# Shocks to transition risk

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We propose and implement a method to identify shocks to transition risk. We identify transition risk shocks as instances where a strong differential valuation of green versus brown firms coincides with significant information on climate change. For that purpose, we combine information from long-short equity portfolios sorted on firms' carbon footprints with information from textual analysis of newspaper archives. We find that shocks increasing transition risk (negative abnormal returns of brown firms) induce a decline in aggregate and sectoral industrial production. Moreover, they significantly affect financial stability, as measured by the excess bond premium or credit conditions more generally. Finally, we document a pronounced asymmetry in the economy's response to shocks increasing or decreasing transition risk.

**Keywords:** Transition risk, climate change, financial stability, portfolio sort, textual analysis

**JEL:** C30, E44, G12, Q43, Q54, Q58

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# 1 Introduction

Evidence on the anthropogenic nature of climate change is mounting. Economically, climate change goes along with a substantial increase in various types of risks, which are typically categorized as being either physical or related to economic transition. Whereas physical risk – risk arising from the more frequent occurrence of extreme weather events, including the costs from the adaptation to it – is at the core of the empirical literature in this field, transition risk has received much less attention.[1]

Out of the many possible reasons for this lack of attention, we want to highlight two: (i) A precise definition of transition risk is still missing. This is in stark contrast to physical risk which requires little clarification. Broadly speaking, transition risk can be thought of as the risk resulting from the process of adjustment towards an economy with lower carbon emissions, which is necessary to mitigate climate change. For instance, in response to the rise in global temperatures, governments formulate policies to support the reduction of carbon emissions. Similarly, technological change or shifts in household preferences can render certain industries, products or firms obsolete. (ii) Related to (i), the measurement of transition risk represents a much larger challenge to economists than the measurement of physical risk. The occurrence of extreme weather events and the achievements of climatological research provide detailed information about physical risks. By contrast, it is impossible to directly measure the expected path (or the distribution of paths) towards a lower-carbon economy. Since it cannot be observed, it must be inferred. However, it is far from clear how the obvious proxies – such as government policies, technologies, or changes in consumer preferences – relate to this path. In addition, the factors potentially affecting this path can be endogenous.

Our paper proposes a method to measure transition risk by detecting instances at which a significant piece of new information about the distribution of possible transition paths is revealed. By defining and identifying such *shocks to transition risk*, we address both challenges sketched above. For an event to qualify as a shock to transition risk, we require the following: it must (i) impact the valuation of green and brown firms differently and (ii) relate to economic news on climate change. To satisfy these requirements, we combine information from long-short equity portfolios sorted on firms' carbon footprints with textual analysis of newspaper archives. Applying our method to U.S. data from 2010 to 2018, we find seven transition risk shocks, five positive and two negative ones. A positive (negative) shock to transition risk can be interpreted as an event that increases (decreases) the likelihood of a fast and orderly transition. As positive shocks we identify Mark Carney's speech on climate change and financial stability (September 2015) and the Paris Agreement (December 2015), among others.

Equipped with these transition risk shocks, we analyze their economic impact within a macro-financial Bayesian VAR framework. We find that a positive transition risk shock significantly lowers the economic outlook for several months, reducing industrial production and prices. A positive shock, on average, explains up to 22% of the variation in industrial production within the first year. Additionally, a positive transition risk shock induces financial instability. We show

[1] For an overview of the empirical literature on physical risks, see, for instance, the survey paper of Tol (2009) or the study of Kahn, Mohaddes, Ng, Pesaran, Raissi, and Yang (2019) featuring a panel of 174 countries.

that it significantly and strongly deteriorates credit conditions as measured by the excess bond premium (EBP) or the credit subcomponent of the national financial conditions index (NFCI). For instance, it explains up to 29% of fluctuations in the EBP within the first year.

Furthermore, our findings for sectoral industrial production and sectoral equity portfolio variances validate our identification of shocks to transition risk. A positive shock causes a strong decline in the industrial production of climate-sensitive sectors like "energy materials", explaining up to 27% of its variation. In contrast, a positive shock hardly impacts industrial production of other sectors. Furthermore, from the variances of Fama-French industry equity portfolios, we conclude that a positive transition risk shock strongly induces uncertainty in climate-sensitive industries such as oil (explaining up to 24% of variation), but not in other sectors.

To address financial stability considerations, we also analyze the variances of financial sector equity portfolios. Our results suggest that the banking sector experiences the strongest increase in uncertainty, with the shock explaining up to 4.4% of variation. The insurance industry is least affected (up to 2.1% of variation).

Finally, we detect pronounced asymmetries between positive and negative shocks to transition risk. That is, a negative transition risk shock hardly impacts the economy, for instance, only explaining up to 1.4% of variation in industrial production. This is consistent with the idea that negative shocks to transition risk are perceived as rather short-lived, while increases in transition risk are more persistent, reflecting the belief that there must be a transition towards a lower carbon economy in the very long run.

Our paper contributes to the literature on transition risk, which is still nascent, but growing fast. The idea to combine equity return data with textual analysis of newspaper archives for identifying transition risk shocks is, to the best of our knowledge, novel. It circumvents shortcomings of previous studies, which follow either of the two approaches separately.

Long-short equity portfolios sorted on variables which proxy for firms' carbon footprints have been studied by quite a few researchers recently, e.g. Oestreich and Tsiakas (2015), In, Park, and Monk (2018), Barnett (2019), Bolton and Kacperczyk (2020), Cornell (2020) and Görgen et al. (2020). Related to this, there have been studies for other asset classes like corporate credit (Delis, de Greiff, and Ongena (2020)) or equity options (Ilhan, Sauter, and Vilkov (2020)). All these approaches come along with several challenges. First, the data availability on firms' carbon footprints like $CO_2$ emissions is limited. Second, equity returns are generally driven by a vast amount of factors other than climate change, and so the identification of shocks is not very clean. Third, an approach based purely on financial returns can only detect changes in the risk-neutral distribution of future cash flows, not the physical distribution. A combination of financial market data with news-based textual analysis can thus deliver superior results, and our findings indeed support this intuition. Moreover, our approach allows for a narrative-based labeling of shocks, giving us a deeper understanding of the economic mechanisms.

Climate indices based on textual analysis of news have been constructed by, among others, Donadelli, Grüning, and Hitzemann (2019), Berkman, Jona, and Soderstrom (2019), and Engle, Giglio, Kelly, Lee, and Stroebel (2020). However, It is unclear whether these indices capture something exogenous to economic decisions or just mirror some endogenous response. An ex-

ample for the latter is the withdrawal of the U.S. from the Paris Agreement in June 2017, which represents a spike in news-based climate indices, but does not show up significantly in equity returns. In addition, textual analysis of news is often used to measure uncertainty (see, for instance, Baker, Bloom, and Davis (2016) or Schüler (2020)). Therefore, news-based climate indices may also relate to uncertainty more generally and not only transition risk.

Finally, researchers who study general equilibrium models of climate change economics very often proxy transition risk with climate variables like temperature or precipitation. Examples of such approaches are Bansal, Kiku, and Ochoa (2017) and Donadelli, Jüppner, Riedel, and Schlag (2017). While data on climate variables is readily available for many countries and regions, such a measurement of transition risk seems rather indirect. Moreover, a clear separation of physical and transition risks appears very challenging when using climate variables as proxy.

## 2 Identifying shocks to transition risk

Our strategy is to identify shocks that affect green and brown firms differently. Importantly, we require that these shocks are due to new information related to climate change. Therefore, we label these as shocks to transition risk. They represent instances where "climate change information" alters the relative valuation of green and brown firms.

Specifically, we identify shocks to transition risk by synthesizing information from two measures. First, we construct long-short equity portfolios by sorting firms according to their carbon footprints. Second, we build a monthly newspaper-based index capturing the amount of major economic news related to climate change. We combine the two measures by identifying months of major news that occur in tandem with extreme portfolio returns. We use the sign of the returns to determine whether the shocks increases or decreases transition risk.

We supplement the portfolio returns with the news index for several reasons. First, stock market returns are inherently noisy and thus may detect many false positives, i.e. false shocks to transition risk. Second, stock market returns are not only driven by information related to transition risk. Many other risk factors pertaining to different economic aspects may induce shocks in our portfolios. These have no basis in transition risk and thus are not of interest to us. Third, the data quality regarding firms' carbon footprints is low. Therefore, the discrimination between green and brown firms might not be perfect, also inducing false shocks to transition risk. Again, the news index serves as an additional verification. Fourth, our combined approach allows for a narrative-based labelling of shocks, giving us a deeper understanding of the underlying mechanisms and the economic impact. Finally, our approach allows us to distinguish more clearly between risk-neutral and physical expectations of equity investors. Transition risk shocks induce changes in physical expectations, for example regarding the riskiness of an asset's future cash flows, and less so influence investor's preferences. While both changes to an asset's expected cash flows as well as to the investor's pricing kernel may be responsible for price movements, we conjecture that it is mainly the former that will react to significant events related to climate change and thus can be identified using the news index.

Our transition risk shocks may be differentiated from shocks to physical risk. This is because physical risk shocks should not systematically affect green and brown firms differently. Still,

physical risk and transition risk (and their shocks) are strongly interrelated. For instance, without any increase in physical risk, most likely there would be no risk of transitioning to a carbon-neutral economy. Our transition risk shocks may also be differentiated from shocks to policy uncertainty in the spirit of Baker et al. (2016). Uncertainty should naturally be reflected in second moments of returns, rather than in first moments, which our approach exploits.

### *2.1 Long-short equity portfolios*

We construct long-short equity portfolios by sorting firms on their climate footprints. Specifically, we merge the CRSP-Compustat database with environmental, social, and governance (ESG) data from Eikon. The availability of data on firms' climate footprints from the ESG database determines the start of our sample period. It covers January 2010 until December 2018.[2]

From the ESG database, we mainly focus on two firm-specific variables: carbon emissions and energy use.[3] We disregard any other ESG variables because of data scarcity, but also in light of the challenges in establishing a reasonable weighting scheme, as reported in Görgen et al. (2020), i.e., we prefer simplicity over complexity. However, due to ESG-data scarcity and potential ESG-data quality issues, we augment our set of long-short portfolios by the brown minus green (BMG) factor, which Görgen et al. (2020) kindly provided to us.[4]

We sort all firms into climate footprint deciles according to their emissions or energy use and form value-weighted decile portfolios. As is standard practice in asset pricing, the composition of the decile portfolios changes only once per year. We then track the monthly returns of these value-weighted decile portfolios. To orthogonalize these returns with respect to systematic risk, we regress each decile portfolio excess return on the three Fama-French factors (one regression for the whole sample) and, throughout the analysis, work with the residuals from this regression. Finally, we form long-short portfolio returns from these residuals as the difference between portfolios ten and one. We thus end up with two climate long-short factors, one for carbon emissions and one for energy usage. A positive value for these factors implies that carbon-intensive or energy-intensive (i.e. "dirty") firms exhibit abnormally high returns in a given month relative to "green" firms.

Figure 1 depicts these factors, next to the BMG factor from Görgen et al. (2020). By construc-

[2]This is in line with Görgen et al. (2020) who also find that the data coverage for climate-related quantities in the standard ESG databases is too low and not reliable before 2010.

[3]Note that we take into account so-called "Scope 1" emissions only. Data on the emissions of energy suppliers (Scope 2) or general suppliers and customers (Scope 3) of a given firm is not readily available with reasonable coverage in the standard databases.

[4] In more detail, the brown minus green (BMG) factor by Görgen et al. (2020) is a portfolio return series mimicking carbon risk. It is constructed using 55 firm-level variables - selected on the basis of expert knowledge - characterizing a firm's value chain, public perception and adaptability. Every year, each firm receives subscores for these three indicators, which are in turn aggregated into a brown minus green score (BGS), resulting in a panel of BGS data. Görgen et al. (2020) double-sort all firms by their market equity and BGS values. The BMG portfolio returns are defined as a linear combination of the "corner portfolios", i.e.

$$\mathrm{BMG}_t = 0.5(\mathrm{SH}_t + \mathrm{BH}_t) - 0.5(\mathrm{SL}_t + \mathrm{BL}_t)$$

where SH, BH, SL and BL are the value-weighted returns of the "low value & high BGS", "high value & high BGS", "low value & low BGS" and "low value & low BGS" portfolios, respectively.

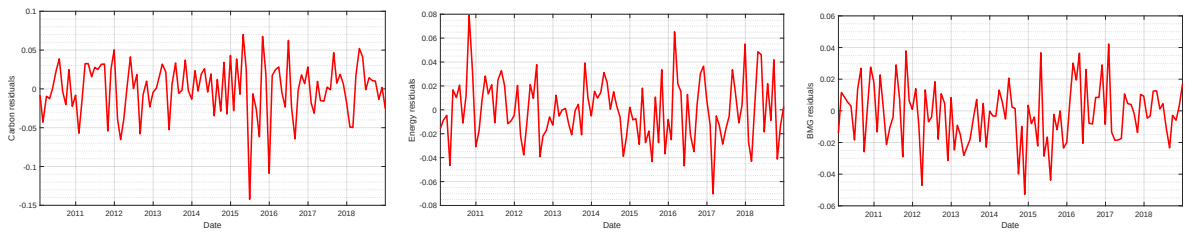


Figure 1: Fama-French 3-factor residuals of carbon (left), energy (middle) and BMG long-short portfolios (right).

*Notes:* A positive value for these monthly factors implies that carbon-intensive or energy-intensive (i.e. "dirty") firms exhibit abnormally high returns. We construct long-short equity portfolios by sorting firms on their carbon emissions (left) and energy usage (middle). We sort all firms into deciles and form value-weighted decile portfolios. To orthogonalize these returns with respect to systematic risk, we regress each decile portfolio excess return on the three Fama-French factors. We take the BMG factor from Görgen et al. (2020). For more details, see footnote 4.

tion, the mean of all three time series is zero. But notably, the first two long-short portfolios (before orthogonalization) have significant Fama-French alphas of +0.1 and -0.005 percentage points monthly over our sample period starting in 2010. At least the positive alpha for the carbon portfolio is in line with previous literature, which has documented a sizeable risk premium for brown firms over green firms (see Bolton and Kacperczyk (2020)). Finally, note that the Fama-French residuals exhibit relatively little heteroskedasticity, indicating that correcting for the Fama-French factors accounts for a large part of the heteroskedasticity in the data. However, already from a visual inspection, one can see that the large spikes of the carbon portfolio are roughly concentrated in the year 2015, which was a very decisive year in terms of shocks to transition risk (see Section 2.3).

### *2.2 News index*

We construct the news index from a textual analysis of newspaper articles using Factiva. Similar to Baker et al. (2016), we search ten different U.S. newspapers and determine the number of articles per month that contain our search phrase.[5]

Our search phrase is "(climate change) AND (economy OR economic)". Therefore, for every month our news index indicates the number of newspaper articles that are related to climate change and the economy. Importantly, we normalize this number by the number of articles that contain the search phrase "economy OR economic". We do so in order to account for the time-varying nature of attention that media pay to economics in general. An elevated level of the news index thus reflects times during which there are many economic news relating to climate change relative to the overall amount of economic news.

Similar to the indices proposed by Engle et al. (2020) or Donadelli et al. (2019), our raw news index is subject to a time trend. News related to climate change and economics have become increasingly relevant over the past decade. However, for our approach we want to focus on news at business cycles frequencies, such that our analysis is not biased by the increasing importance of climate change. Therefore, similar to Bloom (2009), we detrend our raw climate news index using a Hodrick and Prescott (1997) (HP) filter with a value for the smoothing parameter of

[5]The ten newspapers are: Los Angeles Times, USA Today, Chicago Tribune, Washington Post, Boston Globe, Wall Street Journal, Miami Herald, Dallas Morning News, Houston Chronicle, and San Francisco Chronicle.

129,600.[6] We show the resulting news index in Figure 3 in Section 2.3, when discussing the identified shocks to transition risk.

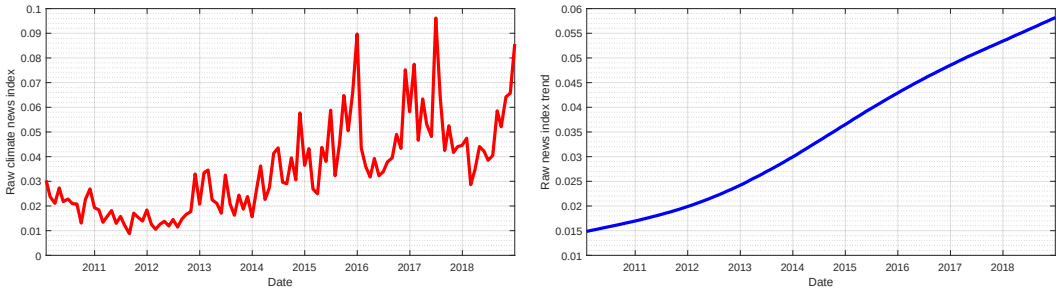


Figure 2: Raw climate news index and its trend component.
*Notes:* The raw climate news index is the fraction of newspaper articles on economics that also involve climate change. We identify the trend component by using a Hodrick and Prescott (1997) (HP) filter with 129,600 as a value for the smoothing parameter and extending the raw climate news index prior and after our sample period to avoid end-of-sample biases.

The raw news index and the identified trend are presented in Figure 2. The pronounced upward trend is insofar remarkable since we normalize the news index by the amount of general economic news. The relative amount of economic news which relate to climate change has grown by a factor of 4 since 2010. Besides, not only has the index grown over time, its volatility has also increased. The standard deviation is about two times as large in the second half of the sample (i.e. from 2014 onwards) as compared to the first half (0.015 vs 0.007).

A few papers in the literature use more complex procedures for constructing conceptually similar climate news indices (see, for example, Engle et al. (2020)). Therefore, we also experiment with other search phrases, but our benchmark news index hardly changes when using more complex search keys.[7] On this ground, we prefer simplicity over complexity in our benchmark setup. The correlation between our index and the Engle et al. (2020) index is around 30%. Part of this difference results from including the word "economics" in our key search phrase and from the subsequent normalization.[8]

### *2.3 Synthesizing information from long-short equity portfolios and the news index*

As the final step of our procedure, we combine the long-short equity portfolio returns and the news index, relying on a coexceedance approach. From the three long-short portfolios, we extract all months in which one of the absolute returns is one standard deviation away from its mean. From the climate news index, we extract all months in which the index is more than one standard deviation above its mean. Finally, our set of uncertainty shocks is defined as the overlap between these two sets of months.

[6]The value of 129,600 for monthly data corresponds to the value of 1,600 for quarterly data (see Ravn and Uhlig (2002)). Furthermore, in order to avoid end-of-sample biases of the HP filter, we detrend a version of the raw news index that starts well before 2010 and ends after 2017, i.e. exceeds the sample period used in the following analysis.

[7]For instance, we use the search phrase "(carbon or (climate near20 change) or emissions or (climate near20 adaptation) or (greenhouse near10 gas) or (global near20 warming) or ozone or emission or (carbon near20 dioxide) or greenhouse or mitigation or temperature or ecosystem or (extreme near20 weather) or (carbon near20 sequestration)) and (economic or economy)". The resulting news index is almost perfectly correlated with our proposed one. Further results can be obtained upon request.

[8]Engle et al. (2020) construct two different news indices. The statements made here refer to the first index based on the Wall Street Journal.

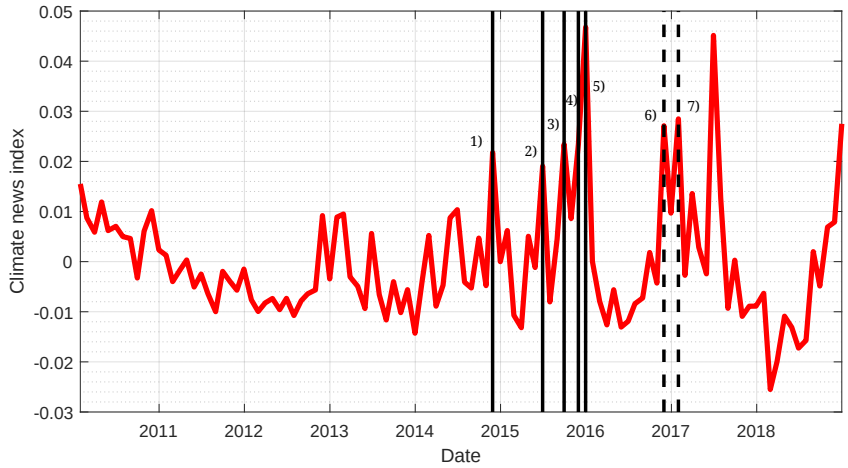


Figure 3: Shocks to transition risk (vertical bars) and climate news index (solid line)
*Notes:* Solid vertical bars indicate shocks that increase transition risk. Dashed vertical bars indicate shocks that decrease transition risk. We identify the shocks by combining the long-short equity portfolio returns and the climate news index, relying on a coexceedance approach. The solid line is the climate news index, i.e. the detrended version of our raw news index (see Section 2.2).

This procedure leaves us with seven identified transition risk shocks, as shown in Figure 3 by the vertical lines. Based on our newspaper search, we are able to attach narratives to each of these shocks, confirming that they are indeed related to the transition to a carbon-neutral economy: 1) In November 2014, the US and China announced a bilateral deal on reducing carbon emissions that reflected "one of the most significant international climate deals ever struck".[9] 2) In June 2015, the Obama administration announced the introduction of new emission rules for trucks, airlines and the energy industry. Moreover, on their yearly summit, the G7 countries agreed to reduce the world's carbon emissions by 40 to 70% until 2050, and to fully decarbonize the world economy until 2100. 3) In September 2015, the governor of the Bank of England, Mark Carney, gave his widely recognized speech on climate change and financial stability, indicating that climate change is also on the radar of central banks. 4) November 2015 is characterized by the run-up to the Paris climate summit, with expectations of a historic climate deal. 183 nations accounting for about 95% of greenhouse gas emissions submitted plans to reduce emission in advance of the summit. 5) In December 2015 the Paris Agreement was reached, with 195 nations participating in a landmark climate deal, committing to reduce greenhouse gas emissions. All of these events represent positive shocks, i.e., increases in transition risk. The two remaining shocks are negative. 6) In November 2016, Trump was elected as U.S. president. One of his promises was to revert President Obama's achievements concerning energy and the environment. 7) In January 2017, he was inaugurated and, as one his first decisions, nominated climate-change-sceptic Scott Pruitt as the administrator of the Environmental Protection Agency (E.P.A.). Scott Pruitt had openly criticised federal rules protecting the environment and fighting climate change.

Our approach ensures that the shocks to transition risk are both economically relevant and meaningful. More precisely, we find that not all months in which the newspaper-based index spikes represent shocks. For instance, from a pure newspaper-based analysis, the withdrawal of the US from the Paris Agreement (announced in June 2017) would be perceived as major

[9] Washington Post: "A landmark climate deal", 13 November 2014

economic news related to climate change, however our long-short equity portfolios reveal that it was by and large anticipated by investors. In a similar vein, extreme portfolio returns do not necessarily relate to a change in transition risk. We find months in which one of the long-short returns was rather extreme, but this was not reflected in the news. Examples for such months are Oct 2010 (+7.9%), Feb 2012 (-6.5%) and Feb 2017 (-7.0%).

# 3 The impact of shocks to transition risk

Having identified the seven shocks to transition risk in our sample, we now study their impact on a large set of macroeconomic and financial variables. This analysis serves mainly two goals. First, we view it as a further validation of our approach besides the narratives that we can assign to each of the shocks. Second, building on this validation, we can draw conclusions for the impact of transition risk shocks on the macroeconomy and on financial stability.

## *3.1 Data*

Our data comprises (aggregated and sectoral) log real industrial production, log real personal consumption expenditure, log PCE deflator, the 3-year Treasury yields, the difference between the 10-year and 3-year Treasury yields, the excess bond premium (Gilchrist and Zakrajšek (2012)), the VIX, and the cumulative excess return of the CRSP value-weighted equity index. We download the monthly macroeconomic data from FRED. We are also interested in the impact of transition risk on investors' uncertainty, which we proxy by the return variances of Fama-French industry portfolios. Specifically, the variances are based on the daily returns of the 17 industry portfolios available on Ken French's webpage. Because a focus of our paper lies on financial stability, the financial industry portfolio is split up into four subportfolios (banking, insurance, real estate, trading), according to the more granular classification which is also provided on Ken French's webpage. For each month, we proxy the return variance by the sum of squared daily returns. All portfolio variances are standardized to unit variance for comparability. Besides the return variances, we also the four subindices of the national financial conditions index (NFCI), computed by the Chicago Fed. The NFCI is a gauge for overall financial conditions. Its subcomponents measure volatility and funding risk (NFCI: Risk), credit conditions (NFCI: Credit), debt and equity measures (NFCI: Leverage), and household and nonfinancial business leverage (NFCI: Non-financial leverage).[10] Similar to the portfolio variances, we standardize the NFCI subcomponents to unit variance for comparability.

Finally, we add our shocks to transition risk to the set of time series. To this end, we construct two dummy variables, one for the five positive shocks to transition risk and one for the two negative shocks to transition risk, and estimate each VAR separately for both dummies. We code two dummy variables in order to allow for asymmetries in the impact of positive and negative shocks to transition risk. We set the value of the dummy to the size of our news index

[10] While NFCI: Risk, NFCI: Credit, and NFCI: Leverage are constructed from a non-overlapping set of indicators of the NFCI, NFCI: Non-financial leverage is not. It is based on a subset of NFCI: Leverage indicators. We include all four of the indicators at the same time, since correlation of NFCI: Leverage and NFCI: Non-financial leverage is -0.75 for our sample period.

in the given month and zero otherwise. We do so to allow for a varying importance of the shocks.[11] For comparison, we then scale both shock series to unit variance, which determines the size of the shock considered in our empirical exercise.

### *3.2 Methodology – Bayesian structural vector autoregression*

The impact of a shock to transition risk can be analyzed in multiple ways. Throughout the paper we rely on a Bayesian structural vector autoregression (BSVAR) in the spirit of Waggoner and Zha (2003). Placing restrictions on the BSVAR model, this setup allows to mimic local projections in the spirit of Jordà (2005). Indeed, Plagborg-Møller and Wolf (2020) prove that local projections and VARs may estimate the same impulse responses. However, this is not yet clear for data with unit roots and cointegration, which we consider.

Let $y_t$ be an $(n \times 1)$ vector of random variables at time $t$ $(t = 1, \ldots, T)$, $C$ a vector of constants, $\mathcal{A}$ and $\mathcal{A}_l$ coefficient matrices of size $n \times n$, and $\varepsilon_t$ an $(n \times 1)$ vector of exogenous structural shocks. Let $p$ denote the lag length. We consider the following structural VAR model:

$$y_t'\mathcal{A} = C + \sum_{l=1}^{p} y_{t-l}'\mathcal{A}_l + \varepsilon_t'. \tag{1}$$

We assume that the structural innovations are normally distributed with

$$E(\varepsilon_t | y_1, \ldots, y_{t-1}) = 0 \quad \text{and} \quad E(\varepsilon_t \varepsilon_t' | y_1, \ldots, y_{t-1}) = \mathbf{I}_n, \tag{2}$$

where $\mathbf{I}_n$ denotes the identity matrix of dimension $n$. The compact form of model (4) is given by

$$y_t'\mathcal{A} = x_t'\mathcal{F} + \varepsilon_t', \tag{3}$$

where

$$x_t' = \begin{bmatrix} y_{t-1}' & \ldots & y_{t-p}' & 1 \end{bmatrix} \quad \text{and} \quad \mathcal{F}' = \begin{bmatrix} \mathcal{A}_1' & \ldots & \mathcal{A}_p' & C' \end{bmatrix}.$$

*Block exogeneity:*

We analyze the impact of the identified shocks to transition risk by separating the SVAR into two groups. The first group is the respective shock series itself. The second group are the macro-financial variables. Denoting the shock series by $y_{1,t}$ $(1 \times 1)$ and the macro-financial variables by $y_{2,t}$ $(n_2 \times 1)$, the total number of variables considered in the VAR is $n = 1 + n_2$. Since we use abnormal equity returns to identify the shocks to transition, we assume that the macro-financial variables cannot predict the shock series. For the same reason, we also assume that the shock series cannot predict itself. With these block exogeneity restrictions the structural model (1)

[11] In a robustness exercise (not reported in this paper), we equally weight the shocks to transition risk. Results remain qualitatively the same.

can be written as

$$y_t'\mathcal{A} = C + \sum_{l=1}^{p} \begin{bmatrix} y_{1,t-l}' & y_{2,t-l}' \end{bmatrix} \begin{bmatrix} 0_1 & \mathcal{A}_{12,l} \\ 0_{n_2} & \mathcal{A}_{22,l} \end{bmatrix} + \varepsilon_t', \tag{4}$$

where, for instance, $0_{n_2}$ is a zero matrix of size $n_2 \times n_2$.[12]

*Structural shock identification: restrictions on contemporaneous relations*

In the VAR, we can specify whether our shock series $y_{1,t}$ may explain contemporaneous movements in some or all other endogenous variables, and vice versa. These assumptions on the transition risk shock – specified in $\mathcal{A}$ – can have major consequences for its impact. For instance, assume that we allow one endogenous variable to contemporaneously explain our shock series. This may alter the impact of our structural transition risk shock $\varepsilon_{1,t}$ on all other macro-financial variables, because the endogenous variable may explain some of the movements in our shock series $y_{1,t}$.

Therefore, we estimate VARs with two different sets of restrictions on $\mathcal{A}$. Both sets impose extreme assumptions on the contemporaneous relations between variables. We argue that the actual impact of the transition risk shock falls within the range defined by the two respective results. We prefer this approach over only specifying one identification scheme, because we have no prior belief on the "correctness" of one specific identification scheme.

Specifically, let TR1 denote our first set of restrictions on $\mathcal{A}$ and TR2 our second one. For TR1, we impose that our shock series is proportional to the structural shock to transition risk, i.e., $y_{1,t} \propto \varepsilon_{1,t}$. Under this identification scheme, the structural transition risk shock is exogenous to all the other shocks in the system, $\varepsilon_{2,t}, \ldots, \varepsilon_{n,t}$. Put differently, none of the other endogenous variables $(y_{2,t}, \ldots, y_{n,t})$ may contemporaneously affect our shock series $y_{1,t}$. We thus specify $\mathcal{A}$ as follows:

$$\mathcal{A}^{(\mathrm{TR1})} = \begin{array}{c} \\ y_1 \\ y_2 \\ \vdots \\ y_n \end{array} \begin{array}{c} \begin{array}{cccc} \text{TR1} & \text{Eq.2} & \cdots & \text{Eq.}n \end{array} \\ \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ 0 & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{nn} \end{pmatrix} \end{array}. \tag{5}$$

We do not specifically label the other equations as we do not aim to identify and analyze other shocks.

For TR2, we allow all other shocks in the system to contemporaneously affect the structural shock to transition risk, $\varepsilon_{1,t}$. We achieve this by allowing all endogenous variables to contemporaneously enter the equation identifying the structural shock to transition risk. Specifically,

[12] In a robustness exercise (not reported in the paper), we relax these restrictions. Results remain qualitatively the same.

we set $\mathcal{A}$ as:

$$\mathcal{A}^{(\mathrm{TR2})} = \begin{array}{c} \\ y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{array} \begin{array}{c} \begin{array}{ccccc} \mathrm{TR2} & \mathrm{Eq.2*} & \mathrm{Eq.3*} & \cdots & \mathrm{Eq.}n^* \end{array} \\ \begin{pmatrix} a_{11} & 0 & 0 & \cdots & 0 \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ a_{31} & 0 & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & 0 & 0 & \cdots & a_{nn} \end{pmatrix} \end{array}. \tag{6}$$

$\mathcal{A}^{(\mathrm{TR1})}$ maximizes the overall importance of the structural transition risk shock, $\mathcal{A}^{(\mathrm{TR2})}$ minimizes it.

*Estimation:*

Since we use monthly data, we set $p = 12$. Following Waggoner and Zha (2003) we use a Gibbs sampler to estimate the joint posterior distribution of $(\mathcal{A}, \mathcal{F})$. First, we draw $\mathcal{A}$ from its marginal posterior distribution. Second, we draw $\mathcal{F}$ from its conditional posterior distribution. For estimating the joint posterior, we do so 15,000 times, discarding the first 5,000 draws as burn-in draws.

We use a random walk prior on the reduced form coefficient matrix $\mathcal{F}\mathcal{A}^{-1}$, expressing the belief that each variable in the system follows a random walk (see Sims and Zha (1998); Litterman (1986)).[13] Furthermore, a lag-decay prior for $\mathcal{F}$, imposed on its conditional prior covariance matrix, decreases the risk of overfitting, which is necessary given our large data set. Finally, we introduce dummy observations as a component of the prior, which is preferable when the data exhibits unit roots and cointegration.[14]

### *3.3 Results*

#### *3.3.1 Aggregate impact*

Figure 4 shows the impulse responses of our aggregate macro-financial variables to a shock that increases transition risk under the TR1 specification. Since the impulse responses under TR2 are very similar, we place those in Appendix A in Figure A.1. However, for both the TR1 and TR2 identification scheme, we report the forecast error variance decomposition in Table 1. It shows the average variance explained over one year after the shock. In general, we refrain from interpreting the size of the impulse responses, because the size of the shock to transition risk has no deeper meaning. The importance of the shock to transition risk can be best understood from the forecast error variance exercise.

[13] Since we place the zero restrictions on the first block of the VAR, this assumption is not imposed for the shock series.

[14] The hyperparameters of this prior are set close to the standard values previously used in Bayesian structural VAR analysis (see, for example, Sims and Zha (1998), Robertson and Tallman (2001), Sims and Zha (2006)). In the notation of Sims and Zha (1998), we employ $\lambda_0 = 1$, $\lambda_1 = 0.5$, $\lambda_2 = 1.0$, $\lambda_3 = 1.2$, $\lambda_4 = 0.1$, $\mu_5 = 5.0$, and $\mu_6 = 5.0$. That is we slightly increase the values for $\lambda_0$ (tightness of beliefs on $\mathcal{A}$) and $\lambda_1$ (tightness of beliefs around the random walk prior) expressing less certainty around these beliefs.

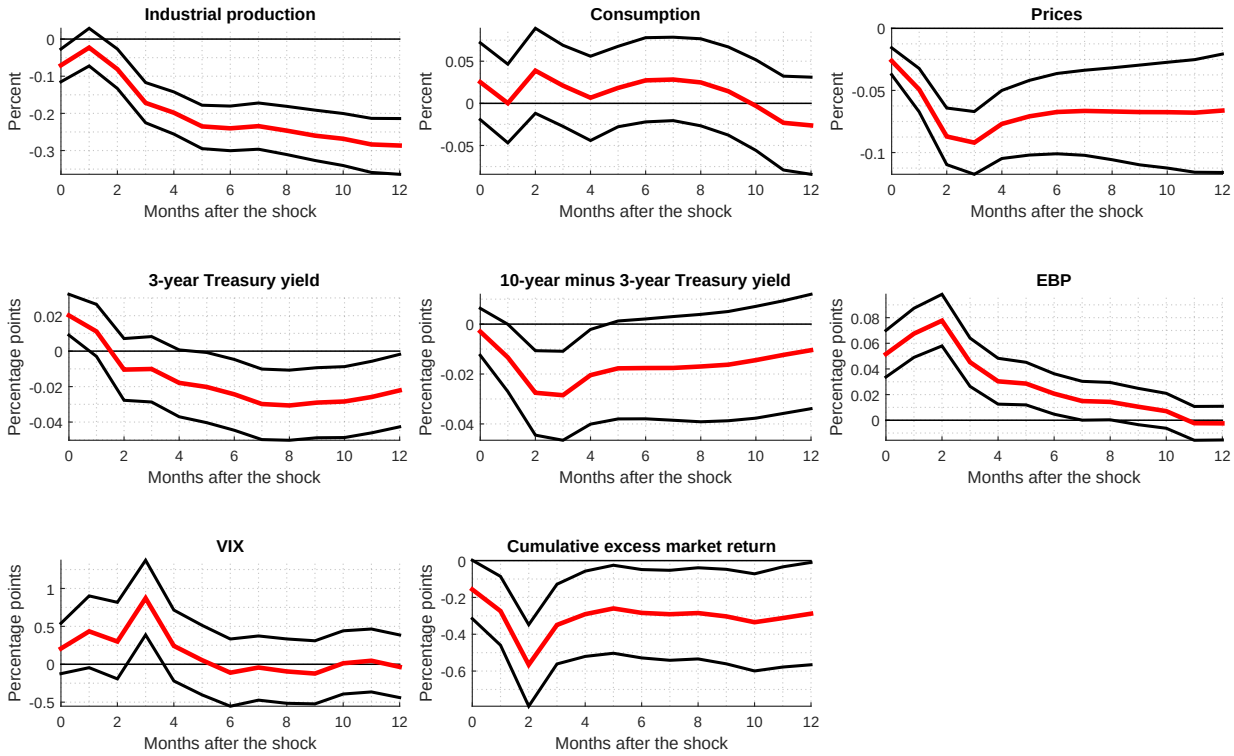


Figure 4: Increase in transition risk using TR1

*Notes:* The figure shows the responses of the indicated variables to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

We find that a shock that increases transition risk persistently lowers industrial production starting from month two and reduces the price level immediately. For TR2, the dynamics are similar, but the impact is delayed by one month. An increase in transition risk explains an important portion of fluctuations in industrial production, ranging from 21.5% (TR1) to 9.4% (TR2). In line with the well-known positive relation between the slope of the yield curve and output growth, the yield curve ("10-year minus 3-year Treasury yield") flattens for months two, three, and four. However, consumption appears not to be affected. One explanation could be that our shock to transition risk mostly affects the prospects of businesses and investments. Therefore, one might expect no effect on personal consumption expenditures.

Financial variables are most strongly affected. The strong and contemporaneous rise in the excess bond premium indicates a reduction in the risk-bearing capacity or willingness to lend of the financial sector, that has potential consequences for the supply of credit (see Gilchrist and Zakrajšek (2012)). This may explain the deterioration of macroeconomic conditions to some degree. For EBP, the importance of the shock ranges ranges from 29.2% (TR1) to 12.5% (TR2). Furthermore, we observe a slight increase in uncertainty three months after the shocks as captured by the VIX (importance: 3.1%-2.0%) and a decline of the excess stock market return (importance: 7.7%-4.7%).

Table 1 also reports the importance of shocks which decrease transition risk. We find that such shocks do not affect most of the macro-financal variables under the conservative TR2 specification (see also the impulse responses in Figure A.3 in Appendix A). Interestingly, though,

Table 1: Importance of shocks to transition risk (in percent)

| | Increase | | Decrease | |
|---|---|---|---|---|
| Variable | TR1 | TR2 | TR1 | TR2 |
| Industrial production | 21.5 | 9.4 | 1.1 | 1.4 |
| Consumption | 0.9 | 0.5 | 1.1 | 0.7 |
| Prices | 13.4 | 6.6 | 0.3 | 0.9 |
| 3-year Treasury yield | 4.5 | 3.7 | 3.5 | 1.3 |
| 10-year minus 3-year Treasury yield | 3.6 | 5.2 | 2.4 | 1.4 |
| EBP | 29.2 | 12.5 | 13.2 | 1.3 |
| VIX | 3.1 | 2.0 | 1.8 | 0.8 |
| Cumulative excess market return | 7.7 | 4.7 | 4.6 | 0.4 |

*Notes:* Table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock to transition risk (increase under TR1, increase under TR2, decrease under TR1, decrease under TR2) on average over the first 12 months after the shock. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously. TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2).

for TR1 we find that a negative shock to transition risk lowers the excess bond premium and thus improves lending conditions of financial institutions up to one month after the shock (see Figure A.2). The shock explains 13.2%-1.3% of the EPB fluctuations. In this sense, our negative shock does reflect the opposite of our positive shock, however without the remaining macroeconomic and financial implications. Overall, this supports the view that increases in transition risk alter agents' expectations and affect the economy, but declines do not. Therefore, in the rest of the paper, we mainly present the responses to shocks increasing transition risk. All other results can be found in Appendix A.

The asymmetry between the two shocks is also in line with recent findings, for instance by Hassler, Krusell, Olovsson, and Reiter (2020). But, of course, one has to acknowledge that the results of the negative shock are based on two events only, namely the election of Donald Trump in November 2016 and his inauguration in January 2017.

### *3.3.2 Impact on sectoral industrial production*

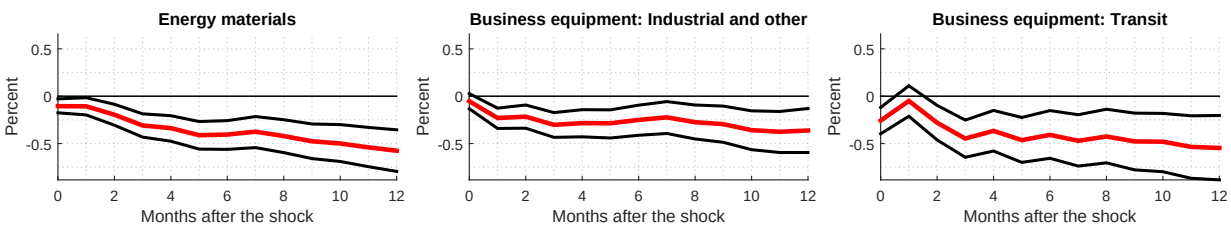


Figure 5: Increase in transition risk under TR1 for selected sectoral industrial production
*Notes:* The figure shows the responses of the indicated variables to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

The previous analysis reveals a large impact of shocks increasing transition risk on industrial production. Of course, this does not imply that all sectors of the economy are equally affected. Therefore, we repeat the VAR analysis, replacing aggregate industrial production with sectoral industrial production. The remaining macro-financial variables are left unchanged. For brevity,

Figure 5 only reports the impulse responses for the three variables for which our shock explains the largest amount of variance. Again, we show the results under specification TR1. Table 2 reports the variance decompositions for TR1 and TR2. For the complete set of impulse responses, see Appendix A.[15]

Table 2: Importance of shocks to transition risk (in percent) for sectoral industrial production

| | Increase | | Decrease | |
|---|---|---|---|---|
| | TR1 | TR2 | TR1 | TR2 |
| Consumer goods: Automotive products | 6.2 | 1.6 | 1.1 | 0.6 |
| Consumer goods: Home electronics | 4.9 | 1.4 | 12.0 | 3.8 |
| Consumer goods: Appliances, furniture, carpeting | 2.5 | 0.8 | 3.0 | 1.5 |
| Miscellaneous durable consumer goods | 15.6 | 17.0 | 1.6 | 2.2 |
| Consumer goods: Foods, tobacco | 2.2 | 4.2 | 17.9 | 12.4 |
| Consumer goods: Clothing | 2.5 | 3.1 | 6.6 | 2.5 |
| Consumer goods: Chemical products | 6.0 | 6.4 | 4.1 | 7.1 |
| Consumer goods: Paper products | 3.3 | 2.9 | 1.0 | 0.3 |
| Consumer energy products | 1.7 | 0.8 | 14.0 | 8.1 |
| Business equipment: Transit | 15.8 | 2.3 | 0.6 | 0.3 |
| Business equipment: Information processing | 5.0 | 0.2 | 2.5 | 1.0 |
| Business equipment: Industrial and other | 18.4 | 11.4 | 4.3 | 0.8 |
| Defense and space equipment | 6.6 | 13.3 | 6.6 | 9.3 |
| Durable materials: Consumer parts | 10.1 | 1.8 | 1.7 | 2.4 |
| Durable materials: Equipment parts | 15.7 | 11.8 | 1.6 | 7.2 |
| Durable materials: Other | 9.5 | 8.3 | 6.5 | 4.6 |
| Nondurable materials: Textile | 8.8 | 5.4 | 1.9 | 5.9 |
| Nondurable materials: Paper | 4.1 | 0.9 | 4.0 | 2.5 |
| Nondurable materials: Chemical | 1.9 | 0.8 | 3.0 | 7.2 |
| Energy materials | 26.5 | 6.0 | 3.7 | 0.1 |
| Construction supplies | 4.8 | 6.2 | 7.9 | 0.9 |
| Business supplies | 14.8 | 2.9 | 5.2 | 1.4 |

*Notes:* Table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock to transition risk (increase under TR1, increase under TR2, decrease under TR1, decrease under TR2) on average over the first 12 months after the shock. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously. TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2).

Similar to the aggregate industrial production, the production of "Energy materials", "Business equipment: Industrial and other", and "Business equipment: Transit" fall in response to a sudden increase in transition risk under TR1. These are the three variables for which our shock explains the largest portion of variance (26.5%-6.0%, 18.4%-11.4%, and 15.8%-2.3%, respectively). We view these results as an additional validation of our measurement of shocks to transition risk. They affect parts of the economy that we expect to be sensitive to increases in transition risk.

Moreover, the pronounced asymmetry between increases and decreases of transition risk also carries over to sectoral industrial production. Interestingly, for some industries (e.g. certain consumer goods industries) the importance of decreases in transition risk is even larger than the importance of increases.

Furthermore, we notice a large difference between the importance of our shock under TR1 and TR2. This is not only indicative of a large range in which the true impact of our shock should fall. It can also be informative about potential underlying economic mechanisms. As an example, consider the production of "Energy materials". A large part of this sector in the U.S.

[15] We do not report the FEVDs and impulse responses for the other macro-financial variables here since we already discuss them in the previous section. The results are available upon request.

is represented by shale oil firms which tend to be highly leveraged. Clearly, financial conditions as measured by the EBP affect the production capacities in this industry. Under TR1, our shock contemporaneously raises the EBP (see Figure 4), which possibly magnifies the shock's impact on "Energy materials". In contrast, under TR2 our shock is less important for EBP, among others, because it cannot impact this variable contemporaneously. This yields one explanation why the importance of the shock for "Energy materials" reduces under TR2 and provides us with a potential mechanism through which increases in transition risk affect certain sectors.

### *3.3.3 Impact on industry portfolio variances and NFCI subcomponents*

Next, we show the responses of the variances of industry equity portfolios and the NFCI subcomponents. We view the variances as proxies for the uncertainty in a given equity market. Furthermore, the analysis of the NFCI subcomponents should provide us with a deeper understanding on the shock's impact on the financial system.

For this exercise, we amend our baseline VAR of Section 3.3.1 with the industry portfolio variances and the NFCI subcomponents. Since the VIX forms part of the NFCI: Risk subindex, we drop the VIX for this specification.[16]

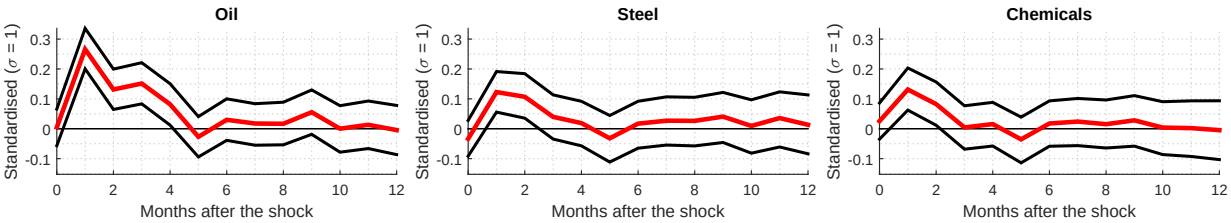


Figure 6: Increase in transition risk under TR1 for selected industry portfolio variances
*Notes:* The figure shows the responses of the indicated industry portfolio variance to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

In Figure 6, we show the three variances that are most affected by a shock that increases transition risk. In line with the interpretation of our shocks as a shock to transition risk, these are the industry portfolios of oil (27.6% - 20.0%), steel (7.3% - 6.1%), and chemicals (6.3% - 2.4%) (see Table 3). Uncertainty in these industries strongly rises in response to a sudden increase in transition risk up to four month after the shock. Clearly, the impact on the oil portfolio is by far the strongest.

A shock decreasing transition risk is also most important for explaining uncertainty in the oil industry portfolio (3.7% under TR1). The comparably low number however indicates that it is much less important than a shock increasing transition risk. Interestingly, the impulse response to a shock decreasing transition risk is slightly negative for the oil portfolio (see Figure 7). Again, in this sense our negative shock does reflect the opposite of our positive shock.

With respect to our financial portfolios (banks, insurance, real estate, financial trading), we find the importance of the shock increasing transition risk to be relatively low. It is largest for

[16]Similar to the analysis of sectoral industrial production, we do not report the results for baseline macro-financial indicators. Results are available upon request.

Table 3: Importance of shocks to transition risk (in percent) for industry portfolio variances and NFCI subcomponents

| | Increase | | Decrease | |
|---|---|---|---|---|
| | TR1 | TR2 | TR1 | TR2 |
| Food | 3.0 | 2.1 | 2.3 | 0.6 |
| Mines | 4.5 | 3.8 | 1.3 | 0.7 |
| Oil | 24.4 | 15.8 | 7.0 | 0.4 |
| Clothes | 2.0 | 1.5 | 1.4 | 0.5 |
| Consumer durables | 1.8 | 1.0 | 1.8 | 1.5 |
| Chemicals | 6.3 | 2.4 | 3.0 | 0.9 |
| Drugs, soap, perfumes, tobacco | 5.4 | 3.3 | 3.9 | 1.1 |
| Construction | 5.7 | 3.5 | 2.4 | 0.7 |
| Steel | 7.3 | 6.1 | 3.9 | 2.0 |
| Fabricated products | 2.2 | 1.3 | 2.7 | 1.4 |
| Machinery | 3.2 | 2.6 | 2.7 | 1.2 |
| Automobiles | 1.8 | 1.2 | 2.6 | 1.0 |
| Transportation | 3.3 | 2.4 | 1.7 | 0.6 |
| Utilities | 4.0 | 2.7 | 3.0 | 0.8 |
| Retail stores | 2.6 | 1.7 | 1.2 | 0.6 |
| Other | 5.8 | 2.6 | 1.7 | 0.8 |
| Banks | 4.4 | 1.1 | 0.8 | 0.7 |
| Insurance | 2.1 | 1.0 | 1.6 | 0.7 |
| Real estate | 3.3 | 2.0 | 2.8 | 0.9 |
| Financial trading | 4.2 | 1.1 | 1.2 | 0.6 |
| NFCI: Risk | 2.2 | 1.5 | 1.5 | 0.6 |
| NFCI: Credit | 10.6 | 3.2 | 16.6 | 0.7 |
| NFCI: Leverage | 1.9 | 0.5 | 5.1 | 0.7 |
| NFCI: Non-financial leverage | 1.7 | 0.2 | 5.5 | 0.5 |

*Notes:* Table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock to transition risk (increase under TR1, increase under TR2, decrease under TR1, decrease under TR2) on average over the first 12 months after the shock. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously. TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2).

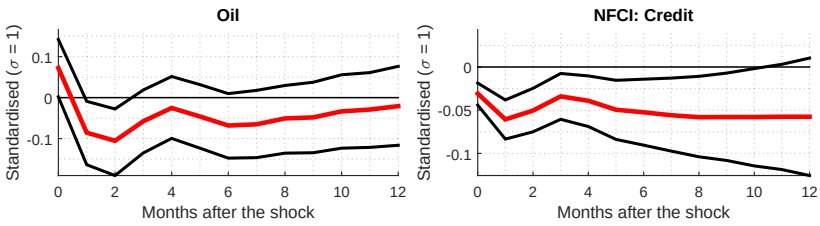


Figure 7: Decrease in transition risk under TR1: Oil industry portfolio variance and NFCI: Credit

*Notes:* The figure shows the responses of the oil industry portfolio variance and the credit subindex of the NFCI to a shock that decreases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

the banking portfolio. Here, a positive transition risk shock slightly increases uncertainty (see Figure 8) and explains 4.4%-1.1% of variation. Furthermore, we find that the shock is least important for the insurance portfolio. This may suggest that equity market investors are very confident that insurances handle transition risks relatively well.

In line with the impact of our shock on the EBP, we find that overall credit conditions tighten. The NFCI: Credit increases one month after the shock and remains elevated for one quarter. The shock explains 10.6%-3.2% of its variance. Interestingly, the impact of the shock is more

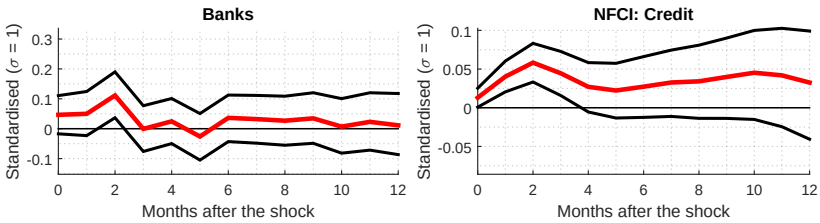


Figure 8: Increase in transition risk under TR1: Banks portfolio variance and NFCI: Credit
*Notes:* The figure shows the responses of the banking industry portfolio variance and the credit subindex of the NFCI to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

pronounced for the negative transition risk shock, persistently improving credit conditions (see Figure 7) and explaining 16.6%-0.7% of its variance. The importance of our shocks to transition risk are relatively low for the other NFCI subcomponents, indicating that indeed a shock to transition risk mainly affects credit conditions and not risk or leverage.

# 4 Discussion and Outlook

Measuring transition risk arising from climate change represents a formidable challenge for economic research. Our paper proposes a method to identify shocks to transition risk through a combination of abnormal financial returns with newspaper-based textual analysis. Applying our method, we find seven transition risk shocks for the U.S. for the period from 2010 to 2018. We then analyze the responses of various macro-financial variables to transition risk shocks in a standard Bayesian VAR setting. We find that a shock that speeds up an orderly transition to a lower carbon economy suppresses the economic outlook. In parallel, it induces financial instability by deteriorating credit conditions. Especially hit is production in climate-sensitive sectors like "energy materials" or uncertainty in climate-sensitive industry portfolios, such as oil. Finally, we detect a pronounced asymmetry between positive and negative shocks to transition risk, whereby negative shocks hardly impact the economic outcome. This suggests a broad belief that the economy will eventually adjust to lower carbon emission standards.

From a policy perspective, the negative implications of shocks increasing transition risk mark an important result. To fully understand its implications, note that in an economy without frictions the transition towards a lower carbon economy would evolve gradually over time. This is also confirmed by the vast majority of theoretical models of climate transition.[17] For instance, if financial markets were informationally efficient, we should expect that the distribution of possible future transition paths are fully and correctly reflected in the prices of financial assets. In an economy without frictions, we would not see the adjustments that occur in response to a shock increasing transition risk. Therefore, the objective of policy must be to mitigate the impact of transition risk shocks. For instance, policymakers could have the role to constantly communicate the most likely transition path, such that adjustments can be gradual, taking into

[17] An overview of such models is, for instance, provided in the report by the Network for Greening the Financial System (NGFS) on macroeconomic and financial stability, which is available at `https://www.banque-france.fr/sites/default/files/media/2019/08/19/ngfs-report-technical-supplement_final_v2.pdf`. Other survey articles include Nordhaus (2019) and Farmer, Hepburn, Mealy, and Teytelboym (2015).

account the status quo of climate change research and consumers' preferences. Clearly, large uncertainties surround climate change results. Against this backdrop, policy makers need to weigh their preference for type I (too slow transition) or type II (too fast transition) errors when communicating such a path.

Finally, given that the research on the empirical identification and measurement of transition risk is still in its infancy, we wish to add a few remarks. First, we motivate our study by the fact that a precise definition of climate-related transition risk is still missing. In fact, this argument may also be turned around in the sense that our measurement approach could help developing such a definition. Events should only be regarded as shocks to transition risk if they receive market-wide attention and if they have a differential impact on green versus brown financial assets. Second, we wish to emphasize that the approach proposed in our paper is very lean, precise and easy to implement. This is of particular importance given the huge amount of uncertainty surrounding anthropogenic climate change, as described, for instance, by Pindyck (2020). Transition risk should be measured in a transparent way that reduces potential degrees of freedom as much as possible. Third, we want to point towards further research and challenges for the analysis going forward. Even though we have tied our hands as much as possible, the measurement of the ESG data is still an issue. Moreover, a necessary next step in the analysis is to better understand the transmission channels of transition risk, perhaps through more granular micro data. And last, but not least, an extension towards a broader set of countries, coming up with a panel dataset of transition risk shocks, is a straightforward agenda for future research.

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# A Detailed Results from Bayesian VARs

## A.1 Aggregate impact

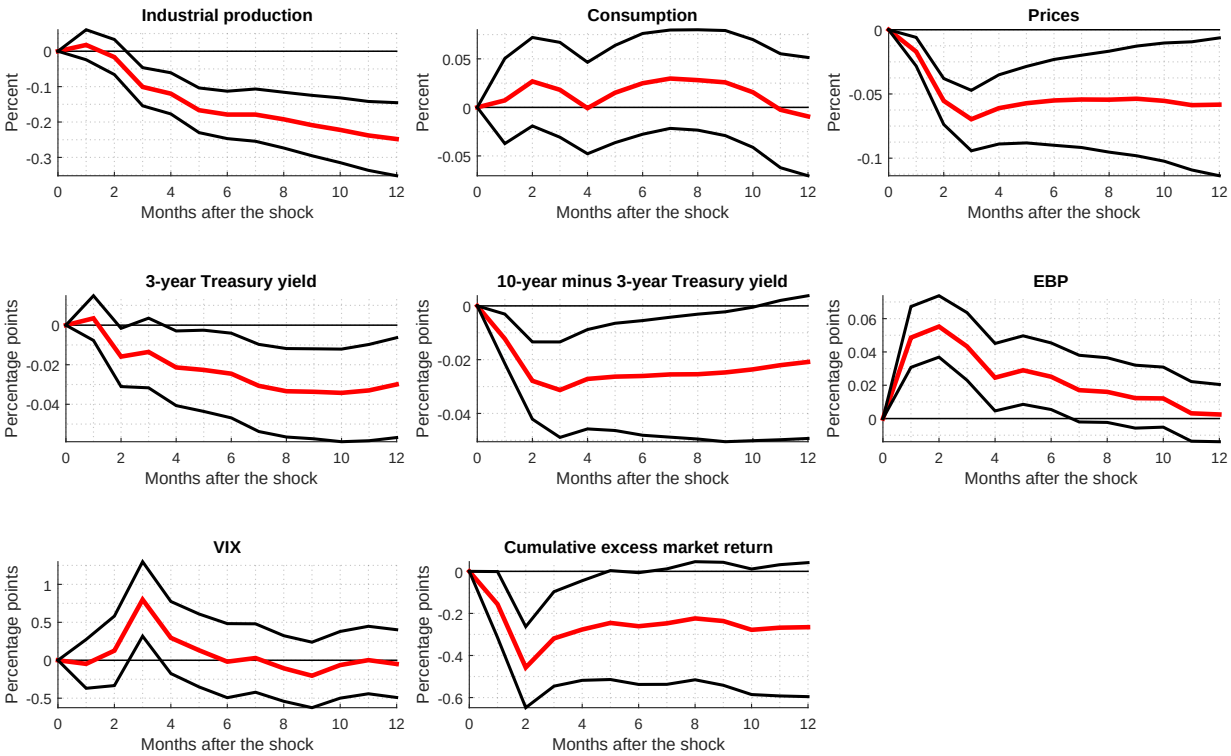


Figure A.1: Increase in transition risk using TR2

*Notes:* The figure shows the responses of the indicated variables to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

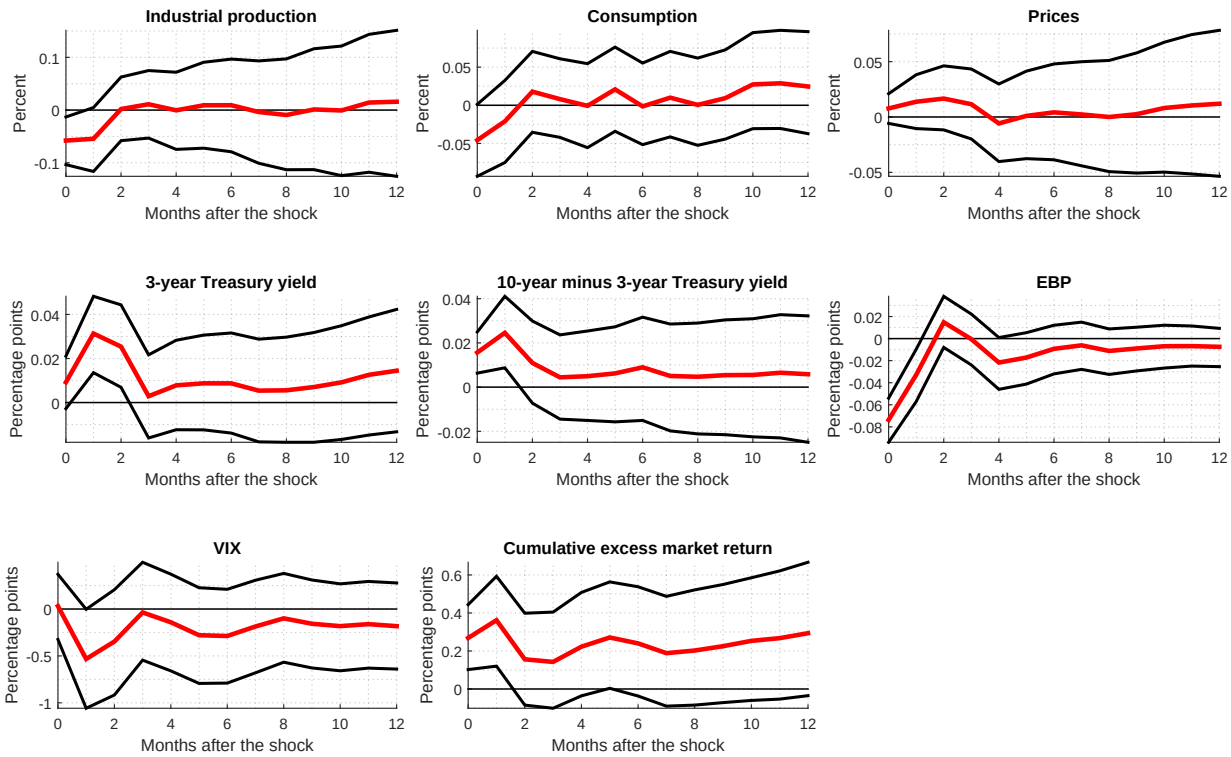


Figure A.2: Decrease in transition risk using TR1

*Notes:* The figure shows the responses of the indicated variables to a shock that decreases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

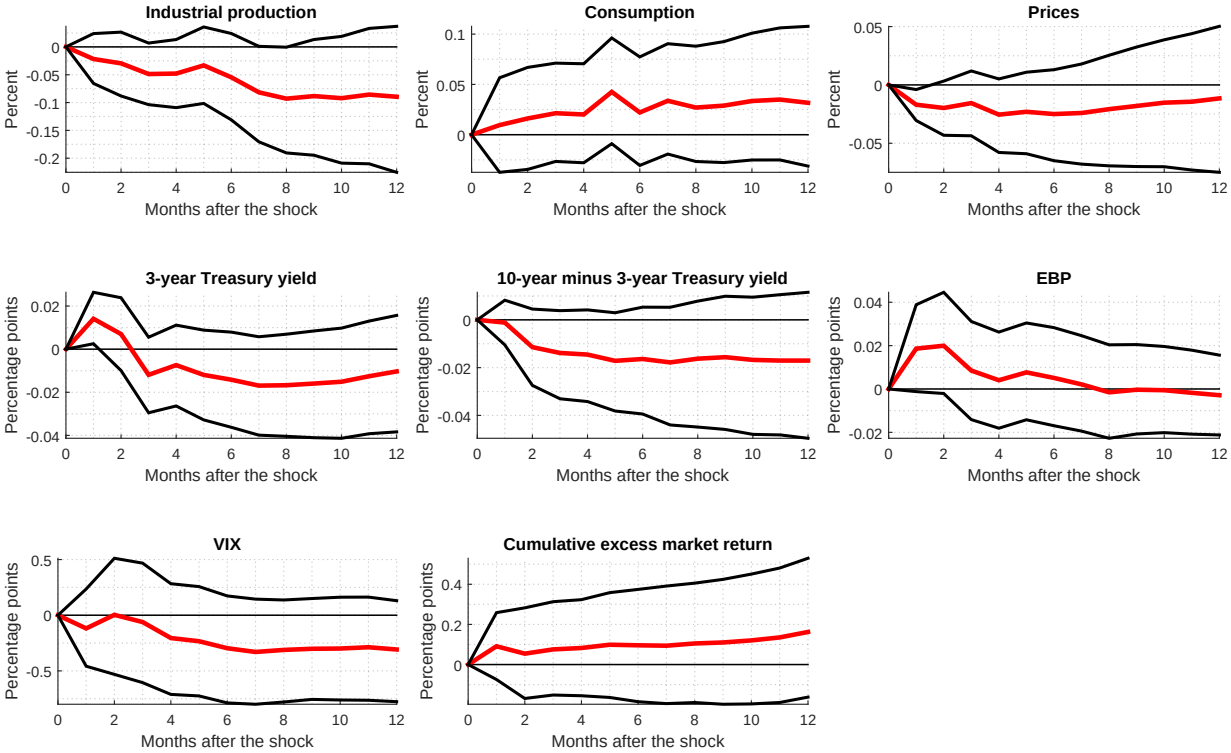


Figure A.3: Decrease in transition risk using TR2

*Notes:* The figure shows the responses of the indicated variables to a shock that decreases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

## *A.2 Sectoral industrial production*

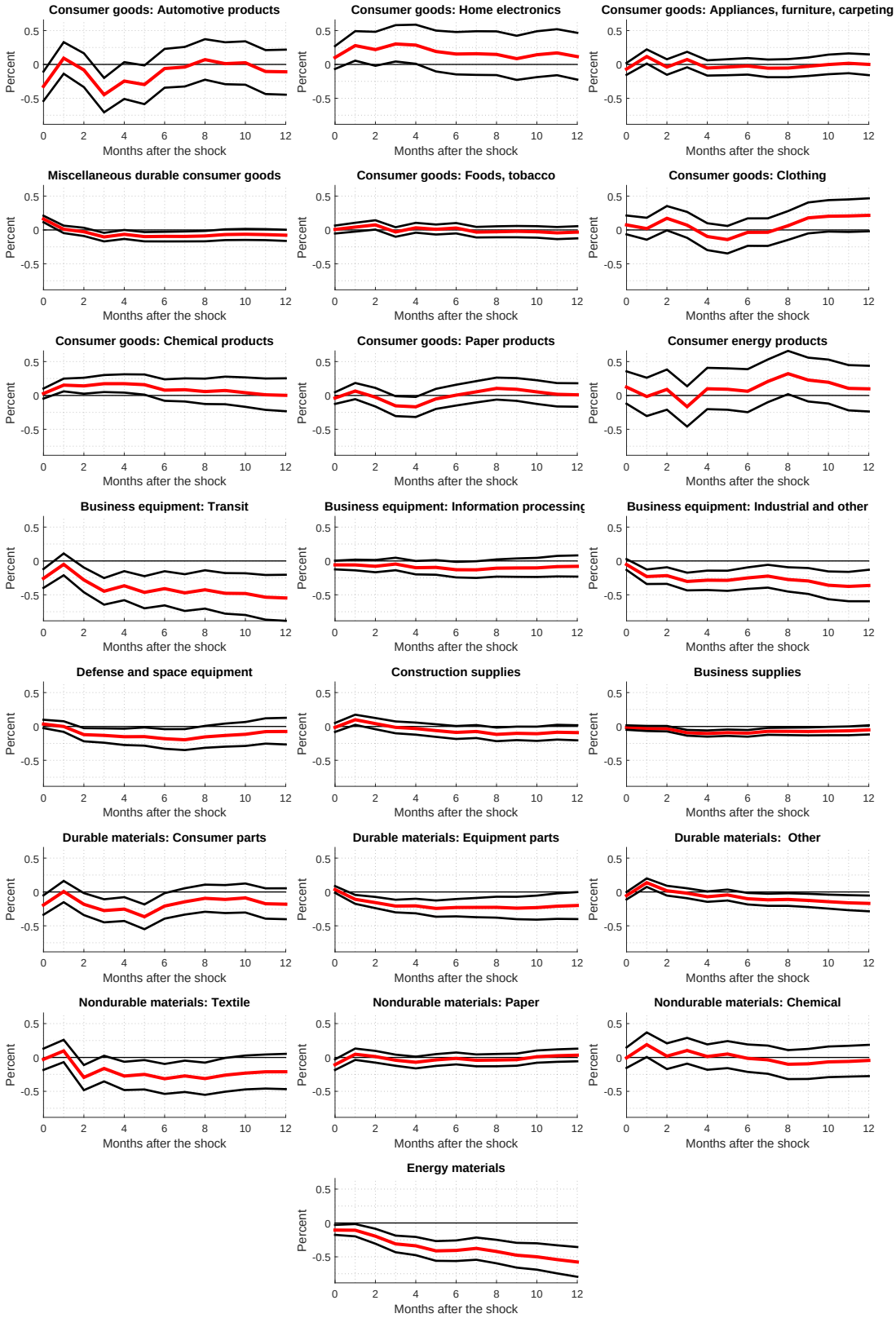


Figure A.4: Increase in transition risk under TR1 for sectoral industrial production

*Notes:* The figure shows the responses of the indicated variables to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

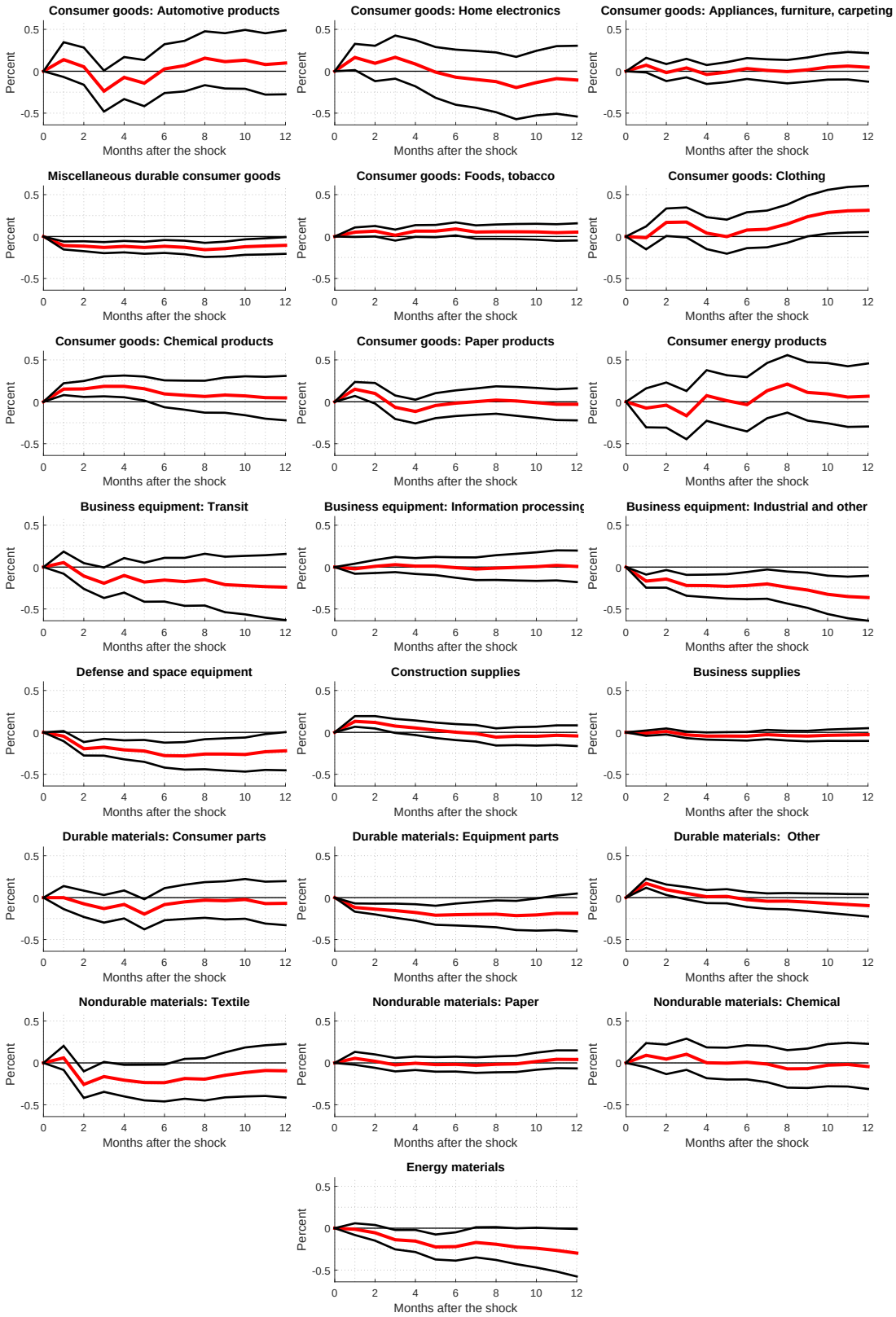


Figure A.5: Increase in transition risk under TR2 for sectoral industrial production

*Notes:* The figure shows the responses of the indicated variables to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

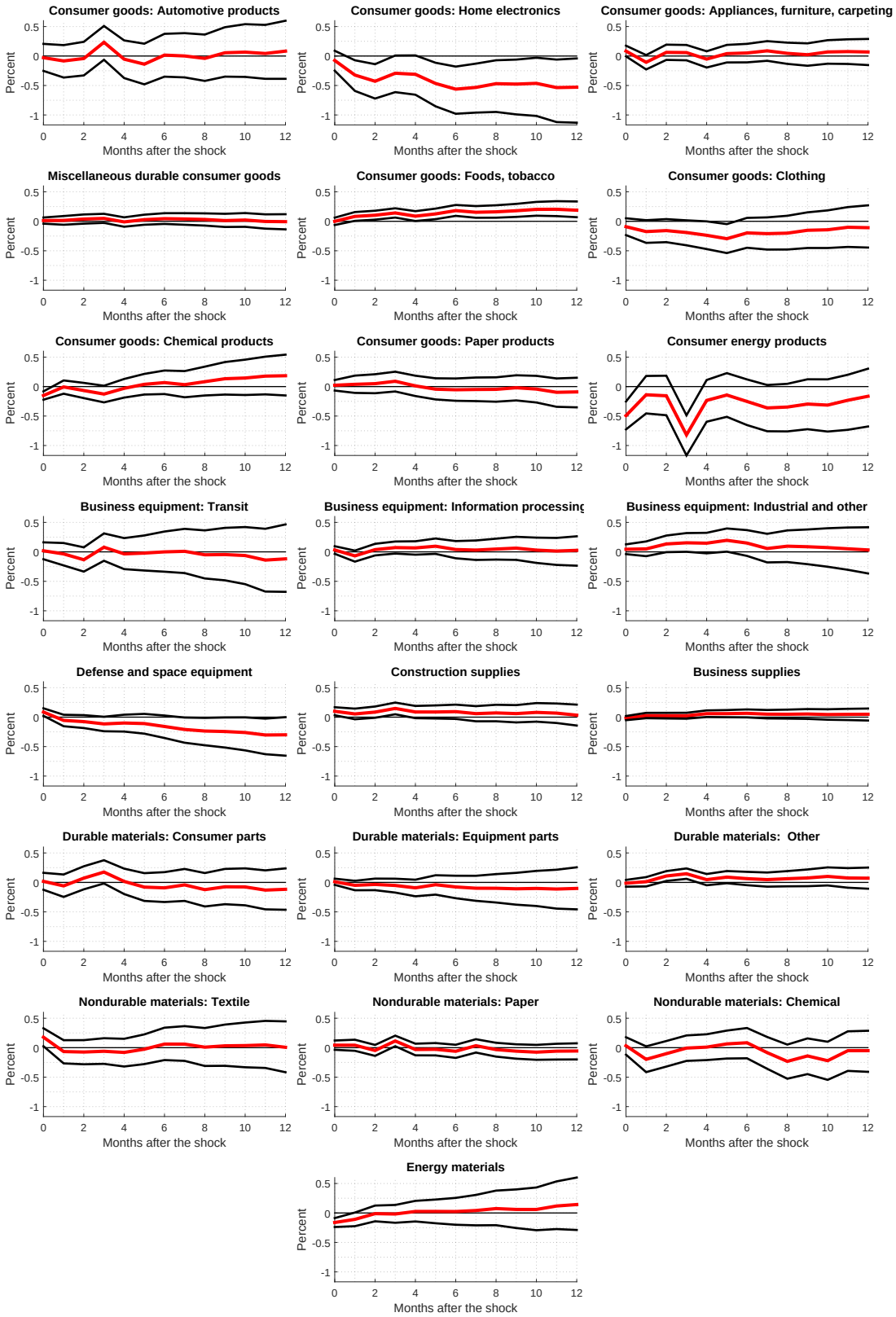


Figure A.6: Decrease in transition risk under TR1 for sectoral industrial production

*Notes:* The figure shows the responses of the indicated variables to a shock that decreases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

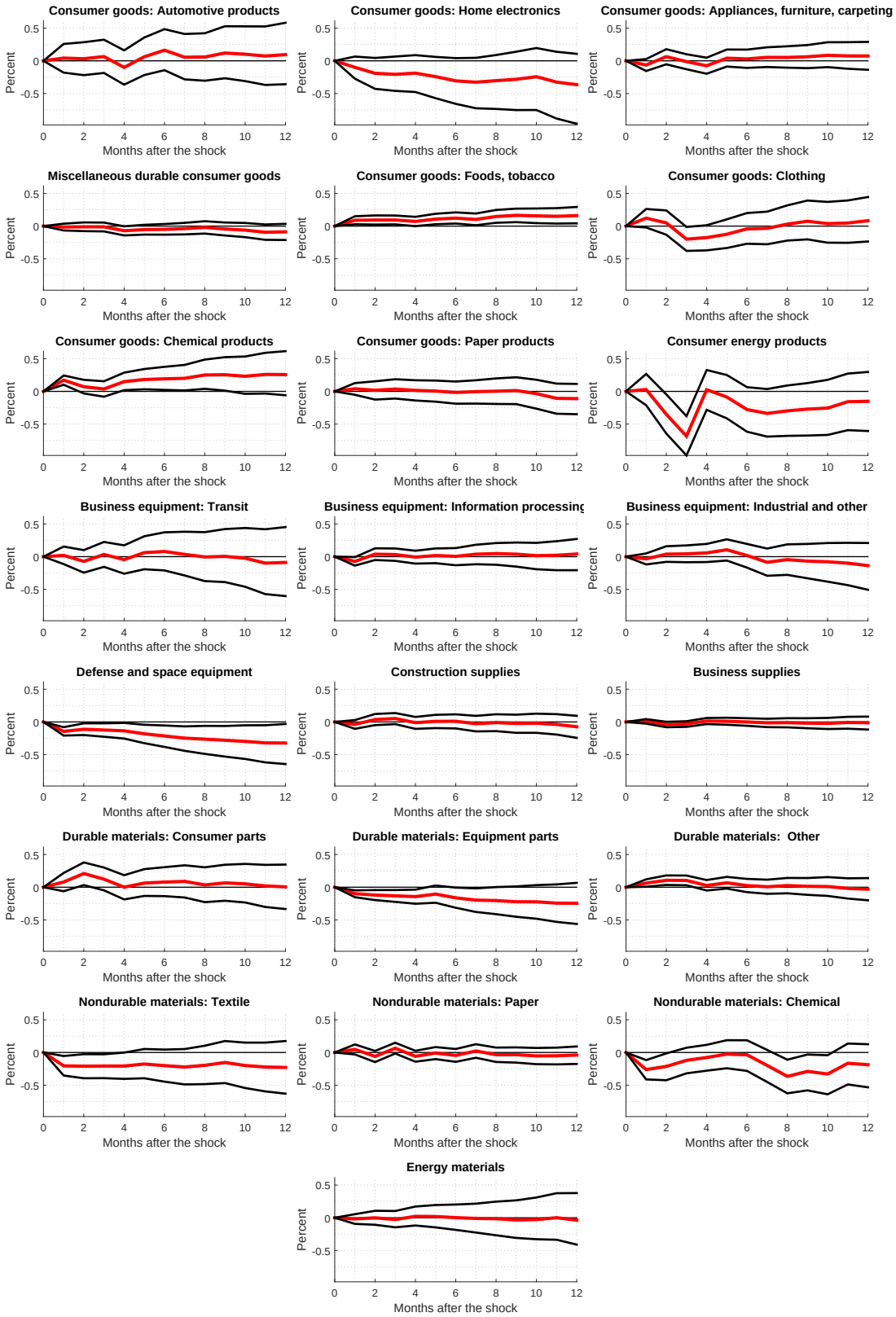


Figure A.7: Decrease in transition risk under TR2 for sectoral industrial production

*Notes:* The figure shows the responses of the indicated variables to a shock that decreases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

## A.3 Industry portfolio variances and NFCI subcomponents

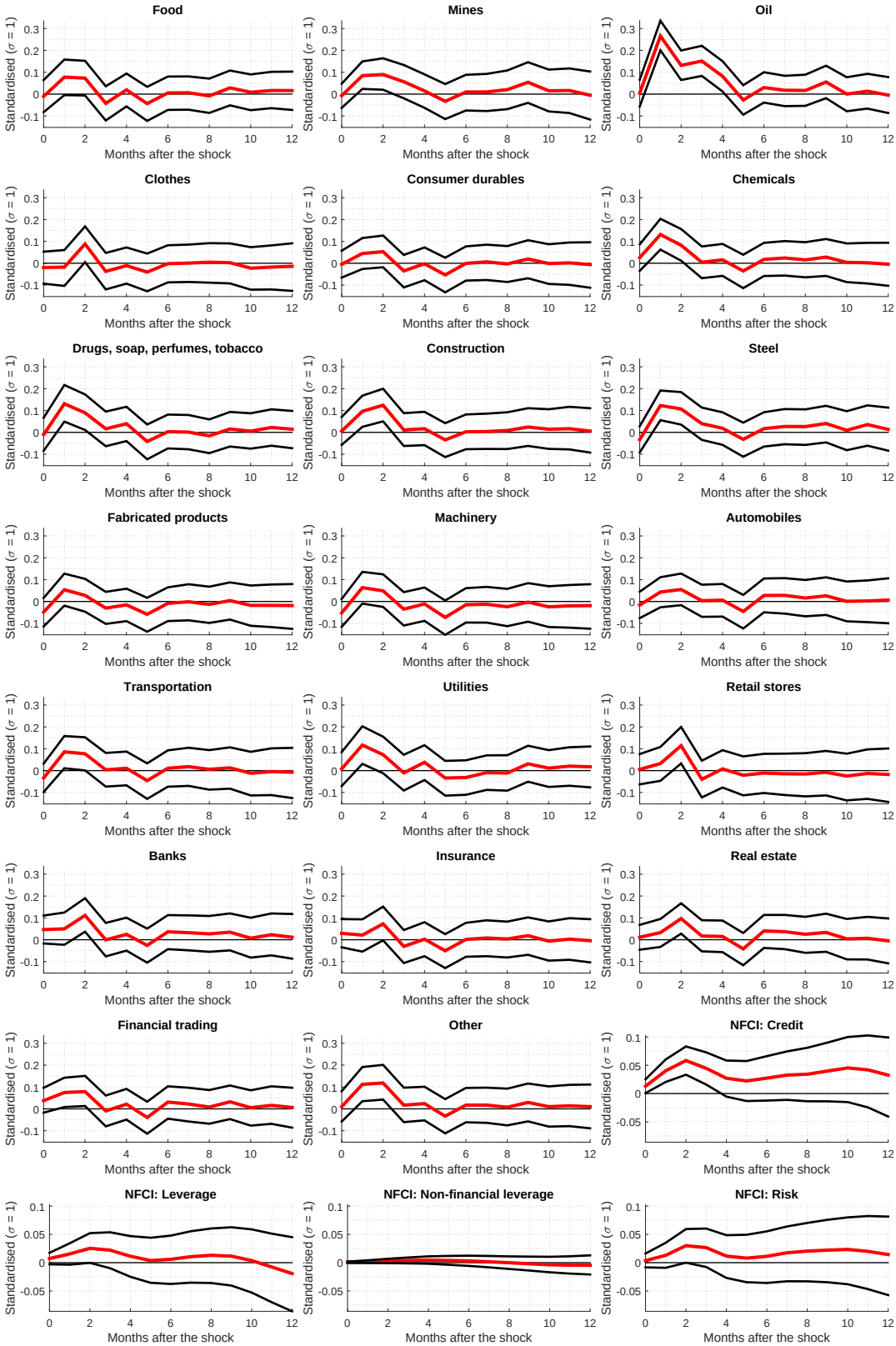


Figure A.8: Increase in transition risk under TR1 for industry portfolio variances and NFCI subcomponents

*Notes:* The figure shows the responses of the indicated variables to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

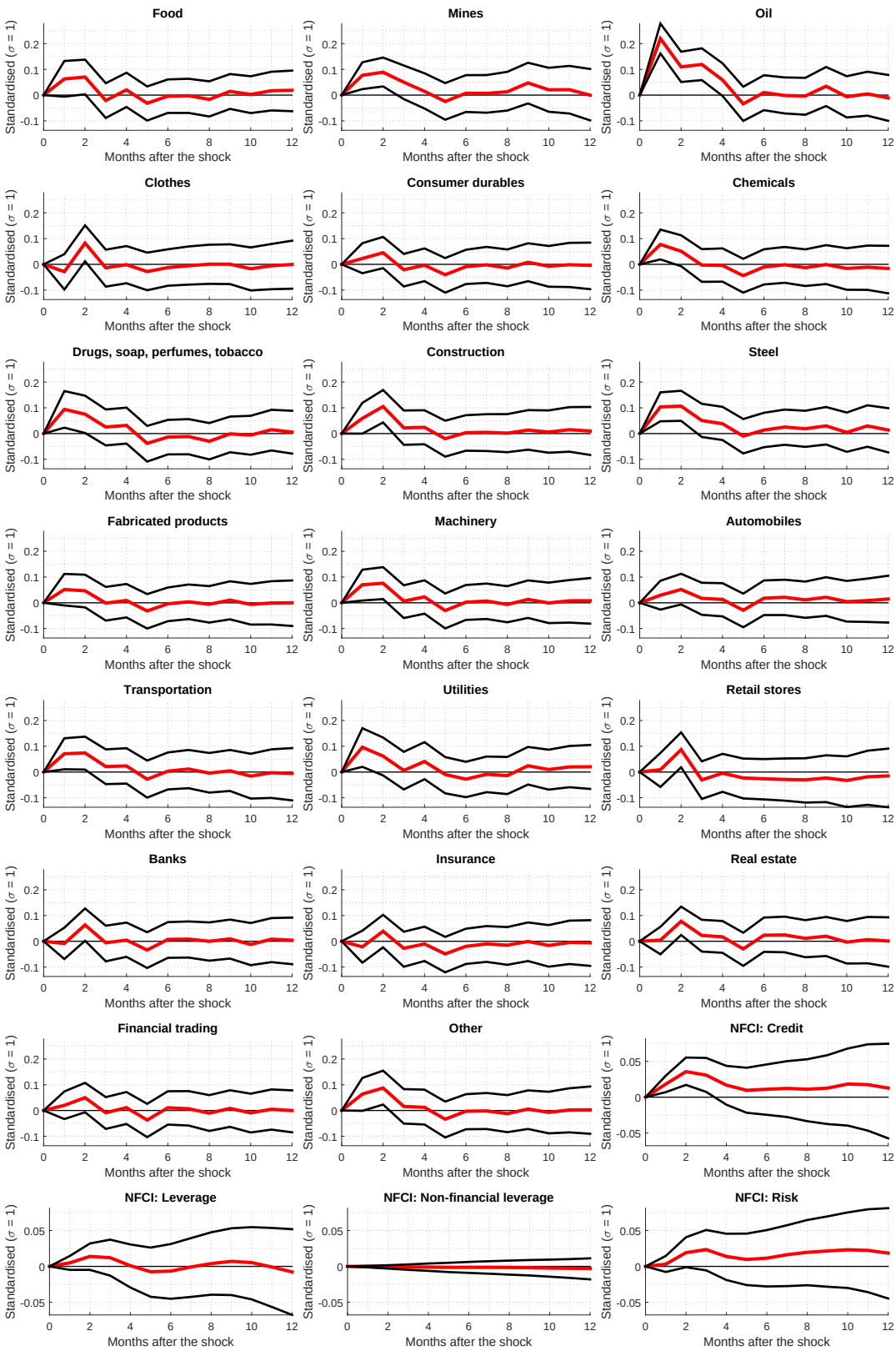


Figure A.9: Increase in transition risk under TR2 for industry portfolio variances and NFCI subcomponents

*Notes:* The figure shows the responses of the indicated variables to a shock that increases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

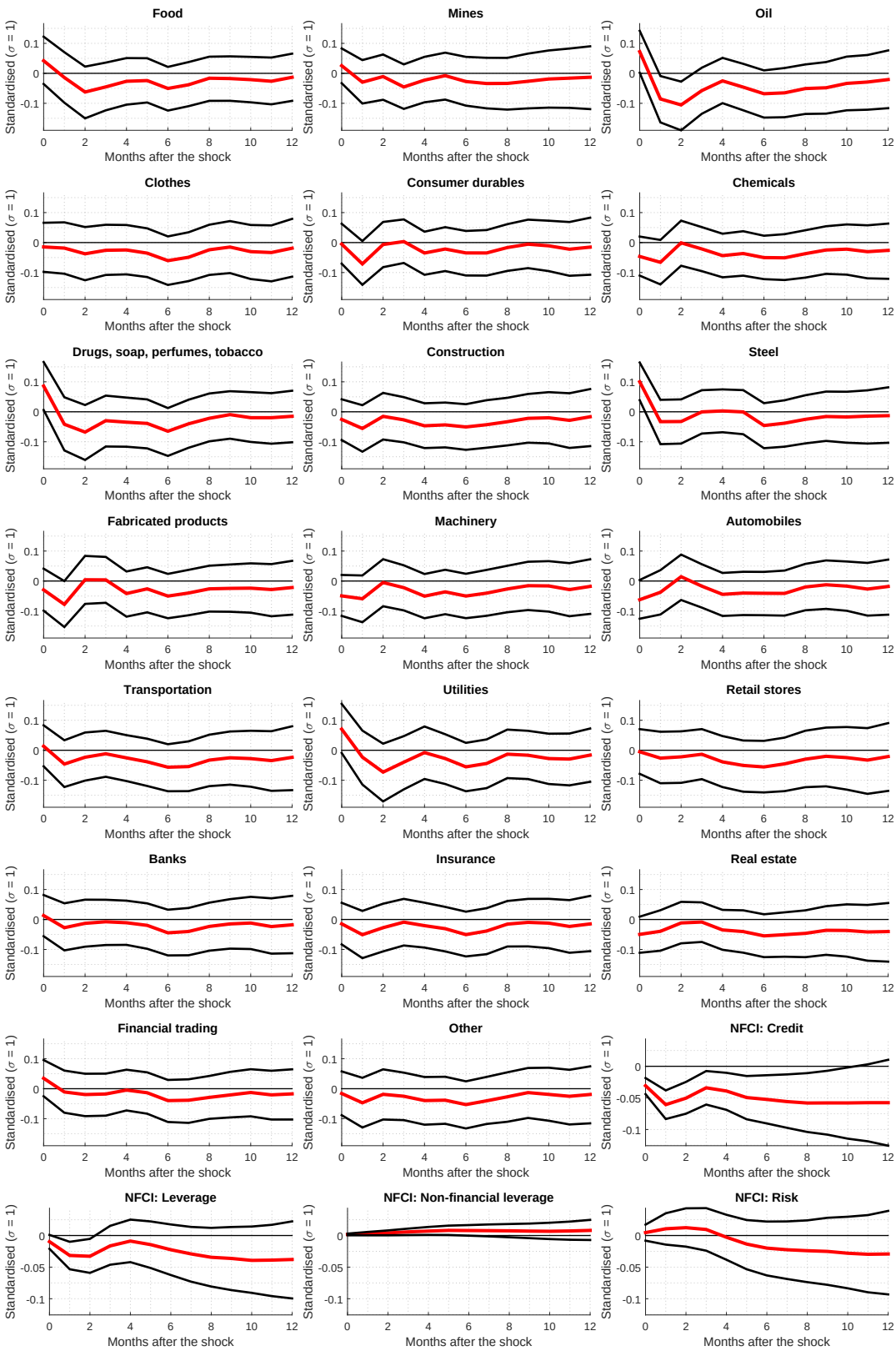


Figure A.10: Decrease in transition risk under TR1 for industry portfolio variances and NFCI subcomponents

*Notes:* The figure shows the responses of the indicated variables to a shock that decreases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR1 means that the structural shock to transition risk can affect all variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.

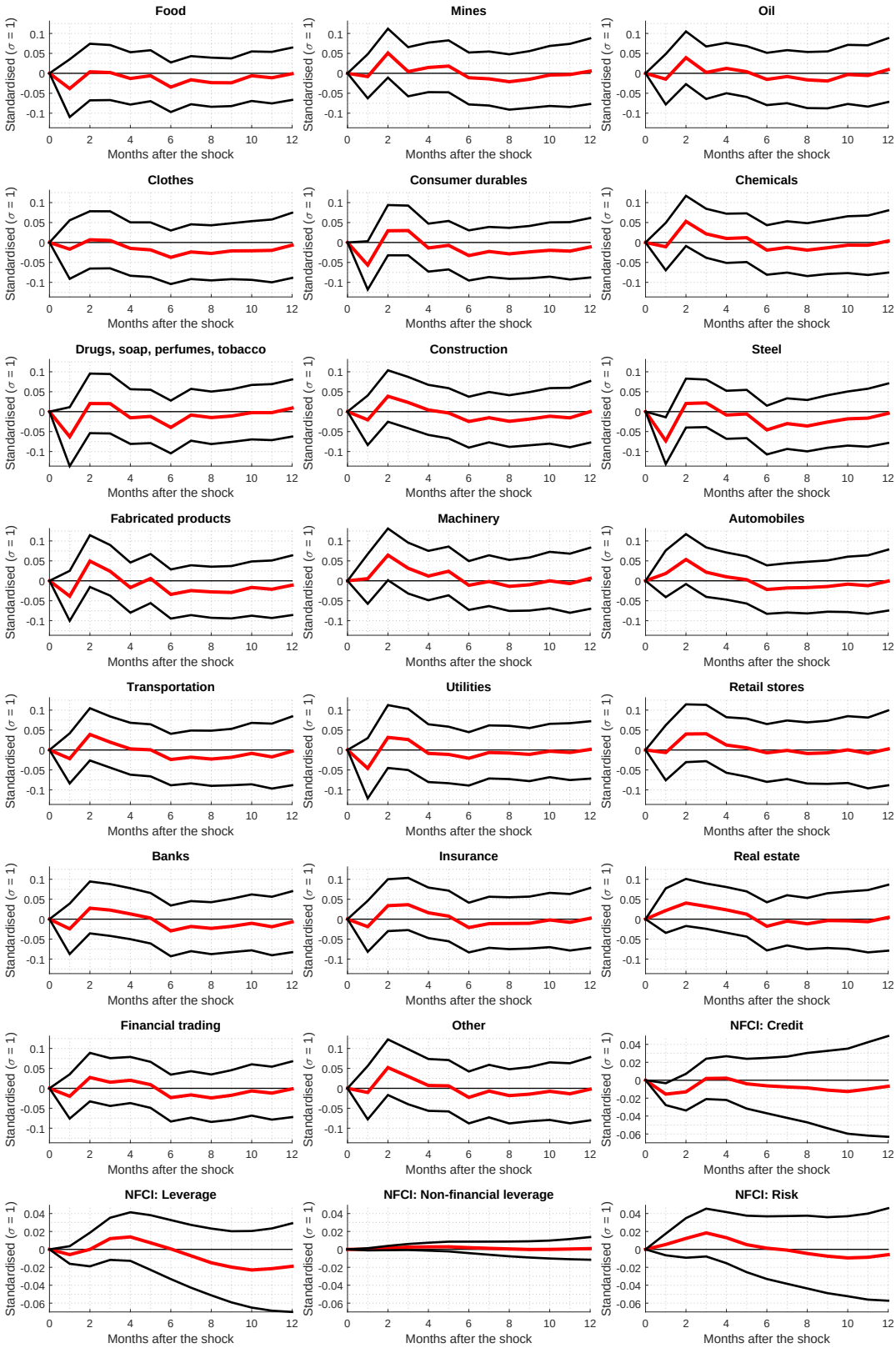


Figure A.11: Decrease in transition risk under TR2 for industry portfolio variances and NFCI subcomponents

*Notes:* The figure shows the responses of the indicated variables to a shock that decreases transition risk. Transition risk shocks are instances where "climate change information" alters the relative valuation of green and brown firms (see Section 2). TR2 means that the structural shock to transition risk cannot affect variables contemporaneously (see Section 3.2). Black lines show the 68% highest density region.