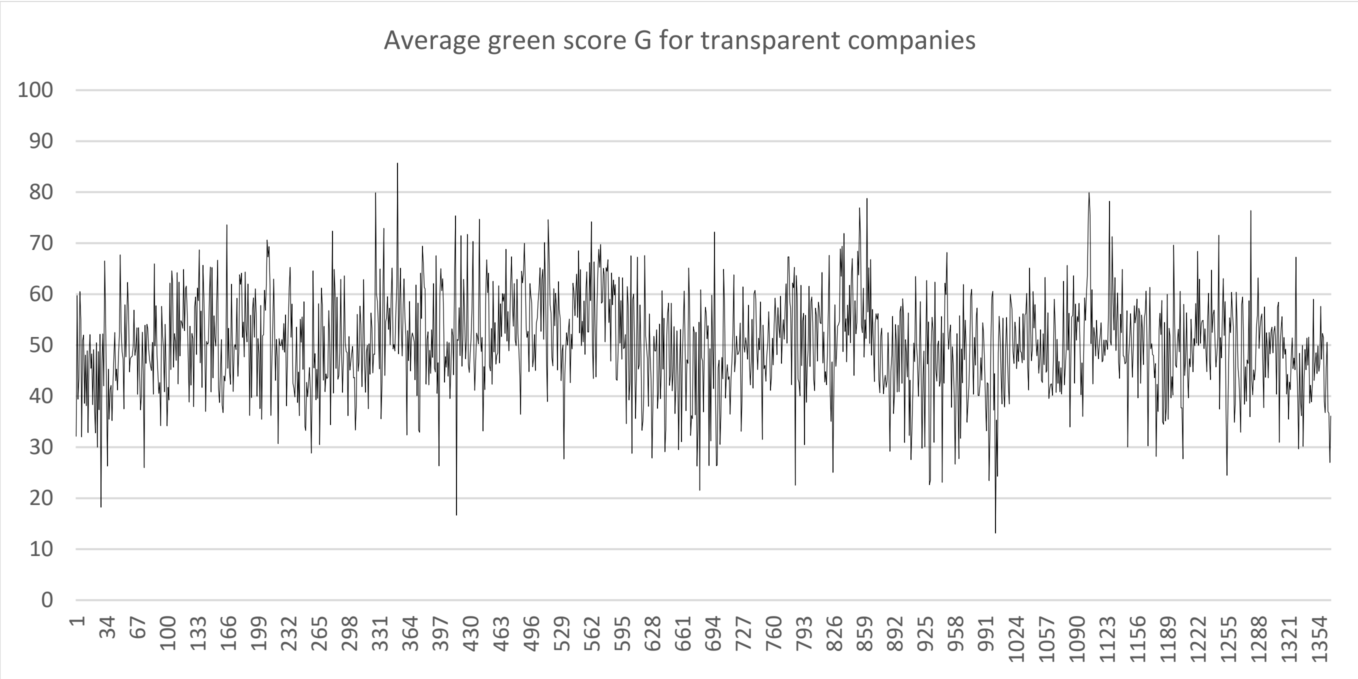
The figure shows the box plots of the average re-scaled greenness and transparency indicator $\overline{\mathbf{G}}_{\mathbf{i}}$. Assets are grouped by the NACE division.

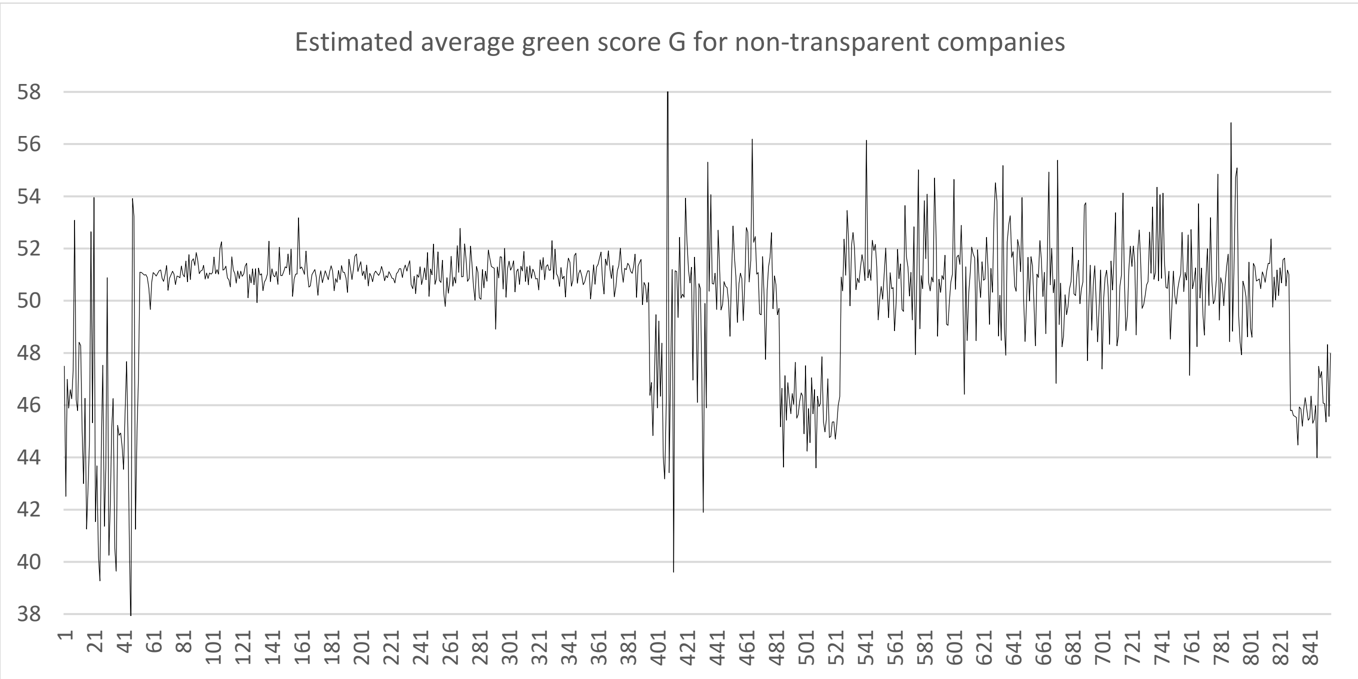
Figure 8: Distribution at the industry level of the estimated average re-scaled greenness and transparency indicator $\bar{G}_i$ for not-transparent companies



The figure shows the box plots of the estimated average re-scaled greenness and transparency indicator $\bar{\mathbf{G}}_{\mathbf{i}}$. Assets are grouped by the NACE division.

Figure 9: Actual average green score for transparent companies (top plot) and estimated average green score for non-transparent companies (bottom plot).





SUPPLEMENTARY MATERIALS

Green risk in Europe

Nuno Cassola, Claudio Morana, and Elisa Ossola

Appendix A.

This Appendix comprehensively describes the data involved (Appendix A.1) and the methodology applied to portfolio formation (Appendix A.2).

Appendix A. 1 Description of the dataset

This Appendix provides an overview of the data used in constructing the European greenness, transparency, and high-carbon portfolios.

The starting dataset is the updated sample of Alessi et al. (2023). The data-cleaning process includes removing financial firms and 'penny stocks'. The sample consists of 3,607 European stocks in the leading European stock market exchanges and covers the periods from January 2006 to August 2020, i.e., $T = 200$ monthly observations. The dataset includes the Environmental score (E-score) and the emission intensity at a yearly frequency from Bloomberg. It is worth mentioning that the environmental information provided in the year y is based on the information disclosed by the company (and/or collected by the data provider) in the year $y - 1$. Thus, environmental information is available from December 2005 to December 2021.

The dataset allows us to distinguish companies as 'Transparent' and 'Not Transparent', applying the definition in Alessi et al. (2023). They define *Transparent companies* as companies that disclose environmental information, i.e., at least the E-score or emission intensity is available. We can compute the 'greenness and transparency' indicator proposed by Alessi et al. (2023) for these companies. At each year y, the indicator is defined as follows:

$$G_{i,y} = \gamma K_{i,y} + (1 - \gamma) E_{i,y},$$

with $\gamma \in [0,1]$, where $K_{i,y}$ is the inverse of the ranking of the firm i in terms of emission intensity and $E_{i,y}$ is the ranking of the firm i in terms of E-score. Parameter γ controls for the relative importance of the two components. Unlike Alessi et al. (2023), we introduce a rescaled measure to allow easy comparisons across the indicators. $G_{i,y}$ is rescaled by the number of transparent companies at year y multiplied by 100. Thus, the rescaled indicator takes a value from 0 to 100. The higher the indicator's value, the greener and more transparent the company. Figure C2 provides the distribution over time of the rescaled indicator, computed for several values of the parameter γ. When $\gamma = 0$ ($\gamma = 1$), the greenness and transparency are only the functions of the rank of E-score (emission intensity). Fixing $\gamma = 0.5$, $G_{i,y}$ yields an equally weighted average of the two ranks. Panels A-E in Figure C1 show the distribution over time of the indicators computed for $\gamma = 0, .2, .5, .8,$ and 1, respectively. The value of the parameter γ affects the distribution of the indicators. The indicators involving only the rank of E-score (Panel A) or the inverse of ranking in terms of emission intensity (Panel E) are uniformly distributed each year, and their distributions are constant over time and characterized by a large interquartile difference. By computing the indicator as a weighted average of weights $\gamma = 0.2, 0.8$, the yearly distribution of the indicator reduces its interquartile difference. Fixing $\gamma = 0.5$, in Panel C, we observe the distribution of the indicators is more concentrated around the median, which is approximately 50 over time. Focusing on the last available year (i.e., 2022), Figure C2 shows the kernel density estimates of the distribution of the indicators computed for different values of γ. The distribution of indicators computed as an equally weighted average approximates the normal distribution.

Following Alessi et al. (2023), *non-Transparent companies* do not disclose environmental information. Among the non-transparent companies, we select the high-carbon companies active in the climate-policy-relevant sectors (CPRS).

The dataset also consists of financial information at the company level: the stock monthly (log) returns and the monthly market capitalization. The panel data of individual stock returns is unbalanced. Thus, we account for this characteristic by defining $T_i = \sum_t I_{i,t}$ as the number of monthly observations of the stock i, where $I_{i,t}$ is an indicator function such that $I_{i,t} = 1$ if the return of asset i is observed at date t, and 0 otherwise. Figure C3 provides the distribution of asset returns w.r.t. T_i. The number of stocks in which T_i is larger than zero is 2,701, and about 70% of the stocks in the panel have more than 120 monthly return observations. Furthermore, the unbalanced characteristic of the data is also evident for the monthly market capitalization. Thus, we define the asset-specific number of observations of the monthly market capitalization $T_i^{mc} = \sum_t I^{mc}{}_{i,t}$, where $I_{i,t}^{mc}$ is an indicator function taking value equal to one if the market capitalization of asset i is observed at time t and zero otherwise. We note that $T_i \leq T_i^{mc}$, with $T_i^{mc} -$

$T_i \leq 1$, for almost all assets.[1]

Appendix A.2. Greenness and transparency, and high-carbon portfolios

Among the transparent companies, each year y, we build the intersections of three portfolios formed on size and five on the greenness and transparency indicator. The size breakpoints for the year y are the market capitalization terciles at the end of June y. We define the size breakpoints as in Fama and French (1993). Instead, Alessi et al. (2023) define the size breakpoints for year y, as the terciles of the distribution of monthly capitalization observed in December $y-1$. However, unlike Frama and French (1993), our portfolios are rebalanced yearly because the environmental data are only available annually. Then, we compute the 3x5 greenness and transparency portfolio returns for each month $t \in y$:

$$r_t^{\mathrm{p}} = \sum_{i \in p} w_{i,t} I_{i,t} r_{i,t}, \text{ where } w_{i,t} = \frac{I_{i,t}^{mc} mc_{i,t}}{\sum_t I_{i,t}^{mc} mc_{i,t}},$$

with $p = 1, \dots, 15$ refers to the 3×5 portfolios formed on size and greenness, and where $mc_{i,t}$ is the market capitalization at month t for company i. Referring to the quintiles of the yearly distribution of the greenness and transparency indicator, we define the q-th green and transparency portfolios as:

$$r_q = \frac{1}{3}\left(r_{q,s} + r_{q,m} + r_{q,l}\right), \qquad \text{with } q = 1, \dots, 5$$

where s, m, l refer to the size characteristic, i.e., small, medium, and large. Alessi et al. (2023) compare the evolution of the indicator for the companies belonging to the top quintile (r_5) and the bottom quintile (r_1) of the indicator distribution. The selection of the top quintile ensures the selection of the greenest and most transparent companies. Hence, $r_{\mathrm{g}} = r_5$.

Among the high-carbon companies, the value-weighted portfolio is defined as the average weighted portfolios formed on size:

$$r_{hc} = \frac{1}{3}\left(r_{hc,s} + r_{hc,m} + r_{hc,l}\right).$$

Then, the greenness and transparency factor (or portfolio) is defined each month t as:

$$GR_t = r_{g,t} - r_{hc,t}.$$

In Figure C4, we compare two different portfolios of greenness and transparency:

[1] The difference $T_i^{mc} - T_i$ is greater than one, only for three assets, i.e., JOBINDEX, SFC ENERGY, and TESMEC. However, this does not affect the computation of portfolio returns since we account for the unbalanced properties through the indicator functions, as described below.

(i) the factor GR_t (blue line) as defined above; (ii) the factor $\widetilde{GR}_t$ (red dashed line) computed as in Alessi et al. (2023). We observe some differences in the patterns of the two factors, mainly due to the difference in the asset allocation selection.

Appendix B. Robustness analysis

In this Appendix, we assess the robustness of our decomposition of the green factor excess return to the γ value used in constructing the indicator, considering two limiting cases, i.e., $\gamma = 0,1$. We denote these alternative unfiltered (filtered) factors GR^0 (GRF^0 and GR^1 (GRF^1), respectively. Figure C5 Panel A compares the monthly returns of the greenness and transparency portfolios GR, GR^0, and GR^1, Panel B displays their year-on-year returns, Panel C shows their cumulative monthly returns. The returns patterns look similar; however, we observe a difference in the returns levels due to the different portfolio selection allocations underlying each factor. Nevertheless, cumulative monthly excess returns are, in all cases, zero mean-reverting processes. We report the decomposition results for GR^0 and GR^1 in Table 1, columns 3-4 and 5-6, respectively.

As shown in Table 1 in the paper, the decomposition results are strongly robust regarding selected specifications, retaining the same regressors, which also show the same signs. However, we note two exceptions. First, concerning the $\gamma = 0$ case, an additional regressor is included in the selected model, i.e., $\hat{\boldsymbol{f}}_{\boldsymbol{a\_1}}$, the demand-side business cycle component. $\hat{\boldsymbol{f}}_{\boldsymbol{a\_1}}$ enters with a positive coefficient, suggesting that excess returns might be procyclical, increasing during expansions and decreasing during contractions. Second, concerning the $\gamma = 1$ case, the short-term financial factor $\hat{\boldsymbol{f}}_{\boldsymbol{a\_3}}$ is not any longer statistically significant (5% level). These specification changes are reflected in the coefficient of determination of the final regressions, raising to 0.76 in the former case and falling to 0.55 in the latter case. The filtered green and transparency stocks excess returns obtained from the estimated residuals from the regression decompositions are highly correlated with the benchmark filtered excess returns, showing a sample correlation coefficient of 0.84 and 0.71, respectively (not reported).

It should be noted that these findings also hold for other available portfolio-based measures of green risk, such as Gimeno and González (2022) and Bauer et al. (2023). For instance, the macro-financial factors account for about 66% of the Gimeno and González (2022) portfolio variance. Business cycle and monetary policy factors are the most critical determinants of the systematic risk component. Similar findings hold at the single country level, as the accounted portfolio variance by the macro-financial factors is 53% to 67%, apart from France (30%). Business cycle and economic policy factors are the most relevant determinants of systematic risk also at the single-country level. See Table C0 for detailed results.

Appendix C. Additional tables and figures

Table C0: Green factor return decomposition regressions

	GMP	**GMP**	**FR**	**FR**	**DE**	**DE**	**IT**	**IT**	**UK**	**UK**
$\hat{f}_{n_1}$	2.119 (1.261)	-	2.858 (3.948)	3.916 (2.172)	-2.069 (2.943)	-	6.776 (6.591)	**8.315** (2.375)	0.092 (3.026)	-
$-\hat{f}_{n_2}$	-1.091 (1.506)	-	-6.558 (3.983)	**-7.215** (2.255)	2.791 (2.507)	-	-5.269 (6.416)	**-7.008** (2.186)	-3.102 (2.786)	**-2.377** (0.879)
$-\hat{f}_{n_3}$	-3.326 (2.065)	-	10.527 (7.906)	**12.29** (4.288)	**-15.74** (4.579)	**-11.30** (2.013)	15.98 (12.98)	19.08 (4.929)	1.331 (5.903)	-
$\hat{f}_{n_4}$	**-2.838** (0.755)	**-3.245** (0.570)	**9.979** (4.686)	**9.808** (3.812)	**8.396** (2.537)	**6.512** (1.750)	1.704 (5.899)	-	-3.119 (4.352)	-
$\hat{f}_{a_1}$	1.607 (0.924)	**2.590** (0.659)	-0.293 (3.126)	-	**-9.504** (2.265)	**-7.201** (0.832)	**-1.936** (6.110)	-	-2.451 (2.123)	**-3.978** (0.834)
$-\hat{f}_{a_2}$	**5.182** (0.595)	**5.034** (0.573)	2.136 (1.135)	-	**-2.598** (1.144)	**-2.263** (1.025)	**3.122** (2.017)	**3.690** (1.703)	**7.152** (1.006)	**6.685** (0.943)
$\hat{f}_{a_3}$	**-1.259** (0.676)	**-1.381** (0.641)	-0.020 (2.112)	-	-1.885 (1.390)	-	-12.11 (3.232)	**-11.25** (2.680)	0.407 (2.294)	-
$\hat{f}_{a_4}$	0.329 (0.680)	-	0.825 (3.123)	-	1.576 (1.696)	-	2.559 (3.485)	-	-2.219 (1.754)	-
μ_{f_g}	1.748 (1.237)	-0.092 (0.611)	**21.35** (5.104)	**22.30** (3.897)	3.171 (7.418)	2.172 (1.839)	3.171 (7.418)	2.797 (3.012)	4.074 (4.479)	**6.310** (1.471)
R^2	**0.682**	**0.663**	**0.332**	**0.304**	**0.672**	**0.662**	**0.530**	**0.525**	**0.562**	**0.540**
$\bar{R}^2$	**0.666**	**0.655**	**0.290**	**0.283**	**0.652**	**0.652**	**0.501**	**0.507**	**0.535**	**0.530**

The Table reports the results of the estimated PC regressions for the monthly year-on-year Gimeno and González (2022), the European green factor (GMP), and the Bauer et al. (2023) single country brown factors with an inverted sign for France (FR), Germany (DE), Italy (IT), and the UK (UK) on selected Morana (2022) common macro-financial factors. Figures in round brackets refer to Newey-West consistent SE. The estimated parameters in bold are significant at the 5% level. The (adjusted) coefficient of determination is ($\bar{R}^2$) R^2.

Table C1, Panel A: Augmented GR five-factor Fama-French model on industry portfolio							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**11.481** (2.347)	3.022 (2.943)	**6.539** (0.470)	**4.893** (1.467)	-3.262 (1.939)	2.186 (1.930)	1.878 (2.238)
MKT	**0.550** (0.170)	**0.970** (0.160)	**0.881** (0.036)	**0.641** (0.107)	**1.156** (0.118)	**1.506** (0.124)	**1.347** (0.116)
SMB	0.096 (0.254)	**-1.904** (0.332)	**-0.397** (0.071)	**-1.018** (0.179)	**-0.943** (0.252)	**0.525** (0.234)	0.367 (0.217)
HML	**1.177** (0.357)	**1.985** (0.366)	-0.134 (0.080)	**0.476** (0.216)	0.233 (0.260)	**-1.062** (0.235)	**-1.279** (0.239)
RMW	0.074 (0.259)	**0.997** (0.394)	**-0.266** (0.063)	-0.155 (0.219)	**0.682** (0.273)	**-0.987** (0.165)	**-0.813** (0.238)
CMA	**-1.620** (0.481)	**-2.144** (0.494)	-0.147 (0.110)	-0.562 (0.295)	-0.699 (0.374)	0.694 (0.367)	**0.787** (0.278)
GR	**-0.516** (0.177)	**-1.395** (0.277)	-0.015 (0.035)	**-0.385** (0.126)	-0.221 (0.142)	0.082 (0.122)	0.189 (0.134)
R^2	**0.777**	**0.834**	**0.978**	**0.843**	**0.791**	**0.893**	**0.842**
$\overline{R}^2$	**0.769**	**0.828**	**0.977**	**0.837**	**0.784**	**0.889**	**0.837**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	**6.300** (1.110)	2.785 (1.785)	**3.565** (0.865)	**7.234** (1.038)	**2.471** (1.202)	**4.399** (1.505)	**10.346** (1.317)
MKT	**1.078** (0.087)	**1.370** (0.118)	**1.001** (0.059)	**0.907** (0.066)	**1.294** (0.092)	**0.861** (0.114)	**0.743** (0.099)
SMB	0.049 (0.152)	-0.366 (0.229)	**-0.375** (0.115)	**0.487** (0.106)	0.309 (0.171)	-0.035 (0.244)	**1.321** (0.217)
HML	0.144 (0.173)	-0.401 (0.275)	**-0.669** (0.104)	**-0.690** (0.138)	**-0.604** (0.213)	**-1.170** (0.260)	**-0.509** (0.237)
RMW	**-0.639** (0.129)	**-0.645** (0.211)	**-0.470** (0.114)	**-0.876** (0.159)	**-0.900** (0.185)	**-0.433** (0.197)	**-0.853** (0.0163)
CMA	-0.403 (0.246)	**0.946** (0.357)	**0.563** (0.164)	0.112 (0.186)	**0.623** (0.258)	**0.825** (0.310)	**-0.977** (0.311)
GR	-0.013 (0.069)	0.115 (0.123)	**-0.212** (0.081)	**0.422** (0.077)	0.037 (0.199)	**-0.289** (0.089)	**0.323** (0.122)
R^2	**0.940**	**0.803**	**0.932**	**0.916**	**0.908**	**0.740**	**0.907**
$\overline{R}^2$	**0.938**	**0.797**	**0.930**	**0.913**	**0.904**	**0.732**	**0.904**

Table C1, Panel B: Augmented GR Carhart model on industry portfolio							
	A	B	C	D	E	F	G
Intercept	**11.946**	**7.622**	**5.786**	2.019	**-3.758**	1.810	3.508
	(2.310)	(2.460)	(0.622)	(1.643)	(1.792)	(1.843)	(2.176)
MKT	**0.920**	**1.266**	**0.956**	**0.899**	**1.321**	**1.388**	**1.119**
	(0.120)	(0.138)	(0.033)	(0.069)	(0.103)	(0.080)	(0.117)
SMB	-0.210	**-1.534**	**-0.631**	**-1.430**	**-0.757**	0.107	0.204
	(0.209)	(0.297)	(0.046)	(0.140)	(0.169)	(0.187)	(0.155)
HML	0.040	0.394	**-0.215**	0.127	-0.277	**-0.533**	**-0.717**
	(0.151)	(0.254)	(0.027)	(0.122)	(0.173)	(0.114)	(0.126)
WML	**-0.368**	**-0.448**	**-0.086**	0.083	**0.219**	**-0.280**	**-0.373**
	(0.081)	(0.139)	(0.031)	(0.106)	(0.065)	(0.099)	(0.109)
GR	**-0.724**	**-1.366**	**-0.117**	**-0.565**	-0.166	-0.066	0.140
	(0.163)	(0.260)	(0.029)	(0.121)	(0.154)	(0.123)	(0.098)
R^2	**0.751**	**0.818**	**0.969**	**0.827**	**0.783**	**0.876**	**0.853**
$\overline{R}^2$	**0.744**	**0.813**	**0.969**	**0.822**	**0.777**	**0.872**	**0.849**
	H	I	J	M	N	Q	R
Intercept	**3.612**	3.050	**2.659**	**4.894**	**2.612**	2.256	**7.159**
	(1.551)	(1.656)	(1.001)	(0.948)	(1.299)	(1.529)	(2.273)
MKT	**1.308**	**1.153**	**0.918**	**1.006**	**1.169**	**0.764**	**1.138**
	(0.061)	(0.070)	(0.054)	(0.069)	(0.075)	(0.064)	(0.091)
SMB	**-0.588**	**-0.489**	**-0.569**	-0.136	-0.041	-0.231	**0.399**
	(0.113)	(0.178)	(0.090)	(0.109)	(0.115)	(0.149)	(0.170)
HML	-0.075	0.281	**-0.246**	**-0.546**	-0.135	**-0.554**	**-1.114**
	(0.074)	(0.233)	(0.083)	(0.065)	(0.140)	(0.129)	(0.132)
WML	-0.127	**-0.124**	-0.011	**-0.164**	**-0.305**	**0.185**	**-0.311**
	(0.085)	(0.059)	(0.053)	(0.052)	(0.056)	(0.046)	(0.156)
GR	**-0.285**	0.101	**-0.264**	0.175	-0.089	**-0.320**	-0.094
	(0.068)	(0.113)	(0.069)	(0.096)	(0.091)	(0.073)	(0.148)
R^2	**0.905**	**0.783**	**0.910**	**0.859**	**0.897**	**0.729**	**0.836**
$\overline{R}^2$	**0.902**	**0.777**	**0.907**	**0.855**	**0.894**	**0.722**	**0.832**

Table C1, Panel C: Augmented GR three Fama-French model on industry portfolio							
	A	B	C	D	E	F	G
Intercept	**8.178**	3.040	**4.910**	**2.865**	-1.516	-1.060	-0.309
	(2.555)	(2.470)	(0.559)	(1.422)	(1.933)	(1.692)	(1.991)
MKT	**1.073**	**1.452**	**0.991**	**0.864**	**1.230**	**1.505**	**1.274**
	(0.107)	(0.132)	(0.036)	(0.060)	(0.103)	(0.080)	(0.115)
SMB	**-0.464**	**-1.843**	**-0.691**	**-1.373**	**-0.606**	-0.086	-0.053
	(0.234)	(0.315)	(0.048)	(0.127)	(0.171)	(0.175)	(0.145)
HML	0.087	0.450	**-0.204**	0.117	-0.304	**-0.497**	**-0.670**
	(0.147)	(0.251)	(0.030)	(0.122)	(0.178)	(0.119)	(0.137)
GR	**-0.803**	**-1.463**	**-0.135**	**0.547**	-0.119	-0.127	0.059
	(0.154)	(0.250)	(0.039)	(0.113)	(0.148)	(0.126)	(0.089)
R^2	**0.713**	**0.793**	**0.965**	**0.824**	**0.768**	**0.858**	**0.810**
$\overline{R}^2$	**0.706**	**0.789**	**0.964**	**0.820**	**0.763**	**0.854**	**0.806**
	H	I	J	M	N	Q	R
Intercept	**2.313**	1.776	**2.544**	**3.213**	-0.512	4.150	**3.977**
	(1.159)	(1.736)	(0.885)	(1.218)	(1.518)	(1.677)	(1.408)
MKT	**1.361**	**1.205**	**0.923**	**1.074**	**1.296**	**0.687**	**1.268**
	(0.063)	(0.070)	(0.044)	(0.060)	(0.083)	(0.067)	(0.107)
SMB	**-0.676**	**-0.575**	**-0.576**	**-0.250**	-0.252	-0.103	0.184
	(0.103)	(0.189)	(0.077)	(0.108)	(0.130)	(0.156)	(0.162)
HML	-0.059	0.297	**-0.245**	**-0.526**	-0.096	**-0.577**	**-1.074**
	(0.076)	(0.239)	(0.082)	(0.063)	(0.148)	(0.124)	(0.138)
GR	**-0.312**	0.074	**-0.266**	0.140	-0.155	**-0.280**	-0.161
	(0.065)	(0.105)	(0.065)	(0.094)	(0.088)	(0.073)	(0.159)
R^2	**0.900**	**0.778**	**0.909**	**0.846**	**0.868**	**0.707**	**0.811**
$\overline{R}^2$	**0.898**	**0.773**	**0.907**	**0.842**	**0.865**	**0.700**	**0.807**

The Table reports estimates of the augmented five-factor Fama-French model (Panel A), the Carhart model (Panel B), and the three-factor Fama-French model (Panel C) from time-series regressions. HACSE standard errors are reported in square brackets. Estimates reported in bold indicate that the parameter estimate is significantly different from zero at the 5% level. The (adjusted) coefficient of determination values is denoted as ($\overline{R}^2$) R^2 **.**

Table C2, Panel A: Augmented GRF^0 five-factor Fama-French model on industry portfolio							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**12.761**	6.062	**6.654**	**5.748**	-2.823	2.023	1.421
	(2.487)	(3.724)	(0.456)	(1.511)	(1.914)	(1.923)	(2.193)
MKT	**0.446**	**0.696**	**0.877**	**0.565**	**1.113**	**1.522**	**1.385**
	(0.170)	(0.171)	(0.031)	(0.103)	(0.114)	(0.118)	(0.101)
SMB	0.378	**-1.213**	**-0.376**	**-0.824**	**-0.842**	**0.487**	0.266
	(0.284)	(0.431)	(0.058)	(0.179)	(0.281)	(0.216)	(0.176)
HML	**1.199**	**2.128**	**-0.149**	**0.512**	0.264	**-1.074**	**-1.290**
	(0.394)	(0.393)	(0.073)	(0.220)	(0.243)	(0.225)	(0.245)
RMW	-0.135	0.555	**-0.295**	-0.282	**0.625**	**-0.966**	**-0.740**
	(0.291)	(0.501)	(0.058)	(0.202)	(0.267)	(0.165)	(0.522)
CMA	**-1.935**	**-3.109**	-0.134	**-0.824**	**-0.865**	**0.755**	**0.906**
	(0.522)	(0.569)	(0.096)	(0.296)	(0.348)	(0.344)	(0.309)
GRF^0	-0.322	**-1.408**	**0.091**	**-0.369**	-0.280	0.102	0.133
	(0.241)	(0.387)	(0.046)	(0.165)	(0.208)	(0.173)	(0.196)
R^2	**0.749**	**0.771**	**0.979**	**0.827**	**0.789**	**0.893**	**0.839**
$\bar{R}^2$	**0.741**	**0.764**	**0.978**	**0.821**	**0.782**	**0.889**	**0.833**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	**6.487**	2.609	**4.152**	**6.273**	**2.507**	**5.442**	**9.767**
	(1.124)	(1.758)	(0.883)	(1.181)	(1.149)	(1.629)	(1.295)
MKT	**1.075**	**1.391**	**0.958**	**0.991**	**1.300**	**0.799**	**0.805**
	(0.084)	(0.114)	(0.064)	(0.083)	(0.081)	(0.117)	(0.089)
SMB	0.076	-0.410	-0.248	**0.271**	**0.311**	0.179	**1.182**
	(0.138)	(0.235)	(0.130)	(0.108)	(0.147)	(0.245)	(0.206)
HML	0.122	-0.427	**-0.672**	**-0.725**	**-0.631**	**-1.226**	**-0.567**
	(0.169)	(0.266)	(0.126)	(0.172)	(0.209)	(0.240)	(0.222)
RMW	**-0.677**	**-0.630**	**-0.574**	**-0.731**	**-0.922**	**-0.645**	**-0.787**
	(0.123)	(0.213)	(0.115)	(0.182)	(0.157)	(0.201)	(0.162)
CMA	-0.379	**1.046**	**0.451**	0.393	**0.681**	**0.741**	**-0.719**
	(0.229)	(0.353)	(0.176)	(0.243)	(0.276)	(0.292)	(0.287)
GRF^0	0.137	0.212	-0.054	**0.374**	0.186	0.239	**0.486**
	(0.091)	(0.178)	(0.104)	(0.154)	(0.116)	(0.194)	(0.202)
R^2	**0.941**	**0.804**	**0.920**	**0.892**	**0.909**	**0.723**	**0.906**
$\bar{R}^2$	**0.939**	**0.797**	**0.918**	**0.888**	**0.906**	**0.714**	**0.903**

Table C2, Panel B: Augmented GRF^0 Carhart model on industry portfolio

	A	B	C	D	E	F	G
Intercept	**12.183**	8.125	**5.817**	2.214	**-3.700**	1.841	3.475
	(3.012)	(4.120)	(0.679)	(1.974)	(1.841)	(1.7711)	(2.294)
MKT	**0.964**	**1.359**	**0.962**	**0.935**	**1.331**	**1.394**	**1.113**
	(0.149)	(0.197)	(0.034)	(0.088)	(0.107)	(0.076)	(0.126)
SMB	-0.182	**-1.483**	**-0.627**	**-1.408**	**-0.751**	0.110	0.199
	(0.236)	(0.382)	(0.050)	(0.163)	(0.184)	(0.186)	(0.164)
HML	-0.278	-0.206	**-0.267**	-0.121	**-0.350**	**-0.561**	**-0.655**
	(0.159)	(0.234)	(0.028)	(0.127)	(0.610)	(0.127)	(0.136)
WML	**-0.469**	**-0.651**	**-0.100**	0.002	**0.195**	**-0.292**	**-0.356**
	(0.119)	(0.220)	(0.035)	(0.128)	(0.074)	(0.092)	(0.109)
GRF^0	-0.414	**-1.378**	0.016	**-0.433**	-0.129	-0.133	-0.061
	(0.291)	(0.465)	(0.069)	(0.202)	(0.232)	(0.182)	(0.177)
R^2	**0.673**	**0.724**	**0.965**	**0.766**	**0.779**	**0.876**	**0.850**
$\bar{R}^2$	**0.664**	**0.717**	**0.964**	**0.760**	**0.773**	**0.872**	**0.846**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	**3.694**	3.016	**2.748**	**4.827**	**2.641**	2.333	**7.159**
	(1.722)	(1.653)	(0.857)	(0.965)	(1.277)	(1.622)	(2.199)
MKT	**1.324**	**1.147**	**0.935**	**0.993**	**1.174**	**0.779**	**1.138**
	(0.069)	(0.070)	(0.048)	(0.070)	(0.074)	(0.066)	(0.090)
SMB	**-0.577**	**-0.493**	**-0.558**	-0.143	-0.038	-0.219	**0.402**
	(0.131)	(0.181)	(0.098)	(0.117)	(0.111)	(0.165)	(0.165)
HML	**-0.201**	0.326	**-0.363**	**-0.470**	-0.174	**-0.695**	**-1.156**
	(0.075)	(0.255)	(0.071)	(0.059)	(0.141)	(0.107)	(0.105)
WML	-0.164	**-0.110**	-0.049	**-0.138**	**-0.318**	**0.147**	**-0.318**
	(0.092)	(0.052)	(0.046)	(0.064)	(0.052)	(0.055)	(0.148)
GRF^0	-0.028	0.070	-0.180	0.204	-0.043	0.121	0.279
	(0.150)	(0.191)	(0.123)	(0.170)	(0.166)	(0.198)	(0.198)
R^2	**0.891**	**0.781**	**0.889**	**0.854**	**0.896**	**0.691**	**0.839**
$\bar{R}^2$	**0.888**	**0.775**	**0.886**	**0.850**	**0.893**	**0.683**	**0.834**

Table C2, Panel C: Augmented GRF^0 Fama-French model on industry portfolio

	A	B	C	D	E	F	G
Intercept	**7.280**	1.325	**4.477**	2.230	-1.661	-1.207	-0.249
	(2.532)	(3.359)	(0.591)	(1.579)	(1.932)	(1.672)	(2.041)
MKT	**1.168**	**1.643**	**1.005**	**0.934**	**1.246**	**1.521**	**1.269**
	(0.121)	(0.148)	(0.034)	(0.065)	(0.105)	(0.078)	(0.121)
SMB	**-0.515**	**-1.938**	**-0.697**	**-1.407**	**-0.614**	-0.094	-0.050
	(0.242)	(0.334)	(0.052)	(0.138)	(0.178)	(0.172)	(0.148)
HML	-0.263	-0.185	-0.264	-0.121	**-0.356**	**-0.552**	**-0.644**
	(0.162)	(0.247)	(0.033)	(0.127)	(0.168)	(0.121)	(0.146)
GRF^0	-0.361	-1.305	0.027	**-0.433**	-0.151	-0.100	-0.021
	(0.316)	(0.526)	(0.077)	(0.200)	(0.228)	(0.186)	(0.171)
R^2	**0.609**	**0.670**	**0.959**	**0.766**	**0.767**	**0.856**	**0.810**
$\bar{R}^2$	**0.600**	**0.663**	**0.958**	**0.761**	**0.762**	**0.853**	**0.806**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	1.980	1.865	**2.240**	**3.388**	-0.678	**3.865**	**3.844**
	(1.293)	(1.732)	(0.930)	(1.238)	(1.508)	(1.778)	(1.3799)
MKT	**1.396**	**1.195**	**0.956**	**1.054**	**1.313**	**0.715**	**1.277**
	(0.061)	(0.069)	(0.040)	(0.058)	(0.085)	(0.067)	(0.100)
SMB	**-0.692**	**-0.570**	**-0.593**	**-0.239**	**-0.260**	-0.116	0.180
	(0.117)	(0.189)	(0.091)	(0.112)	(0.127)	(0.169)	(0.153)
HML	**-0.196**	0.329	**-0.361**	**-0.495**	-0.164	**-0.700**	**-1.146**
	(0.080)	(0.257)	(0.072)	(0.060)	(0.147)	(0.106)	(0.117)
GRF^0	-0.010	0.082	-0.174	0.219	-0.008	0.105	0.314
	(0.164)	(0.189)	(0.124)	(0.167)	(0.162)	(0.198)	(0.526)
R^2	**0.883**	**0.777**	**0.888**	**0.845**	**0.863**	**0.677**	**0.812**
$\bar{R}^2$	**0.881**	**0.773**	**0.885**	**0.842**	**0.860**	**0.670**	**0.808**

The Table reports estimates of the augmented five-factor Fama-French model (Panel A), the Carhart model (Panel B), and the three-factor Fama-French model (Panel C) from time-series regressions. HACSE standard errors are reported in square brackets. Estimates reported in bold indicate that the parameter estimate significantly differs from zero at the 5% level. The (adjusted) coefficient of determination values is denoted as ($\bar{R}^2$) R^2 .

Table C3, Panel A: Augmented GRF[1] five-factor Fama-French model on industry portfolio							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**12.611** (2.696)	4.482 (3.730)	**6.504** (0.471)	**4.909** (1.793)	-2.808 (2.066)	2.480 (2.094)	1.697 (2.386)
MKT	**0.456** (0.178)	**0.770** (0.193)	**0.880** (0.035)	**0.598** (0.100)	**1.117** (0.120)	**1.505** (0.120)	**1.374** (0.104)
SMB	0.366 (0.288)	**-1.396** (0.422)	**-0.399** (0.064)	**-0.931** (0.197)	**-0.832** (0.292)	**0.548** (0.200)	0.301 (0.200)
HML	**1.180** (0.399)	**2.114** (0.382)	-0.128 (0.075)	**0.542** (0.217)	**0.236** (0.261)	**-1.099** (0.241)	**-1.298** (0.245)
RMW	-0.119 (0.296)	0.828 (0.468)	**-0.256** (0.059)	-0.116 (0.259)	0.606 (0.321)	**-1.061** (0.199)	**-0.794** (0.272)
CMA	**-1.923** (0.522)	**-3.189** (0.558)	-0.165 (0.097)	**-0.906** (0.298)	**-0.833** (0.379)	**0.810** (0.367)	**0.932** (0.317)
GRF[1]	-0.129 (0.185)	**-0.862** (0.260)	-0.026 (0.042)	-0.363 (0.196)	-0.065 (0.239)	0.173 (0.178)	0.122 (0.167)
R^2	**0.745**	**0.751**	**0.978**	**0.831**	**0.785**	**0.894**	**0.839**
$\bar{R}^2$	**0.737**	**0.743**	**0.978**	**0.825**	**0.778**	**0.890**	**0.833**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	**6.410** (1.257)	3.571 (1.928)	**3.552** (0.917)	**7.133** (1.263)	**2.845** (1.154)	**4.797** (1.830)	**9.648** (1.456)
MKT	**1.075** (0.088)	**1.356** (0.113)	**0.979** (0.055)	**0.957** (0.078)	**1.285** (0.082)	**0.817** (0.121)	**0.802** (0096)
SMB	0.061 (0.150)	-0.281 (0.234)	**-0.330** (0.129)	**0.381** (0.114)	**0.353** (0.149)	0.083 (0.244)	**1.153** (0.206)
HML	0.141 (0.165)	-0.481 (0.278)	**-0.631** (0.118)	**-0.756** (0.168)	**-0.639** (0.216)	**-1.154** (0.253)	-0.511 (0.269)
RMW	**-0.653** (0.131)	**-0.832** (0.273)	**-0.443** (0.130)	**-0.901** (0.202)	**-0.987** (0.185)	**-0.489** (0.220)	**-0.734** (0.190)
CMA	-0.405 (0.223)	**1.162** (0.381)	**0.379** (0.167)	0.477 (0.243)	**0.710** (0.288)	**0.623** (0.302)	**-0.787** (0.341)
GRF[1]	**0.010** (0.100)	0.363 (0.205)	-0.206 (0.108)	**0.371** (0.121)	0.156 (0.090)	-0.148 (0.176)	0.084 (0.135)
R^2	**0.940**	**0.812**	**0.927**	**0.897**	**0.909**	**0.720**	**0.895**
$\bar{R}^2$	**0.938**	**0.806**	**0.924**	**0.893**	**0.906**	**0.711**	**0.892**

Table C3, Panel B: Augmented GRF[1] Carhart model on industry portfolio							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**11.868** (3.030)	**7.305** (3.941)	**5.685** (0.660)	1.693 (1.943)	-3.611 (1.824)	1.653 (1.856)	3.372 (2.317)
MKT	**0.982** (0.155)	**1.400** (0.226)	**0.974** (0.031)	**0.972** (0.087)	**1.320** (0.107)	**1.408** (0.077)	**1.121** (0.123)
SMB	-0.186 (0.237)	**-1.491** (0.411)	**-0.629** (0.047)	**-1.414** (0.151)	**-0.750** (0.182)	0.108 (0.185)	0.198 (0.162)
HML	-0.297 (0.156)	-0.254 (0.249)	**-0.275** (0.026)	-0.153 (0.120)	**-0.344** (0.157)	**-0.573** (0.134)	**-0.662** (0.137)
WML	**-0.450** (0.118)	**-0.596** (0.218)	**-0.095** (0.032)	0.029 (0.106)	**0.194** (0.073)	**-0.282** (0.095)	**-0.351** (0.112)
GRF[1]	-0.279 (0.183)	-0.698 (0.358)	**-0.135** (0.046)	**-0.485** (0.182)	0.103 (0.218)	-0.177 (0.199)	-0.099 (0.167)
R^2	**0.671**	**0.701**	**0.968**	**0.785**	**0.779**	**0.878**	**0.851**
$\bar{R}^2$	**0.662**	**0.693**	**0.968**	**0.779**	**0.773**	**0.874**	**0.846**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	**3.416** (1.703)	3.139 (1.733)	**2.375** (0.827)	**4.893** (0.956)	2.471 (1.266)	2.026 (1.647)	**6.937** (2.311)
MKT	**1.349** (0.068)	**1.137** (0.070)	**0.965** (0.038)	**0.992** (0.075)	**1.189** (0.071)	**0.810** (0.066)	**1.166** (0.093)
SMB	**-0.580** (0.130)	**-0.492** (0.178)	**-0.563** (0.086)	-0.142 (0.120)	-0.040 (0.115)	-0.222 (0.168)	**0.399** (0.174)
HML	**-0.219** (0.073)	0.333 (0.256)	**-0.386** (0.074)	**-0.466** (0.059)	-0.184 (0.147)	**-0.715** (0.125)	**-1.171** (0.107)
WML	-0.153 (0.087)	**-0.116** (0.202)	**-0.031** (0.039)	**-0.144** (0.064)	**-0.310** (0.055)	**0.156** (0.046)	**-0.314** (0.151)
GRF[1]	-0.278 (0.111)	0.118 (0.202)	**-0.360** (0.099)	-0.047 (0.156)	-0.168 (0.138)	**-0.321** (0.156)	-0.250 (0.155)
R^2	**0.899**	**0.782**	**0.912**	**0.851**	**0.899**	**0.713**	**0.841**
$\bar{R}^2$	**0.896**	**0.776**	**0.910**	**0.847**	**0.896**	**0.705**	**0.836**

Table C3, Panel C: Augmented GRF[1] Fama-French model on industry portfolio							
	A	**B**	**C**	**D**	**E**	**F**	**G**
Intercept	**7.127**	1.027	**4.679**	1.995	-1.569	-1.319	-0.329
	(2.568)	(3.403)	(0.570)	(1.611)	(1.970)	(1.668)	(2.022)
MKT	**1.184**	**1.667**	**1.017**	**0.959**	**1.233**	**1.534**	**1.279**
	(0.128)	(0.171)	(0.032)	(0.068)	(0.104)	(0.077)	(0.114)
SMB	**-0.500**	**-1.908**	**-0.695**	**-1.294**	**-0.614**	-0.089	-0.048
	(0.246)	(0.373)	(0.048)	(0.128)	(0.174)	(0.173)	(0.147)
HML	-0.286	-0.239	-0.273	-0.154	**-0.349**	**-0.566**	-0.653
	(0.155)	(0.254)	(0.031)	(0.120)	(0.163)	(0.129)	(0.148)
GRF[1]	-0.328	-0.764	-0.146	-0.481	0.124	-0.208	-0.137
	(0.214)	(0.406)	(0.052)	(0179)	(0.214)	(0.189)	(0.143)
R^2	**0.613**	**0.655**	**0.963**	**0.784**	**0.767**	**0.859**	**0.812**
$\bar{R}^2$	**0.604**	**0.648**	**0962**	**0.779**	**0.762**	**0.856**	**0.808**
	H	**I**	**J**	**M**	**N**	**Q**	**R**
Intercept	1.805	1.918	**2.043**	**3.380**	-0.798	**3.671**	**3.636**
	(1.255)	(1.780)	(0.786)	(1.287)	(1.475)	(1.767)	(1.433)
MKT	**1.418**	**1.189**	**0.979**	**1.057**	**1.328**	**0.740**	**1.306**
	(0.060)	(0.068)	(0031)	(0.062)	(0.080)	(0072)	(0.104)
SMB	**-0.687**	**-0.573**	**-0.585**	**-0.243**	**-0.257**	-0.113	0.180
	(0118)	(0.188)	(0.081)	(0.113)	(0.130)	(0.174)	(0.161)
HML	**-0.215**	0.336	**-0.385**	**-0.462**	-0.177	**-0.719**	**-1.163**
	(0078)	(0.259)	(0074)	(0.060)	(0.154)	(0.124)	(0.119)
GRF[1]	-0.294	0.105	-0.363	0.031	-0.202	-0.304	-0.284
	(0.114)	(0.195)	(0.098)	(0.144)	(0.120)	(0.152)	(0.179)
R^2	**0.892**	**0.778**	**0.911**	**0.841**	**0.868**	**0.697**	**0.814**
$\bar{R}^2$	**0.890**	**0.773**	**0.909**	**0.837**	**0.865**	**0.690**	**0.810**

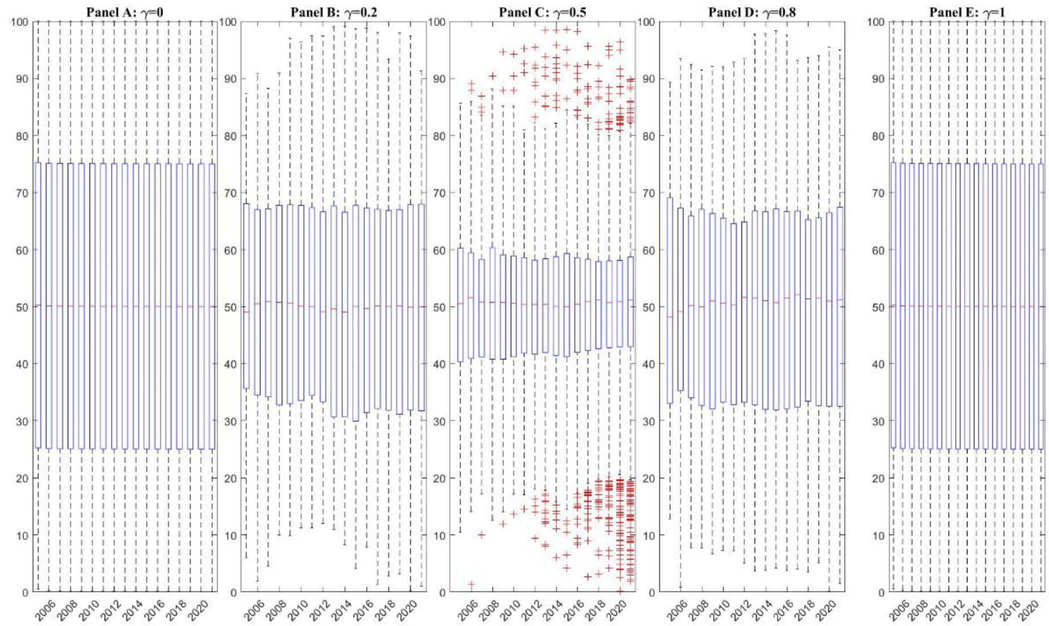
The Table reports estimates of the augmented five-factor Fama-French model (Panel A), the Carhart model (Panel B), and the three-factor Fama-French model (Panel C) from time-series regressions. HACSE standard errors are reported in square brackets. Estimates reported in bold indicate that the parameter estimate significantly differs from zero at the 5% level. The (adjusted) coefficient of determination values is denoted as ($\bar{R}^2$) R^2 **.**

Table C4: Green score unrestricted vs. restricted auxiliary regression, unfiltered green factors

	GR	**GR***	**GR^1**	**GR^{1*}**	**GR^0**	**GR^{0*}**	**GR^{ALL}**	**GR^{ALL*}**
gB	**44.731**	**45.737**	**43.827**	**45.324**	**43.879**	**45.713**	**44.071**	**45.591**
	(2.520)	(0.596)	(2.296)	(0.616)	(2.453)	(0.610)	(1.303)	(0.347)
gC	**51.138**	**50.901**	**51.102**	**50.933**	**51.184**	**50.989**	**51.147**	**50.944**
	(0.412)	(0.289)	(0.400)	(0.289)	(0.392)	(0.284)	(0.231)	(0.166)
gD	**46.816**	**45.737**	**46.712**	**45.324**	**47.355**	**45.713**	**46.976**	**45.591**
	(1.532)	(0.596)	(1.676)	(0.616)	(1.403)	(0.610)	(0.851)	(0.347)
gF	**51.396**	**50.901**	**51.713**	**50.933**	**51.391**	**50.989**	**51.492**	**50.944**
	(1.202)	(0.289)	(1.246)	(0.289)	(1.215)	(0.284)	(0.687)	(0.166)
gG	**52.258**	**50.901**	**52.277**	**50.933**	**52.136**	**50.989**	**52.205**	**50.944**
	(0.952)	(0.289)	(0.945)	(0.289)	(0.936)	(0.284)	(0.539)	(0.166)
gH	**45.764**	**45.737**	**45.818**	**45.324**	**45.603**	**45.713**	**45.729**	**45.591**
	(1.365)	(0.596)	(1.366)	(0.616)	(1.393)	(0.610)	(0.782)	(0.347)
gI	**47.169**	**45.737**	**46.392**	**45.324**	**46.491**	**45.713**	**46.718**	**45.591**
	(1.724)	(0.596)	(1.366)	(0.616)	(1.393)	(0.610)	(0.782)	(0.347)
gJ	**50.369**	**50.901**	**50.412**	**50.933**	**50.455**	**51.006**	**50.415**	**50.944**
	(0.704)	(0.289)	(0.709)	(0.289)	(0.660)	(0.285)	(0.393)	(0.166)
gM	**49.797**	**50.901**	**49.748**	**50.933**	**49.871**	**51.006**	**49.809**	**50.944**
	(1.044)	(0.289)	(1.028)	(0.289)	(1.060)	(0.285)	(0.589)	(0.166)
gN	**49.075**	**50.901**	**48.954**	**50.933**	**49.396**	**51.006**	**49.087**	**50.944**
	(1.141)	(0.289)	(1.156)	(0.289)	(1.220)	(0.285)	(0.655)	(0.166)
gQ	**44.859**	**45.737**	**44.509**	**45.324**	**44.862**	**45.713**	**44.720**	**45.591**
	(1.747)	(0.596)	(1.765)	(0.616)	(1.916)	(0.610)	(0.955)	(0.347)
gR	**45.299**	**45.737**	**44.774**	**45.324**	**45.716**	**45.713**	**45.257**	**45.591**
	(1.186)	(0.596)	(1.293)	(0.616)	(1.161)	(0.610)	(0.652)	(0.347)
bB	0.842	**0.576**	0.334	**0.497**	0.068	**0.307**	0.336	**0.404**
	(1.691)	(0.259)	(2.124)	(0.325)	(1.399)	(0.253)	(0.883)	(0.166)
bC	-0.270	-0.576	-0.479	-0.497	-0.167	-0.307	-0.293	**-0.404**
	(0.423)	(0.259)	(0.441)	(0.325)	(0.395)	(0.253)	(0.239)	(0.166)
bD	-3.408	**-3.441**	-2.774	-4.057	-1.892	**-2.073**	**-2.665**	**-3.293**
	(2.623)	(1.174)	(2.333)	(1.516)	(2.092)	(0.859)	(1.245)	(0.779)
bF	**2.271**	**2.100**	2.085	**1.914**	1.603	**1.326**	**1.949**	**1.914**
	(1.050)	(0.766)	(1.430)	(0.727)	(1.105)	(0.525)	(0.653)	(0.439)
bG	0.559	**0.576**	0.658	0.497	0.187	0.307	0.446	**0.404**
	(0.734)	(0.259)	(0.694)	(0.325)	(0.595)	(0.253)	(0.380)	(0.166)
bH	1.315	**0.576**	1.152	**1.254**	1.223	**1.326**	**1.229**	**1.062**
	(0.805)	(0.259)	(0.933)	(0.608)	(0.796)	(0.525)	(0.460)	(0.321)
bI	-4.132	**-3.441**	-4.995	**-4.057**	-2.090	**-2.073**	**-3.442**	**-3.293**
	(2.439)	(1.174)	(3.232)	(1.516)	(2.750)	(0.859)	(1.365)	(0.779)
bJ	-0.537	**-0.576**	-0.366	-0.497	-0.399	-0.307	-0.436	**-0.404**
	(0.628)	(0.259)	(0.791)	(0.325)	(0.481)	(0.253)	(0.350)	(0.166)
bM	-0.971	**-0.576**	-1.292	**-1.254**	-1.077	**-1.326**	**-1.107**	**-1.062**
	(1.021)	(0.259)	(0.900)	(0.608)	(0.982)	(0.525)	(0.524)	(0.321)
bN	1.061	0.576	2.166	**1.914**	-0.204	-0.307	0.933	**1.062**
	(1.336)	(0.259)	(1.352)	(0.727)	(1.302)	(0.253)	(0.752)	(0.321)
bQ	-2.266	**-3.441**	-1.403	**-1.254**	-1.687	**-2.073**	-1.771	**-1.914**
	(2.292)	(1.174)	(2.211)	(0.608)	(2.475)	(0.859)	(1.197)	(0.439)
bR	-1.744	**-2.100**	-1.943	**-1.914**	-1.934	**-2.073**	**-1.823**	**-1.914**
	(1.181)	(0.766)	(1.143)	(0.727)	(1.455)	(0.859)	(0.640)	(0.439)
R^2	0.064	0.057	0.064	0.057	0.058	0.052	0.061	0.055
$\bar{R}^2$	0.048	0.054	0.048	0.054	0.042	0.049	0.055	0.054
SBC	4.599	4.506	4.600	4.511	4.605	4.516	4.524	4.494
p-val	-	0.903	-	0.928	-	0.982	-	0.051
N	1367	1367	1366	1366	1367	1367	4100	4100

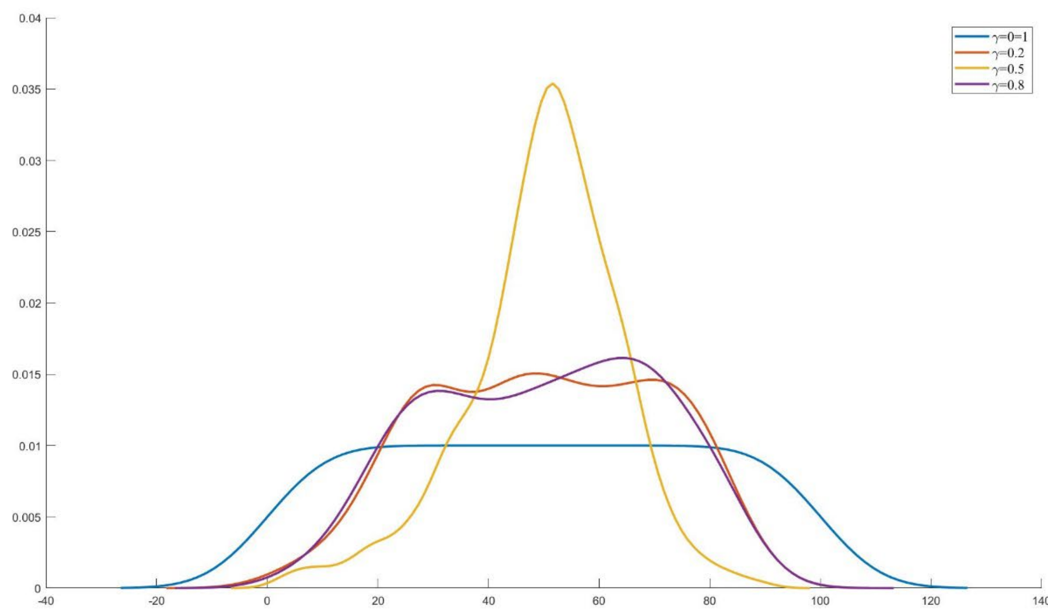
The table reports the estimated coefficients from the auxiliary regressions of the average green score for the transparent companies on the green factor company beta from the augmented five-factor Fama-French model. Heteroskedasticity-robust standard errors are reported in brackets. The results in columns one, three, five, and seven refer to the case where the unfiltered green factors **GR**, $\mathbf{GR^1}$, and $\mathbf{GR^0}$, are used in the *unrestricted* asset pricing regressions; column seven reports the results from the joint model. Columns two, four, six, and eight refer to the case of restricted regressions. Figures in bold are significant at the 5% level. R^2 ($\overline{R}^2$) is the (adjusted) coefficient of determination, SBC the Bayes-Schwarz information criterion, p-val the p-value of the Likelihood-ratio test for the restricted (Panel B) versus the unrestricted (Panel A) models, and N is the sample size.

Figure C1: Distribution over years of the re-scaled greenness and transparency indicators.



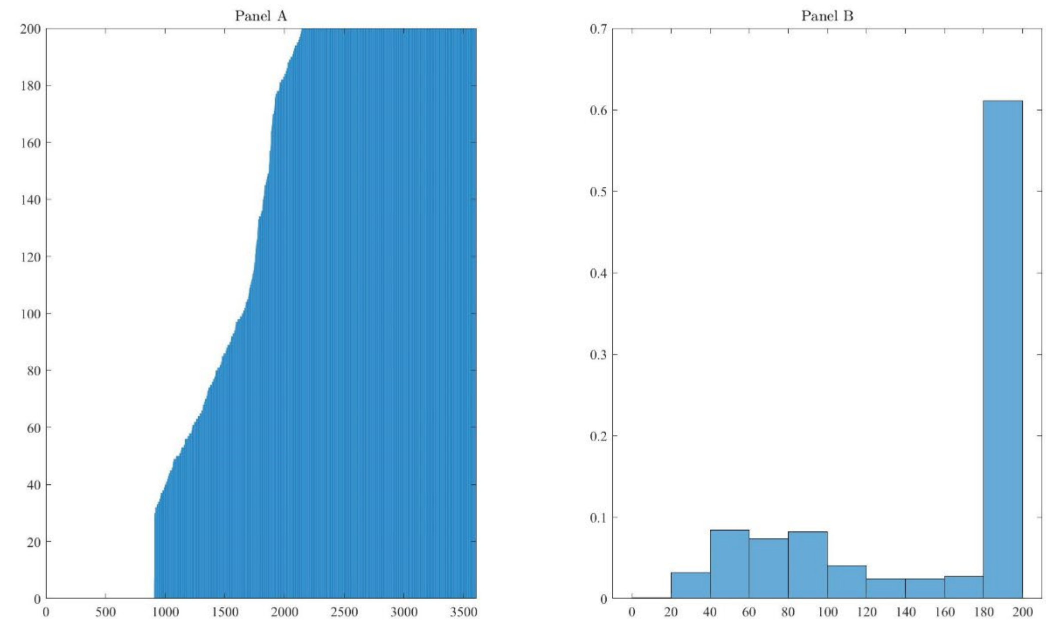
Panels A-E report the distribution of yearly indicators computed for $\gamma = 0, .2, .5, .8, 1,$ respectively.

Figure C2: Distribution of the re-scaled greenness and transparency indicators in 2022.



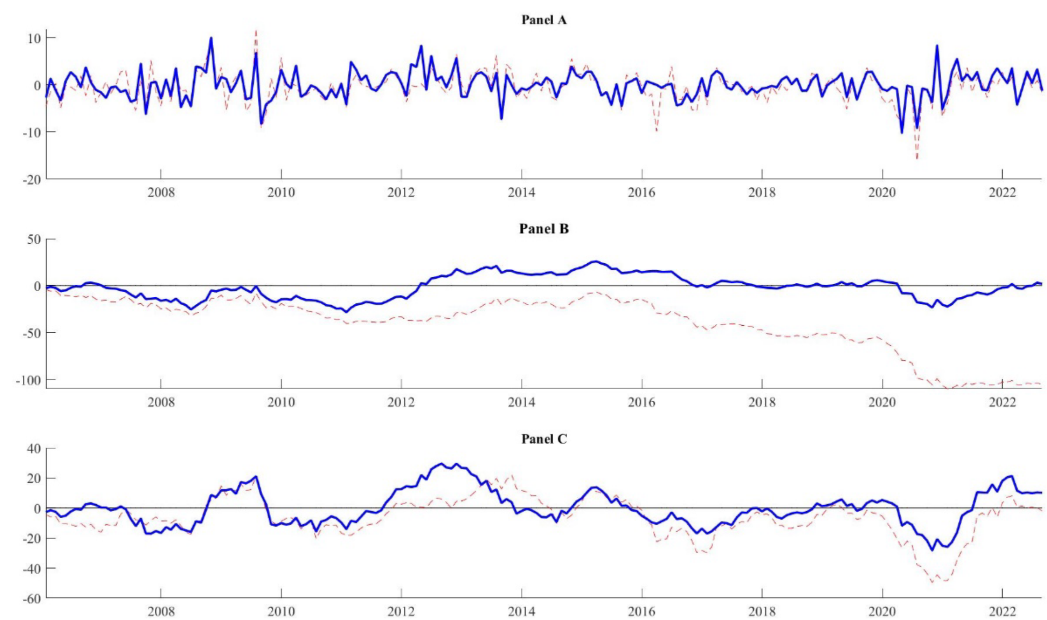
The distribution is estimated by a kernel estimator and the indicators are computed for several values of γ.

Figure C3: Distribution of individual stocks with respect to T_i.



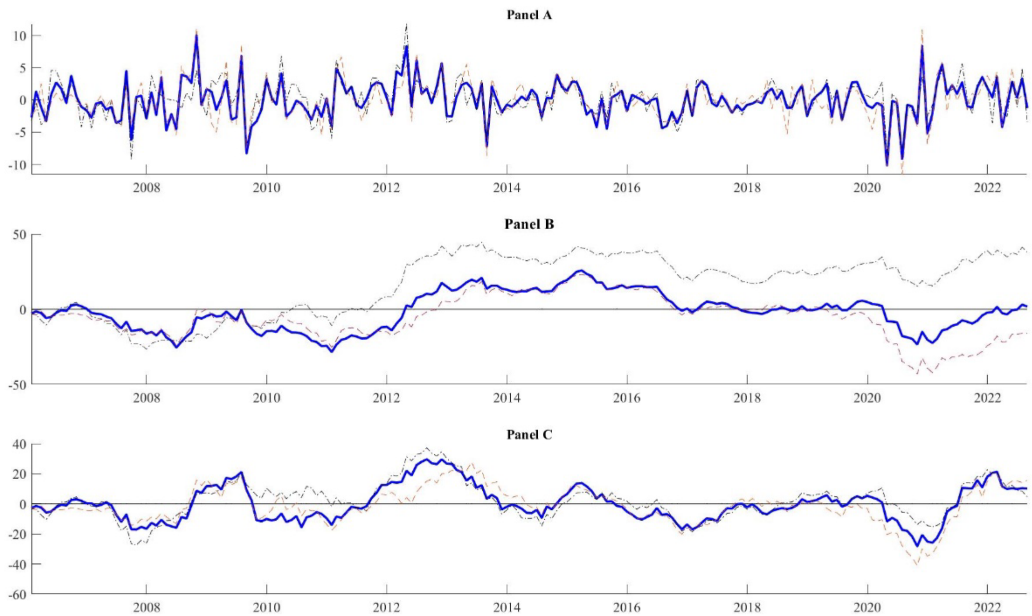
Panel A plots the sorted number of T_i. Panel B shows the frequency counts of the individual stocks w.r.t. their buckets of sample size T_i.

Figure C4: Greenness and transparency factors: GR_t $(blue\ line)$, and $\widetilde{GR}_t$ $(red\ dotted\ line)$



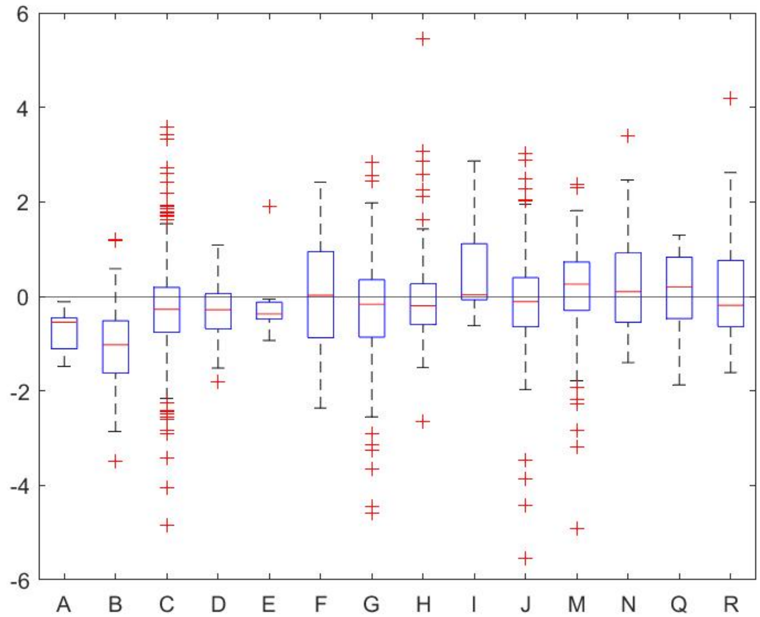
Panel A shows the time series of monthly returns (in percentage) of the two greenness and transparency factors $GR_t(blue\ line)$, and $\widetilde{GR}_t(red\ dotted\ line)$. Panels B and C report the cumulative returns and the year-to-year returns of the factors, respectively.

Figure C5: Greenness and transparency factors: GR_t $(blue\ line)$, $GR^0{}_t(black\ dashed - dotted\ line)$ and $GR^1{}_t$ $(red\ dotted\ line)$



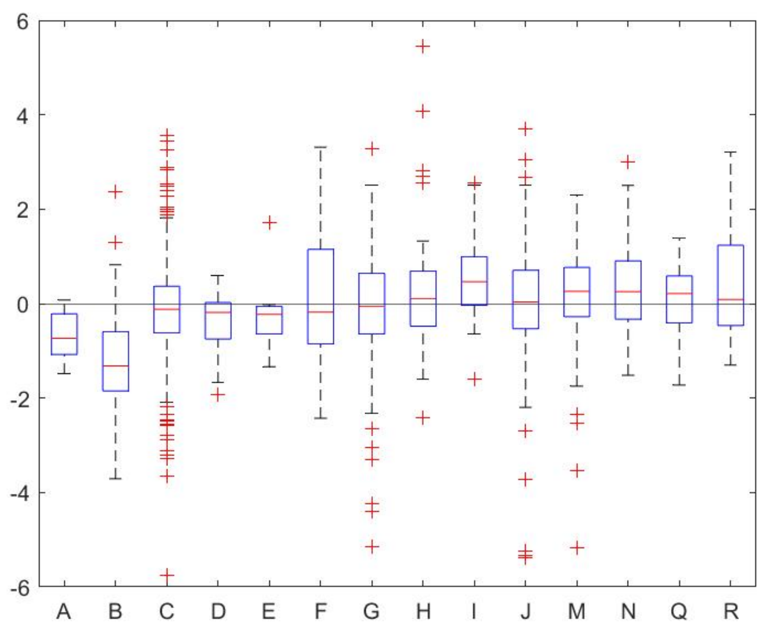
Panel A shows the time series of monthly returns (in percentage) of the greenness and transparency factors GR_t $(blue\ line)$, $GR^0{}_t(black\ dashed - dotted\ line)$ and $GR^1{}_t$ $(red\ dotted\ line)$. Panels B and C report the cumulative returns and the year-to-year returns of the factors, respectively.

Figure C8: Distribution at industry level of estimated loadings for the greenness and transparency factor GR.



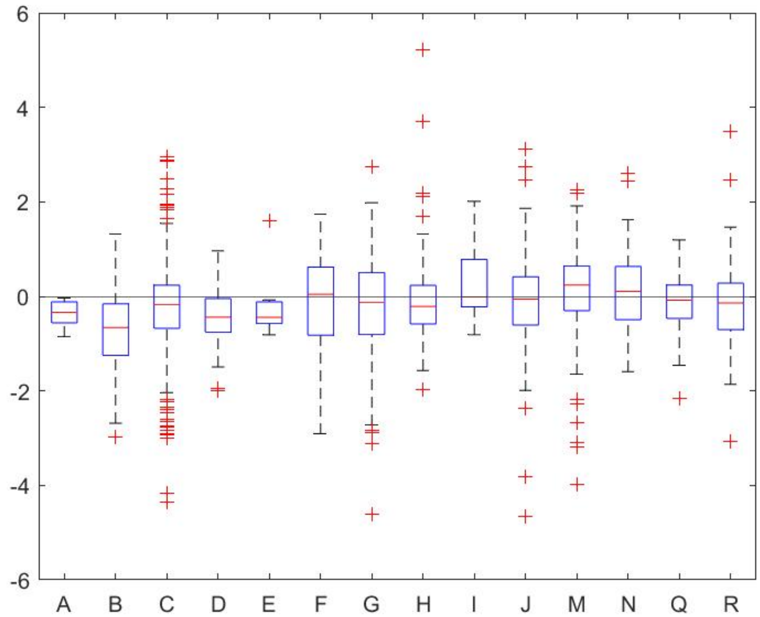
The figure shows the box plots of the estimated loadings for the greenness and transparency factor GR, at industry level. The estimates are computed from the augment five-factor Fama-French model.

Figure C9: Distribution at industry level of estimated loadings for the greenness and transparency factor GR^0.



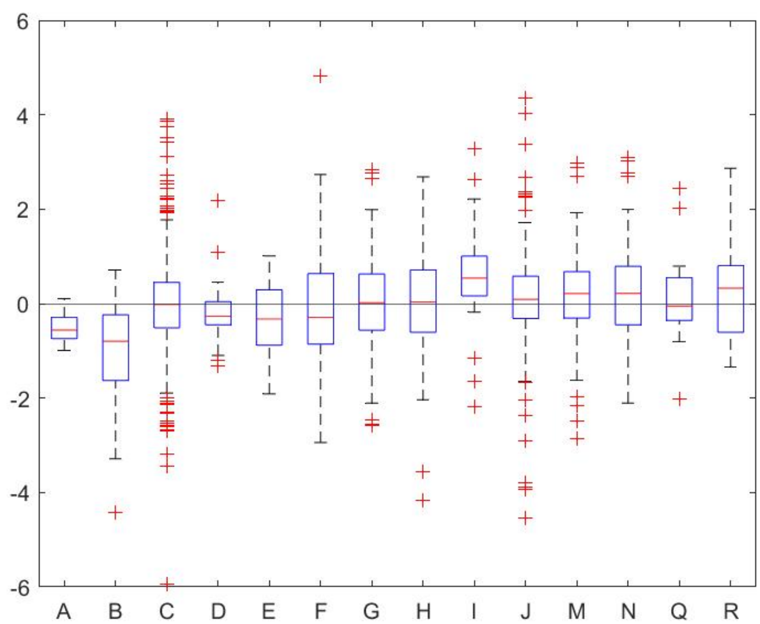
The figure shows the box plots of the estimated loadings for the greenness and transparency factor GR^0, at industry level. The estimates are computed from the augment five-factor Fama-French model.

Figure C10: Distribution at industry level of estimated loadings for the greenness and transparency factor GR^1.



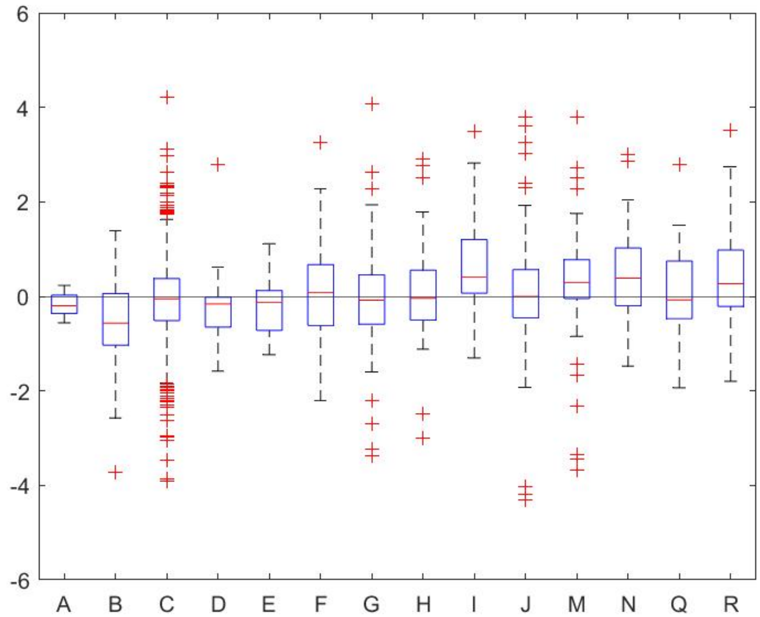
The figure shows the box plots of the estimated loadings for the greenness and transparency factor GR^1, at industry level. The estimates are computed from the augment five-factor Fama-French model.

Figure C11: Distribution at industry level of estimated loadings for the greenness and transparency residual factor GFR^0.



The figure shows the box plots of the estimated loadings for the greenness and transparency residual factor GFR^0, at industry level. The estimates are computed from the augment five-factor Fama-French model.

Figure C12: Distribution at industry level of estimated loadings for the greenness and transparency residual factor GFR[1].



The figure shows the box plots of the estimated loadings for the greenness and transparency residual factor GFR[1], at industry level. The estimates are computed from the augment five-factor Fama-French model.