Online Appendix to "The Macro-Financial Effects of Climate Policy Risk: Evidence from Switzerland"

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A Keywords CPR index

I consider the following keywords for the construction of the CPR index:

- **Climate:** *climat*, CO2, greenhouse gas, renewable energy, global warming*
- **Policy:** *Bern, government, parliament, law, regulation, federal, politic**
- **Risk:** *risk, uncertain*, doubt, unforeseen, unpredictable, unstable, unclear, unsafe, unknown*

Each of these keywords are then translated in both French and German by native speakers.

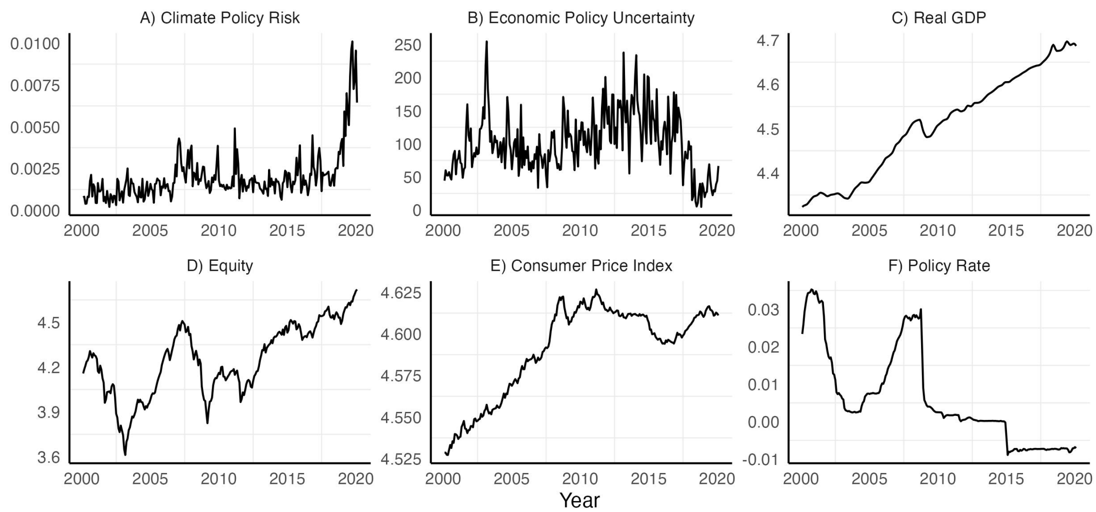
B Data Appendix

Table B.1 NUMBER OF ARTICLES BY MEDIA OUTLETS

Media	Language	N. Articles
Blick	DE	427,359
NZZ	DE	940,309
Tages Anzeiger	DE	830,819
20 Minuten	DE	420,133
Tribune de Genève	FR	482,228
Le Matin	FR	285,097
Le Temps	FR	364,064
Total		3,750,009

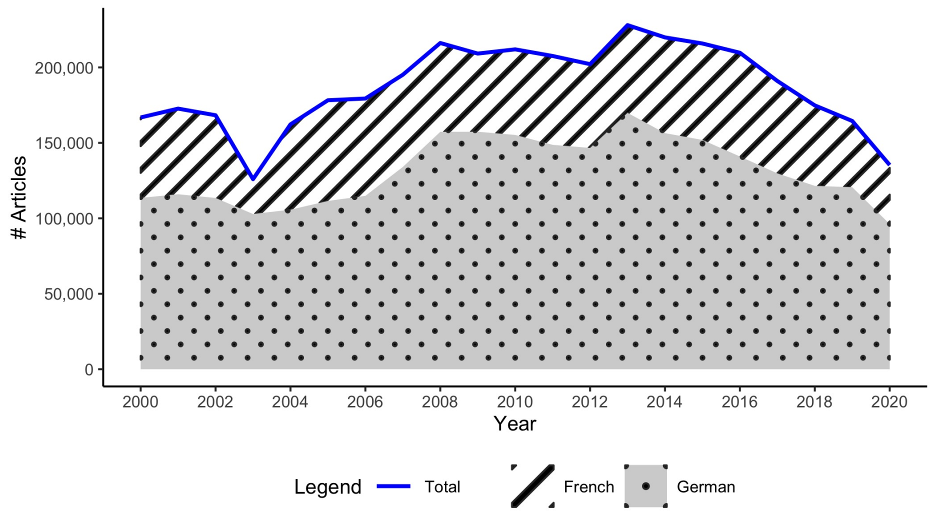
NOTE: This table displays the total number of articles per media outlet. The share of articles in German is 69.8% (30.2)% in French).

Figure B.1 MACROECONOMIC DATA



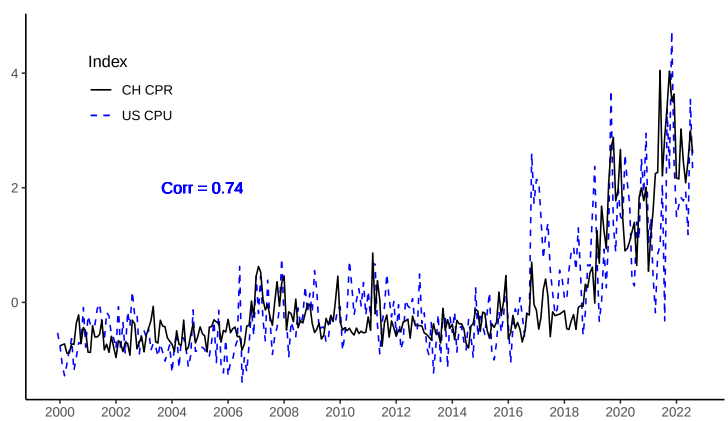
NOTE. This Figure plots the macroeconomic data from the VAR. The EPU index is obtained from the KOF website https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-uncertainty-indicator.html. Section 4 details the construction of the CPR index. The source for the other variables is Datastream.

Figure B.2 Number of Articles over time (by language)



Note. This Figure plots the total number of articles per year and by language over the sample period 2000-2020. The source of the data is Swissdox@LiRi.

Figure B.3 Swiss CPR vs US Climate Policy Uncertainty



Note. This Figure compares the Swiss CPR index from this paper to the US Climate Policy Uncertainty Index from Gavriilidis (2021). Both series are scaled to have zero mean and a unit standard deviation for comparison purposes.

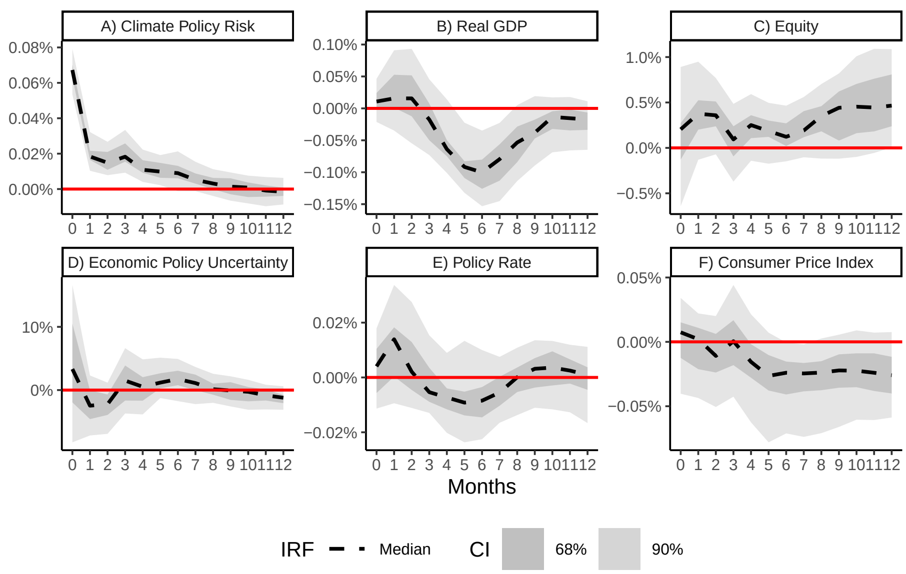
Table B.2 Summary Statistics for Swiss Public Firm Data

Sector	Firms	Obs.	Share CO2	Scope 1 + 2 (mean)
Industrials	60	289,832	55%	4081
Consumer Staples	14	63,704	57.1%	1187
Basic Materials	8	45,603	50%	616
Health Care	32	12,4892	34.4%	379
Technology	13	63,341	38.5%	74
Consumer Discretionary	21	101,599	42.9%	65
Utilities	3	14,688	66.7%	47
Financials	42	224,678	40.5%	34
Telecommunications	3	17,724	100%	25
Real Estate	21	78,906	28.6%	13
Total	217	1,024,967	45.2%	1596

Note: This table provides some summary statistics regarding the number of firms and observations, as well as the CO2 data coverage for public firms listed in the Swiss Performance Index (SPI), which is considered as Switzerland's overall stock market index. The original CO2 variable is expressed in tons and is divided by 1,000 in the table.

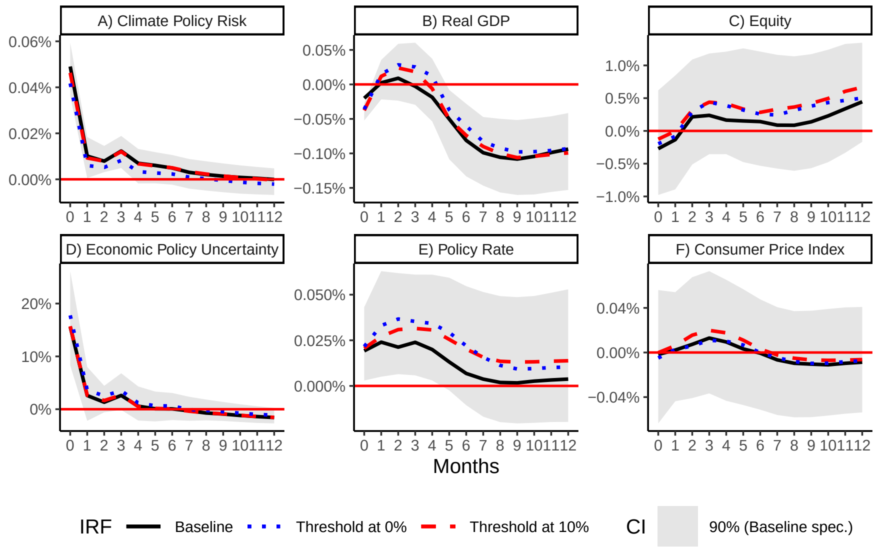
C Macroeconomic Evidence : Robustness

Figure C.1 Robustness IRF : Excluding GFC



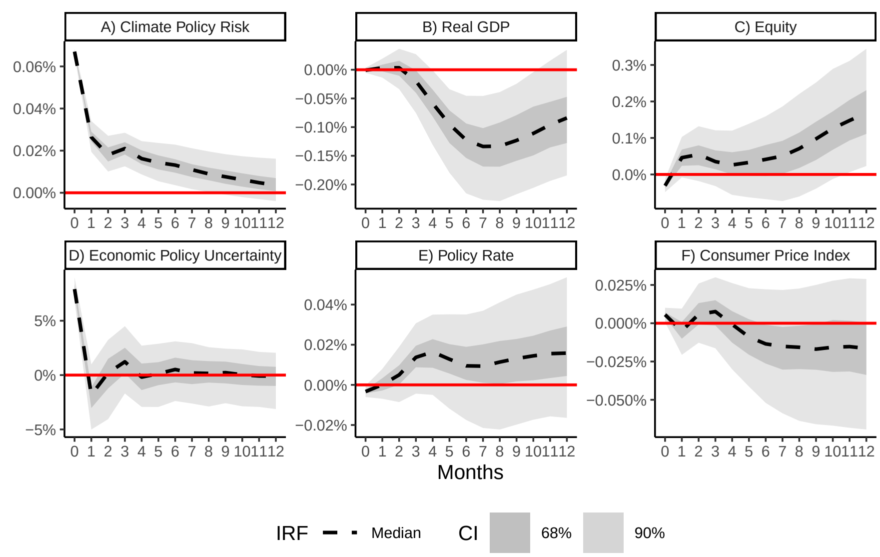
Note. This Figure re-estimates the IRFs to a one standard-deviation CPR shock excluding the Great Financial Crisis period and using 2010M1-2020M2 as the sample period. Shocks are set-identified using narrative restrictions around the transition risk events from Table 1 which take place before the end of the sample in 2020M2 and after 2010M1.

Figure C.2 Robustness IRF : Alternative Thresholds Narrative Restrictions



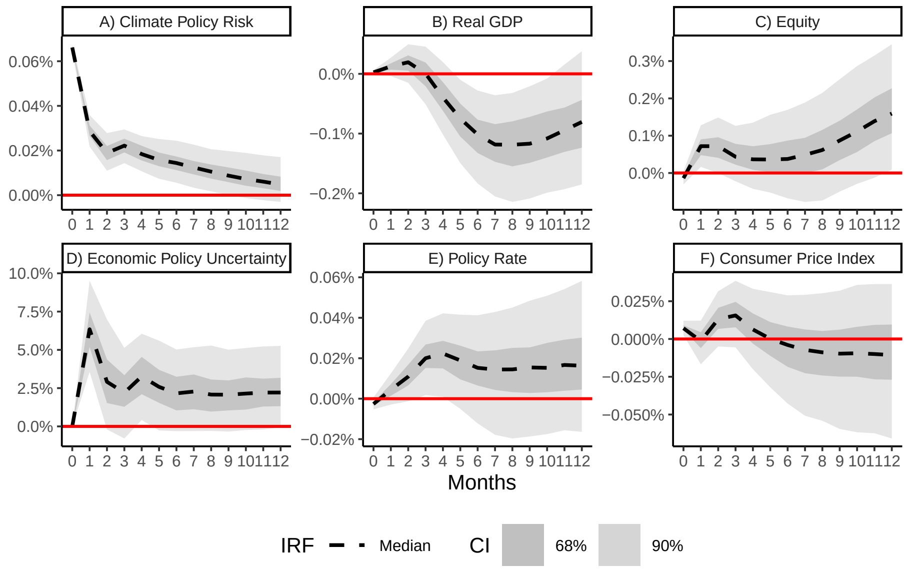
Note. This Figure re-estimates the IRFs to a one standard-deviation CPR shock by considering alternative threshold values for the historical contribution restrictions. In particular, I restrict the CPR shocks to have contributed more than 0%, respectively 10% to the unexpected variation in the CPR variable around the transition risk events from Table 1 (as compared to 20% in the baseline).

Figure C.3 Robustness IRF : Cholesky I



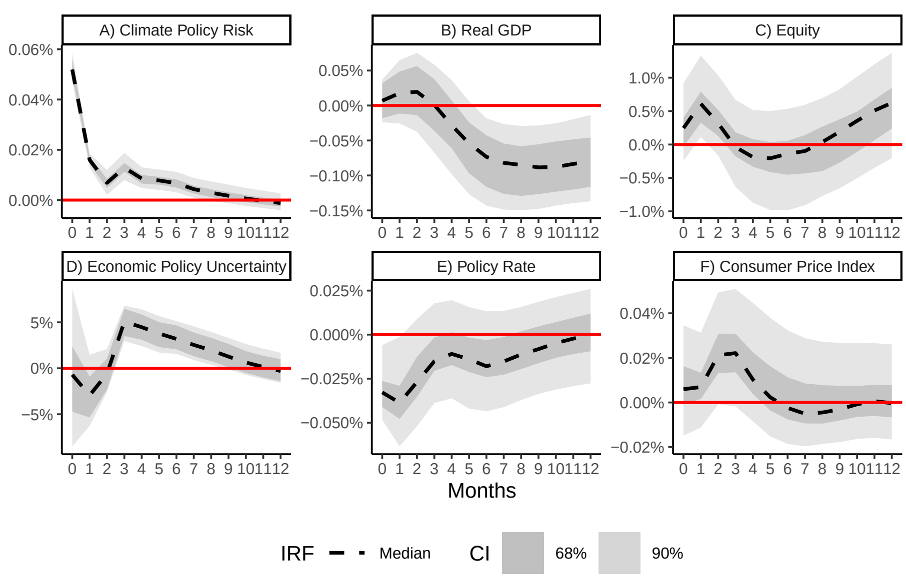
Note. This Figure re-estimates the IRFs to a one standard-deviation CPR shock using a Cholesky identification scheme instead of the shock-based approach. The CPR index is ordered first. The sample period is 2000M1 to 2020M2.

Figure C.4 Robustness IRF : Cholesky II



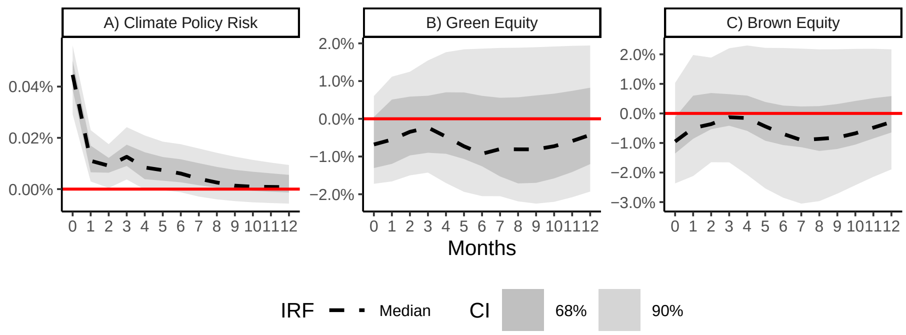
Note. This Figure re-estimates the IRFs to a one standard-deviation CPR shock using a Cholesky identification scheme instead of the shock-based approach. The CPR index is ordered second after the Swiss EPU index. The sample period is 2000M1 to 2020M2.

Figure C.5 Robustness IRF : US EPU instead of Swiss EPU



Note. This Figure re-estimates the IRFs to a one standard-deviation CPR shock using the US EPU from Baker et al. (2016) instead of the Swiss EPU as in the baseline. The sample period is 2000M1 to 2020M2.

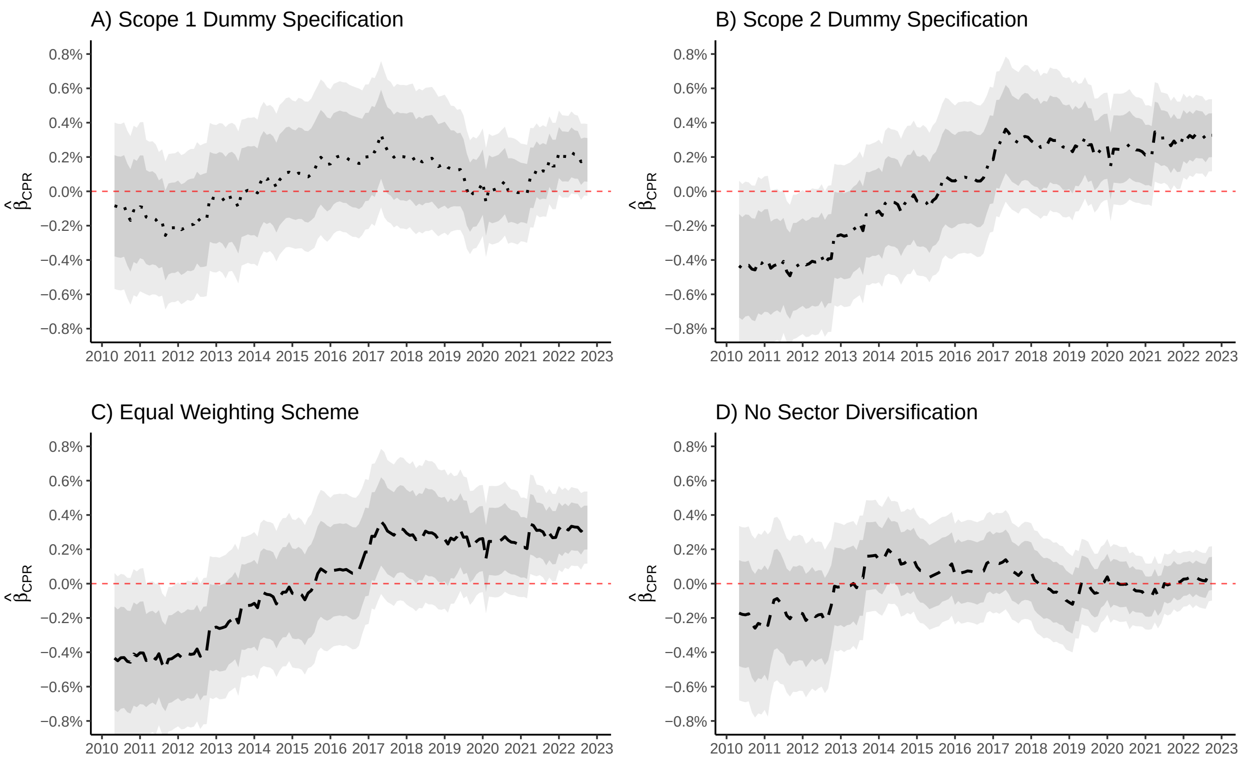
Figure C.6 Robustness IRF : Green vs Brown Equity Indices)



Note. This Figure re-estimates the IRFs to a one standard-deviation CPR shock by adding a green and brown equity stock price index instead of the aggregate index as in the baseline. The brown and green equity price index is obtained by taking the total cumulative return of the brown and green portfolio using the "relative specification" of the brown dummy variable (using the "absolute specification" yields similar results). CPR shocks are narratively identified as in the baseline. The sample period is 2000M1 to 2020M2. The dynamic responses of the other endogenous variables are omitted for clarity but remain very similar to the baseline.

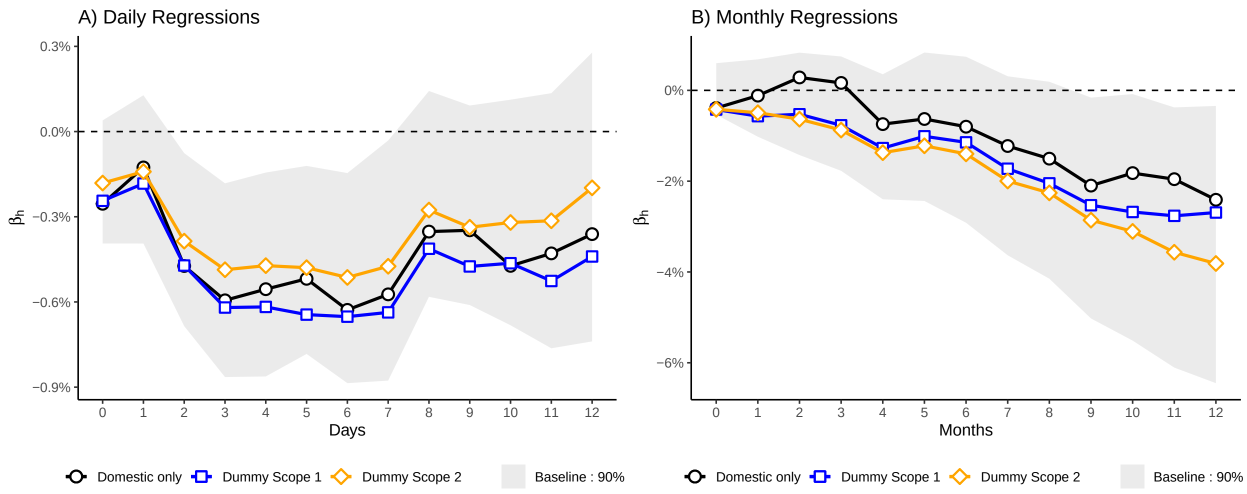
D Financial Evidence : Robustness

Figure D.1 Robustness Checks : Time-Series Properties



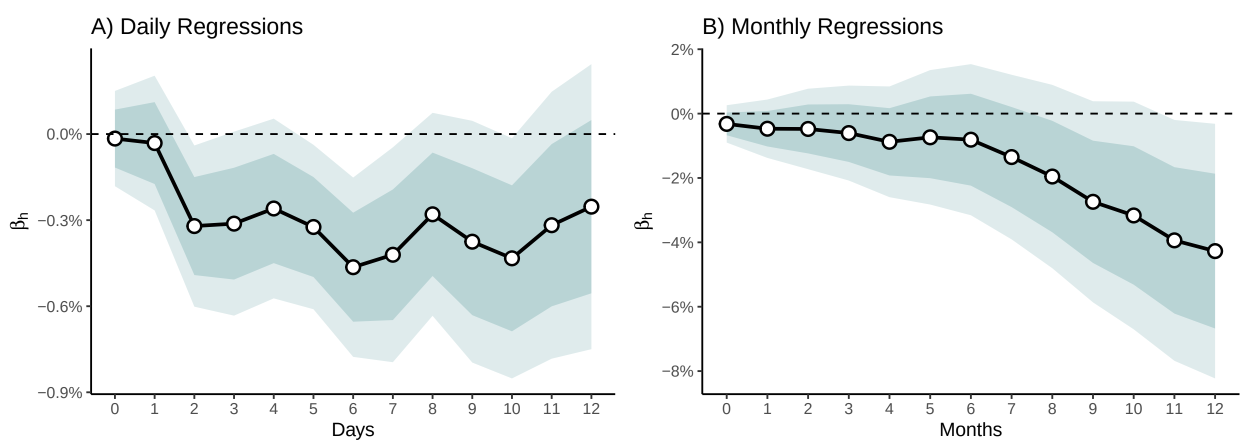
Note. This Figure plots four different robustness check s regarding the time-series properties of the GMB portfolio. In Panel A), I estimate the regression (2) using a trailing 10-year sample window defining the brown dummy by relying on scope 1 (direct) CO2 emissions only (rather than the sum of scope 1 and 2 as in the baseline). Panel B) estimates the same regression but uses scope 2 (indirect) CO2 emissions to define the brown dummy. Panel C) uses an equal weighting scheme to build the GMB portfolio (rather than one based on CO2 emissions as in the baseline). Panel D) uses the absolute dummy specification (rather than the relative dummy specification as in the baseline).

Figure D.2 ROBUSTNESS EVENT-STUDY : DAILY MONTHLY REGRESSIONS



NOTE. This Figure re-estimates equation (4) $h = 1, ..., 12$ and plots the estimated coefficient β_h using different specifications of the brown dummy ($Brown_{i,t}$)) and the transition risk events. In particular, I consider a dummy using only scope 1, only scope 2. I also consider a case where I only rely on domestic transition risk events (rather than both domestic and international events as in the baseline). Panel A) estimates the equation using daily stock prices, while Panel B) uses monthly stock prices.

Figure D.3 ROBUSTNESS EVENT-STUDY : DUMMY ACROSS ALL SECTORS



NOTE. This Figure re-estimates equation (4) $h = 1, ..., 12$ and plots the estimated coefficient β_h using the absolute specification of the brown dummy (instead of the relative specification as in the baseline). Panel A) estimates the equation using daily stock prices, while Panel B) uses monthly stock prices. Standard errors are clustered two-ways at the date and firm level. Confidence bands display the 68 and 90% intervals, respectively.

E Identification strategy

E.1 Shock-based identification scheme

In this section, I detail the shock-based identification strategy of CPR shocks. Formally, I consider the following notation for the SVAR. Let $\boldsymbol{Y}_t$ be a $n \times 1$ vector of endogenous variables:

$$\boldsymbol{Y}_t = \boldsymbol{\Phi}(L)\boldsymbol{Y}_{t-1} + \boldsymbol{B}\boldsymbol{\varepsilon}_t \tag{E.1}$$

Where $\boldsymbol{B}$ is the $n \times n$ impact matrix that governs the dynamic effect of structural shocks $\boldsymbol{\varepsilon}_t$ on the endogenous variables. $\boldsymbol{\Phi}(L)$ is the lag matrix in companion form. Note that I dropped the constant/trend term for notation convenience. I further assume a linear mapping between the structural shocks and the reduced form residuals $\boldsymbol{u_t}$ $(n \times 1)$:

$$\boldsymbol{u_t} = \boldsymbol{B}\boldsymbol{\varepsilon}_t \tag{E.2}$$

Assuming invertibility, it is easy to see that structural shocks can be recovered from reduced form residuals according to:

$$\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u_t} \tag{E.3}$$

As is well known, $\boldsymbol{B}$ is not uniquely identified without further restrictions. In particular, there is an infinite number of solutions. To see this, let $\boldsymbol{C}$ be the Cholesky decomposition of the reduced form residuals (a $n \times n$ matrix) and $\boldsymbol{Q}$ be a random $n \times n$ orthonormal matrix (which by definition satisfies $\boldsymbol{Q}\boldsymbol{Q}' = \boldsymbol{I}_n$ where $\boldsymbol{I}_n$ is the identity matrix of dimension n). It follows:

$$\boldsymbol{\Sigma}_{uu} = \boldsymbol{C}\boldsymbol{C}' = \boldsymbol{C}\boldsymbol{Q}\boldsymbol{Q}'\boldsymbol{C} \tag{E.4}$$

Defining $\boldsymbol{B} = \boldsymbol{C}\boldsymbol{Q}$, we can easily see that this implies an infinite number of $\boldsymbol{B}$ matrices which satisfy this restriction. A standard way to identify the matrix $\boldsymbol{B}$ is to perform a Cholesky decomposition, that is to set $\boldsymbol{Q} = \boldsymbol{I}_n$. Another potential solution is to rely on so-called "sign-restrictions." In a nutshell, the idea is to draw random orthonormal matrices $\boldsymbol{Q}$ and keep only the resulting $\boldsymbol{B}$ matrices which satisfy a set of (generally theory-based) sign-restrictions. Finally, another approach is to come up with valid (that is relevant *and* exogenous) external instruments to uniquely identify the first column of $\boldsymbol{B}$.

In this paper, I consider a "shock-based" identification scheme à la Ludvigson et al. (2021), and recently applied in Berthold (2023). Rather than imposing restrictions on the impact matrix as is common, the idea is to restrict *structural shocks* to behave in a certain way during some carefully selected economic events. In practice, I draw K (a large number) of $\boldsymbol{Q}$ matrices and recover structural shocks according to (E.3), and check that they fulfil the set of restrictions.[1] In the bootstrap replications, I work with $K = 1$ million. I collect each of these matrices in a set denoted by $\mathcal{B} = \{\boldsymbol{B} = \boldsymbol{CQ}, \boldsymbol{Q} \in \mathcal{O}_n, diag(\boldsymbol{B}) \geq 0, \boldsymbol{BB}' = \boldsymbol{\Sigma_{uu}}\}$ where $\mathcal{O}_n$ is the set of $n \times n$ random orthonormal matrices. The restriction $diag(\boldsymbol{B})$ is for convenience and ensures that a positive structural shock implies an increase in the variable of interest. I refer to $\mathcal{B}$ as the "unconstrained set". For each K elements of the set $\mathcal{B}$, I can retrieve the related structural shocks $\boldsymbol{\varepsilon}_t$ using $\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t$. I denote the set of unconstrained structural shocks $\mathcal{E} = \{\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t, \boldsymbol{B} \in \mathcal{B}\}$. Note that, for notation convenience, the dependence of $\boldsymbol{B}$ and $\boldsymbol{\varepsilon}_t$ on the draw k is dropped, but keeping in mind that they correspond to a particular draw $k \in \{1, ..., K\}$. Identification is then achieved by only keeping models (defined by a particular draw of the $\boldsymbol{B}$ matrix) which satisfy the narrative restrictions. Obviously, if the restrictions are too strict or incompatible with the data, the constrained set (denoted by $\tilde{\mathcal{B}}$) is empty. On the other hand, if restrictions are too lax, the unconstrained set is very similar to the constrained one and thus does not provide any identification gains.

E.2 Empirical restrictions

In this paper, I consider "historical contribution" restrictions around the transition risk events from Table 1 that take place before the end of the sample in 2020M2. Historical contribution restrictions are defined as restrictions on the share of the unexplained variation in a given variable that can be explained by a certain variable. Formally, I define the absolute contribution of the structural shocks at time t from a given draw (k) as follows:

$$\boldsymbol{C}_t = \boldsymbol{B}' \odot \boldsymbol{\varepsilon}_t \tag{E.5}$$

Where $\odot$ is the Hadamard (or element-wise) product. The i, j-th element of $\boldsymbol{C}_t$ is the (absolute) effect at time t of the i-th structural shock on the j-th variable contained in $\boldsymbol{Y}_t$. It should be noted that the sum of each column j is equal to the reduced form residual $u_{j,t}$. To get a sense of the relative importance of each structural shock i in the overall unexplained variation of variable j, we can normalise $\boldsymbol{C}_t$ by the respective reduced form residuals. I

[1] To obtain a candidate $\boldsymbol{Q}$ matrix, I first draw a $n \times n$ matrix $\boldsymbol{M}$ from a normal distribution with mean zero and unit standard deviation. $\boldsymbol{Q}$ is then obtained via the $\boldsymbol{QR}$ decomposition of $\boldsymbol{M}$.

define the resulting matrix as:

$$\boldsymbol{S}_t = \boldsymbol{C}_t \oslash \boldsymbol{u}_t' \tag{E.6}$$

Where $\oslash$ is the Hadamard (or element-wise) division. The i, j-th element of $\boldsymbol{S}_t$ corresponds to the share at time t of the i-th structural shock in the overall reduced-form residual variation of variable j. "Historical contribution" restrictions can be formally defined as:

$$g(i, j, t, \lambda) = S_{i,j,t} \geq \lambda \in \{0, 1\} \tag{E.7}$$

In words, the restriction $g(i, j, t, \lambda)$ requires that the contribution of the structural shock of variable i to the unexplained variation in variable j at time t is greater or equal to λ, with λ being between 0 and 1. Intuitively, an example would be $g(CPR, CPR, 2019M10, 0.3)$ which restricts the set of models considered to those that feature a structural CPR shock that can explain at least 30% of the unexpected rise in the CPR in October 2019, that is during the "green wave" at the federal elections. I highlight the fact that this type of restriction does not rule out that other structural shocks were important. Rather, it merely restricts that a given shock has occurred, and has contributed meaningfully to the unexpected variation of the variable of interest. It should be noted that this type of restriction is similar to the narrative restrictions considered in Antolin-Diaz and Rubio-Ramirez (2018) but differ in one key aspect. In particular, the narrative restrictions from Antolin-Diaz and Rubio-Ramirez (2018) generally assume that a given shock is the *largest* contributor to the unexpected variation of a given variable. In that sense, I see the historical contribution restrictions as less restrictive, as it could very well be the case that another shock contributes more.

E.3 Inference : extending the wild bootstrap procedure

To conduct inference, I follow Mertens and Ravn (2013) and Gertler and Karadi (2015) in using the wild bootstrap method developed in Gonçalves and Kilian (2004), and extend it to our setting. Standard wild bootstrap re-samples the reduced form residuals by switching the sign of the reduced form vector of estimated shocks at random periods, usually using a Rademacher distribution (Davidson and Flachaire (2008)). In our setting, however, the sign of the reduced form shock is important during the events considered for the narrative restrictions. In the spirit of Ludvigson et al. (2021), I thus leave the sign of the reduced form residual unchanged at these dates. For each draw (with the adjusted signs), I identify the model by drawing $1,000$ orthonormal matrices and only keep the draws which satisfy the restrictions (as discussed above). I repeat this procedure 1,000 times (effectively drawing 1 million candidate matrices). Confidence intervals and median response are then obtained by targeting different percentiles over all selected models. It should be noted that, in a frequentist setting, there is no widely agreed-upon method to conduct inference for set-identified models. However, as the set identified shocks display large departures from Gaussianity, it would be very challenging to handle in a Bayesian framework, as argued in Ludvigson et al. (2021). It is the reason why I decide to rely on a frequentist approach to gauge the sampling uncertainty of the approach.

F Risk-Factors for Switzerland

As in Ammann and Steiner (2008), I consider a four-factor model for asset prices in Switzerland:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML + \beta_4 UMD + e_{it} \tag{F.1}$$

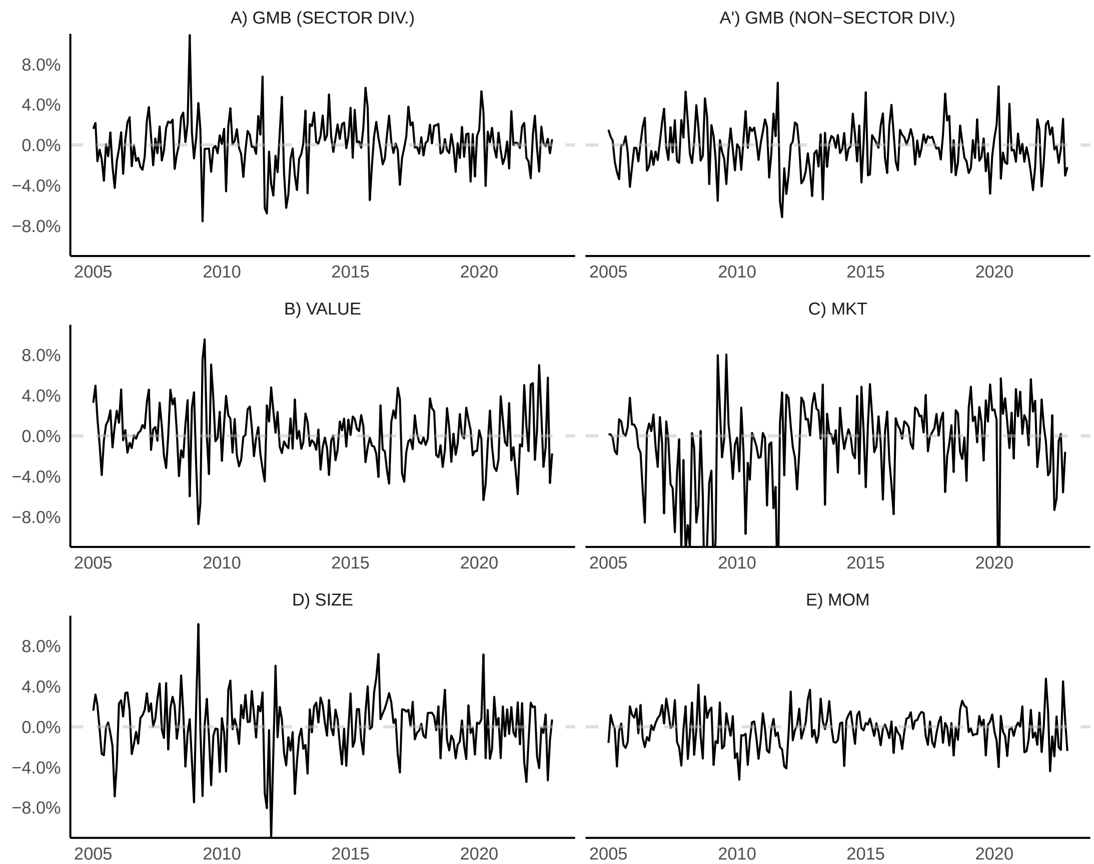
Where $R_{i,t}$ is the monthly (end-of-period) return of stock i and $R_{f,t}$ is the risk-free rate, and $RMRF_t$, SMB_t, HML_t and UMD_t are the excess returns from, respectively, the market portfolio, the small-minus-big portfolio (size factor), the high-minus-low portfolio (value factor), and the up-minus-down portfolio (momentum factor). Ammann and Steiner (2008) show the relevance of these four risk factors model for excess returns in Switzerland.

The market factor is obtained by computing the excess return of a market value weighted portfolio. To construct the three other factors, I proceed as follows. First, all stocks are divided into two sub-groups, namely big (B) and small (S), where the division is achieved by using the median market capitalization as the threshold. At the same time, the stocks are divided in two groups according to their book-to-market ratio ("High" (H), and "Low" (L)), and their one-year past return ("Up" (U), and "Down" (D)), again using the median as the threshold. I then create 8 portfolios based on the combinations of these characteristics, namely S/H/U, S/H/D, S/L/U, S/L/D, B/H/U, B/H/D, B/L/U, or B/L/D. The portfolios' weights are defined using the market capitalization. The three risk factors are then computed as follows:

$$SMB = 1/4 * ((S/H/U - B/H/U) + (S/H/D - B/H/D) + (S/L/U - B/L/U) + (S/L/D - B/L/D))$$
$$HML = 1/4 * ((S/H/U - S/L/U) + (S/H/D - S/L/D) + (B/H/U - B/L/U) + (B/H/D - B/L/D))$$
$$UMD = 1/4 * ((S/H/U - S/H/D) + (S/L/U - S/L/D) + (B/H/U - B/H/D) + (B/L/U - B/L/D))$$

Intuitively, the SMB portfolio can be interpreted as a portfolio going long small firms, while controlling for market, value, and momentum effects. The HML and UMD portfolios can be interpreted similarly. The resulting four risk factors as well as the returns from the two specification of the GMB portfolios (sector diversified and non sector diversified) are displayed in Figure F.1.

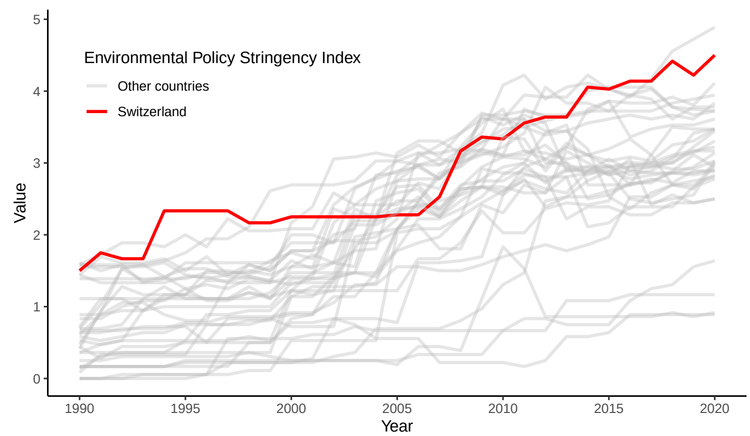
Figure F.1 Risk Factors



Note. This Figure displays the two specifications of the GMB portfolios as well as the four risk factors following the methodology developed in Ammann and Steiner (2008) and summarised in Appendix F. The sector diversified GMB portfolio is constructed using the relative specification of the brown dummy. The non sector diversified GMB portfolio uses the absolute specification of the dummy.

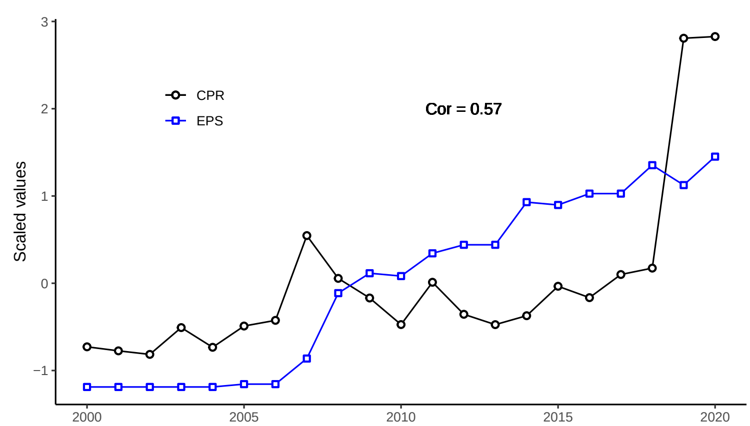
G Additional results

Figure G.1 Environmental Policy Stringency Index



Note. This Figure displays the Environmental Policy Stringency Index from the OECD for all countries for which the index is available. The blue line depicts this index for Switzerland. According to this measure, Switzerland is the second best performing country in 2021.

Figure G.2 Comparison EPS vs CPR



Note. This Figure compares the CPR to the Environmental Policy Stringency Index from the OECD for Switzerland. To match the frequency of the OECD index, the CPR is aggregated at the yearly frequency by taking the mean.

H Hedging Climate Policy Risk in Real Time

In this section, I implement the portfolio-mimicking approach from Engle et al. (2020) to hedge CPR in real time. The underlying argument is that, as CPR appear to have macroeconomic costs, and as additional and more stringent climate policies are likely to be adopted in the future, it becomes increasingly relevant for investors to find strategies that can help them insulate from the financial risks related to climate policies. In this context, I propose to test the out-of-sample performance of different specifications of the GMB portfolio.

H.1 Portfolio-Mimicking Approach : Theory

To construct the hedge portfolio, I closely follow the approach laid out in Engle et al. (2020). I provide a concise summary of the different steps below but refer the reader to the original article for additional information.

Let r_t denote a $n \times 1$ vector of monthly excess returns over the risk-free rate of n assets at time t and let assume that these returns follow a linear factor model. I postulate that these factors include innovations to CPR (i.e. the CPR factor denoted as ΔCPR_t) as well as p other factors denoted by F_t. Formally:

$$r_t = \beta_{CPR}\gamma_{CPR} + \beta_{CPR}\Delta CPR_t + \beta_F\gamma_F + \beta_F F_t + u_t \tag{H.1}$$

The vector β_{CPR} $(n \times 1)$ is the risk exposure to the CPR factor, and β_F $(n \times p)$ denotes the risk exposures to the other p risk factors. γ_{CPR} and γ_F denote the risk-premium associated with the CPR factor and the other p risk factors, respectively. The objective is to construct a hedge portfolio, that is a portfolio with unit exposure to the CPR factor ($\beta_{CPR} = 1$) but no exposure to the other p risk factors. This ensures that investors can change their exposure to climate risk by trading in this portfolio, without modifying their exposure to the other risk factors. I refer interchangeably to the CPR factor as the "hedge target". Empirically, ΔCPR_t is estimated by taking the residual of an auto-regressive process on the CPR index displayed in Figure 1.

In the mimicking portfolio approach, we directly project the CPR factor (or equivalently the hedge target) onto a set of portfolios with excess returns denoted by $\tilde{r}_t$. Formally:

$$\Delta CPR_t = \alpha + w'\tilde{r}_t + e_t \tag{H.2}$$

The hedge portfolio is then constructed using the weights (denoted by w) from this regression. As shown in Engle et al. (2020), a sufficient condition for this equation to retrieve the desired hedge portfolio is that the portfolio returns (defined by $\tilde{r}_t$) span the same space as the true factors.

To build the hedge portfolio, we need a set of well-diversified portfolios such that their excess returns $\tilde{r}_t$ capture different dimensions of risk and can be assumed to span the factor space. A further restriction from equation (H.1) is that the portfolios need to have constant risk exposure over time. A standard way to achieve this is to form portfolios by sorting assets based on their characteristics. Formally, let Z_t denote a matrix of firm-level characteristics appropriately cross-sectionally normalized, we can rewrite the portfolio excess returns as:

$$\tilde{r}_t = Z'_{t-1} r_t \tag{H.3}$$

such that equation (H.2) becomes:

$$\Delta CPR_t = \alpha + w' Z'_{t-1} r_t + e_t \tag{H.4}$$

Equation (H.4) can be interpreted as a projection of the hedge target CPR_t onto characteristic-sorted portfolios ($Z'_{t-1} r_t$) that are assumed to have constant risk exposure, and which span the entire factor space.

H.2 Constructing the Hedge Portfolios

We now need to construct a mimicking hedge portfolio for the hedge target (CPR_t) which has constant risk exposure and span the entire factor space. To do so, and similarly to Engle et al. (2020), I consider one portfolio sorted on climate characteristics (which I refer to as the GMB portfolio), to which I add four additional factors why may be correlated with CPR and which are known to be important in explaining the cross-section of asset returns. In particular, I consider size, value, momentum, and the market as in Ammann and Steiner (2008). This effectively gives rise to 5 portfolios that can be used to build the mimicking hedge portfolio.

As in the main text, I consider two specifications of the GMB portfolio. In the first, I consider the relative brown dummy specification. This gives rise to the sector-diversified GMB portfolio. In the second, I consider the absolute brown dummy specification. This gives rise to the non sector-diversified GMB portfolio. I refer the reader to Section D of the main text for additional information. I denote the excess returns from the GMB portfolio by $r_{GMB} = Z^{CO2}_{t-1} r_t$.

Replacing equation (H.4) with the five portfolios, we can write:

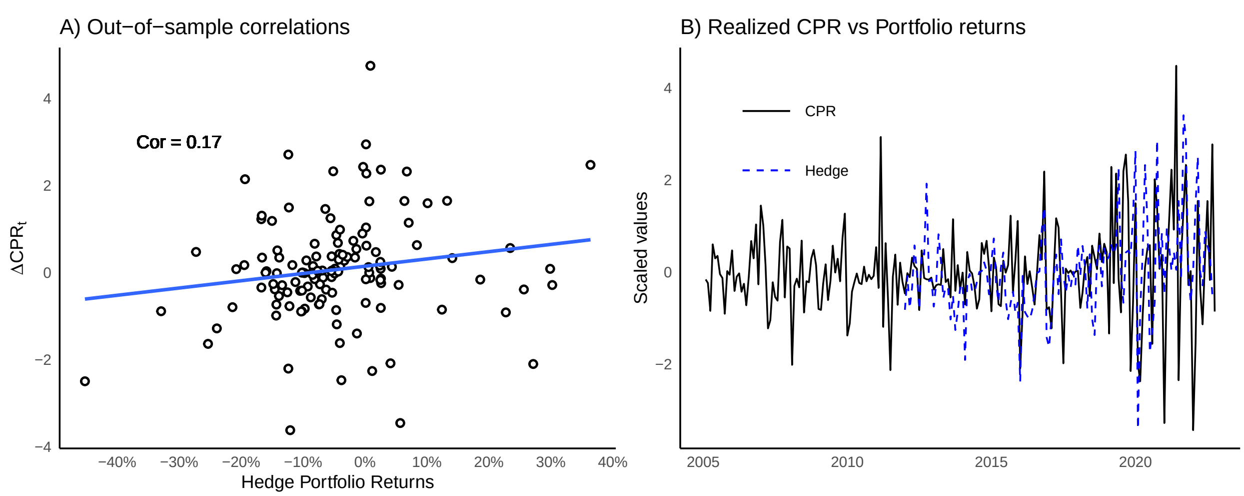
$$CPR_t = \alpha + w_{GMB} Z^{CO2}_{t-1} r_t + w_{SIZE} Z^{SIZE}_{t-1} r_t + w_{HML} Z^{HML}_{t-1} r_t + w_{MOM} Z^{MOM}_{t-1} r_t + w_{MKT} Z^{MKT}_{t-1} r_t \tag{H.5}$$

where $w_{GMB}, w_{SIZE}, w_{HML}, w_{MOM}, w_{MKT}$ are scalars that capture the weight of the corresponding portfolios in the mimicking (hedge) portfolio for ΔCPR_t.

H.3 Hedging CPR Risk in Real Time

To test the real-time hedging properties of the mimicking hedge portfolio, I follow Engle et al. (2020): at time t, I use data from t_{min} up to $t-1$ to estimate equation (H.5) and retrieve the optimal weights of each portfolio. i then compute the return of this portfolio in t and compare it with the actual realization of the CPR factor. In practice, I consider t_{min} =2005M1 to have sufficient data to estimate the model and report out-of-sample results starting from 2012M1. First, I consider using the sector diversified GMB portfolio. Panel A) of Figure H.1 plots the correlations between realized ΔCPR_t values and the return of the GMB portfolio. The correlation is significant at around 17%, which is comparable to the performance of the hedge portfolio considered in Engle et al. (2020). Panel B) proposes a graphical representation of the real-time hedging exercise by comparing the realized ΔCPR_t with the actual portfolio returns. In summary, the sector-diversified GMB portfolio performs remarkably well in hedging CPR out-of-sample.

Figure H.1 Out-of-sample : Sector-Diversified Portfolio portfolio

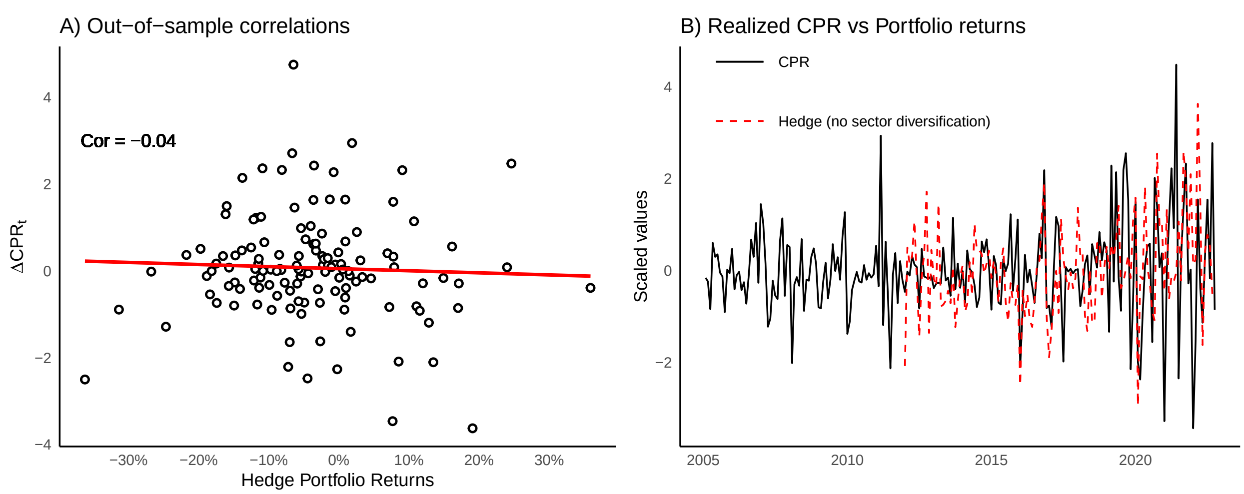


Note. This Figure assesses graphically the out-of-sample hedging properties of the sector-diversified GMB portfolio. Panel A) displays the cross-sectional correlation between the actual CPR innovation (ΔCPR_t on the y-axis) and the returns of the hedge portfolio in real-time using equation (H.5) to form the weights. Panel B) plots the (scaled) time-series of the hedge portfolio returns and the actual CPR innovation.

As mentioned, the GMB portfolio is defined in order to ensure sector diversification (i.e.

50% of firms within each sector are labelled as green while the rest is brown). How important is that type of diversification? To answer this question, I consider the non sector-diversified portfolio and re-runs the real time hedging exercise. Figure H.2 plots the out-of-sample results from this approach. Clearly, this non-diversified GMB portfolio does not provide any hedging, as can be seen from the negative out-of-sample correlation of 4%. This highlights the importance of diversification when constructing hedge portfolios, and suggest that a within-sector approach may be more effective when trying to hedge climate-related risks. While I do not see the sector-diversified GMB portfolio as the ultimate hedge and acknowledge the limitations of the CPR measure , I interpret the results as suggesting that a CO2-based portfolio is a sensible starting point to hedge such risks.

Figure H.2 Out-of-sample : No Diversification of Sectors



Note. This Figure assesses graphically the out-of-sample hedging properties of the GMB portfolio when the brown dummy is *not* defined by sector, and thus the hedging portfolio is not sector-diversified. Panel A) displays the cross-sectional correlation between the actual CPR innovation (ΔCPR_t on the y-axis) and the returns of the hedge portfolio in real-time using equation (H.5) to form the weights. Panel B) plots the (scaled) time-series of the hedge portfolio returns and the actual CPR innovation.

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