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. 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 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, asset pricing models, European Union.

JEL Classification: G01; G11; G12; Q54.

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1. Introduction

Climate change raises two main challenges: mitigation and adaptation. Mitigation concerns the containment of greenhouse gas (GHG) emissions; it generates transition risk and losses from stranded assets as portfolios shift towards sustainable investment. Adaptation involves adjusting the economic and financial systems and human societies to make them resilient to climate change's physical risk, as entailed in changes in extreme weather episodes, i.e., heatwaves, droughts, wildfires, floods, storms, and hurricanes. 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. 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 as compensation 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 and Gimeno and González (2022) for Europe. In contrast, Alessi et al. (2021) find a negative risk premium linked to firms' carbon emissions and environmental transparency, indicating that European investors might prefer a hedging strategy to reduce their exposure to climate risk, particularly after the Paris Agreement, the first global climate strike, and the announcement of the EU Green Deal (Alessi et al., 2023). Rebonato (2023) argues that mispricing of climate risk is the most likely explanation for failing to identify a robust and significant climate risk premium.

Our paper makes four main contributions to the literature motivated by the conflicting empirical evidence mentioned above. First, we show that measures of green-brown investment performance contain information that goes beyond what could have been attributed to the pricing of climate risks. To capture green risk, financial and business cycle components, and firm-level characteristics should be filtered out of green vs. brown excess return measures. We further dig into the information content of the proposed filtered green factor by assessing its interconnection with measures of climate change concern and physical risk. Second, using a filtered green factor, we find evidence that climate risks are priced in the European stock market but not as pervasively as previously reported in the literature. This is confirmed by sectorial analysis, which shows that climate risks are negatively priced in typically brown sectors, but with low statistical significance. Third, we find evidence that over the last two decades, green investments have been a hedge over the business and financial cycle and, perhaps surprisingly, that restrictive monetary and budgetary policies have negatively impacted green vs. brown returns. Importantly, these findings on the time variation of green vs. brown returns are independent of the pricing of climate risks. Moreover, we find empirical evidence of rising investors' environmental concerns following EU policy initiatives such as the launch of the Green Deal (possibly also because of the COVID-19 pandemic). This might explain the higher performance of green vs. brown stocks. Fourth, we propose a market-oriented rating tool based on the improved green risk measurement, yielding complementary information to standard ESG ratings, and improving existing approaches to rate non-transparent or non-disclosing companies.

The paper is organized as follows. Section 2 discusses the construction of the green vs. brown risk factor return factor and its filtered version. Sections 3 and 4 present the data and the evidence for the empirical factors, their information content, and their 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-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. Construction and filtering of the green factor

Following Alessi et al. (2021, 2023), we construct a portfolio that goes long on greener and more transparent stocks and short on high carbon/brown assets. 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 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 ($r_{hc,s}, r_{hs,m},$ and $r_{hc,l}$). The monthly t greenness and transparency factor return GR (green factor henceforth) is defined as follows:

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

GR_t yields the difference between the average return on the three green portfolios and the average return on the three brown portfolios. Time variation in GR_t should reveal the shocks and risks that drive green vs. brown stock returns.

To study the sources of systematic risk, we decompose GR_t as follows,

$$\mathrm{GR}_t = E[\mathrm{GR}_t|\mathbf{f}_{n,t}, \mathbf{f}_{a,t}] + \mathrm{GRF}_t, \tag{2}$$

where $E\left[\mathrm{GR}_t\middle|\mathbf{f}_{n,t}, \mathbf{f}_{a,t}\right] = E\left[\mathrm{GR}_t\middle|\mathbf{f}_{n,t}\right] + E\left[\mathrm{GR}_t\middle|\mathbf{f}_{a,t}\right]$ is the expected green factor return conditional to two sets of factors informative on the drivers of medium to long-term ($\mathbf{f}_{n,t}$) and short-term ($\mathbf{f}_{a,t}$) macro-financial fluctuations for the Eurozone. Following Morana (2023), medium to long-term fluctuations are associated with the financial cycle and the concurrent long swings in economic activity; 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.

Hence, $\mathrm{GRF}_t = \mathrm{GR}_t - E[\mathrm{GR}_t|\mathbf{f}_{n,t}, \mathbf{f}_{a,t}]$ is the unexpected green factor return component, which should be informative on transition and climate change physical risk, in so far as these risks are priced in the stock market. The decomposition allows us to measure *green risk* more accurately by controlling and filtering out sources of systematic risk unrelated to the green transition and the climate change challenge.

3. The data

We compute the green factor return GR defined in Eq. (1) using 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 details). The sample begins in January 2006 and ends in August 2022. Figure 1 Panel A shows the GR monthly returns; Panel B displays year-on-year returns. In contrast, Panel C shows the cumulative monthly returns. The light grey shaded areas correspond to periods of financial distress (the dot-com bubble, the subprime financial crisis, and the Euro Area sovereign debt crisis) and geopolitical distress (Russia's war in Ukraine); the dark grey shaded areas highlight recessions.

As shown in Figure 1, GR 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 clearer from the year-on-year and cumulative monthly green factor returns displayed in Panels B and C, respectively. A decrease in the range of 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, green stocks outperformed brown stocks from mid-2012 until mid-2016. However, considering the fifteen years included in the analysis, the returns are (mean-reverting to) zero. 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.

3.1 The filtered green factor

Morana (2023) establishes eight stylized facts concerning Euro Area macro-financial fluctuations, i.e., the financial cycle ($\hat{\mathbf{f}}_{\mathbf{n}_1}$), the demand ($\hat{\mathbf{f}}_{\mathbf{a}_1}$) 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 ($\hat{\mathbf{f}}_{\mathbf{a}_3}$, $\hat{\mathbf{f}}_{\mathbf{a}_4}$). The data is available to researchers upon request.

Given the scope of the paper, we focus on the stylized facts that are most informative in accounting for the systematic green factor component unrelated to transition and climatic physical risks, as it will become apparent from the empirical results. In Figure 2, the top plot displays the financial cycle ($\hat{\mathbf{f}}_{\mathbf{n}_1}$), followed by the fiscal and monetary policy factors ($-\hat{\mathbf{f}}_{\mathbf{n}_3}$, $\hat{\mathbf{f}}_{\mathbf{n}_4}$) 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 between the end of the Great Recession and the beginning of the sovereign debt crisis recession (June 2009-October

2011). No evidence of the winding down of the second cycle can be found as of August 2022. 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 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 (a $-\hat{\mathbf{f}}_{\mathbf{a}_2}$ decrease corresponds to weakening real activity conditions). 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 short-term financial conditions). See Morana (2023) for complete details.

4. Decomposition of the green factor

We decompose the year-on-year green factor return GR by its OLS regression 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. The return measure is selected to match the observation frequency of the macro-financial data and does not affect the validity of unconditional asset pricing models (Jagannathan et al., 2012).

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 $\hat{\mathbf{f}}_{\mathbf{a}_1}$, and the short-term financial factor $\hat{\mathbf{f}}_{\mathbf{a}_4}$. Despite the omissions, the proportion of variance accounted for by the regression is virtually unchanged (about 60%). 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 green factor performance since 2007. Concerning its medium to long-term (trend) developments, the financial cycle accounts for about 7% of the variance of the GR return and the fiscal and monetary policy components for about 11% and 22%, respectively. Concerning short-term (cyclical) 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 green factor returns; 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 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 stocks have been a hedge against weakening short-term financial conditions, moving countercyclically to the Fama-French value factor, and co-moving with the real estate in this context. Finally, restrictive monetary and fiscal policies negatively impact returns, consistent with its hedging property over the business cycle and the countercyclical use of economic policy in the Euro area in the sample investigated.

Following Eq. (2), GR is decomposed into expected and unexpected components. Considering the auxiliary regression results and the information content of the estimated common factors, the expected component

$$E\left[GR_t \middle| \hat{f}_{n_1,t}, -\hat{f}_{n_3,t}, \hat{f}_{n_4,t}, -\hat{f}_{a_2,t}, \hat{f}_{a_3,t}\right] \tag{4}$$

can be further decomposed into a trend component,

$$f_{gT,t} \equiv E\left[GR_t | \hat{f}_{n_1,t}, -\hat{f}_{n_3,t}, \hat{f}_{n_4,t}\right] = \hat{\mu}_{GR} + \hat{\beta}_1 \hat{f}_{n_1,t} + \hat{\beta}_2\left(-\hat{f}_{n_3,t}\right) + \hat{\beta}_3 \hat{f}_{n_4,t} \tag{5}$$

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

$$f_{gC,t} \equiv E\left[(GR_t - \hat{\mu}_{GR}) | -\hat{f}_{a_2,t}, \hat{f}_{a_3,t}\right] = \hat{\beta}_4\left(-\hat{f}_{a_2,t}\right) + \hat{\beta}_5 \hat{f}_{a_3,t} \tag{6}$$

that measures the expected (demeaned) GR return conditional to the short-term macro-financial information set subsumed by the supply-side business cycle ($-\hat{\mathbf{f}}_{\mathbf{a}_2}$) component and the short-term financial ($\hat{\mathbf{f}}_{\mathbf{a}_3}$) component.

The unexpected component,

$$\begin{aligned} GRF_t &\equiv GR_t - E\left[GR_t | \hat{f}_{n_1,t}, -\hat{f}_{n_3,t}, \hat{f}_{n_4,t}, -\hat{f}_{a_2,t}, \hat{f}_{a_3,t}\right] \\ &\equiv GR_t - f_{gT,t} - f_{gC,t} \end{aligned} \tag{7}$$

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

Figure 3 plots the historical decomposition of the green factor into its trend, cyclical, and residual components. Figure 4 further shows the financial cycle, monetary policy, and fiscal policy contributions to the GR trend component, the supply-side business cycle component, and the short-term financial factor contributions to the GR cyclical component. Figure 3 Panel A shows that green stocks outperformed brown stocks during most of the Great Recession and the Euro Area sovereign debt crisis. However, it underperformed during the pandemic recession. Green 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 stock 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 stocks can be observed from mid-2015 through the end of 2020. The downward trend is mainly determined by its exposition to the financial cycle and the fiscal stance: the loose monetary policy regime set in since the later phase of the Great Recession has yielded a partially offsetting contribution (Figure 4, Panel A).

Figure 3 Panel B shows that green stocks' overperformance during the Great Recession was primarily cyclical and driven by supply-side cyclical factors (Figure 4, Panel B). Green stock underperformance was also largely cyclical during the COVID-19 crisis, which was 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 stock 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 in 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. Hence, it should provide a more accurate measure of green risk, having been purged from other sources of systematic risk. As shown in Figure 3 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.

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

$$GRF_t = \alpha_0 + \alpha_1 PA_t + \alpha_2 GD_t + \sum_{i=1}^{5} \beta_i x_{i,t} + \sum_{i=1}^{5} \gamma_i \left(x_{i,t} \times PA_t \right) + \sum_{i=1}^{5} \delta_i \left(x_{i,t} \times GD_t \right) + \varepsilon_t. \qquad (8)$$

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 $x_i = CC, -PC_1, \ldots, PC_4$, 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 (8) 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 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. A lower-than-average green factor return characterizes 2016-2021, while a higher-than-average green factor return 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 and their performance. 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 was also negatively priced during 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 perform multifactor asset pricing analysis using time-series regressions for the value-weighted industry portfolios based on the European statistical classification of economic activities (NACE) at division levels (see Appendix A.2 in the SM for details). In addition to the five-factor model by Fama and French (2015), we consider the four-factor model by Carhart (1997) and the three-factor model by Fama and French (1993), all augmented by the filtered green factor GRF. For instance, the augmented five-factor Fama-French time-series regression specification for the generic industry stock index i is

$$r_{i,t} = \alpha_i + \beta_{i,1} MKT_t + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + \beta_{i,4} RMW_t + \beta_{i,5} CMA_t + \beta_{i,6} GRF_t + \varepsilon_{i,t}, \tag{9}$$

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 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. Furthermore, we regress the GRF (GF) on the five Fama-French factors. For the GRF regression, we get an estimate for the intercept that is more strongly significant (p-value 0.022) than for one obtained by regressing the GF (p-value 0.051). All 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 negative and significant sign can be found for the information and communication (J) sector, which could be related to the high intensity of energy consumption of (part of) this 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.

For comparison, in Table C1 in the SM, we provide the regression analysis results on industry portfolios by estimating augmented models, including the unfiltered 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 (9). We report summary results in Figure 5. 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 5, 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

The GRF *beta* or loading of a stock implicitly yields information on the market assessment of a stock's "greenness" and is available for both disclosing and non-disclosing companies. It provides complementary information to green scores computed out of ESG ratings or carbon footprint measures, which, on the other hand, are only available for disclosing firms. Intuitively, if climate risks are priced in the stock market, we can expect a direct mapping between market measures and the green scores for disclosing firms. Furthermore, we can set up a market-based green scoring tool to rate non-disclosing firms, exploiting the mapping uncovered for the disclosing firms.

We then explore the linkage between our green score, i.e., the time average of the rescaled greenness and the transparency indicator proposed by Alessi et al. (2023), for the generic stock i, $\overline{G}_i$, and its estimated loading on the filtered green factor GRF, $\hat{\beta}_{6,i}$. Figure 6 provides the distributions of the average indicator by grouping companies at the industry level. We aim to set up a market-based tool that can be used to compute a *predicted* greenness and transparency indicator value $\overline{G}_i$ when it 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.

$$\overline{G}_i = \sum_{j=1}^{n} g_j I_{j,i} + \sum_{j=1}^{n} b_j I_{j,i} \hat{\beta}_{6,i} + \varepsilon_i, \tag{10}$$

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 $\bar{G}_i$, 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:

$$\begin{aligned}
\bar{G}_i &= \sum\nolimits_{j=1}^{n} g_j I_{j,i} + \sum\nolimits_{j=1}^{n} b_j I_{j,i} \hat{\beta}_{6,i} + \varepsilon_i \\
\bar{G}_i &= \sum\nolimits_{j=1}^{n} g_{j,1} I_{j,i} + \sum\nolimits_{j=1}^{n} b_{j,1} I_{j,i} \hat{\beta}_{6,\gamma=1,i} + \varepsilon_{i,1} \\
\bar{G}_i &= \sum\nolimits_{j=1}^{n} g_{j,0} I_{j,i} + \sum\nolimits_{j=1}^{n} b_{j,0} I_{j,i} \hat{\beta}_{6,\gamma=0,i} + \varepsilon_{i,0}
\end{aligned} \tag{11}$$

and the corresponding stacked model

$$\bar{G}_i^* = \sum\nolimits_{j=1}^{n} g_j I_{i,j}^* + \sum\nolimits_{j=1}^{n} b_j I_{i,j}^* \hat{\beta}_{i,6}^* + \varepsilon_i^* \tag{12}$$

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

$\hat{\boldsymbol{\beta}}_{6,\gamma=1} = \begin{bmatrix} \hat{\beta}_{6,\gamma=1,1}^* & \hat{\beta}_{6,\gamma=1,2}^* & \dots & \hat{\beta}_{6,\gamma=1,N}^* \end{bmatrix}'$, $\hat{\boldsymbol{\beta}}_{6,\gamma=0} = \begin{bmatrix} \hat{\beta}_{6,\gamma=0,1}^* & \hat{\beta}_{6,\gamma=0,2}^* & \dots & \hat{\beta}_{6,\gamma=0,N}^* \end{bmatrix}'$.

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 6. 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 5. 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 green 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 Figure 6, where we compare the average green score for the 1,367 transparent companies in our sample (Panel A) with the estimated average green score for the 855 non-transparent companies (Panel B). 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 Alessi et al. (2023)'s greenness and transparency factor and decomposes it into expected and unexpected components. We find that stocks' exposition to macro-financial systematic risk accounts for the first component. The residual part, i.e., the filtered green factor, provides a more accurate measure of *green* risk, as yield by climate concerns and physical risk, than the excess return of green stocks vs. brown stocks. We find evidence that green risk is priced in the European stock market. At the aggregate level, since 2007, green investments have allowed hedging over the business and financial cycle developments. Moreover, climate concerns and physical risks have been hedged in the European stock market to a higher extent since the launch of the European Green Deal strategy. Within an unconditional multifactor asset pricing model context, we find that 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

Panel A: Estimated coefficients

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

Panel B: % green factor variance accounted for by any of the common factors

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	-

Panel A reports the estimated coefficients with HACSE in square brackets for the green factors GR, GR^0, and GR^1 regressions on the macro-financial factors. Panel B reports the green factors' variance decomposition.

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**
$\overline{R}^2$	**0.450**	**0.432**	**0.251**	**0.256**	**0.485**	**0.477**

In Panel A, EV denotes the estimated eigenvalues, while % VAR is the proportion of total variance accounted by each associated principal component PC, and % CUM is the cumulative percentage of variance. The eigenvectors' composition is also reported. Panel B reports the estimated coefficients with HACSE in square brackets for the filtered green factors GRF, GRF^0, and GRF^1 regressions on the climate concern and physical risk measures.

Table 3: Distribution at NACE division levels of individual 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 organizations and bodies	0	0
-	NaN NACE	449	270

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

The upper triangular part reports Pearson's correlation coefficients between all pairs of factors. The lower triangular part reports the p-values (in *italics)* for the test of zero correlation for each pair of variables.

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**
$\bar{R}^2$	**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**
$\bar{R}^2$	**0.894**	**0.779**	**0.905**	**0.847**	**0.897**	**0.692**	**0.831**

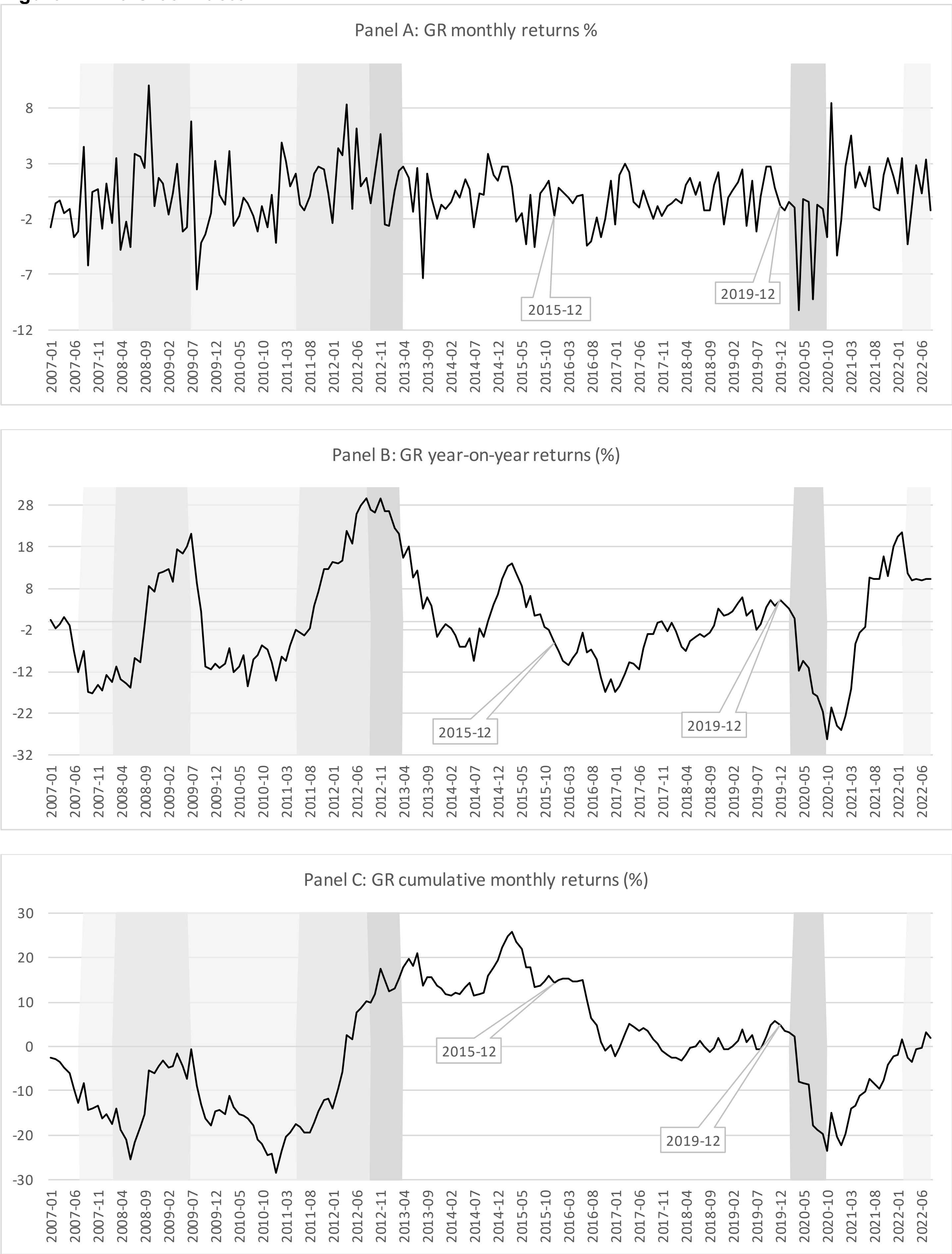
Table 5, Panel C: Augmented three-factor Fama-French model on industry portfolios							
	A	B	C	D	E	F	G
Intercept	**7.027**	1.033	**4.719**	2.046	-1.669	-1.330	-0.285
	(2.496)	(3.322)	(0.593)	(1.557)	(1.963)	(1.682)	(2.045)
MKT	**1.210**	**1.686**	**1.014**	**0.964**	**1.247**	**1.542**	**1.275**
	(0.123)	(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**
$\bar{R}^2$	**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**
$\bar{R}^2$	**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 the three-factor Fama-French model (Panel C) from time-series regressions with HACSE standard errors are reported in square brackets.

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
$\overline{R}^2$	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. HACSEs are reported in square brackets. Columns one, three, and five report results for the unrestricted disjoint regressions, and columns two, four, and six for the corresponding restricted cases (*). Columns 7 and 8 report results for the joint regressions in the unrestricted and restricted cases, respectively. R^2 ($\overline{R}^2$) is the (adjusted) coefficient of determination, SBC the Bayes-Schwarz IC, p-val the p-value of the LR test for the restricted versus the unrestricted models, and N is the sample size.

Figure 1: The Green factor



Panels A, B, and C show the green factor GR's monthly, year-on-year, and cumulative monthly returns, respectively. The light and dark grey shaded areas correspond to periods of financial distress and recessions, respectively. The signing of the Paris Agreement (2015-12) and the launch of the European Green Deal (2019-12) are indicated in the plot.

Figure 2: Euro area macro-financial factors

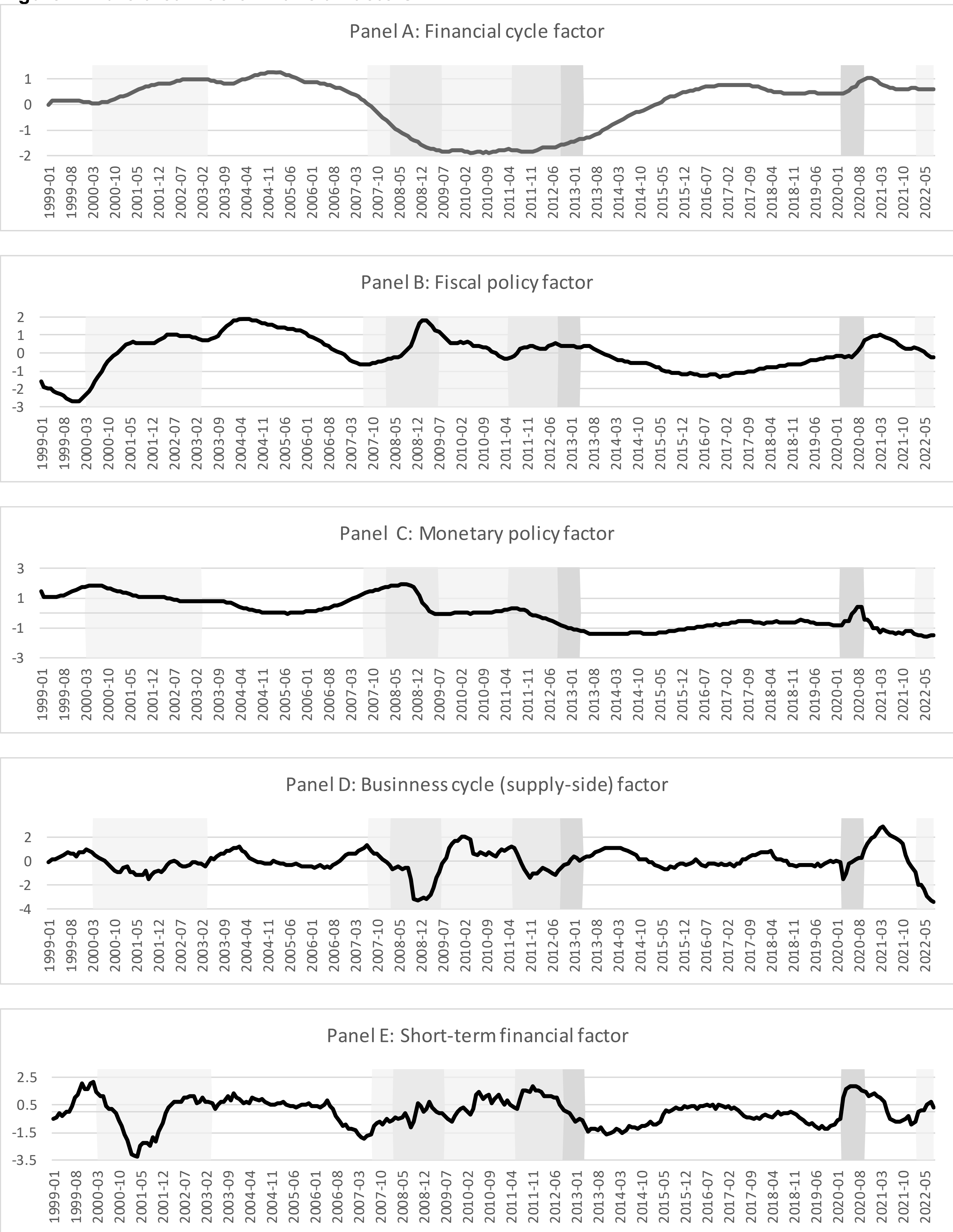


Figure 3: Green factor historical decomposition in trend (Panel A), cyclical (Panel B), and residual (Panel C) components

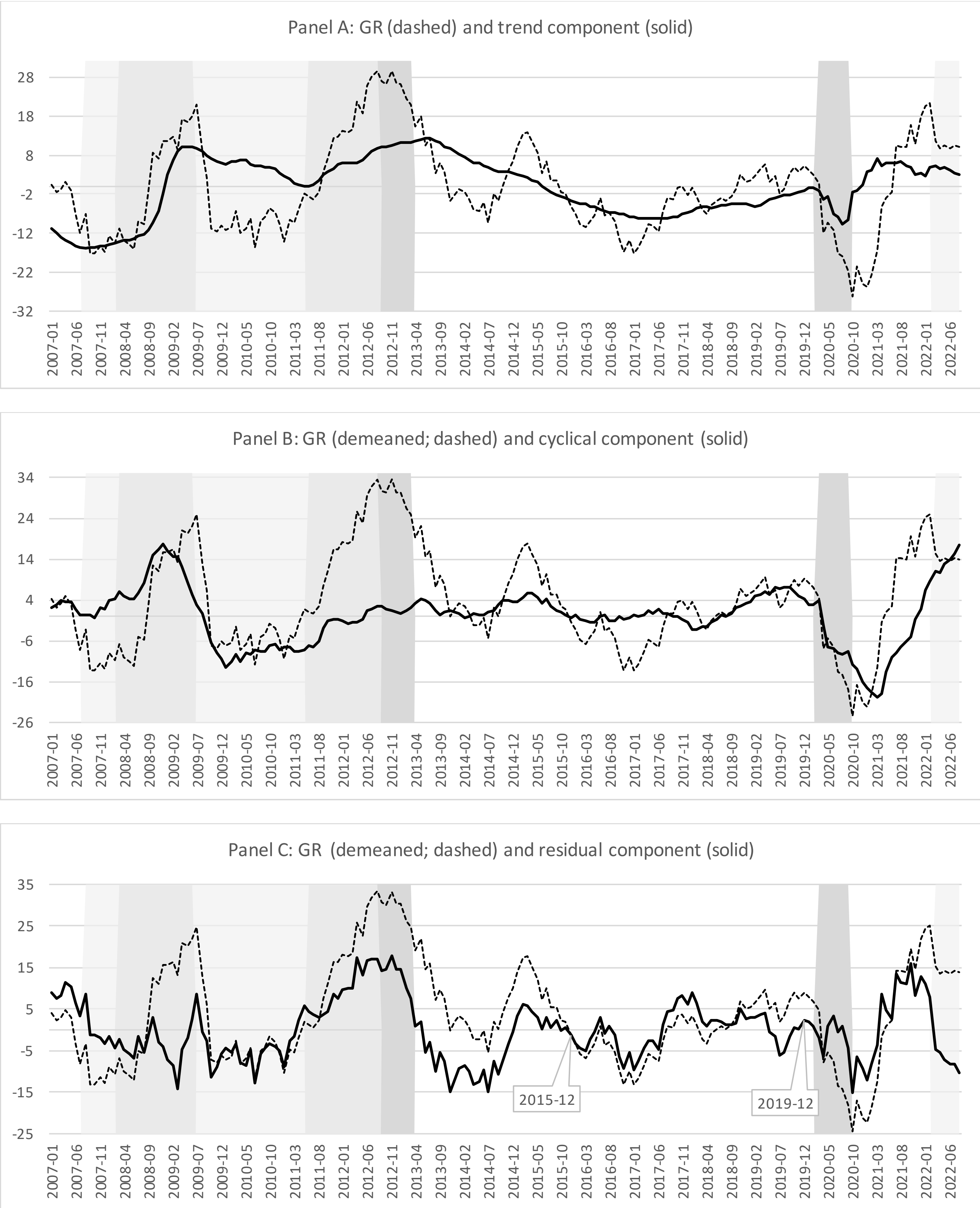


Figure 4: Trend and cyclical green factor components (net of mean level)

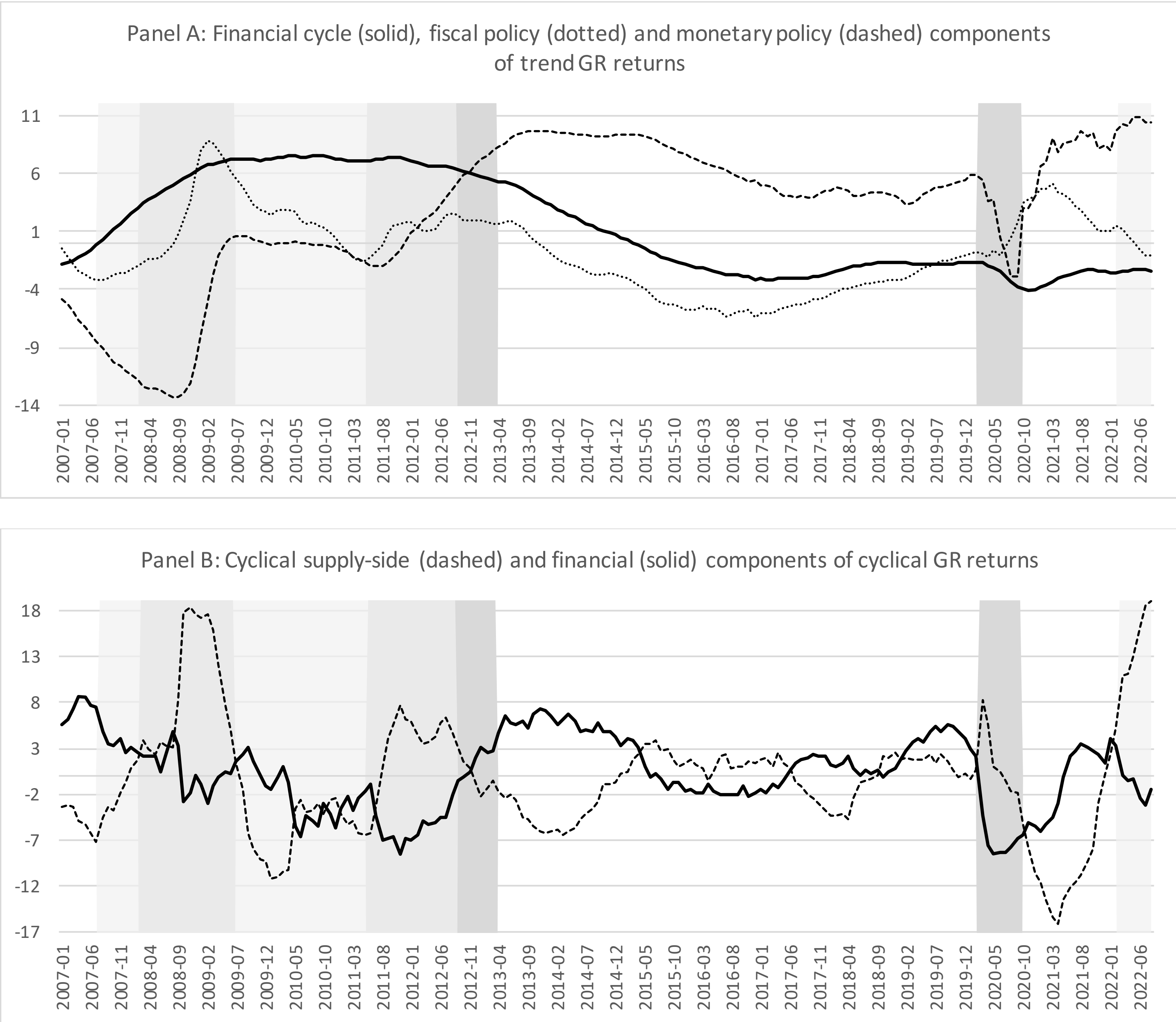
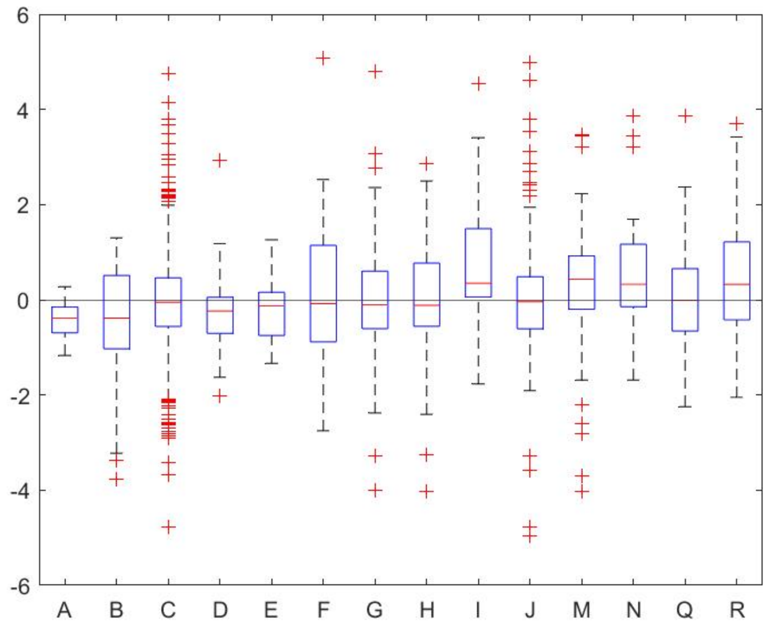


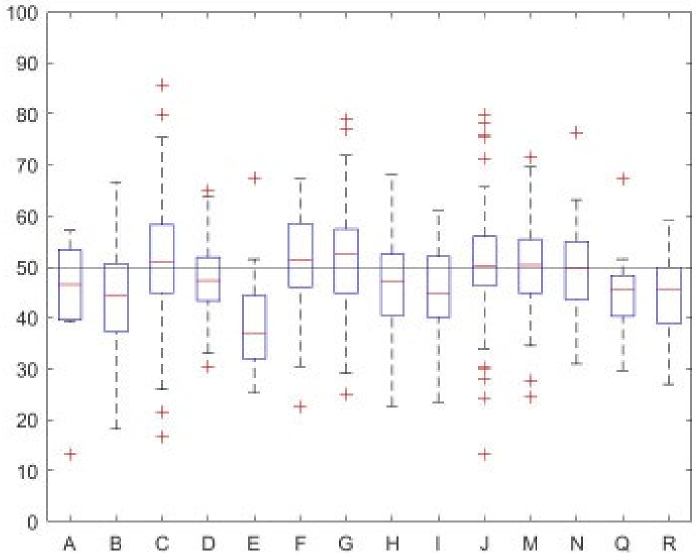
Figure 5: Distribution at the industry level of estimated loadings for the filtered green factor GRF



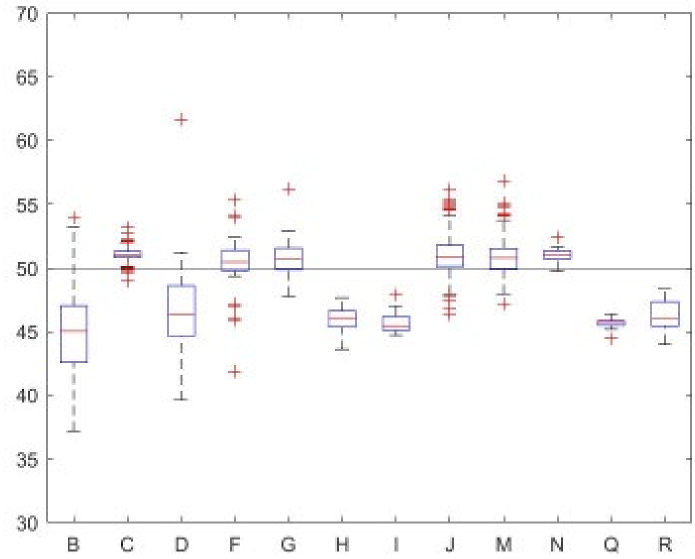
The figure shows the box plots of the estimated loadings for the filtered green factor GRF at the industry level. The estimates are computed from the augmented five-factor Fama-French model. Stocks are grouped by the NACE division.

Figure 6: Distribution at the industry level of the average re-scaled greenness and transparency indicator $\bar{G}_i$

Panel A: Transparent firms



Panel B: Non-transparent firms



Panel A (B) shows the box plots of the indicator $\bar{\mathbf{G}}_\mathbf{i}$ computed for the transparent (non-transparent) firms. Stocks are grouped by the NACE division.