Discussion Paper

Shocks to transition risk

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Non-technical summary

Research question

Climate change is associated with a substantial increase in various types of risks. One of these risks is transition risk. It can be thought of as the risk resulting from the process of adjustment towards an economy with net zero carbon emissions. As this process unfolds, assets may lose value, which in turn can have repercussions for the aggregate economy. Industries with higher carbon emissions will tend to be more exposed to transition risk as their production processes are affected more strongly by the transition. To date, however, the measurement of transition risk is still fragmented. In this paper, we propose a lean, transparent and yet comprehensive approach to analyze transition risk.

Contribution

Our method overcomes two key challenges regarding the definition and measurement of transition risk. (i) Typically, economists measure transition risk only by isolating certain prominent drivers, such as fiscal policies that support the reduction in carbon emissions. (ii) Consequently, the associated implicit definition of transition risk encompasses only one or two particular features of transition risk. Our approach combines equity return data with a textual analysis of newspaper archives in an innovative way. The resulting measurement and definition of transition risk is comprehensive, accommodating the variety of reasons why transition risk may change over time.

Results

We apply our method to data from the United States from 2010 to 2018 and discover four transition risk shocks. Our narrative analysis indicates that all these shocks can be interpreted as events that increase the likelihood of an orderly transition. For instance, we identify the climate deal between the United States and China in November 2014 and the Paris Agreement in December 2015, among others. We then show that our transition risk shocks have important effects on the economy and on financial stability for the United States. A shock reduces both industrial production – especially in climate-sensitive sectors like "energy materials" – and prices, which points towards transition risk shocks being rather deflationary. Additionally, a shock significantly deteriorates credit conditions and raises volatility on financial markets. When applying our method to data from Germany and the United Kingdom, we again find that transition risk shocks have important effects on the economy and on financial stability. Yet, country specificities play an important role in this regard.

Nichttechnische Zusammenfassung

Fragestellung

Der Klimawandel geht mit einer starken Zunahme bestimmter Risiken einher. Eines dieser Risiken ist das sogenannte Transitionsrisiko. Darunter versteht man ganz allgemein das Risiko, das aus dem Prozess der Annäherung an das Ziel einer CO2-neutralen Wirtschaft resultiert. Im Zuge dieses Prozesses können Vermögensgegenstände an Wert verlieren, was wiederum Auswirkungen auf die Volkswirtschaft als Ganzes haben kann. Wirtschaftszweige mit höheren CO2-Emissionen sind diesem Transitionsrisiko im Allgemeinen in größerem Maße ausgesetzt, da ihre Produktionsprozesse von der Transition stärker berührt werden. Die Messung des Transitionsrisikos erweist sich bislang allerdings als schwierig. In diesem Papier schlagen wir einen einfachen, transparenten und gleichzeitig umfassenden Ansatz zur Analyse des Transitionsrisikos vor.

Beitrag

Unsere Methode überwindet zwei zentrale Herausforderungen hinsichtlich der Definition und Messung des Transitionsrisikos. (i) Ökonomen messen das Transitionsrisiko in der Regel, indem sie sich lediglich auf einzelne Einflussfaktoren konzentrieren, beispielsweise fiskalpolitische Maßnahmen zur Reduktion von CO2-Emissionen. (ii) Folglich erfasst die damit einhergehende implizite Definition nur einige wenige Ausprägungen des Transitionsrisikos. Unser Ansatz basiert auf einer innovativen Kombination von Daten zu Aktienrenditen mit einer Textanalyse von Zeitungsartikeln. Die resultierende Messung und Definition des Transitionsrisikos ist umfassend und berücksichtigt die Vielzahl von Ursachen, die das Transitionsrisiko im Zeitablauf variieren lassen.

Ergebnisse

Wir wenden unsere Methode auf US-amerikanische Daten der Jahre 2010-2018 an und identifizieren dabei vier Transitionsrisikoschocks. Unsere narrative Analyse ergibt, dass alle vier Schocks als Ereignisse interpretiert werden können, die eine geordnete Transition wahrscheinlicher machen. Beispiele sind der Klimavertrag zwischen den USA und China im November 2014 sowie das Pariser Klimaabkommen im Dezember 2015. Im Anschluss zeigen wir, dass Transitionsrisikoschocks starke Auswirkungen auf die US-amerikanische Volkswirtschaft und auf die Finanzstabilität haben. Ein Schock reduziert sowohl die Industrieproduktion – vor allem in klimarelevanten Sektoren wie fossiler Energieerzeugung – als auch das Preisniveau, was auf einen eher deflationären Charakter von Transitionsrisikoschocks hindeutet. Außerdem stellen wir fest, dass Kreditkonditionen beeinträchtigt werden und die Volatilität an Finanzmärkten steigt. Wir wenden unsere Methode auch auf Daten aus Deutschland und dem Vereinigten Königreich an. Hier finden wir ebenfalls starke Auswirkungen auf die jeweilige Volkswirtschaft und die Finanzstabilität, allerdings spielen länderspezifische Faktoren eine große Rolle.

SHOCKS TO TRANSITION RISK

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We propose and implement a method to identify shocks to transition risk, addressing key challenges regarding its definition and measurement. Our shocks are instances where significant new information about the economic relevance of climate change increases the valuation of green firms over brown firms. To illustrate our method, we identify shocks to transition risk in the United States. These shocks have important aggregate effects, also inducing financial instability. They are associated with events that increase the likelihood of an orderly transition, and they specifically affect parts of the economy related to fossil fuels and energy. We show that these main results carry over to Germany and the United Kingdom. Still, we find an important role for country specificities.

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

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

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1 Introduction

Economically, climate change goes along with a substantial increase in various types of risks. These are typically categorized as being either physical or related to economic transition. Physical risk is the risk arising from an increase in the severity and frequency of extreme weather events, including potential costs from the adaptation to it. It has been at the core of the empirical literature in this field for years.[1] In contrast, transition risk has received much less attention in the past, but the political and economic debate about costs and benefits of the transition to net zero carbon emissions has intensified.[2]

The growing attention being given to transition risk has uncovered key challenges for empirical research, of which we want to highlight two. First, a precise definition of transition risk that may guide analyses is still missing. Broadly speaking, transition risk can be thought of as the risk resulting from the process of adjustment towards an economy with net zero carbon emissions. But this rough definition is hard to operationalize. Therefore, economists typically resort to defining transition risk by isolating particular drivers, for instance, fiscal policies that support the reduction of carbon emissions, but also technological change or shifts in household preferences that can render certain industries, products or firms obsolete.[3]

Second, the lack of a precise definition makes the measurement of transition risk challenging. For one thing, it is impossible to directly quantify transition risk, because the expected path (or the distribution of paths) towards a lower-carbon economy is unobservable. Rather, it must be inferred. For another, a variety of factors shape transition risk. As a result, the vast majority of (both theoretical and empirical) researchers rely on proxies that typically capture only one or two particular features of transition risk.[4] In tandem, it is far from clear how these proxies – possibly endogenously (see, for example, Metcalf and Stock (2020)) – relate to this expected path to a lower carbon economy.[5]

Against this background, this paper proposes a lean, transparent and, at the same time, comprehensive approach to studying transition risk, addressing both challenges sketched above. We derive a method to extract (i.e. to measure) an empirical time series of transition risk shocks, i.e. instances at which there is a significant change in the distribution of paths towards a lower-carbon economy. Our method relies on two very mild and uncontroversial assumptions only.

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[1]A comprehensive overview of the current state of climatological research is provided, for instance, in the regular reports of the Intergovernmental Panel on Climate Change (IPCC).

[2]The need for academic guidance in this debate is illustrated, for instance, by the former US President Donald Trump, who justified the withdrawal from the Paris Accord by the "draconian financial and economic burdens" that were (seemingly) implied by the agreement (`https://it.usembassy.gov/statement-president-trump-paris-climate-accord/`, last accessed 29.06.2022).

[3]An overview of such examples is, for instance, provided in a report by the Network for Greening the Financial System (2020).

[4]For instance, Ciccarelli and Marotta (2021) resort to a climate policy stringency index and the amount of green patent filings as proxies. Kaenzig (2022) relies on carbon price data from the EU ETS futures markets. In theoretical macroeconomic research, like integrated assessment models in the spirit of Nordhaus (2018), the transition dynamics are often embodied in a single variable called the social cost of carbon. In spirit, perhaps closest to our paper is Moench and Soofi-Siavash (2022), who extract shocks that explain the maximum share of variation in emission intensity at a 20-year horizon from country-level carbon emissions data.

[5]For physical risk neither of the challenges apply, being easily defined and measured. Specifically, the observation of extreme weather events and the achievements of climatological research provide detailed information about physical risks.

Specifically, we assume that a sudden, economy-wide increase in transition risk (i) raises the valuation of green firms over brown firms and (ii) is accompanied by important public information. In this sense, our understanding of transition risk is comprehensive, accomodating the variety of reasons why transition risk may change. The interpretation of our shock series is thus also different from simple proxies like, for instance, changes in carbon taxation. Essentially, our paper can also be regarded as providing an implicit definition of shocks to transition risk.

Practically, our approach combines information from long-short equity portfolios sorted on firms' carbon footprints with textual analysis of newspaper archives. We first construct monthly long-short (brown-minus-green) equity portfolios by sorting firms according to their carbon footprints. Next, we build a monthly newspaper-based index capturing the amount of major economic news related to climate change. As the final step, our methodology identifies months of major news that occur in tandem with extreme negative portfolio returns, i.e. instances at which green firms abnormally outperform brown firms.

Besides its robust and transparent design, this reduced-form approach is best suited to our purpose for a number of other reasons. First, our approach is designed to meaningfully and robustly exploit data with low reliability, as is the case with data on firms' carbon footprints (see also Giglio, Kelly, and Stroebel (2021)). Second, our monthly frequency aligns the portfolio and the news index more reliably than, for instance, resorting to a daily frequency. Third, including information from newspapers deepens our understanding of transition risk, since they provide narratives (see, for example, Romer and Romer (2004, 2017)). Fourth, the brown-minus-green portfolios help us disentangle transition risk and physical risk, which are deeply interrelated. This is because changes in physical risk typically do not affect green and brown firms differently. Fifth, including information from equity returns makes our approach rather forward-looking, in the sense that it dissects future paths towards a lower-carbon emissions, as opposed to rather backward-looking approaches like Koch, Naumann, Pretis, Ritter, and Schwartz (2022), who rely on historical carbon emissions. Section 2.5 provides a more detailed discussion of the benefits of our methodology.

We illustrate our method by applying it to data from the United States from 2010 to 2018. For this time period, we find four transition risk shocks. Subsequently, we use narrative and econometric analyses to deepen our understanding of these shocks. Our narrative analysis indicates that all months can be interpreted as events that increase the likelihood of an orderly transition. For instance, we identify the climate deal between the United States and China in November 2014 and the Paris Agreement in December 2015, among others. We also apply our method to data from Germany and the United Kingdom as robustness checks. Again, our method reveals major political events that can convincingly be regarded as transition risk shocks, like the aftermath of the parliamentary elections in the United Kingdom in May 2015 and in Germany in November 2017. Arguably, this finding indicates that abrupt *shocks* to transition risk are mostly related to political decisions. Clearly, there may be other sources of time variation in transition risk, like changes in consumer preferences or technological progress. However, these events are not selected by our method. One argument is that these developments play out over longer horizons and, therefore, do not represent abrupt shocks.

Using a macro-financial Bayesian VAR, we show that our transition risk shocks have important

aggregate effects on the United States economy, also inducing financial instability. A shock significantly lowers the economic outlook for several months, reducing both industrial production and prices. Remarkably, our shock, on average, explains up to 24% of the variation in industrial production within the first year. The response of the price level points towards transition risk shocks being rather deflationary, confirming previous findings in the literature. Additionally, we show 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 34% of fluctuations in the EBP within the first year. It also significantly raises volatility on financial markets as indicated by the VIX.

Complementing the narrative analysis, we further validate our transition risk shocks by analyzing sectoral industrial production and sectoral Fama-French equity portfolio variances within the VAR. In line with the narratives, we find that a shock causes a strong decline in the industrial production of climate-sensitive sectors like "energy materials", explaining up to 25% of its variation. Most other sectors are hardly affected. The analysis of portfolio variances suggests that a transition risk shock strongly induces uncertainty in climate-sensitive industries such as oil (explaining up to 22% of variation), but not in other sectors.

Some of our empirical findings are confirmed for Germany and the United Kingdom. First, transition risk shocks have important aggregate effects, for instance inducing financial instability in equity and corporate bond markets. Second, the sectoral analysis further validates the shocks to transition risk. Similar to the United States, we find that transition risk shocks significantly affect fossil fuel and energy sectors.

However, there are also differences to the United States, most importantly concerning the response of aggregate industrial production and of the price level to a transition risk shock. For Germany, the response of industrial production is positive and the response of the price level is insignificant. For the UK, both responses are slightly negative, but hovering around zero. Altogether, one may thus argue that transition risk shocks generally resemble positive or negative demand shocks whose sign may be related to different economic structures of the respective countries, possibly linking to varying degrees of their economies' "greenness". In fact, the impulse responses line up well with publicly available indices like the Environmental Performance Index published by Yale University that claim to assess the climate policies of different countries or quantify the "readiness" of their economies for the transition to net zero. In such rankings, Germany and the United Kingdom have typically been among the global top 20, with Germany being "readier" than the United Kingdom. Still, the United Kingdom has been catching up considerably in recent years. In contrast, the United States has been lagging far behind all along.

We also detect other country specificities. For instance, we observe a strong reaction of the equity return variance of the "automobiles and parts" sector in Germany, possibly pointing towards elevated transition risk in this sector. For the United Kingdom, we find that transition risk shocks induce a large amount of uncertainty in the financial industry, perhaps pointing towards an elevated risk of stranded assets on banks' balance sheets.

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 (2017), Barnett (2019), Bolton and Kacperczyk (2021), Cornell (2020), Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2020) and Pastor, Stambaugh, and Taylor (2021). Related to this, there have been studies for other asset classes like corporate credit (Delis, de Greiff, and Ongena (2020)), equity options (Ilhan, Sautner, and Vilkov (2021)), or CDS spreads (Blasberg, Kiesel, and Taschini (2022)). Importantly, the majority of this literature tries to understand whether climate-related risks are priced in financial markets *at all*. This literature is not concerned with questions of market efficiency, i.e. whether climate-related risks are priced *correctly*. This is also true for our paper. While our approach builds on the assumption that transition risks are priced, we abstain from overinterpreting the exact size of the extreme brown-minus-green return observations.

Moreover, all these approaches present 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, as is also illustrated by Ardia, Bluteau, Boudt, and Inghelbrecht (2020). These authors find that, on days with an unexpected increase in climate change concerns, green firms' stock prices tend to increase while brown firms' prices decrease. A similar approach is taken by Pastor et al. (2021). While using similar data, our paper has a different focus, that is extracting shocks through a coexceedance approach and subsequently understanding their macrofinancial impact. Combining return data with news also allows 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), Kapfhammer, Larsen, and Thorsrud (2020), Bua, Kapp, Ramella, and Rognone (2021) 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 example of the latter is the withdrawal of the United States 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 to transition risk. Fried, Novan, and Peterman (2021) develop a theoretical model of climate policy uncertainty and show that climate policy risk causes the capital stock to shrink, but also to become cleaner. Gavrilidis (2021), Wang (2022) and Basaglia, Carattini, Dechezleprêtre, and Kruse (2022), among others, use climate policy uncertainty indices in empirical applications.

There is a growing literature that studies the effects of transition risk on macroeconomic vari-

ables. But as explained above, most papers in this direction rely on proxies that capture only a few dimensions of transition risk. Their macroeconomic results, typically derived via VAR methods, exhibit both similarities and differences when compared to ours. Kaenzig (2022) identifies carbon policy shocks with European data from futures on EU-ETS emission allowances. He finds that tighter carbon pricing leads to an uptick in green innovation, a temporary fall in economic activity, a rise in consumption inequality, a lower real effective exchange rate, a lower policy rate, and a higher HICP price level. This contrasts with the rather deflationary nature of transition risk shocks that we find for the United States. Metcalf and Stock (2020) use data on carbon prices and carbon taxes from 31 European countries. Using local projections, they find that carbon taxes have positive, but mostly insignificant effects on GDP and employment, which is perhaps roughly compatible with our results for Germany. Ciccarelli and Marotta (2021) resort to a climate policy stringency index and the amount of green patent filings as proxies. Differently from our results, they find that transition policies or technology improvements resemble downward supply rather than demand shocks. Moench and Soofi-Siavash (2022) extract a series of carbon intensity shocks from country-level carbon emissions data. They show that their carbon intensity shock is highly correlated with a measure of TFP news shocks and explains similar fractions of GDP at longer horizons.

Structural macroeconomic models, for example integrated assessment models in the spirit of Nordhaus (2018) or Golosov, Hassler, Krusell, and Tsyvinski (2014), typically incorporate a carbon price as the single tool to internalize climate externalities and study the properties and implications of the so-called social cost of carbon in equilibrium.[6] In applications, the Network for Greening the Financial System (NGFS) and its members resort to scenario analyses to further reduce the enormous complexity and address the lack of a proper way to capture all relevant dimensions of transition risk. But historical evidence on the transition that we have seen so far indicates that actual climate policy is much more complicated than implementing theoretically optimal policy instruments like a proper carbon price. It involves a plethora of further issues like, for instance, the timing of policy actions, the (almost always suboptimal) policy mix, the uncertainty around policies, the international coordination of policies, the evolution of technology pathways to reduce emissions, or the evolution of consumer preferences.[7]

Finally, researchers who study general equilibrium models of climate change economics sometimes 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.

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[6]For a comprehensive synopsis of the pros and cons of these models, see, for instance, Nordhaus (2019), Pindyck (2017) or Farmer, Hepburn, Mealy, and Teytelboym (2015).

[7]See, e.g., Network for Greening the Financial System (2020)

2 Identifying shocks to transition risk

2.1 Key assumptions

The brief literature review above demonstrates that a growing number of researchers and policymakers have been analyzing transition risk. However, this discussion is lacking a concise and widely accepted definition of transition risk to begin with.

Complexity is the most likely reason for this lack of a broadly accepted definition of transition risk. A vast range of climate policies (think of carbon taxes, subsidies for electric cars, support for energy-efficient housing, etc.) links to transition risk. Similarly, technological change or shifts in household preferences that render certain industries, products or firms obsolete can contribute to transition risk. But transition risk can go far beyond and, for instance, also result from changes in the regulatory framework, such as policies related to sustainability reporting and disclosure, and geopolitical developments. On top of that, the factors that are tied to transition risk likely vary over time, for instance, when moving towards a decarbonized economy.

The key contribution of our paper is to move the debate on transition risk one step further. Specifically, we provide a methodology that allows to measure – and therefore implicitly define – *shocks* to transition risk. To do so, we make use of two, in our view, mild and uncontroversial structural assumptions about the observability of such shocks.

Assumption 1 *A sudden, economy-wide increase in transition risk raises the valuation of green firms over brown firms.*

Assumption 2 *A sudden, economy-wide increase in transition risk is accompanied by important public information.*

By relying only on these very basic assumptions, we make sure that our methodology encompasses a broad set of factors that may affect transition risk, accommodating various and varying reasons why transition risk may change. Thus, our understanding of transition risk is comprehensive and the interpretation of our shock series is going to be different from simple proxies like, for instance, changes in carbon taxation. In this sense, our methodology can also be regarded as a step towards a comprehensive definition of transition risk.

More specifically, we identify shocks to transition risk by synthesizing information from two distinct sources that are related to the above two assumptions. To operationalize the first assumption, we construct long-short (brown-minus-green) equity portfolios by sorting firms according to their carbon footprints. For the second assumption, we build a monthly newspaper-based index capturing the amount of major economic news related to climate change. Our methodology then identifies months of major news that occur in tandem with extreme negative portfolio returns, i.e. instances at which green firms abnormally outperform brown firms. Put differently, one can think of our shocks to transition risk as instances where significant new information about the economic relevance of climate change increases the valuation of green firms over brown firms.

Importantly, Assumption 1 does not imply that an abnormal return of green over brown firms is a sufficient condition for the identification of transition risk shock; neither is the revelation of important public information (Assumption 2). By themselves, both may occur for a variety of reasons. Most obviously, there may be new important public information about climate change, which, however, does not feed into transition risk. But also stock market returns are inherently noisy and not only driven by information about transition risk. Therefore, we argue that by combining these two conditions – and focusing on times of both *abnormal* returns and *important* news (see Section 2.4) – we are able to measure shocks to transition risk, i.e. to establish sufficiency.

In the remainder of this section, we operationalize the two key assumptions, arrive at a time series of shocks to transition risk for the United States, and provide some further discussion on our methodology.

2.2   Long-short equity portfolios

We construct three long-short (brown-minus-green) US equity portfolios by sorting firms according to their carbon footprints. Importantly, we stick to standard procedures in order to keep our results replicable, easy-to-implement and robust. This also implies that our procedure is particularly suitable for a situation with low data coverage, as it is the case for measurement of transition risk. For robustness, we use two different data sources for firms' carbon footprints.

For the first portfolio sort, we rely on carbon emissions data from Eikon and equity returns from CRSP. We sort firms into portfolios based on their level of Scope 1 carbon emissions. The availability of data on firms' carbon footprints determines the start of our sample period. It covers January 2010 until December 2018.[8] We disregard all other ESG variables in Eikon because of data scarcity. In general, the data coverage for historical carbon footprints in Eikon is low, with only a few hundred firms per year towards the end of our sample period.

For the second and third portfolio sort, we rely on carbon emissions data from ISS-ESG and equity return data from Eikon. We sort firms into portfolios based on their levels of Scope 1 carbon emissions and on their Scope 1 carbon intensities, where intensity is defined as the ratio of a firm's carbon emissions over its revenues (in USD). The sample period of these two portfolio sorts covers July 2013 until December 2018. We disregard all other ESG variables (in particular Scope 2 or 3 emissions) because the reliability of such data is unclear. Altogether, our sample covers about 3,000 firms towards the end of our sample period. But one has to acknowledge that a large fraction of the carbon emissions in the ISS-ESG database are estimated by ISS-ESG and not disclosed by the respective firms themselves.

The portfolio sorting procedure itself follows standard practice in asset pricing. We sort all firms into carbon footprint quintiles according to their emissions in the previous year and form value-weighted quintile portfolios. The composition of the quintile portfolios changes only once per year, in July. We then track the monthly returns of these value-weighted quintile portfolios. We orthogonalize these returns with respect to systematic risk, i.e. we regress each quintile

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[8]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.

portfolio excess return on the three Fama-French factors (one regression for the whole sample period) 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 5 and 1. We thus end up with three climate long-short factors, interpreted as "brown-minus-green". A positive value for these factors implies that carbon-intensive ("brown") firms exhibit abnormally high returns in a given month relative to carbon-unintensive ("green") firms.

Since the ISS-ESG data only starts in mid 2013, we disregard the first 3.5 years of Eikon ESG data for the results presented here. However, in a previous version of this paper, we have also included results for the period starting in 2010. In fact, we do not detect any transition risk shocks in the United States in this period with our method (also when we include other sorting variables from Eikon), which is in line with the narrative that there was no stringent transition towards net zero at all in the early 2010s in the United States.
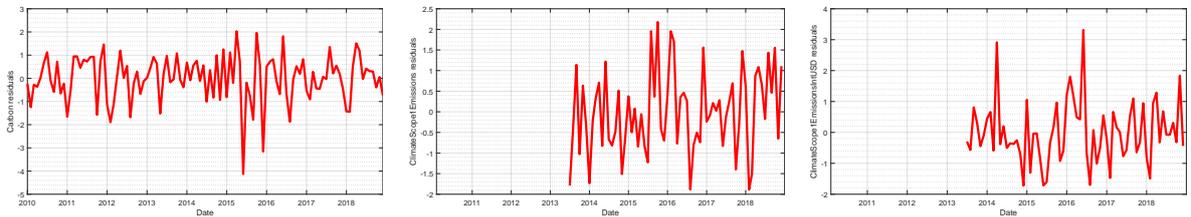

Figure 1: Fama-French 3-factor residuals of the returns of the brown-minus-green portfolios

Notes: A positive value for these monthly factors implies that carbon-intensive (i.e. "dirty") firms exhibit abnormally high returns. We construct brown-minus-green equity portfolios by sorting firms on their carbon emissions (with Eikon data for the left picture and ISS data for the middle picture) and emissions intensity (right picture). We sort all firms into quintiles and form value-weighted quintile portfolios. To orthogonalize these returns with respect to systematic risk, we regress each quintile portfolio excess return on the three Fama-French factors. Residuals are standardized to unit variance.

Figure 1 depicts the Fama-French residuals of the returns of these three long-short portfolios. By construction, the mean of all three time series is zero. But brown-minus-green portfolios (before orthogonalization) typically do have significant Fama-French alphas. The literature has documented a sizeable risk premium for brown firms over green firms (see, for example, Bolton and Kacperczyk (2021)), and we also find this in our sample. For instance, the first long-short portfolio has an alpha of +0.1 percentage point monthly over our sample period starting in 2010. 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.

2.3   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 United States newspapers and determine the number of articles per month that contain our search phrase.[9]

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

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[9]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.

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 is a great deal of 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 has become increasingly relevant over the past decade. We want our analysis to be unbiased by the overall 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 129,600.[10] We show the resulting news index in Figure 3 in Section 2.4 when discussing the identified shocks to transition risk.
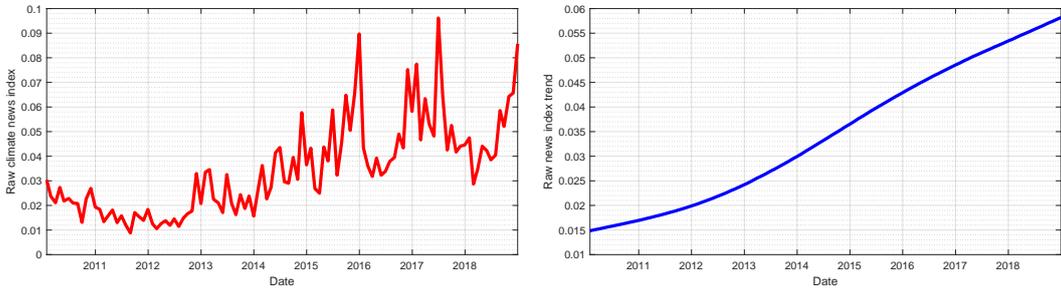

Figure 2: Raw climate news index and its trend component.
Notes: The raw climate news index is the fraction of newspaper articles on economics that also involve climate change. We identify the trend component by using a Hodrick and Prescott (1997) (HP) filter with 129,600 as a value for the smoothing parameter and extending the raw climate news index prior to 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 remarkable insofar as we normalize the news index by the amount of general economic news. The relative amount of economic news which relates 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.[11] On this ground, we prefer simplicity over completeness in our benchmark setup. The correlation between our index and the Engle et al. (2020) index is around 30%. Part of

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[10]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 2018, i.e. exceeds the sample period used in the following analysis. For our purpose, the use of a two-sided filter is important so as to avoid phase shifts that would disturb the identification of months of transition risk shocks (see Schüler (2018)).

[11]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.

this difference results from including the word "economics" in our key search phrase and from the subsequent normalization.[12]

Importantly, our search phrase is not specifically targeted towards transition risk, but might in principle capture any other climate-related news, for instance also news related to the occurence of natural disasters. Rather, it is the combination with equity returns in the next step that lets us separate physical and transition risks, reflecting the idea that natural disasters do not hit brown and green firms differently. Moreover, our simplistic search phrase also makes sure that our search is not biased towards a specific form of transition risk (like changes in carbon taxation or other climate policies). The characteristics of the transition risk shocks that we find are not driven by the choice of a dedicated search phrase.

2.4 Synthesizing information from long-short equity portfolios and the news index

As the final step of our procedure, we combine the brown-minus-green equity portfolio returns and the news index, relying on a coexceedance approach. From our return time series, we extract all months in which at least one of the three returns of our brown-minus-green portfolios is more than one standard deviation below its mean (which is zero, by construction). From the climate news time series, we extract all months in which the index is more than one standard deviation above its mean. Finally, our set of transition risk shocks is defined as the overlap between these two sets of months.[13]
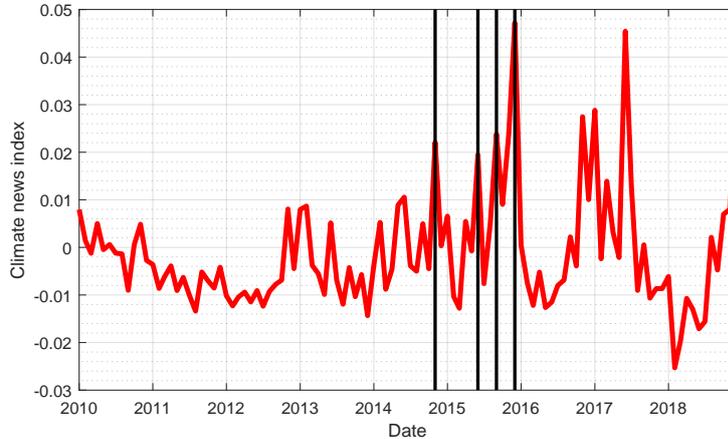

Figure 3: Shocks to transition risk (vertical bars) and climate news index (solid line)
Notes: Solid vertical bars indicate transition risk shocks. The solid line is the climate news index, i.e. the detrended version of our raw news index (see Section 2.3).

This procedure leaves us with four identified transition risk shocks, as shown in Figure 3 by the vertical lines. We discuss the economic narratives as well as the macro-financial implications of these shocks in more detail in Section 3.

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

[13]We perform extensive robustness checks and confirm that our results are, by and large, robust to the choice of the one standard deviation threshold.

It is important to emphasize that we only focus on shocks that increase transition risk. We do so for two reasons. First, given the current debate, policymakers and regulators require detailed analyses on the effects of transitioning to net zero, i.e. positive transition risk shocks, so as to guide their policy decisions. Second, the literature suggests that shocks which decrease transition risk should be very different from shocks which increase transition risk. For instance, it is not clear to what extent negative shocks to transition risk are credible events. Their effects – if any – may be rather transitory. In a recent paper, Ramelli, Wagner, Zeckhauser, and Ziegler (2021) show that both carbon-intensive firms as well as firms which are on a credible path towards net zero experience stock price *appreciations* after the election of Donald Trump in 2016. The authors explain the latter finding with long-term investors betting on a "boomerang" in climate policy. We confirm this intuition in an exercise that we report in Appendix C, where we also analyze negative transition risk shocks.[14]

2.5   Discussion

As we have outlined above, synthesizing information from portfolio returns and news is supposed to establish sufficiency for our two key assumptions. But our approach is best suited to our purpose for a number of further reasons.

First, our approach is designed to meaningfully and robustly exploit data with low reliability, as is the case with data on firms' carbon footprints (see also Giglio et al. (2021)). On the one hand, we use the top and the bottom quintile portfolios, i.e. only firms with very extreme carbon footprints that can clearly be labeled as green or brown. On the other hand, we supplement this portfolio with an analysis of news. Furthermore, we also focus on Scope 1 emissions data only. This data is more robust to data quality issues. Finally, the sorting variables are (almost) publicly available and rather stable over time, which reduces the concern of a potential look-ahead bias in the portfolio sorts.

Second, using monthly data makes our analysis more robust as well. Monthly data, in contrast to daily data, smoothes the information such that the news index and the portfolio returns can be brought in accordance more reliably. On the one hand, it is not clear how reliable a single portfolio return can be linked to its single causal event using daily data. On the other hand, the focus on a monthly period ensures that we identify rather large shocks to transition risk. This is because our shocks represent abnormal returns and important news over this longer time-span.

Third, the focus on potentially larger events also facilitates a narrative-based understanding of the shocks. For this, we evaluate the newspaper archives in more detail in Section 3. This allows us to gain a deeper understanding of the different factors driving transition risk, which is vitally important for policymakers and regulators (see, for example, Romer and Romer (2004, 2017)).

Fourth, physical risk and transition risk (and their shocks) are obviously interrelated: without any increase in physical risk, there would be no risk of transitioning to a carbon-neutral

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[14]We find that shocks decreasing transition risk are indeed less important than shocks increasing transition risk. In addition, their macro-financial impact deviates from the impact of positive shocks. Taken together, this justifies our approach to analyze positive and negative shocks separately and to focus on positive shocks for the benchmark case.

economy in the first place. Incorporating the brown-minus-green portfolio returns allows us to differentiate shocks to transition risk from shocks to physical risk. Damages from climate-related extreme weather events should not hit green and brown firms in a systematically different way. Of course, extreme weather events may affect the differential valuation of green and brown firms indirectly, for instance if they increase the likelihood of stricter climate policy going forward or if they provoke an abrupt change in consumer preferences. But such an instance would then constitute exactly the sort of shock to transition risk that we are interested in.

Fifth, studying first moments of returns implies that our transition risk shocks may also be differentiated from shocks to policy uncertainty in the spirit of Baker et al. (2016). Uncertainty should be reflected in second moments of returns rather than first moments. This distinction is also confirmed by our narrative analysis in Section 3. The shocks that we identify are often related to the aftermath of political decisions, through which significant information on the most likely transition path to a lower carbon economy is revealed. If at all, they should thus rather be interpreted as a *reduction* in uncertainty.

Sixth, augmenting our analysis by the news index addresses a concern that is sometimes raised when researchers extract market expectations from financial returns only. Without further adjustments, financial returns – like the brown-minus-green portfolio returns – can only give us information about changes in transition risk under the risk-neutral probability measure. However, for any subsequent macrofinance analysis, we require expectations under the physical probability measure. Our coexceedance approach represents a rough and indirect way of addressing this concern. While both changes to an asset's cash flow distribution as well as changes to the investors' pricing kernel may be responsible for price movements, we conjecture that the news index allows us to detect the former rather than the latter. As the subsequent qualitative and quantitative analysis reveals, our identified transition risk shocks are indeed linked to changes in expectations under the physical probability measure, for example regarding the riskiness of an asset's future cash flows, and do not just represent changes in investors' risk preferences.

Seventh, including information from equity returns makes our approach rather forward-looking, in the sense that it dissects future paths towards a lower-carbon emissions, as opposed to rather backward-looking approaches like Koch et al. (2022), who rely on historical carbon emissions.

3 Understanding shocks to transition risk

Having identified shocks to transition risk, this section aims to facilitate our understanding of these shocks. For this purpose, we first discuss underlying narratives. Second, we assess macro-financial implications by estimating a set of Bayesian VARs.

3.1 Narrative analysis: Evaluating newspaper archives

The construction of our news index leaves us with a set of newspaper articles for each month. For the index, we simply count these articles, but of course they are rich with content. Using these sets of articles, we can attach narratives to each of the transition risk shocks.

Our identified shocks can be related to meaningful events, i.e. events that can be reasonably linked to changes in transition risk. For some months, we even find multiple events in the news archives. It turns out that transition risk shocks occur for a variety of reasons. But the majority of events reflect instances where political deals on carbon emission reductions have been reached. Interestingly, we find that some potential sources of transition risk do not appear as shocks. For instance, according to recent policy discussions, changes in consumer preferences or technological progress could also be drivers of transition risk.[15] However, these events are not selected by our method. One argument is that these developments play out over longer horizons and, therefore, do not represent an abrupt shock to transition risk.

November 2014 is the month of our first shock. In this month, the US and China announced a bilateral deal on reducing carbon emissions that reflected "one of the most significant international climate deals ever struck".[16] The deal was prepared quietly between the administrations of the world's two largest polluters over the previous nine months. For the first time in history, China committed to reduce the growth rate of its emissions to zero after 2030. At the same time, President Obama announced that, by 2025, the US would reduce their carbon emissions by 26-28% of their 2005 level.

Our second shock, June 2015, can be related to two events. First, the Obama administration announced the introduction of new emission and fuel efficiency rules for trucks, airlines and the energy industry. Second, on their yearly summit, which was held in Schloss Elmau in Germany, the G7 countries agreed to reduce the world's carbon emissions by 40-70% by 2050, and to fully decarbonize the world economy by 2100.

For our third shock, September 2015, we find at least three distinct events. First, rumors started to emerge that President Obama could block the expansion of the important Keystone Pipeline System (which he then officially did in November 2015). Second, the Governor of the Bank of England, Mark Carney, gave his widely recognized speech on climate change and financial stability, in which he coined the term "tragedy of the horizon". This speech can be broadly interpreted as first evidence that climate change is also on the radar of central banks. Third, the UN Sustainable Development Goals were set by the UN General Assembly. These goals replaced and expanded the UN Millennium Development Goals that were primarily aimed at developing countries. The new, *global* goals were instead designed to apply to every country and comprise, among others, the aim to adapt to or mitigate climate change.

Finally, the Paris Agreement in December 2015 represents the largest transition risk shock in our sample, as indicated by the big spike in our news index. 196 countries adopted this landmark climate deal at the COP 21, the global climate summit in Paris. The goal is to limit global warming to at least 2, but preferably 1.5 degrees Celsius, as compared to pre-industrial levels. This goal is supposed to be achieved by curbing greenhouse gas emissions as quickly as possible and making the world fully climate-neutral until 2050.

Importantly, beyond identifying narratives for our shocks, the newspaper archives are also useful to learn about "significant" news that our methodology does *not* classify as shocks to transition risk. Specifically, not all months in which the newspaper-based index spikes represent shocks.

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[15]See, e.g., Network for Greening the Financial System (2020)

[16]A landmark climate deal (November 13, 2014), The Washington Post.

For instance, from a pure newspaper-based analysis, the withdrawal of the US from the Paris Agreement (officially announced in June 2017) would be perceived as major economic news related to climate change. However our brown-minus-green equity portfolios reveal that it was by and large anticipated by investors. The events that are connected to the election of President Trump or to political decisions during his presidency are also somewhat controversial in nature. From reading the newspaper articles from our Factiva search, we find that the economic response to President Trump's decisions is extremely diverse and heterogeneous. This is also in line with recent literature (see e.g. Ramelli et al. (2021)).

On the other hand, extreme portfolio returns alone do not necessarily identify as transition risk shocks either. We find months in which one of the long-short returns was rather extreme, but this was not reflected in the news. Examples of such months are February 2012 (-6.5%, standardized: -1.9%), August 2012 (-5.8%, standardized: -1.7%) and August 2016 (-6.5%, standardised: -1.9%). These returns do not coincide with significant news on climate change that could give rise to respective narratives. For instance, for February 2012 Factiva gives 37 articles, of which not one relates to an increase in transition risk. But clearly, in theory there could be events that relate to transition risk, but they were not big enough to be included in our analysis. As discussed, we use our approach to ensure sufficiency of the two assumptions.

3.2 Econometric analysis: Macro-financial implications of transition risk shocks

The second exercise serves two purposes. In line with the narrative analysis, it provides further validation of our proposed methodology for identifying shocks to transition risk. For instance, we evaluate whether the estimated macro-financial consequences fit the narratives outlined above. Second, the exercise allows us to assess whether and in what way shocks to transition risk are economically relevant. This is important for informing policymakers and regulators when going forward with the net zero transition.

3.2.1 Data

Our data comprises (aggregate and sectoral) log real industrial production, log real personal consumption expenditures, the log PCE deflator, 3-year Treasury yields, the difference between 10-year and 3-year Treasury yields, the excess bond premium of Gilchrist and Zakrajšek (2012), the VIX, and the cumulative excess return of the CRSP value-weighted equity index, which we label as equity prices in our graphs for simplicity. 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 17 industry portfolios available on Ken French's webpage. Because a focus of our paper lies on financial stability, we split the financial industry portfolio 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 add the four subindices of the national financial conditions index (NFCI), published 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).[17] Similar to the industry portfolio return 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 a dummy variable for the shocks to transition risk. Then, we multiply the dummy variable with our news index, such that it takes the value of the news index during the months of a shock and zero otherwise. We do so to allow for a varying importance of the shocks.[18] We then finally scale the shock series to unit variance again.

3.2.2 Methodology – Bayesian structural vector autoregression

To explore the macro-financial implications of transition risk shocks, we rely on a Bayesian structural vector autoregression (BSVAR) in the spirit of Waggoner and Zha (2003). Placing restrictions on the BSVAR model allows to mimic local projections (Jordà (2005)). Indeed, Plagborg-Møller and Wolf (2020) prove that local projections and VARs may estimate the same impulse responses under certain conditions. However, this is not yet clear for data with unit roots and cointegration which we have in our paper.

Let y_t be an $n \times 1$ vector of random variables at time $t = 1, \ldots, T$, C a vector of constants, $\mathcal{A}$ and $\mathcal{A}_l$ coefficient matrices of size $n \times n$, and ε_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. The compact form of model (1) is given by

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

where

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

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[17]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 indicators at the same time, since correlation of NFCI: Leverage and NFCI: Non-financial leverage is -0.75 for our sample period.

[18]In a robustness exercise (not reported in this paper), we undo the scaling and give equal weight to all shocks. Results remain qualitatively the same.

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 $y_{1,t}$ (1×1) 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 have used abnormal equity returns for the shock identification in Section 2, 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) 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 $n_2 \times 1$.

Structural shock identification: Restrictions on contemporaneous relations The procedure we propose to identify shocks to transition risk involves the dating of abnormal equity returns. Shocks only occur if the abnormal returns fall in a month with extreme values of the climate change news index. For our main analysis, we therefore assume that our shocks to transition risk are exogenous to other shocks in the economy. In the VAR setup this translates into the condition that our transition risk shock series can impact all variable contemporaneously, which we specify in $\mathcal{A}$.

Specifically, 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 upper-triangular.

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. Then we draw $\mathcal{F}$ from its conditional posterior distribution. We do so 15,000 times to estimate the joint posterior, 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)).[19] 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.[20]

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

[20]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 λ_0 (tightness of beliefs on $\mathcal{A}$) and λ_1 (tightness of beliefs

Robustness checks: The design of our shock identification procedure presented in Section 2 should ensure the exogeneity of our shock series. Furthermore, we think of our BSVAR specification as well-suited to analyze the macro-financial impact of transition risk shocks, given the large dimension of the VAR (e.g. with sectoral industrial production) and the limited number of observations. Still, in robustness checks we explore the sensitivity of our results to the choices we made. Results and further details for the checks discussed in the following are reported in Appendix E and F.

As a first exercise, we order our shock series last in the BSVAR. This alleviates concerns with respect to the exogeneity of our shock series. Ordering the shock series last means that transition risk shocks are identified after controlling for all other shocks that are identified in the system. In this case, the transition risk shock does not have a contemporaneous effect on any other variable in the system. Of course, this assumption is strong, given that we identify the shocks via contemporaneous effects on financial markets. However, one can think of this exercise as sketching a lower bound for the effects of transition risk shocks. Qualitatively, the results are the same as in our benchmark analysis.

Next, we augment the BSVAR by narrative sign restrictions following Antolín-Díaz and Rubio-Ramírez (2018). One might argue that a Cholesky decomposition imposes too strong assumptions on the structural shock series (for instance, exogeneity of shocks). SVARs with narrative sign restrictions need fewer assumptions for shock identification. They are especially attractive in situations with only few shocks, which is the case here. The idea is that there may be specific dates for which the researcher already knows the sign of the impact of a shock on a certain variable.[21] Unfortunately, however, there is no straightforward theory that could guide the choice of sign restrictions, i.e. that informs the way in which a shock to transition risk impacts aggregate macro-financial variables. To accommodate this requirement, we therefore include a brown-minus-green factor in the VAR for this exercise, arguing that one could defend certain assumptions on the signs for this factor as well as for equity prices. Given the few assumptions on shock identification, we can only estimate the VAR for our benchmark setup and not for the larger systems which include, for instance, sectoral industrial production. Reassuringly, for our benchmark setup, we find that our results remain qualitatively unchanged.[22]

3.2.3 Aggregate impact

Figure 4 shows the impulse responses of our aggregate macro-financial variables to a shock to transition risk. The size of the shock to transition risk has no deeper meaning in our exercise, so that these impulse responses rather indicate the *qualitative* importance of the shocks. For a more *quantitative* assessment, we report the forecast error variance decomposition in Table 1. It shows the average variance explained over one year after the shock.

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around the random walk prior) expressing less certainty around these beliefs.

[21] Alternatively, one can also specify narrative sign restrictions as indicating dates where a certain shock was more important than other shocks in the system. In our view, such an assumption is difficult to justify for our shocks to transition risk. Therefore, we stick to restrictions about the direction of the shock.

[22] In theory, external instrument VARs could also represent a natural choice for our setup. That is, one could argue that our shock series is not really the structural shock of interest. Rather, it is only a proxy for a structural transition risk shock series. However, we find that the number of shock dates is too small to inform an external
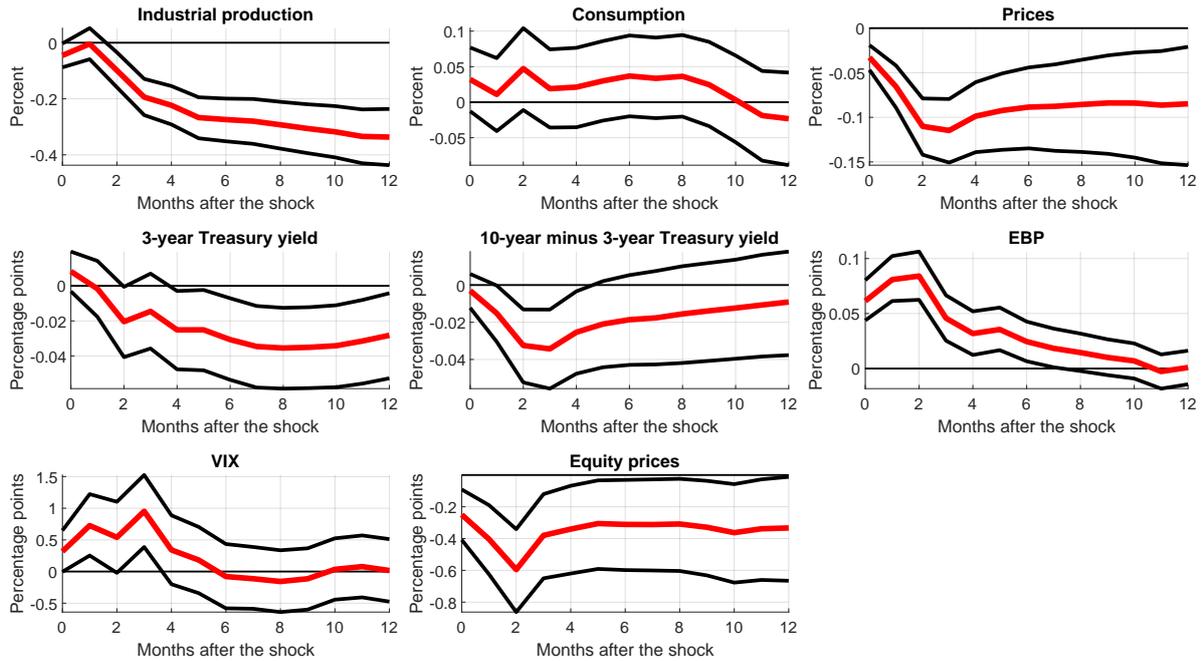
Figure 4: The impact of shocks to transition risk
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

We find that a transition risk shock has important aggregate effects. It persistently lowers industrial production two months later. Remarkably, a transition risk shock explains 24.3% of fluctuations in industrial production. In line with the typical 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, but not personal consumption expenditures.

Interestingly, a shock to transition risk reduces the price level immediately. This is an important result, informing the current policy debate about the inflationary or deflationary nature of transition risk. Our finding that shocks to transition risk are deflationary, i.e. they resemble demand rather than supply shocks, is tentatively in line with the nascent literature on transition risk and inflation. For instance, Moench and Soofi-Siavash (2022) construct a series of emission intensity shocks that explain the maximum share of variation in aggregate emission intensity. Their emission intensity shock partly resembles a positive TFP news shock and inflation drops in response to it. Similarly, Ferrari and Nispi Landi (2022) argue theoretically that the inflationary pressure from carbon taxes is only temporary. In the longer run, the tax depresses demand, which puts downward pressure on prices. Kaenzig (2022) finds that shocks to EU ETS emission prices have no effect on core inflation (but a positive effect on energy price and headline inflation). Metcalf and Stock (2020), Moessner (2022) as well as Konradt and Weder di Mauro (2021) argue that carbon taxes have little and at most temporary effects on macro outcomes including inflation.

In Appendix D, we report results from a robustness check, where we include the CPI Energy instrument VAR.

as an additional variable in the VAR. The impulse response resembles the one for headline inflation reported above, which is in contrast to the findings reported by Kaenzig (2022). We view this as confirming the idea that our understanding of transition risk shocks in this paper is rather broad and is different from increases in carbon taxes or carbon prices. Furthermore, our results are specific for the United States, while the other papers typically report findings for large panels of countries.

Financial variables are strongly affected as well. The strong and contemporaneous rise in the excess bond premium (EBP) indicates a reduction in the risk-bearing capacity or willingness to lend of the financial sector, which 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 exceeds 34%. Furthermore, we observe a slight increase in uncertainty three months after the shocks as captured by the VIX (importance: 5.7%) and a decline of the excess stock market return (importance: 10.4%).

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

Variable		Variable	
Industrial production	24.3	Consumption	1.5
Prices	19.2	3-year Treasury yield	5.0
10-year minus 3-year Treasury yield	4.9	EBP	34.2
VIX	5.7	Equity prices	10.4

Notes: The table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock to transition risk on average over the first 12 months after the shock.

3.2.4 Impact on sectoral industrial production

Figure 5: Impact of transition risk shock on selected sectoral industrial production
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

The previous analysis reveals a large impact of transition risk shocks on industrial production. Of course, this does not imply that all sectors of the economy are equally affected. We repeat the VAR analysis, replacing aggregate industrial production with a set of sectoral industrial production time series. The remaining macro-financial variables are left unchanged. For brevity, Figure 5 only reports the impulse responses for three sectors for which the transition risk shock explains a large share of its forecast error variance (see Table 2). The complete set of impulse responses is documented in Appendix A.[23]

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

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

Variable		Variable	
Consumer goods: Automotive products	5.1	Consumer goods: Home electronics	9.1
Consumer goods: Appliances, furniture, carpeting	2.3	Miscellaneous durable consumer goods	19.3
Consumer goods: Foods, tobacco	1.8	Consumer goods: Clothing	5.6
Consumer goods: Chemical products	14.9	Consumer goods: Paper products	3.1
Consumer energy products	1.7	Business equipment: Transit	12.1
Business equipment: Information processing	5.7	Business equipment: Industrial and other	23.8
Defense and space equipment	13.6	Durable materials: Consumer parts	6.7
Durable materials: Equipment parts	19.2	Durable materials: Other	10.9
Nondurable materials: Textile	15.0	Nondurable materials: Paper	3.1
Nondurable materials: Chemical	1.6	Energy materials	25.2
Construction supplies	5.9	Business supplies	19.0

Notes: The table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock to transition risk on average over the first 12 months after the shock.

Similar to the aggregate industrial production, the production of "Energy materials", "Business equipment: Industrial and other", and "Business equipment: Transit" falls in response to a sudden increase in transition risk. Our shock explains 25.2%, 23.8%, and 12.1% of the forecast error variance, respectively.

We can draw two conclusions. First, these results validate our measurement of shocks to transition risk. The shocks affect parts of the economy that we expect to be sensitive to transition risk shocks. Second, time series like "Business equipment" or "Durable materials" may serve as a proxy for investment, which is not included in our baseline VAR because we do not have investment data on a monthly basis. Against this backdrop, we can conclude that sudden increases in transition risk depress aggregate investment by depressing investment in (seemingly) brown technologies, which is again roughly in line with findings in previous literature.

3.2.5 Impact on industry portfolio return variances and NFCI subcomponents

Last, but not least, we show the responses of the return variances of industry equity portfolios and the NFCI subcomponents. We view the variances as proxies for the uncertainty in a given equity market. The analysis of the NFCI subcomponents should provide us with a deeper understanding of the shock's impact on the financial system.

For this exercise, we amend our baseline VAR of Section 3.2.3 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.[24]

Figure 6 shows the three variances that are most affected by a shock to transition risk. These are the variances of the oil (22.1%), mines (5.3%), and steel (5.2%) portfolios (see Table 3). Uncertainty in these industries rises in response to a transition risk shock up to four months after the shock. Clearly, the impact on the oil portfolio is by far the strongest. Similar to the analysis of sectoral industrial production, these findings further validate our identification of

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[24]As in the previous subsection about sectoral industrial production, we skip the impulse responses for the baseline macro-financial indicators here for brevity. Results are available upon request.
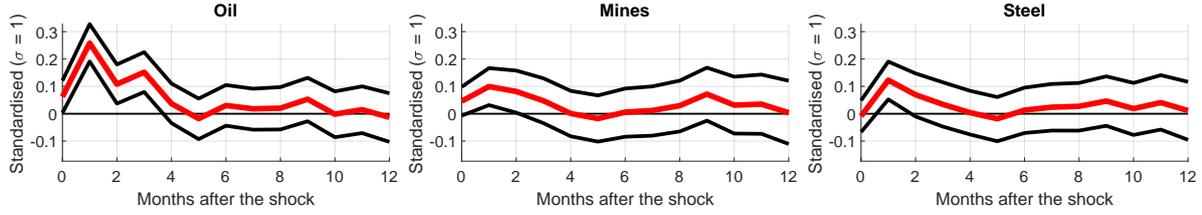
Figure 6: Impact of transition risk shock on selected industry portfolio variances
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

transition risk shocks. The most affected portfolios are the ones that we expect to be sensitive to transition risk shocks.

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

Variable		Variable	
Food	2.0	Mines	5.3
Oil	22.1	Clothes	1.5
Consumer durables	1.1	Chemicals	4.0
Drugs, soap, perfumes, tobacco	3.9	Construction	3.9
Steel	5.2	Fabricated products	1.4
Machinery	2.1	Automobiles	1.0
Transportation	1.5	Utilities	2.3
Retail stores	1.3	Other	3.9
Banks	3.5	Insurance	1.1
Real estate	2.3	Financial trading	2.4
NFCI: Risk	0.8	NFCI: Credit	5.3
NFCI: Leverage	1.5	NFCI: Non-financial leverage	0.6

Notes: The table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock to transition risk on average over the first 12 months after the shock.

Zooming in on our financial portfolios (banks, insurance, real estate, financial trading), we find the importance of the transition risk shock to be relatively low. It is largest for the bank equity portfolio. Here, a transition risk shock slightly increases uncertainty (see Figure 7) and explains 3.5% 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.
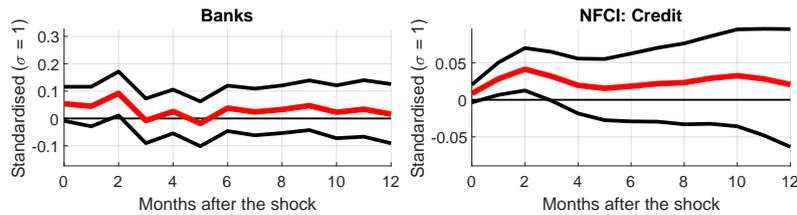

Figure 7: Impact of transition risk shock on banks portfolio variance and NFCI: Credit
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

In line with the impact of our shock on the EBP shown above, 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 5.3% of its variance. The importance of our transition risk shock is relatively low for the other NFCI subcomponents, indicating that a shock to transition risk indeed mainly affects credit conditions and not risk or leverage.

4 Applying the identification strategy to further countries: The cases of Germany and the United Kingdom

In the previous sections, we identify and interpret shocks to transition risk in the United States. As long as the necessary data is available, the identification strategy easily carries over to further countries. To exemplify, we discuss the cases of Germany and the United Kingdom in this section.

4.1 Identification of shocks to transition risk

The procedure is essentially identical to the procedure outlined in Section 2, with a few notable exceptions. The data provider ISS-ESG has a reasonable coverage of firm-level carbon emissions in both the United Kingdom and Germany, but Eikon does not. Therefore, we stick to ISS-ESG for emissions data and run the analysis with two portfolio sorts (Scope 1 carbon emissions and Scope 1 carbon intensities) instead of three. Equity returns are taken from Eikon. The sample period goes from July 2013 to December 2018 for both countries and our sample covers roughly 1,200 firms for the UK and 550 firms for Germany towards the end of the sample period.

Given the shorter time span, we lower the threshold for shock identification. Specifically, we extract all months in which one of the two brown-minus-green portfolio returns is 0.66 standard deviations below its mean zero. The same threshold is applied to the news index, identifying months during which the news index is 0.66 standard deviations above its mean. With this smaller threshold, the total number of shocks is comparable to the case of the United States.

As for the United States, we construct the climate news indices using the Factiva news archive. But for the United Kingdom and Germany, we deviate from Baker et al. (2016) by including a larger set of newspapers in the analysis.[25] We do so to increase the robustness of our results. Preliminary exercises have shown that broadening the set of newspapers substantially increases the likelihood of clearly identifying local maxima in our news index.[26]

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[25]Baker et al. (2016) use only two newspapers for the United Kingdom and Germany. We, instead, use all newspapers that are available in Factiva except for sources with negligible article count ($\leq$ 3% of the article count of the largest newspaper in that country).

[26]As an anecdotal example, in one of these preliminary exercises with only two newspapers, we detected a cluster of several months in a row in which the news index for the UK was elevated. The reason for this was a long series of scientific background articles on climate change published in the Guardian. Clearly, the resulting extreme values of the news index did not relate to any updated information regarding transition risk. Including more newspapers, therefore, successfully reduces such noise in our climate change news index.

4.2 Narrative analysis

Figure B.1 in the Appendix depicts the news indices and the shocks that we identify. Again, we start by analyzing potential narratives behind these shocks, building on an in-depth reading of the respective newspaper articles that were filtered out by Factiva.

Similarly to the United States, we can confirm that the events match changes in transition risk. About half of the events per country are associated with political deals on carbon emission reductions. But again, our shocks to transition risk occur for a variety of reasons and there are months for which we find multiple events.

For Germany, we find two shocks: December 2015 and November 2017. The shock in December 2015 is clearly linked to the Paris Climate Summit and the related Paris Agreement. The shock in November 2017 can be traced back to a number of political events in Germany. First, the German federal election on 24 October was followed by intense coalition negotiations. Until 24 November, when the first round of coalition negotiations officially failed, it was perceived as likely that the Green party would end up being part of the newly formed government (which they ultimately were not). Second, at the 23rd Conference of the Parties (COP23) in Bonn, a number of countries committed to phasing out coal energy by 2030 or even earlier. While Germany was not among them, scenarios for such a coal phase-out were discussed intensively during the coalition negotiations, even after the Green Party dropped out. Eventually, in February 2018, the newly formed grand coalition agreed that a concrete plan for such a coal phase-out should be put together within one year, but the rumors about it had already started in November. Finally, in November 2017, a German court agreed to approve a court trial of a Peruvian farmer against the German coal energy supplier RWE for being responsible for increased flood risk in Peru. This unprecedented trial is still ongoing in 2022 and represents another source of a shock to transition risk for German utility companies.

For the United Kingdom, we identify four shocks: May 2015, November 2015, December 2015 and May 2016. While November and December 2015 are again clearly linked to the (run-up to the) Paris Agreement, the other two shocks hint towards two major political events in the United Kingdom. The election of the House of Commons on 07 May 2015 resulted in a clear win for the Tory party, and politicians sent several relevant climate policy signals after the election. For instance, the new government announced a commitment to climate goals in the Queen's speech after the election. Green groups also welcomed the appointment of Amber Rudd as Secretary for Energy and Climate Change by prime minister Cameron.

May 2016 was characterized by two distinct events. First, and probably most importantly, as part of the G7, the United Kingdom set – for the first time – a deadline for phasing out most fossil fuel subsidies (end of 2025). Second, during this month, the public discourse during the run-up to the Brexit referendum prominently raised awareness of the challenges arising from climate change.[27]

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[27]For instance, Jeremy Corbyn and Ed Miliband publicly announced they would join forces and warned that Britain's membership of the European Union would be vital in the fight against climate change. Furthermore, in a public letter, Labour party members of parliament stated that remaining in the European Union was the only way to guarantee stricter political measures against climate change.

4.3 Macro-financial analysis

We now turn to our macro-financial VAR analysis. Technically, the Bayesian structural VAR estimation is identical to the one in the previous section. However, for Germany and the United Kingdom the sectoral analysis turns out to be less granular, given fewer time series for sectoral industrial production and industry portfolio return variances. For these countries, we download all data from Refinitiv Eikon. The exact data series, including the identifiers, are listed in Appendix B.2.1.

Figures F.2, B.7, and B.9 in the Appendix show impulse responses for Germany, Figures F.3, B.8, and B.10 for the UK. Table B.2 reports the forecast error variance decomposition results for both countries.

This exercise by and large confirms the key result of the VAR analysis for the United States, namely that transition risk shocks have large aggregate effects. Moreover, the analysis of sectoral industrial production and portfolio return variances confirms that transition risk shocks significantly affect fossil fuel and energy sectors in all three countries. Still, we detect some important country specificities that we discuss in the following.

Germany In contrast to the United States, aggregate industrial production in Germany increases after a transition risk shock, while still being strongly affected (9.6% of variation explained). Moreover, the price level does not decrease in Germany either. While transition risk shocks resemble negative demand shocks in the United States, they seem to go more in the direction of positive demand shocks in Germany. This movement may be related to the different composition of the German economy, i.e. the exposure of aggregate industrial production to transition risk is different because the German economy is generally "greener". In fact, a range of international organizations or research networks have come up with indices that claim to assess the climate policies of different countries or quantify the "readiness" of their economies for the transition. Examples are the Energy Transition Index from the World Economic Forum, the Environmental Performance Index calculated at Yale University, or the Energy Trilemma Index from the World Energy Council. In basically all rankings that can be derived from such indices, the United States has been lagging far behind Germany and also behind the United Kingdom throughout our sample period, indicating that the United States economy may not be ready enough for the transition to net zero and may thus be prone to transition risk. Our evidence on the impulse responses of industrial production to a transition risk shocks confirms this intuition.

The finding for prices in itself is interesting, as it indicates that transition risk shocks must not necessarily be deflationary. Still, in a robustness check with the CPI Energy included (see Appendix D for the results), we find that energy prices decline in response to a transition risk shock both in the United Kingdom and in Germany. Corporate spreads and the volatility index rise in response to a shock, and our shocks explain 26.9% and 7.5% of the variation, respectively. Treasury yields are not materially affected.

The analysis of sectoral industrial production shows that the production of fossil fuels (crude oil and gas, mining coal), electricity and energy decreases. Of these, the production of crude

oil and gas is most strongly affected (13.0%). The largest share of variation is explained for the manufacturing sector (16.2%), whose production increases in response to a transition risk shock. In this sense, the sectoral findings corroborate the aggregate result.

Interestingly, the corporate credit spread increases in response to a transition risk shock, indicating elevated risk of financial instability, even though aggregate industrial production (and even manufacturing production) responds positively to a transition shock. This seeming contradiction reflects another specificity of the German (or, more generally, the euro area) economy that relates to firms' financing structure. The corporate credit spread that we use in our analysis represents the spread of BBB over AAA-rated corporate bonds. But only a small fraction of the overall corporate debt in the euro area is actually raised through the corporate bond market. Bank loans are still the dominant source of funding, in particular for small and medium-sized enterprises.[28] On top of that, Papoutsi, Piazzesi, and Schneider (2022) show empirically that the sectors which rely heavily on fossil fuel inputs are largely overrepresented in the euro area corporate bond market as compared to their overall output share in the economy. Taken together, even though the German economy as a whole seems to respond positively to a transition risk shock, firms which finance themselves through corporate bonds are negatively affected. We interpret this as evidence for a pronounced risk of stranded assets in the German corporate bond market.

The results for the portfolio return variances confirm this reasoning. Uncertainty in the energy portfolio strongly increases (12.0%). We also find that the automobiles and parts portfolio is strongly affected (10.5%), which suggests an elevated exposure of the German car industry to transition risk. With respect to the financial industry, we find that a shock most strongly raises uncertainty in the banking and insurance sector (14.7% and 12.5%). These numbers are much higher than for the United States.

Since we identify only two shock dates for Germany, we check the robustness of the rise in Germany's industrial production in response to a shock (the results are available upon request). Specifically, we want to robustify the finding that industrial production rises while the adverse effects on financing conditions and uncertainty are comparable to the United States. We therefore lower the threshold for shock identification from 0.66 to 0.5, which leaves us with four shocks. We find that the results are robust to this change. In fact, the fall in prices in response to a shock even turns statistically significant in this specification.

United Kingdom For the United Kingdom, aggregate industrial production declines, but only for a short period. Overall, the impulse response of industrial production in the United Kingdom lies somewhere between the positive response for Germany and the negative response for the United States. This finding can again be aligned with the intuition about the "readiness" of the United Kingdom's economy for the transition to net zero. While the United Kingdom is essentially among the top 10 in most global climate policy rankings by the year 2022, it was lagging somewhat behind at the beginning of our sample period. The overall muted response of industrial production to transition risk shocks for the United Kingdom thus again seems to reflect country specificities in terms of the overall "greenness" of the economy. Still, transition

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[28]See, e.g., Darmouni and Papoutsi (2022)

risk shocks explain a large share of the forecast error variance over the first year after the shocks (9.1%).

The response of prices is much more muted than in the Uinted States, implying that transition risk shocks are only mildly deflationary for the United Kingdom. The level of yields decreases and the yield curve appears to flatten for a month, similar again to our results for the United States. Corroborating previous results from the other countries, corporate spreads and the volatility index increase. A shock to transition risk explains 10.3% and 11.2% of variation in these variables, respectively. For the United Kingdom, the 3-year government bond yield is most strongly affected: a shock explains 15.4% of the variation of this variable.

The most striking finding for the United Kingdom relates to the mining of coal. In response to a transition risk shock, this variable declines strongly and persistently. The shock explains 41.2% of its variation, emphasizing its extraordinary role. But also the responses of the other sectoral industrial productions are in line with previous findings. For instance, the production of electricity and gas (19.8%) and the production of energy (13.7%) decline for the first months after the shock, eventually returning to previous level, however. Overall, the analysis of sectoral industrial production confirms that the fossil fuel sector and energy sector are primarily affected.

This is different, though, when turning to the portfolio return variances. For the United Kingdom we do not find the fossil fuel or energy sectors to be particularly affected. However, similar to Germany, uncertainty among banks and insurance companies increases substantially, whereby a shock explains 24.3% and 16.3% of the variation, respectively. These numbers are actually even higher than for Germany. This could potentially point towards an elevated risk of stranded assets in these sectors in the United Kingdom.

5   Discussion and Outlook

Understanding transition risk arising from climate change represents a formidable challenge for economic research. Our paper proposes a lean and, at the same time, comprehensive approach to studying transition risk, addressing key challenges regarding its definition and measurement. To do so, our approach builds on two – in our view – mild and uncontroversial assumptions about the observability of those shocks. Broadly speaking, one can think of our shocks to transition risk as instances where significant new information about the economic relevance of climate change increases the valuation of green firms over brown firms. In this sense, our paper also provides an implicit definition of shocks to transition risk.

To illustrate our method, we identify shocks to transition risk in the United States, Germany, and the United Kingdom. For all of these countries, we observe that our transition risk shocks have major aggregate effects, also inducing financial instability. The narratives linked to these shocks can be associated with an increase in the likelihood of an orderly transition. For instance, the Paris Agreement in December 2015 is among the major milestones, while there are also less famous political events like the bilateral deal between the US and China on carbon emission reductions in November 2014. In line with the narratives, we also find that the shocks to transition risk most strongly affect parts of the economy that we expect to be most sensitive to transition

risk shocks, such as sectors related to fossil fuels and energy. Still, the results across countries also suggest an important role for country specificities, such as strong sectoral responses (as for the "automobiles and parts" sector in Germany), but also the aggregate responses that appear to be related to a country's economic "readiness" for the net zero transition.

Our paper is important for policymakers and regulators for a set of reasons. First, our method to define and measure shocks to transition risk is easy to implement, transparent, but still comprehensive, as we show for a selection of countries. For instance, our approach does not require any special data on transition risk proxies. That is, while offering a comprehensive interpretation of transition risk, our approach can be easily extended to a broader set of countries when going forward with the net zero transition.

Second, the results for the United States, Germany, and the United Kingdom give guidance for the net zero transition. For one thing, our study supports the view that sectors related to the fossil fuels and energy are specifically vulnerable to transition risk. But more generally, we find strong aggregate effects on the economy, also with implications for financial markets. This is interesting because one might also conjecture that the net zero structural transformation is already fully incorporated in financial markets and the real economy. Specifically, note that in an economy without frictions the transition towards a lower carbon economy would evolve gradually and predictably over time, and we should not see the adjustments that occur in response to a shock to transition risk. This is also confirmed by the vast majority of theoretical models of climate transition.[29] Therefore, the objective of policy must be to mitigate the impact of transition risk shocks, for instance by establishing a transparent and consistent communication of the most likely transition path, such that adjustments can be gradual and predictable, taking into account the status quo of climate change research and consumers' preferences. Clearly, climate change itself is surrounded by large uncertainties. Against this backdrop, policymakers need to weigh their preference for type I (too slow transition) or type II (too fast transition) errors when communicating such a path.

Third, the impact of the net zero transition on prices has been widely debated. The often used buzzword "greenflation" suggests that there is a specific cost attached to it. Our results seem to suggest that the overall effects of transition risk shocks may be rather deflationary.

Fourth, our results across countries indicate that country specificities play a major role for the impact of transition risk shocks. For Germany, we even find that aggregate industrial production may rise in response to a shock, again alleviating concerns regarding the overall costs of the net zero transition.

A necessary next step in the analysis of transition risk shocks is to better understand the transmission channels, perhaps through more granular micro data, but possibly also through the lens of theoretical models. And last but not least, an extension towards a broader set of countries, coming up with a panel dataset of transition risk shocks and their detailed narratives, is a straightforward agenda for future research.

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[29]An overview of such models is provided, for instance, in a technical document from the Network for Greening the Financial System (2019). The pros and cons of such models are discussed, for instance, by Nordhaus (2019), Pindyck (2017), or Farmer et al. (2015).

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A   Results for the United States
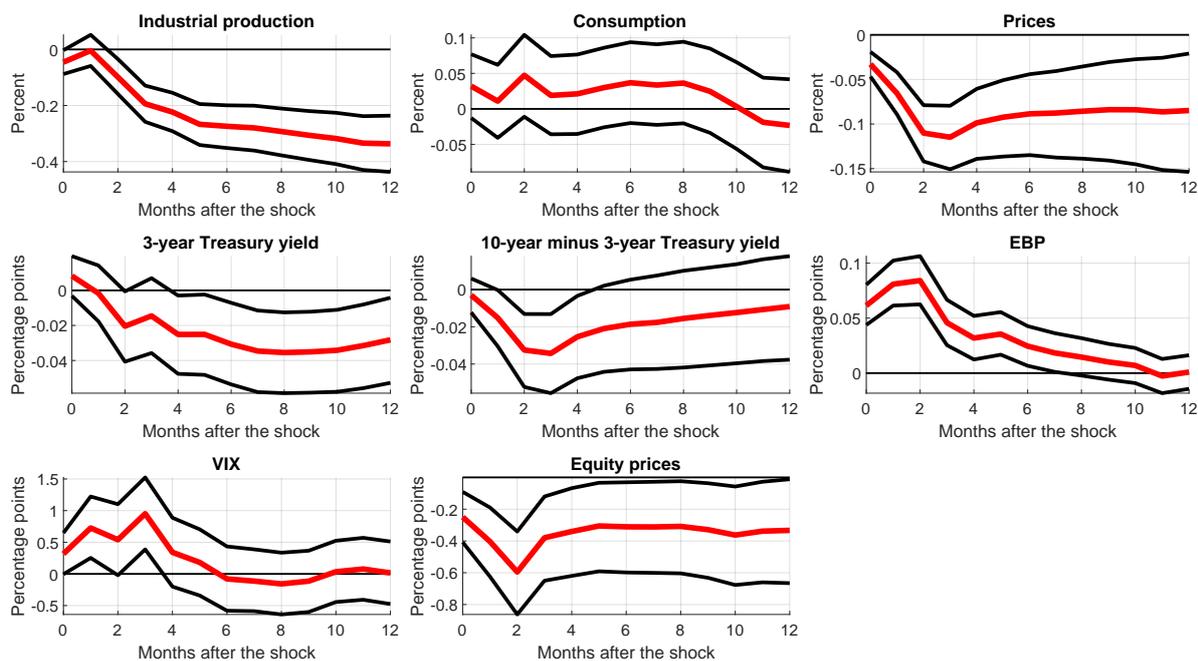
Figure A.1: United States: Baseline
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.
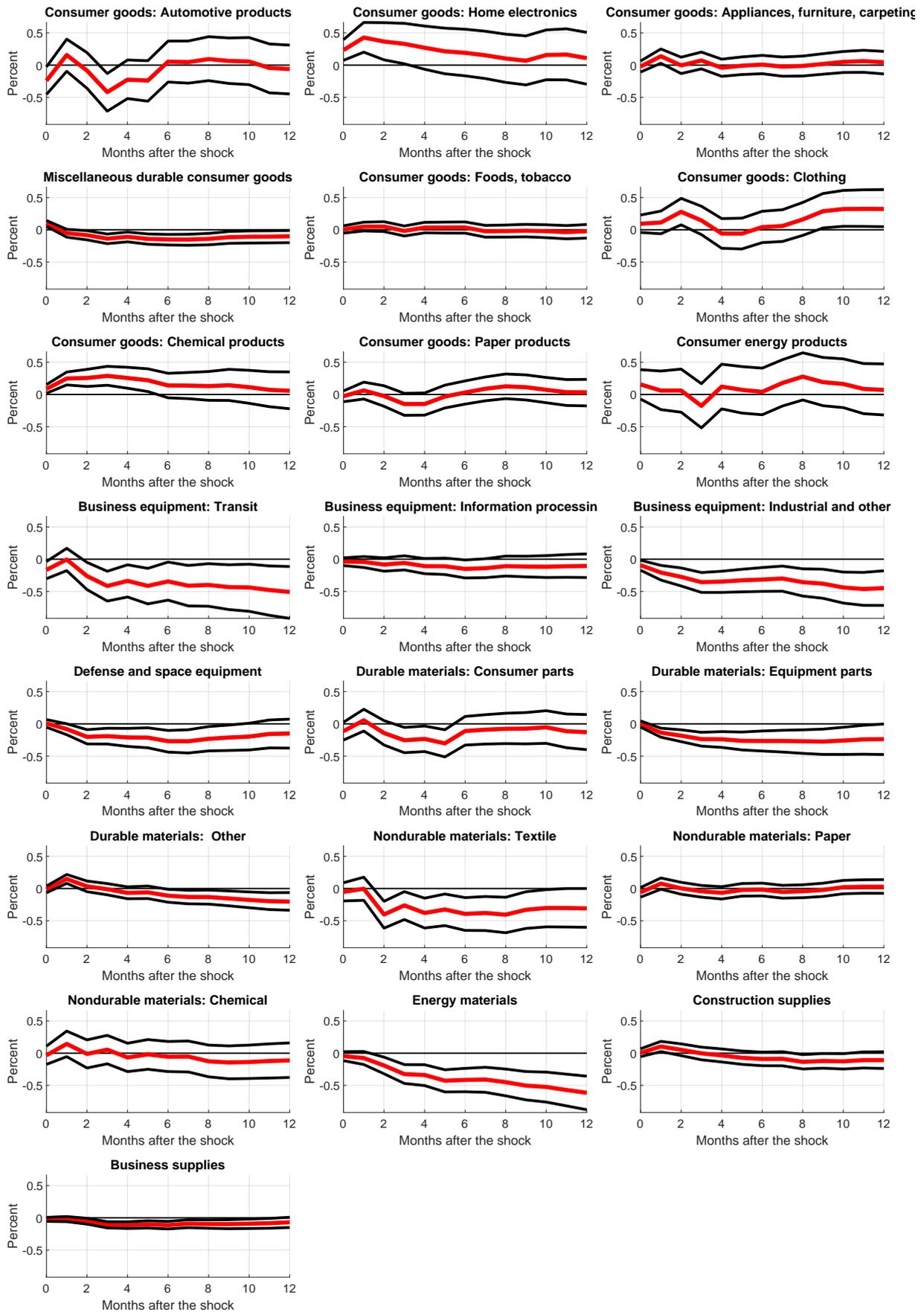
Figure A.2: United States: Sectoral industrial production
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.
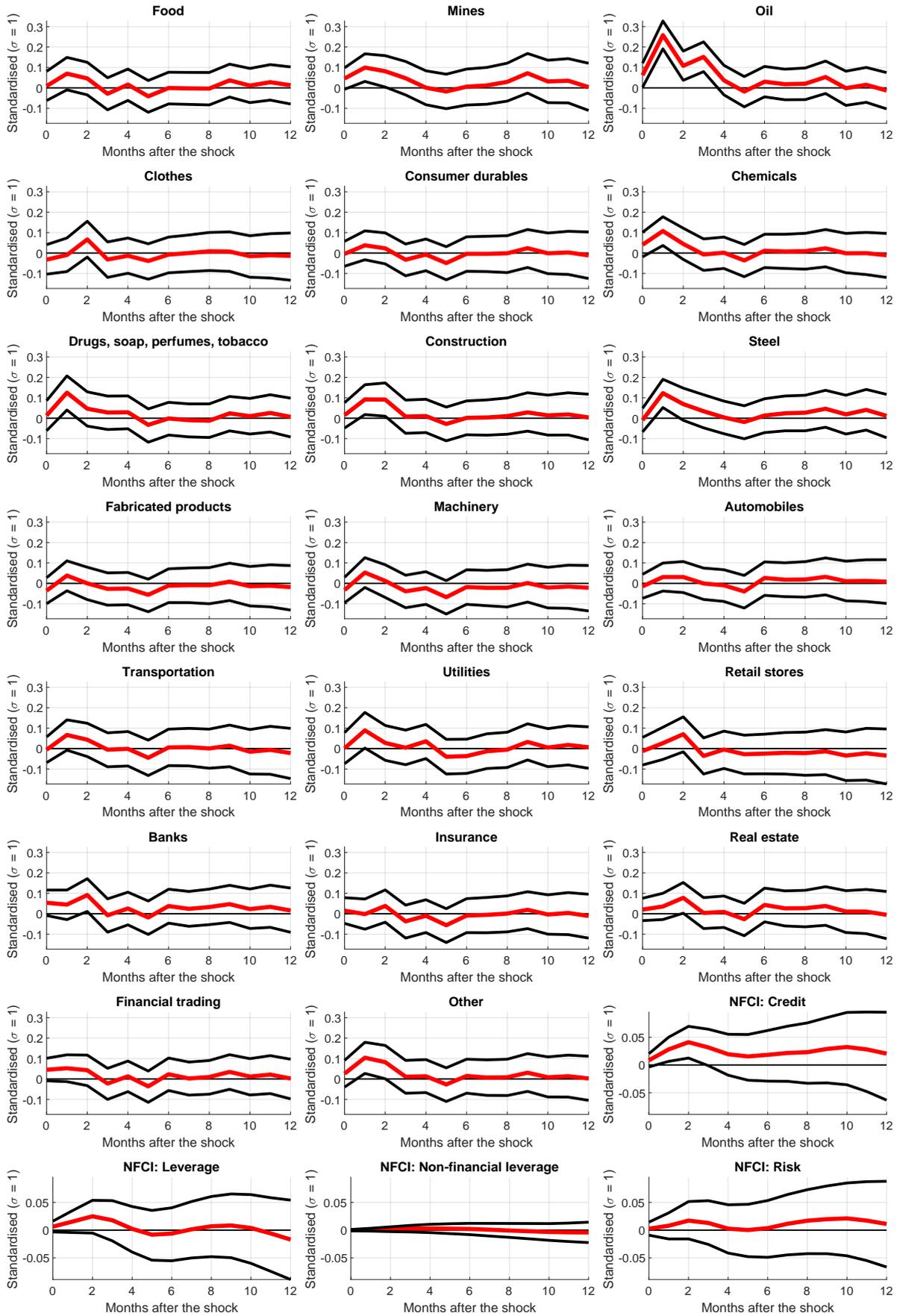
Figure A.3: United States: Industry portfolio variances and NFCI subcomponents

Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

B   Results for Germany and United Kingdom

B.1   Portfolio sorts and news indices
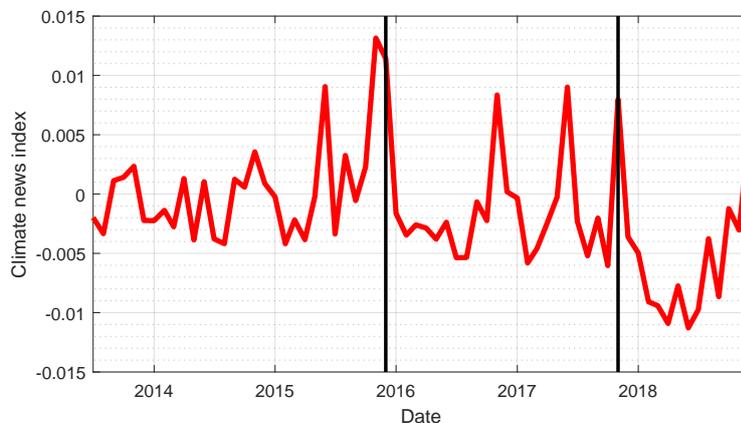
Figure B.1: Climate news index Germany

*Notes:* Solid vertical bars indicate transition risk shocks. The solid line is the climate news index.
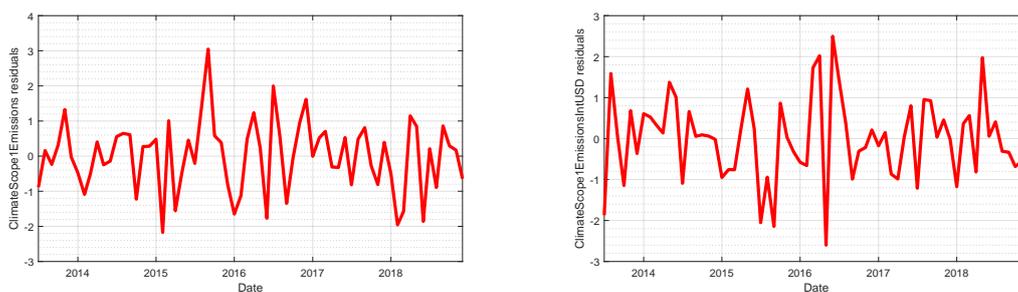
Figure B.2:   Fama-French 3-factor residuals of ClimateScope1Emissions (left) and ClimateScope1EmissionsIntUSD (right).

Notes: A positive value for these monthly factors implies that carbon-intensive (i.e. "dirty") firms exhibit abnormally high returns. We construct brown-minus-green equity portfolios by sorting firms according to their carbon emissions (left picture) and emissions intensity (right picture). To orthogonalize these returns with respect to systematic risk, we regress each quintile portfolio excess return on the three Fama-French factors. Residuals are standardized to unit variance.
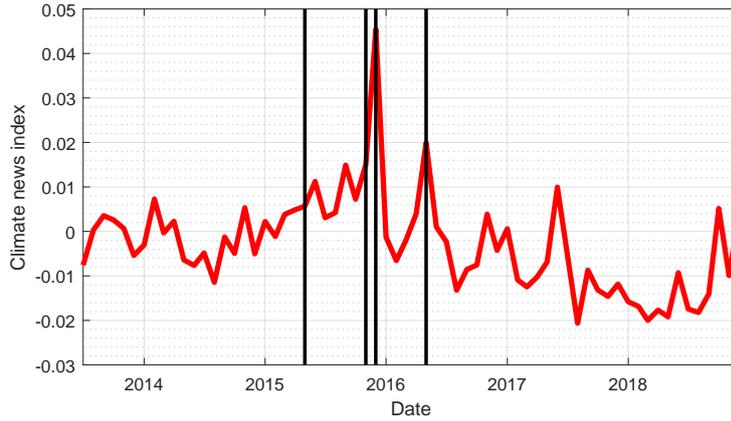
Figure B.3: Climate News Index UK

Notes: Solid vertical bars indicate transition risk shocks. The solid line is the climate news index.
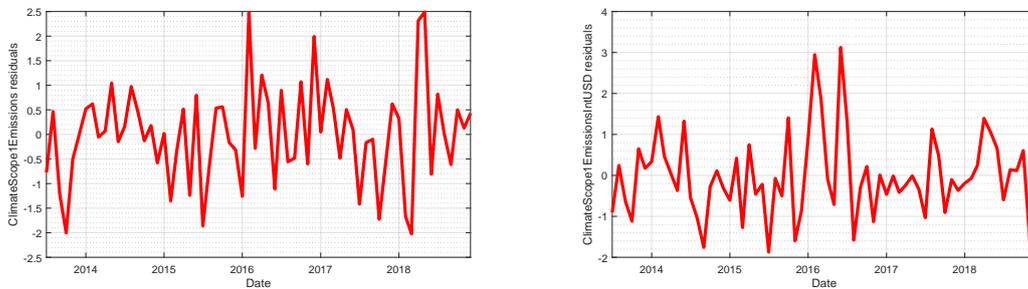
Figure B.4: Fama-French 3-factor residuals of ClimateScope1Emissions (left) and ClimateScope1EmissionsIntUSD (right).

Notes: A positive value for these monthly factors implies that carbon-intensive (i.e. "dirty") firms exhibit abnormally high returns. We construct brown-minus-green equity portfolios by sorting firms according to their carbon emissions (left picture) and emissions intensity (right picture). To orthogonalize these returns with respect to systematic risk, we regress each quintile portfolio excess return on the three Fama-French factors. Residuals are standardized to unit variance.

B.2 VAR analysis

B.2.1 Data

Table B.1: Data for Germany and United Kingdom

	Germany	United Kingdom
Benchmark		
Industrial production	BDCIND..G	UKCIND..G
Prices	BDCCPI..E	UKCCPI..E
3-year government bond yields	TRBD3YT	TRUK3YT
10-year government bond yields	TRBD10T	TRUK10T
Corporate bond yields (AAA)	SPEIA3E(RY)	SPUKI3A(RY)
Corporate bond yields (BBB)	SPEIB3E(RY)	SPUKI3B(RY)
Volatility index	VDAXNEW	VFTSEIX
Stock market index	.dMIDE00000P(MSRI)	.dMIGB00000P(MSRI)
Sectoral industrial production		
Energy	BDIPENG.G	UKK24T..G
Chemicals	BDUSNA25G	UKK232..G
Mining and quarrying	BDIPMIN.G	UKK224..G
Mining coal	BDIPCAL.G	UKK225..G
Manufacturing	BDIPMAN.G	UKIPMAN.G
Electricity and gas	BDIPEGS.G	UKK248..G
Crude oil and gas	BDIP.ECNG	UKK226..G
Coke and petrol	BDIPCPN.G	UKK22Y..G
Wood and paper	BDIPWAP.G	UKK22T..G
Basic materials	BDIPBAS.G	
Transport equipment		UKK23T..G
Metal		UKK23G..G
Industry portfolio variances		
Oil		F1UKO1£(RI)
Energy	ENEGYBD(RI)	ENEGYUK(RI)
Banks	BANKSBD(RI)	BANKSUK(RI)
Financial services	FINSVBD(RI)	FINSVUK(RI)
Insurance	INSURBD(RI)	INSURUK(RI)
Autos & parts	AUTMBBD(RI)	AUTMBUK(RI)
Technology	TECNOBD(RI)	TECNOUK(RI)
Utilities	UTILSBD(RI)	UTILSUK(RI)
Chemicals	CHMCLBD(RI)	CHMCLUK(RI)
Industrial materials	INMATBD(RI)	
Metal	INDMTBD(RI)	INDMTUK(RI)

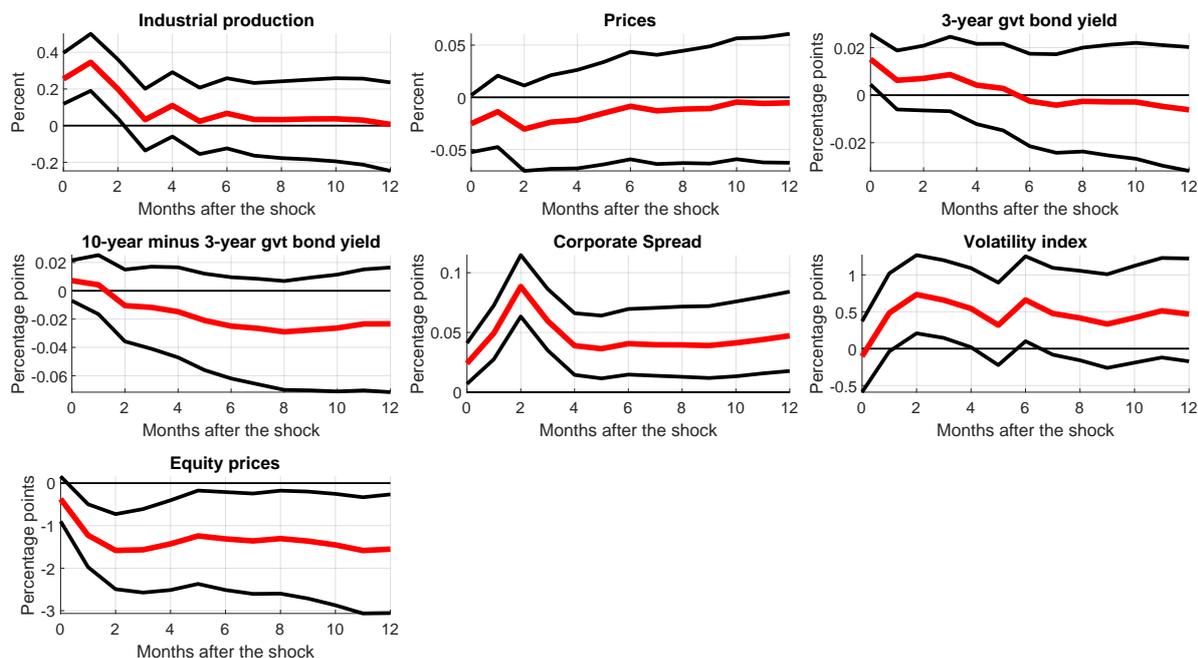*Notes:* Table shows Refinitiv Eikon identifiers.

B.2.2   Results

Figure B.5: Germany: Baseline
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.
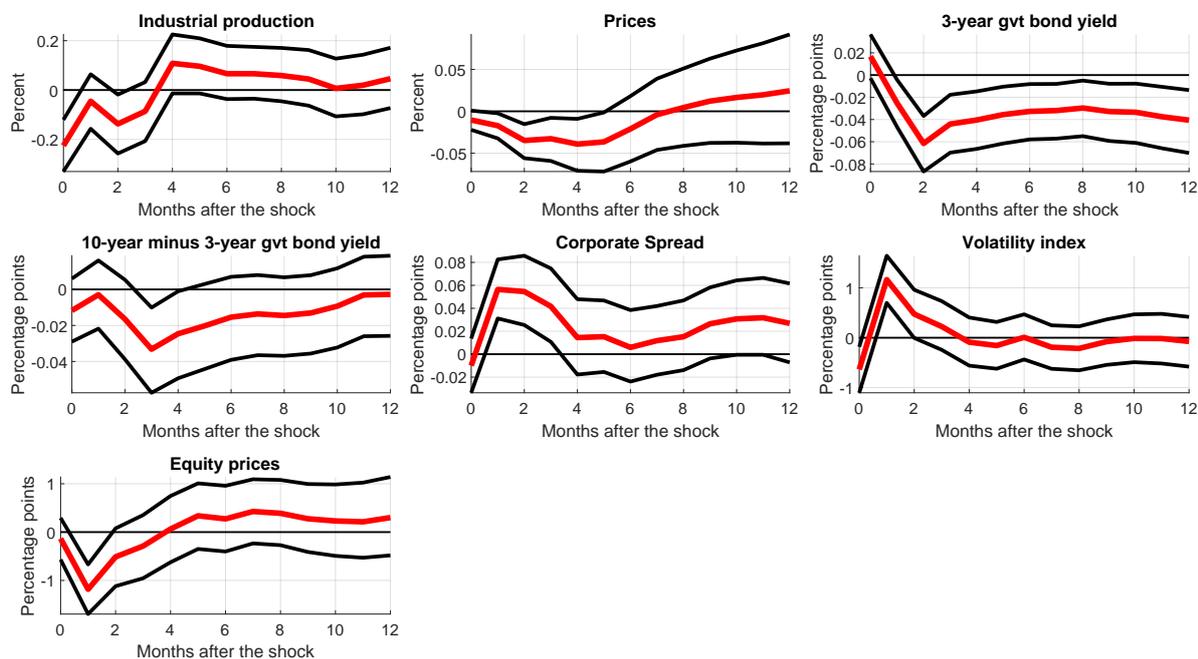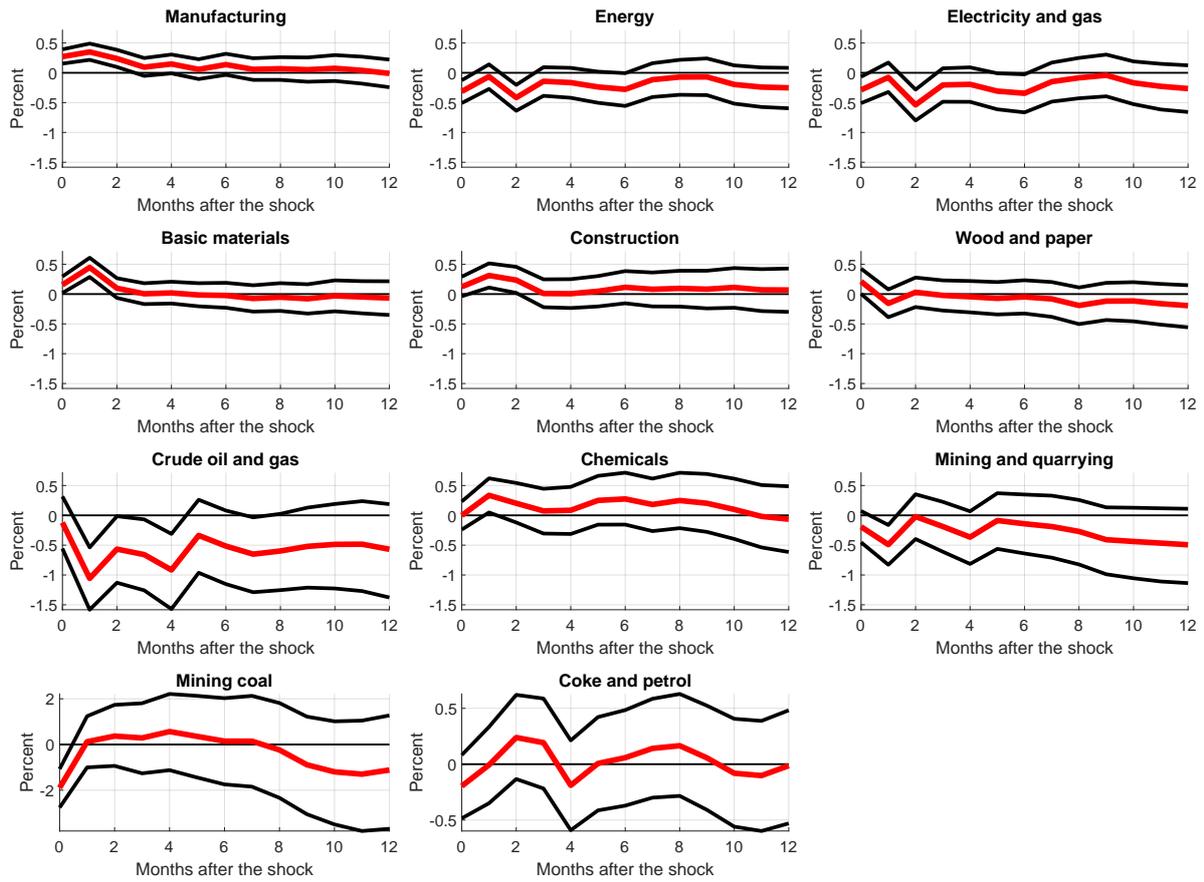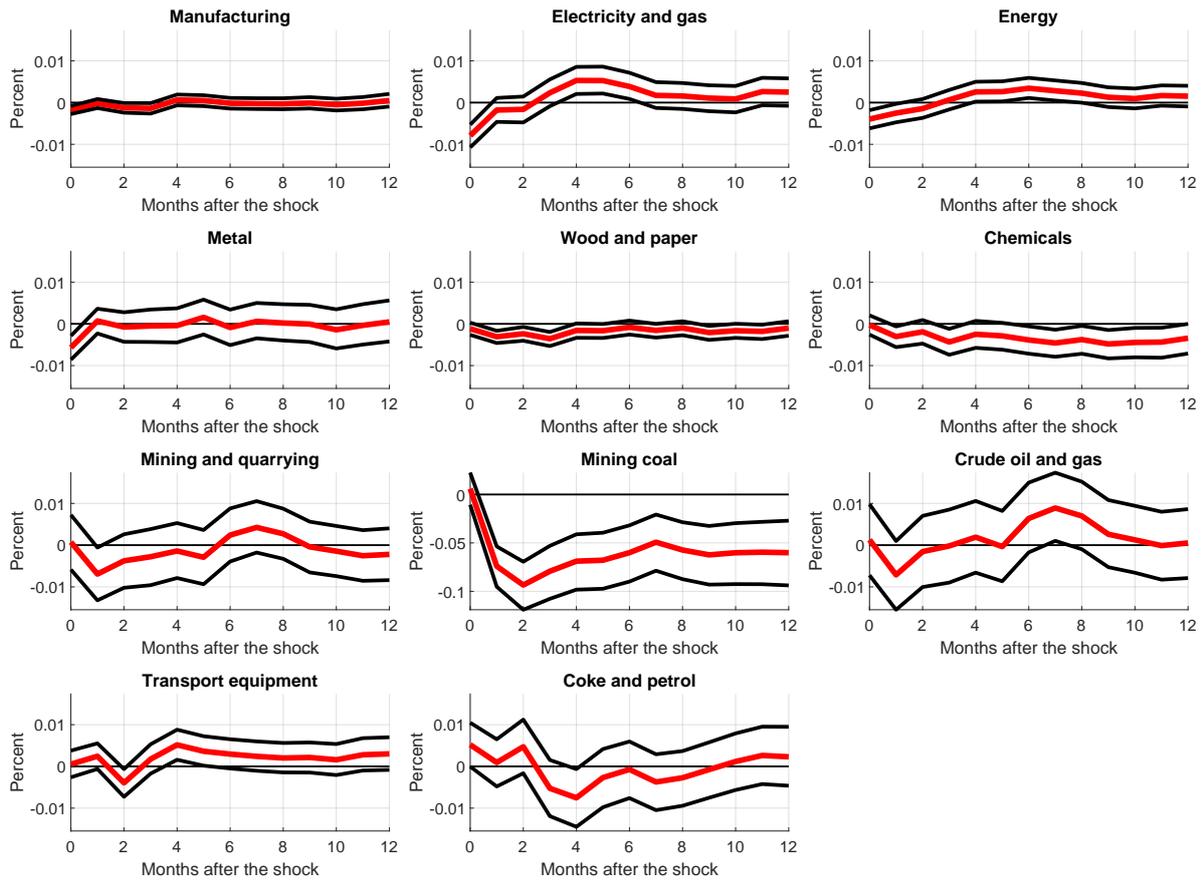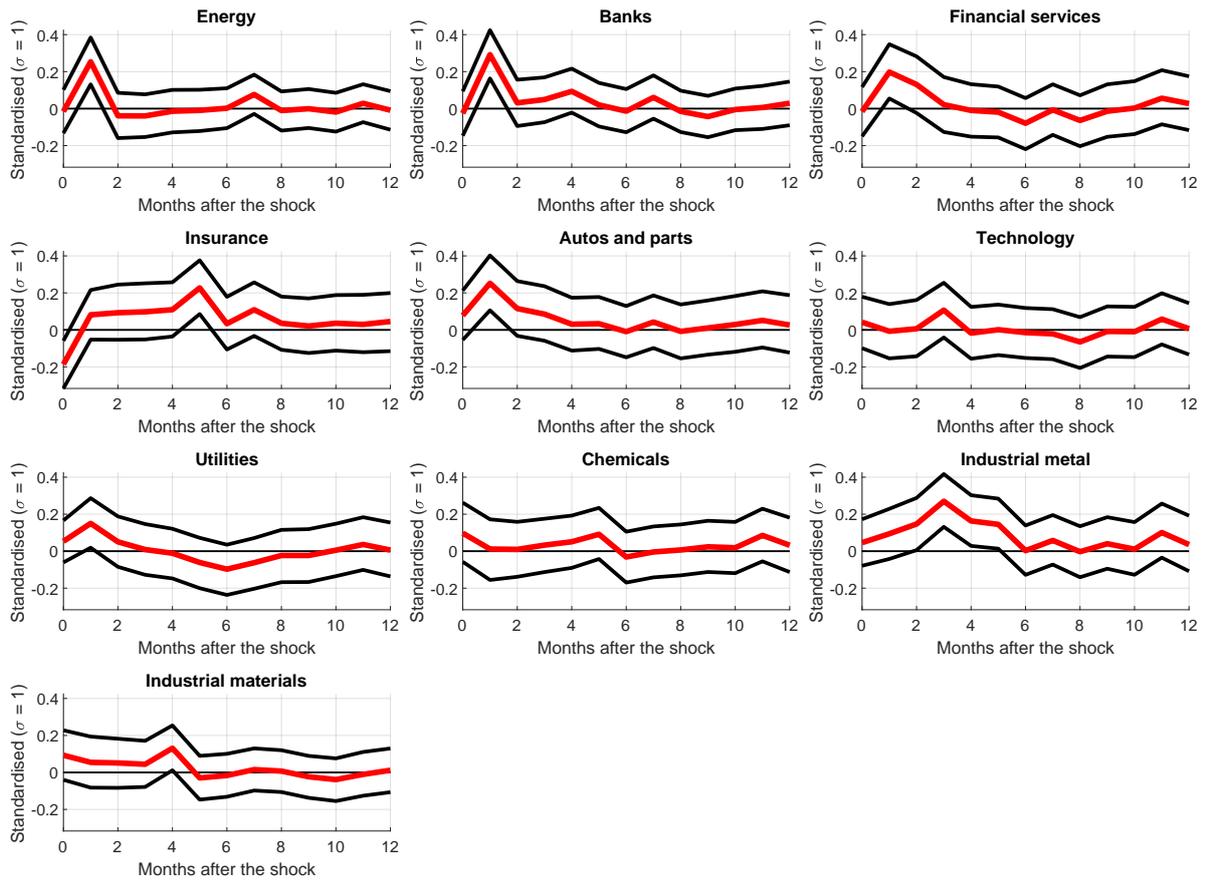

Figure B.6: United Kingdom: Baseline
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

Figure B.7: Germany: Sectoral industrial production

Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.
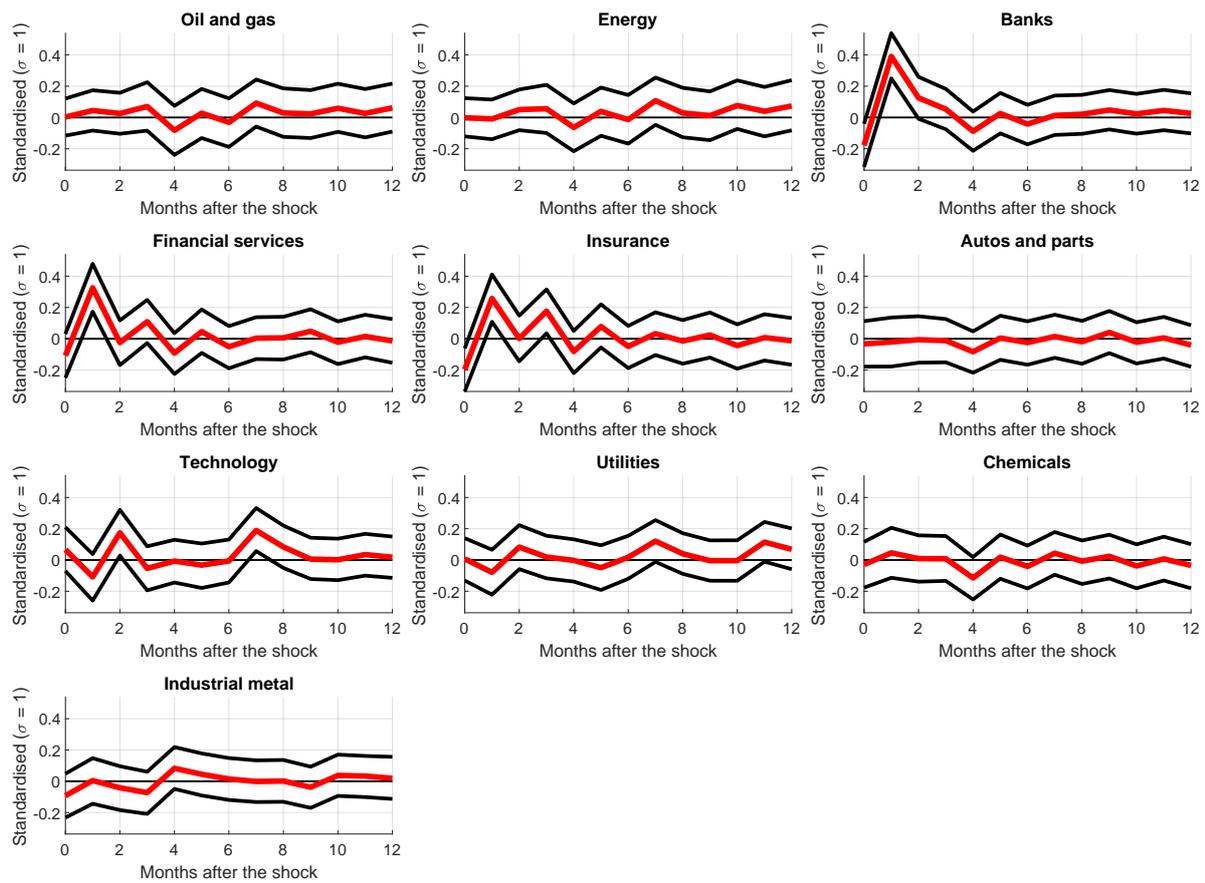
Figure B.8: United Kingdom: Sectoral industrial production

Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

Figure B.9: Germany: Industry portfolio variances

Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

Figure B.10: United Kingdom: Industry portfolio variances

Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

Table B.2: Germany and United Kingdom: Importance of shocks (in percent): Baseline

Variable		Variable	
Germany			
Industrial production	9.6	Prices	1.9
3-year gvt bond yield	2.4	10-year minus 3-year gvt bond yield	2.5
Corporate spread	26.9	Volatility index	7.5
Equity prices	12.9		
Manufacturing	16.2	Energy	9.6
Electricity and gas	9.7	Basic materials	10.7
Construction	5.0	Wood and paper	2.6
Crude oil and gas	13.0	Chemicals	3.1
Mining and quarrying	5.1	Mining coal	4.4
Coke and petrol	1.9		
Energy	12.0	Autos and parts	10.5
Technology	1.7	Utilities	5.4
Chemicals	2.5	Industrial metal	15.3
Industrial materials	5.2	Banks	14.7
Financial services	7.4	Insurance	12.5
United Kingdom			
Industrial production	9.1	Prices	5.2
3-year gvt bond yield	15.4	10-year minus 3-year gvt bond yield	5.1
Corporate spread	10.3	Volatility index	11.2
Equity prices	5.9		
Manufacturing	7.6	Electricity and gas	19.8
Energy	13.7	Metal	5.1
Wood and paper	17.8	Chemicals	10.4
Mining and quarrying	4.0	Mining coal	41.2
Crude oil and gas	3.4	Transport equipment	8.1
Coke and petrol	5.3		
Oil and gas	1.9	Energy	1.8
Autos and parts	1.0	Technology	8.2
Utilities	3.3	Chemicals	1.8
Industrial metal	3.3	Banks	24.3
Financial services	15.9	Insurance	16.3

Notes: Table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock to transition risk on average over the first 12 months after the shock.

C Further analysis: Shocks decreasing transition risk

The main focus of this paper is on shocks that increase transition risk. This is because the effects of an increase are of major interest to policymakers. Furthermore, the literature suggests that shocks which decrease transition risk should be very different from shocks which increase transition risk. For instance, it is not clear to what extent negative shocks to transition risk shocks are credible events. Their effects – if any – may be rather transitory. In a recent paper, Ramelli et al. (2021) show that both carbon-intensive firms as well as firms which are on a credible path towards net zero experience stock price *appreciations* after the election of Donald Trump in 2016. The authors explain the latter finding with long-term investors betting on a "boomerang" in climate policy.

For completeness, we discuss the impact of shocks that decrease transition risk for our United States benchmark setup in this section. Applying the procedure outlined for the United States, we identify only one shock (December 2018). In this month, the climate package at the U.N. Climate Summit in Kattowice was struck. However, it fell short of expectations. The fact that we can identify only one negative shock with our benchmark procedure highlights once more the intuition that the overall direction has been towards a net zero economy over our sample period.

Since the VAR analysis cannot proceed with only one shock, we adapt the shock identification procedure slightly. Specifically, we use a lower threshold of 0.66 when identifying the negative shocks from the two brown-minus-green portfolios that have a shorter sample period, exactly mirroring the shock identification procedure for Germany and the United Kingdom.[30] This leaves us with two further negative shocks (June 2014 and March 2017). In June 2014, the Environmental Protection Agency (EPA) announced plans to cut domestic carbon emissions by 30% until 2030. Even though the Supreme Court approved the general plan, it also decided that the EPA went too far in trying to regulate small emitters. March 2017 combines several events. First, Scott Pruitt (the newly appointed head of the EPA) dismissed climate science in a speech in which he denied that carbon dioxide contributes to global warming. Second, President Trump removed the federal block from the Keystone Pipeline. Third, President Trump rolled back on environmental protection laws more generally, signing an executive order that undid most of President Obama's Clean Power Plan.

Using these three months as negative transition risk shocks, Figure D.1 and Table C.1 display the results for the United States benchmark case. Indeed, the findings support the notion that shocks decreasing transition risk play a much less important role than shocks increasing transition risk. For instance, industrial production does not change significantly. The shock only accounts for 0.6% of fluctuations in this variable. Results are similar for prices, the EBP, and the VIX. In contrast, all these variables are strongly impacted by a shock that increases transition risk.

Still, it is noteworthy that a negative transition risk shock has a strong contemporaneous impact on consumption (where the response is insignificant for a positive shock) and the 3-year Treasury

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[30]We also run another exercise in which we lower the threshold for the third portfolio as well. The VAR results remain qualitatively the same.

yield. This emphasizes once more the fact that shocks decreasing transition risk are very different from shocks increasing transition risk. Overall, it supports our focus on shocks that increase transition risk in the main paper.
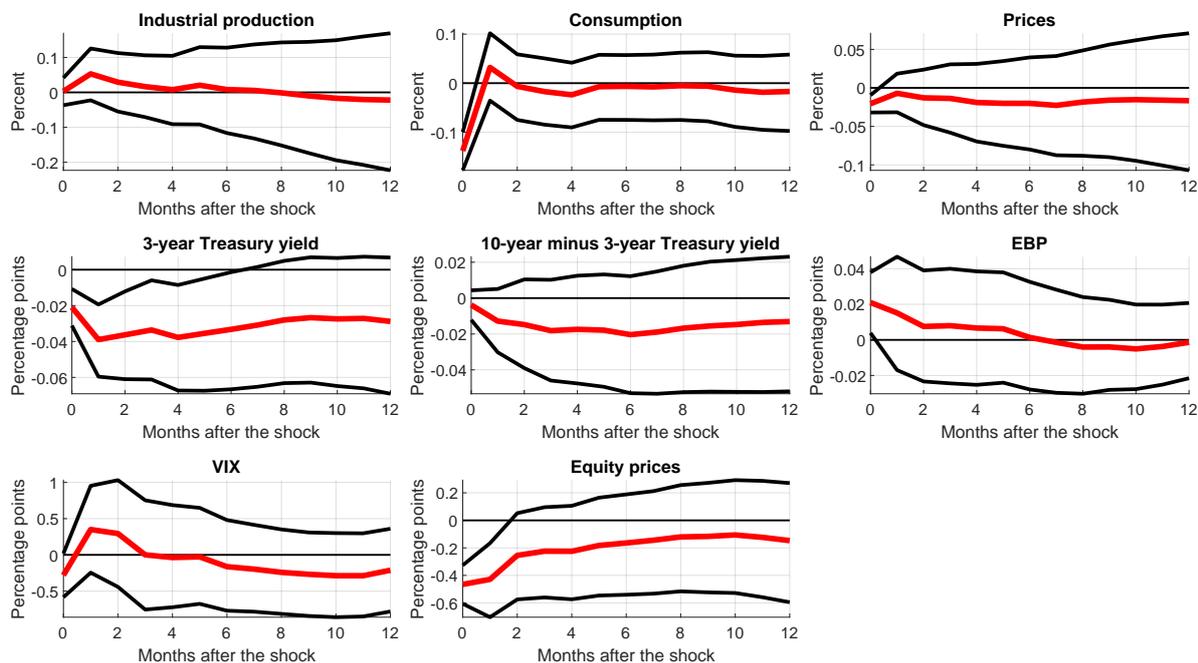

Figure C.1: The impact of shocks decreasing transition risk
Notes: The figure shows the responses of the indicated variables to a negative transition risk shock. Black lines show the 68% highest density region.

Table C.1: Importance of shocks decreasing transition risk (in percent)

Variable		Variable	
Industrial production	0.6	Consumption	7.3
Prices	1.2	3-year Treasury yield	11.1
10-year minus 3-year Treasury yield	2.4	EBP	1.5
VIX	1.4	Equity prices	8.1

Notes: The table shows the forecast error variance decomposition. It is the variance of a given variable explained by a shock decreasing transition risk on average over the first 12 months after the shock.
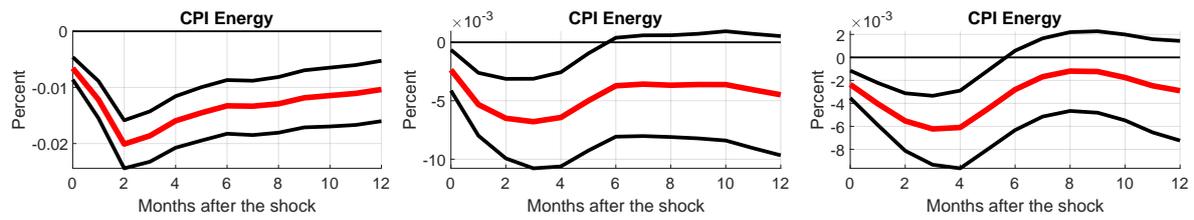
D   Robustness: Energy prices

Figure D.1: Energy prices: United States (left), Germany (middle), and the United Kingdom (right)
Notes: The figure shows the responses of the indicated variables to a shock increasing transition risk. Black lines show the 68% highest density region.

E Robustness: No contemporaneous impact of transition risk shocks

We also estimate a VAR specification in which all other shocks in the system contemporaneously affect the structural shock to transition risk. We achieve this by allowing all endogenous variables to contemporaneously enter the equation identifying the structural shock to transition risk. More specifically, we set $\mathcal{A}$ as:

$$
\mathcal{A} = \begin{array}{c} \\ y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{array}
\begin{array}{ccccc} \text{TRS} & \text{Eq.2*} & \text{Eq.3*} & \cdots & \text{Eq.}n\text{*} \end{array}
\left(\begin{array}{ccccc}
a_{11} & 0 & 0 & \cdots & 0 \\
a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\
a_{31} & 0 & a_{33} & \cdots & a_{3n} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
a_{n1} & 0 & 0 & \cdots & a_{nn}
\end{array}\right).
\tag{5}
$$

Note, however, $\mathcal{A}$ as in Equation (5) imposes strong assumptions on our shock series. For instance, the VAR shock identification assumes that the stock market (and all other financial variables) react with a delay of one month, even though we define shocks to transition risk through negative abnormal returns of one of our green-minus-brown portfolios.

In this sense, this exercise minimizes the importance of the transition risk shocks. Still, we report this exercise because we believe that it is instructive. Even under these strong assumptions, the main results of our paper hold ((i) strong aggregate effects, also on financial stability; (ii) materially affecting fossil fuel and energy sectors). The impulse responses and forecast error variance decompositions for the United States, Germany, and the United Kingdom are reported below.
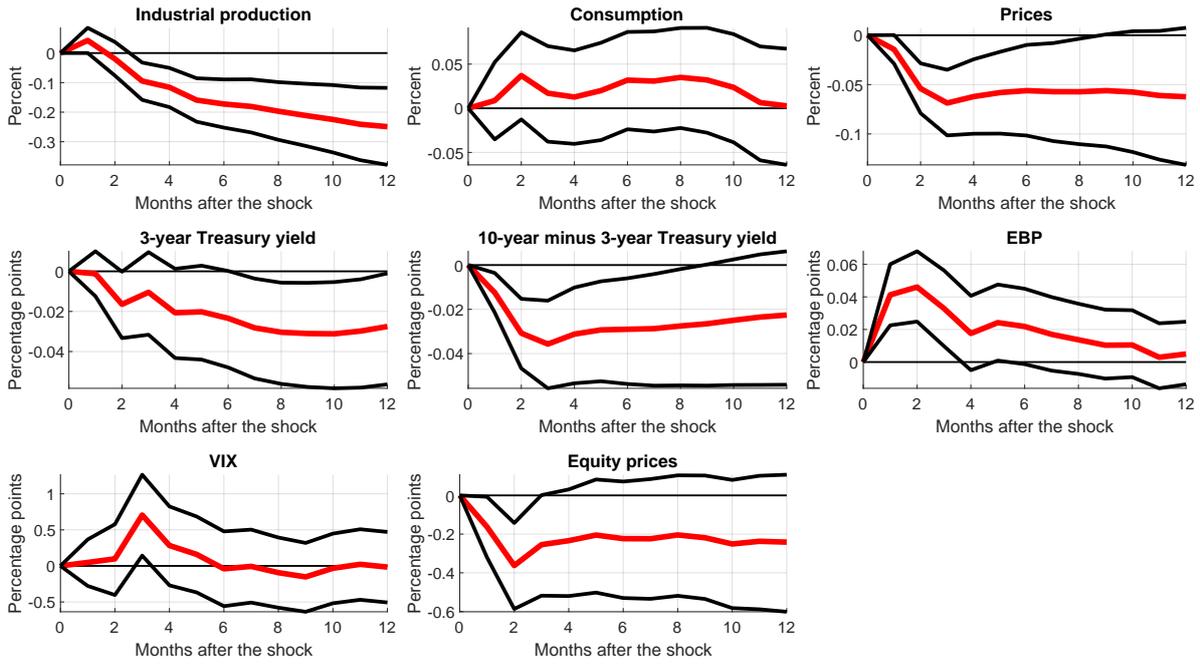
Figure E.1: United States: No contemporaneous impact: Baseline

Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.
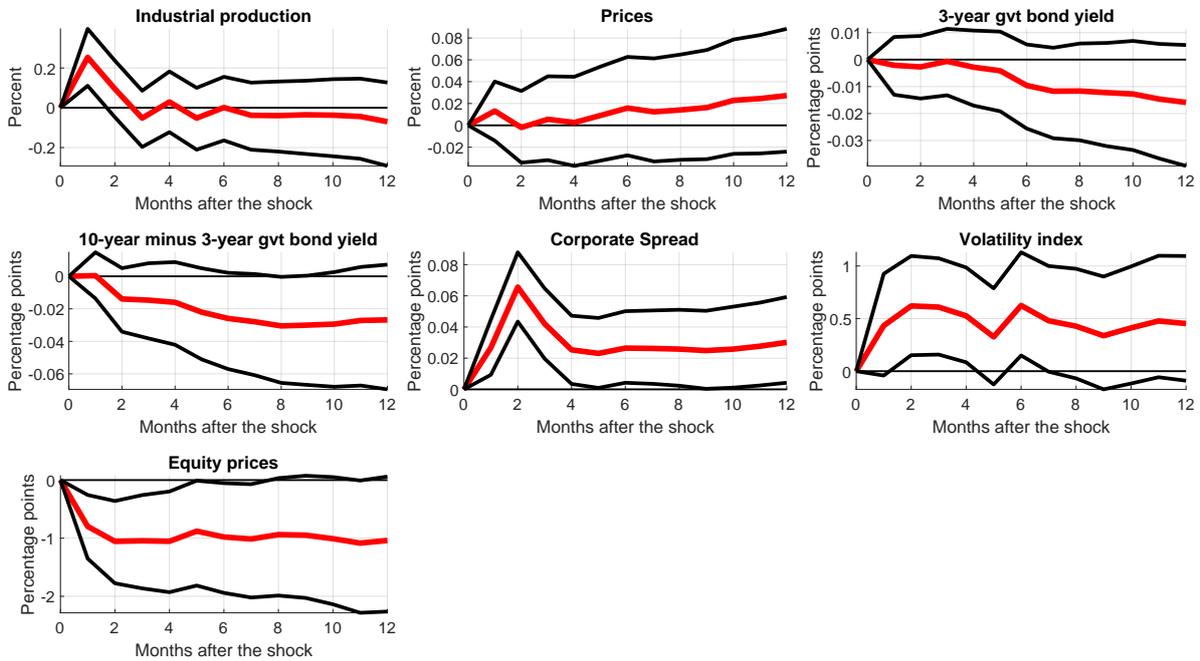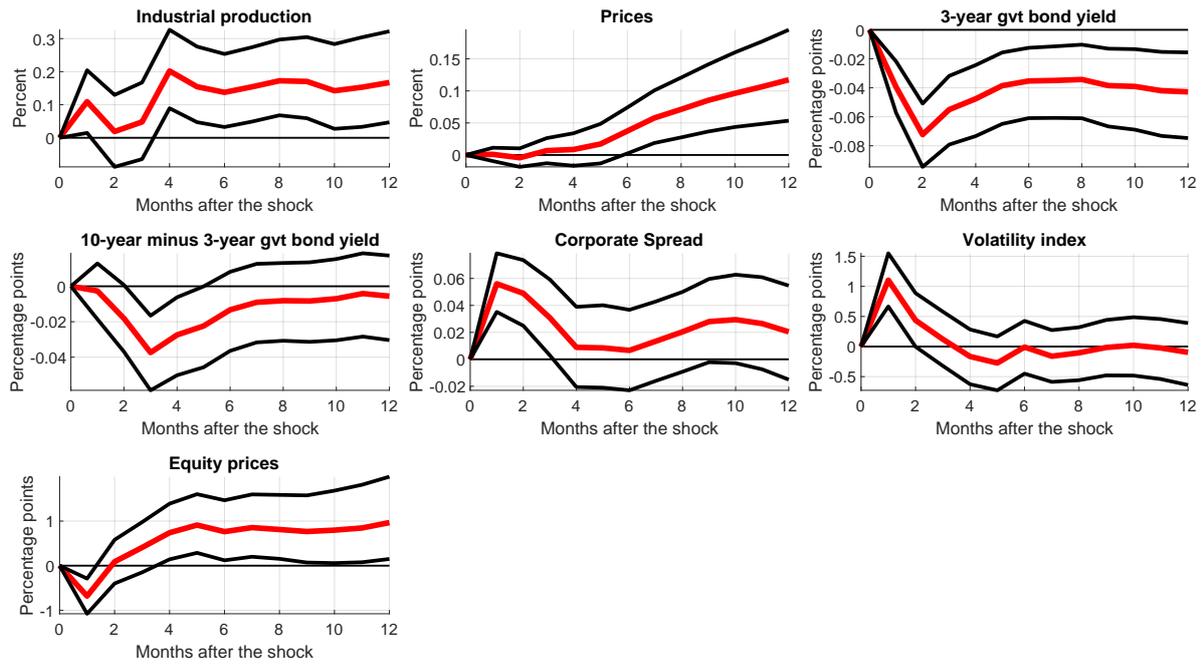

Figure E.2: Germany: No contemporaneous impact: Baseline

Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.
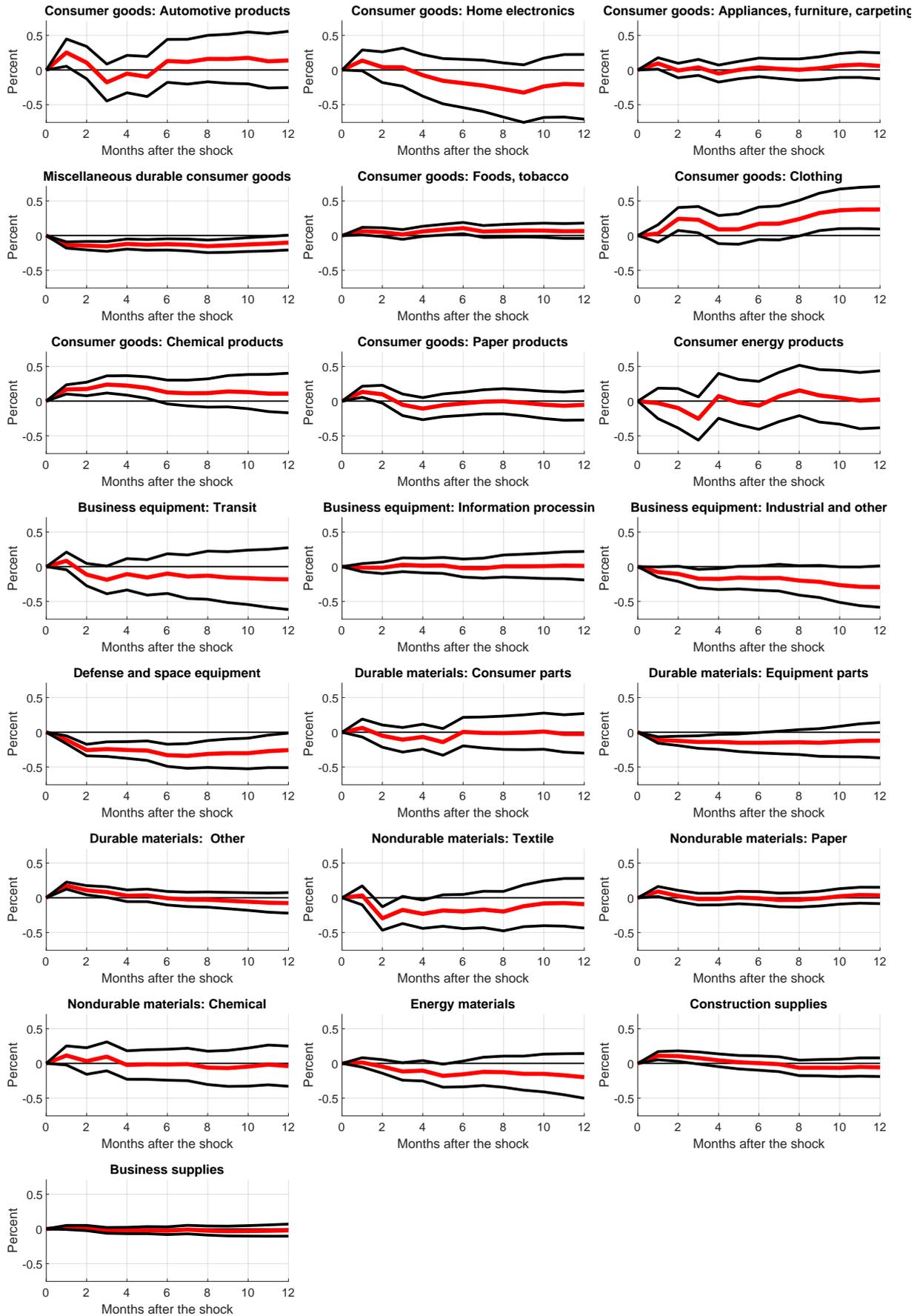
Figure E.3: United Kingdom: No contemporaneous impact: Baseline
Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.

Figure E.4: United States: No contemporaneous impact: Sectoral industrial production
Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.
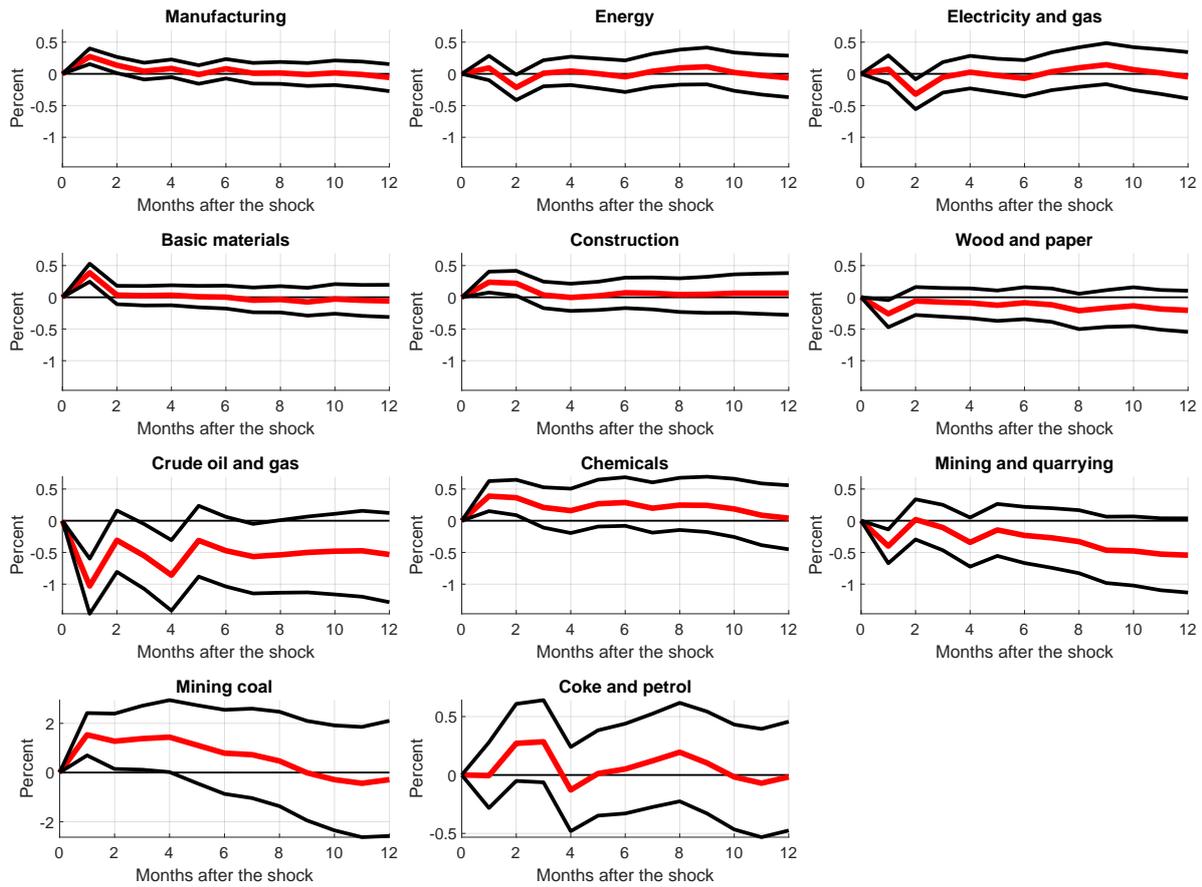
50

Figure E.5: Germany: No contemporaneous impact: Sectoral industrial production

Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.
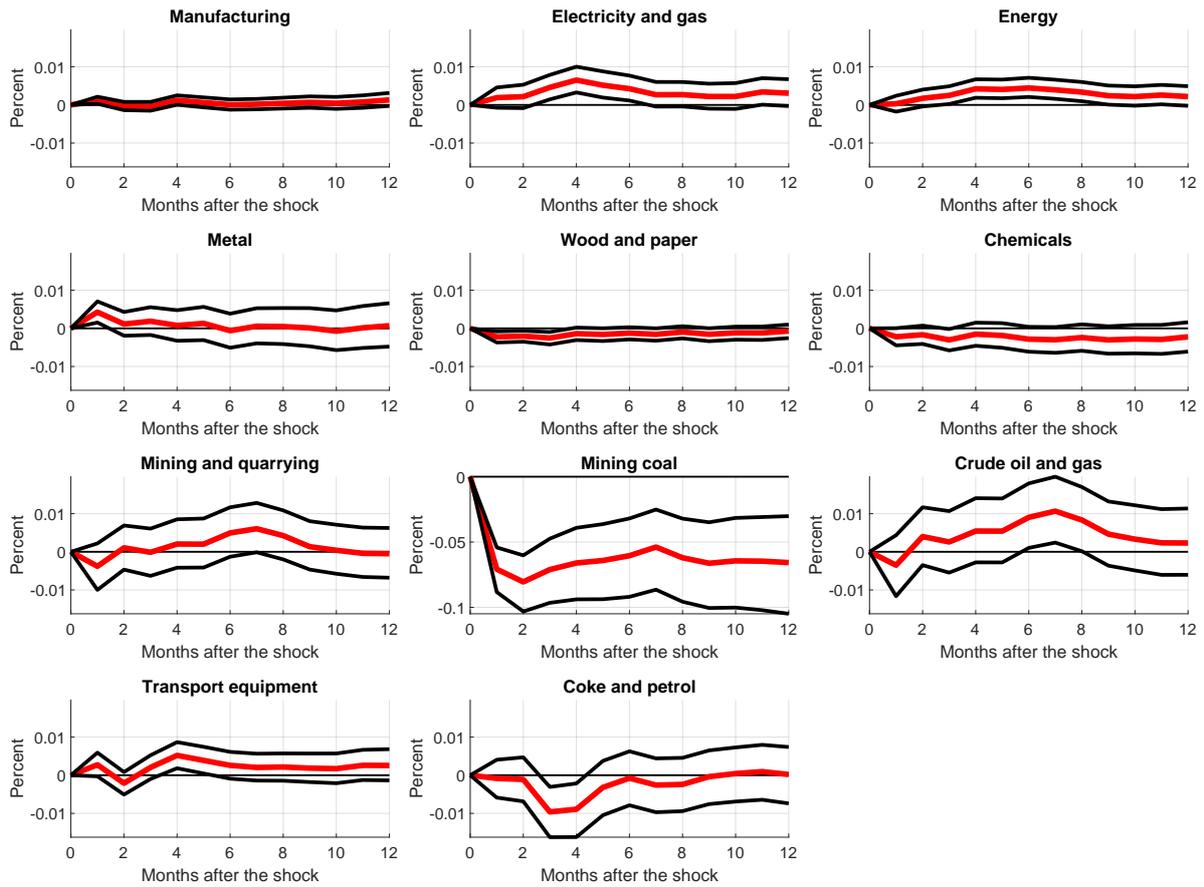
Figure E.6: United Kingdom: No contemporaneous impact: Sectoral industrial production

Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.

Figure E.7: United States: No contemporaneous impact: Industry portfolio variances and NFCI subcomponents

Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.
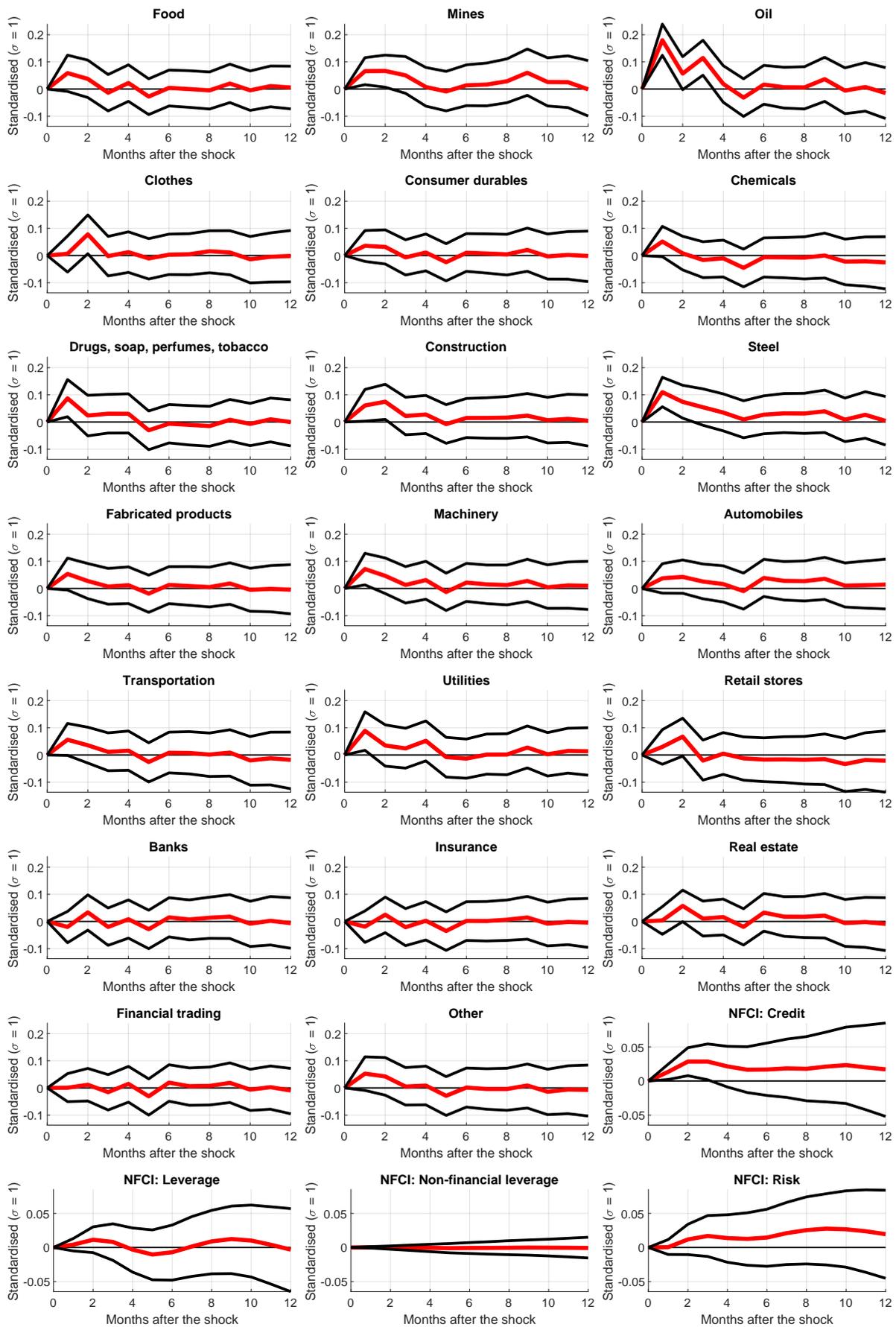
Figure E.8: Germany: No contemporaneous impact: Industry portfolio variances

Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.
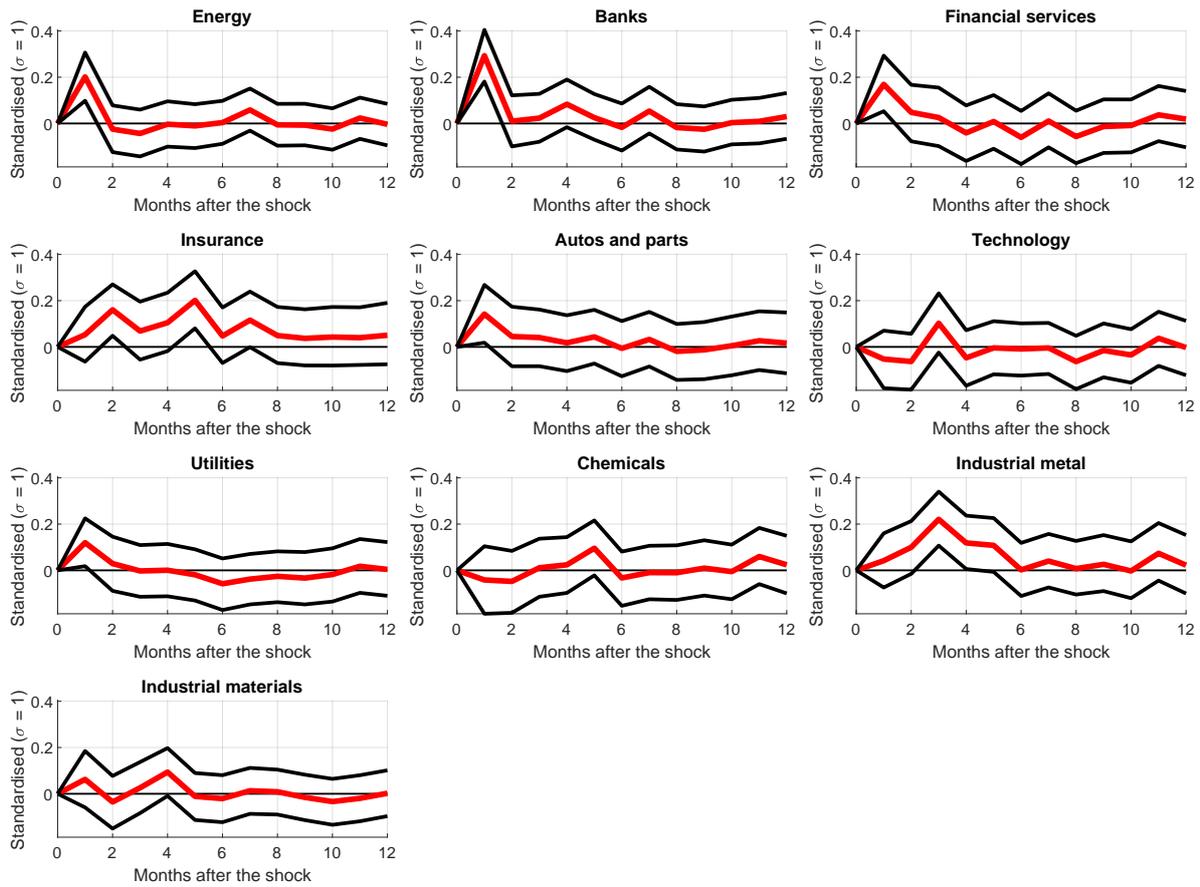
Figure E.9: United Kingdom: No contemporaneous impact: Industry portfolio variances

Notes: The figure shows the responses of the indicated variables to a transition risk shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously. Black lines show the 68% highest density region.
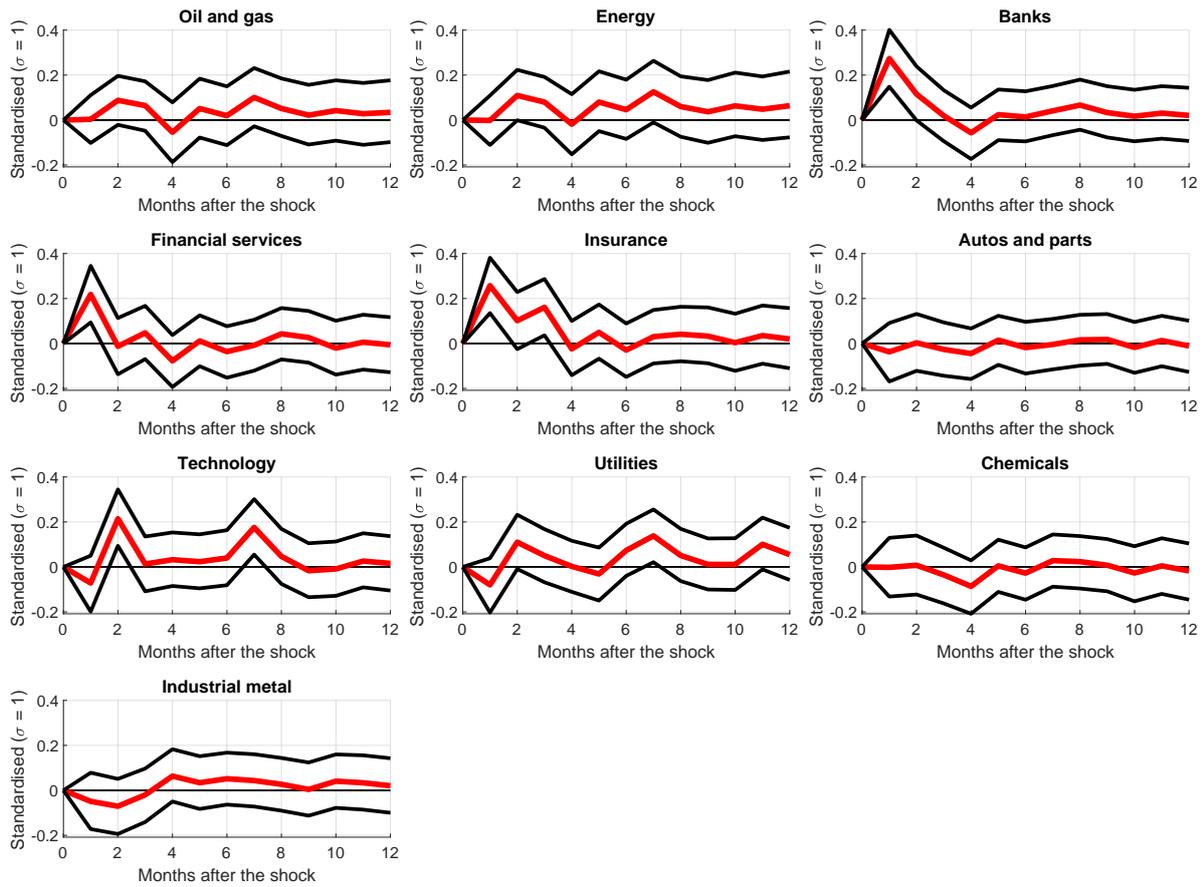
Table E.1: Importance of shocks (in percent): No contemporaneous effect

Variable		Variable	
United States			
Industrial production	8.7	Consumption	0.9
Prices	6.3	3-year Treasury yield	3.2
10-year minus 3-year Treasury yield	6.6	EBP	8.6
VIX	1.6	Cumulative excess market return	3.4
Consumer goods: Automotive products	2.3	Consumer goods: Home electronics	2.1
Consumer goods: Appliances, furniture, carpeting	1.2	Miscellaneous durable consumer goods	21.0
Consumer goods: Foods, tobacco	5.1	Consumer goods: Clothing	6.8
Consumer goods: Chemical products	9.6	Consumer goods: Paper products	2.7
Consumer energy products	1.1	Business equipment: Transit	2.0
Business equipment: Information processing	0.2	Business equipment: Industrial and other	6.4
Defense and space equipment	20.0	Durable materials: Consumer parts	1.1
Durable materials: Equipment parts	8.1	Durable materials: Other	9.4
Nondurable materials: Textile	5.5	Nondurable materials: Paper	1.9
Nondurable materials: Chemical	0.9	Energy materials	3.3
Construction supplies	5.2	Business supplies	1.4
Food	1.3	Mines	3.0
Oil	10.5	Clothes	1.3
Consumer durables	0.7	Chemicals	1.1
Drugs, soap, perfumes, tobacco	2.1	Construction	2.5
Steel	5.5	Fabricated products	1.0
Machinery	2.0	Automobiles	1.5
Transportation	1.2	Utilities	2.3
Retail stores	1.1	Other	1.1
Banks	0.6	Insurance	0.5
Real estate	1.2	Financial trading	0.4
NFCI: Risk	1.4	NFCI: Credit	2.7
NFCI: Non-financial leverage	0.0	NFCI: Leverage	0.4
Germany			
Industrial production	3.3	Prices	0.4
3-year gvt bond yield	1.0	10-year minus 3-year gvt bond yield	2.8
Corporate spread	14.3	Volatility index	6.3
Equity prices	6.6		
Manufacturing	6.2	Energy	1.5
Electricity and gas	2.1	Basic materials	7.1
Construction	3.0	Wood and paper	3.0
Crude oil and gas	11.0	Chemicals	5.0
Mining and quarrying	4.0	Mining coal	4.6
Coke and petrol	1.7		
Energy	7.9	Autos and parts	3.3
Technology	2.3	Utilities	2.8
Chemicals	1.4	Industrial metal	9.1
Industrial materials	2.2	Banks	14.2
Financial services	4.6	Insurance	8.4
United Kingdom			
Industrial production	7.2	Prices	4.1
3-year gvt bond yield	19.8	10-year minus 3-year gvt bond yield	5.3
Corporate spread	8.9	Volatility index	7.9
Equity prices	6.1		
Manufacturing	3.1	Electricity and gas	12.0
Energy	12.8	Metal	2.4
Wood and paper	11.9	Chemicals	5.7
Mining and quarrying	2.4	Mining coal	38.2
Crude oil and gas	4.5	Transport equipment	7.0
Coke and petrol	5.3		
Oil and gas	2.4	Energy	3.5
Autos and parts	0.6	Technology	8.0
Utilities	4.8	Chemicals	1.0
Industrial metal	2.0	Banks	12.0
Financial services	7.1	Insurance	11.5

Notes: For each country, the top panels shows the results for the baseline, the middle panel for the sectoral industrial productions, and the bottom panel for the industry portfolio variances (and the NFCI for the United States). Figures are the forecast error variance decompositions. It is the variance of a given variable explained by a shock to transition risk on average over the first 12 months after the shock. The robustness exercise assumes that the structural shock to transition risk cannot impact variables contemporaneously.

F Robustness: Narrative sign restrictions

In this robustness exercise, we analyze the impact of transition risk shocks using a BSVAR with narrative sign restrictions following Antolín-Díaz and Rubio-Ramírez (2018). In order to exploit their methodology, we construct a brown-minus-green factor for each country that we include in the VAR. We can arguably assume that, on the identified dates, a shock to transition risk had a negative impact on this factor. We construct the factor as the standardized average of all brown-minus-green portfolios used in our identification procedure.[31]

The second identification assumption is that a shock to transition risk has a negative impact on aggregate equity prices, i.e. the CRSP value-weighted equity index. Clearly, the assumption on the aggregate equity price response is stronger than the assumption on the brown-minus-green factor. But given the structure of this broad US equity index, we argue that it is still justifiable, and it is also in line with the response of equity prices when using the BVAR following Waggoner and Zha (2003). Finally, in order to keep the additional assumptions to a minimum, we also use a flat prior instead of a Minnesota prior. Given the flat prior, we adjust the lag lengths such that we can still estimate the VAR ($p = 7$ for the US and $p = 2$ for the UK and Germany). As highlighted in the main text, we are only able to run this analysis for our benchmark setup, since otherwise the system would be too large for the few assumptions taken. By and large, we find that the results below are qualitatively the same as in our main analysis in the paper.
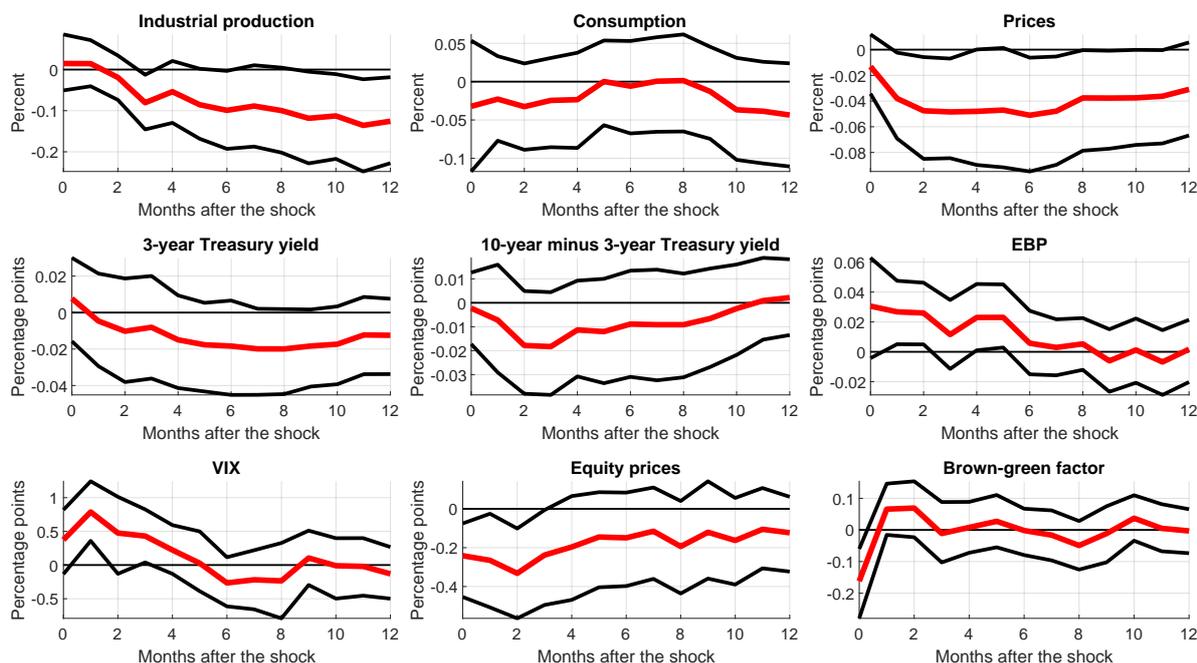

Figure F.1: United States: Baseline using narrative sign restrictions
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

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[31]Note that this exercise is only proxying our shock identification. This is because we use several portfolio sorts to identify our shocks to transition risk. Therefore, to explicitly mimic our shock identification, we would have to include three (or two for Germany and the United Kingdom) portfolio sorts in the BSVAR and impose the narrative sign restrictions only on the relevant portfolio for each date. This, however, would increase the number of variables and would decrease the number of narrative sign restrictions we can impose on the series. Therefore, we argue that the approach followed here is the most reasonable and robust one.
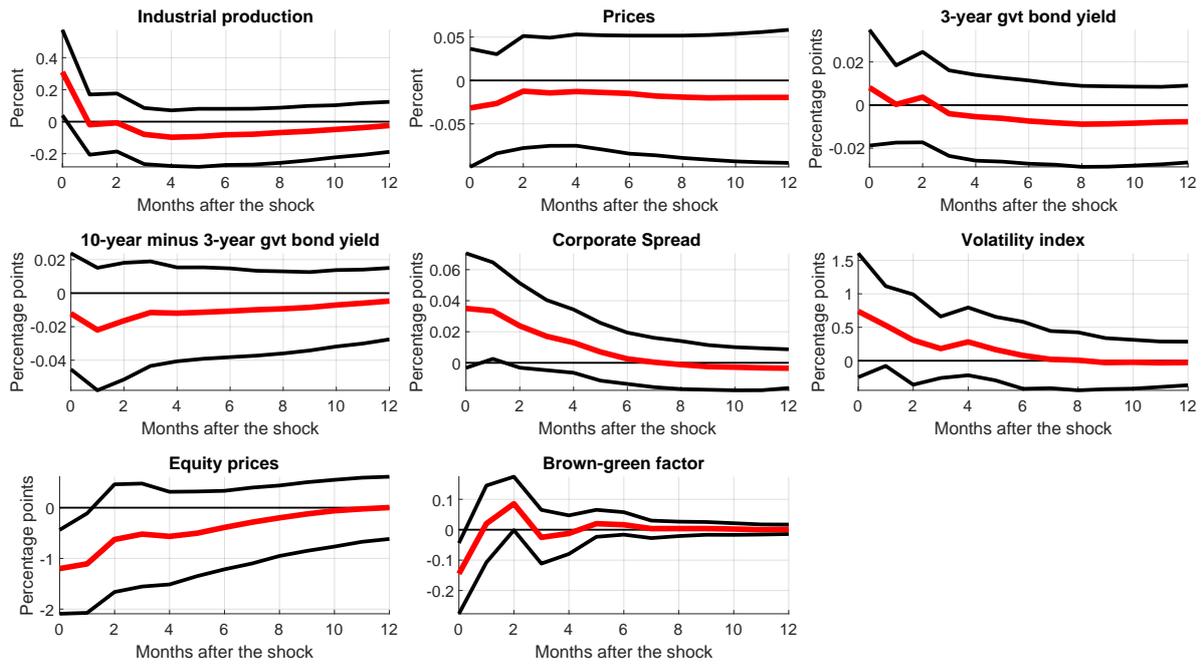
Figure F.2: Germany: Baseline using narrative sign restrictions
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.
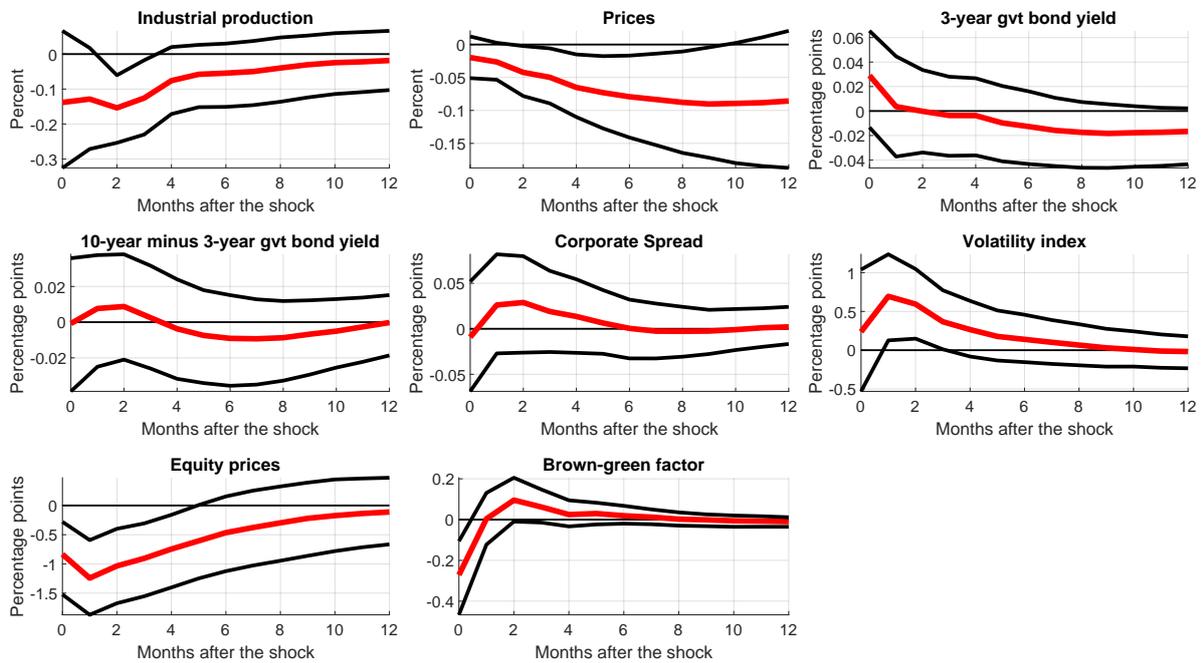

Figure F.3: United Kingdom: Baseline using narrative sign restrictions
Notes: The figure shows the responses of the indicated variables to a transition risk shock. Black lines show the 68% highest density region.

Table F.1: Importance of shocks (in percent): Narrative sign restrictions

Variable		Variable	
United States			
Industrial production	8.6	Consumption	6.3
Prices	10.4	3-year Treasury yield	6.8
10-year minus 3-year Treasury yield	7.6	EBP	11.6
VIX	12.0	Cumulative excess market return	9.0
Brown-green factor	10.8		
Germany			
Industrial production	10.5	Prices	7.1
3-year gvt bond yield	8.6	10-year minus 3-year gvt bond yield	8.2
Corporate spread	11.4	Volatility index	11.2
Equity prices	6.8	Brown-green factor	10.2
United Kingdom			
Industrial production	12.2	Prices	13.3
3-year gvt bond yield	9.0	10-year minus 3-year gvt bond yield	8.3
Corporate spread	6.9	Volatility index	10.7
Equity prices	17.2	Brown-green factor	14.8

Notes: For each country, the top panel shows the results for the baseline with narrative sign restrictions. Figures are the forecast error variance decompositions. It is the variance of a given variable explained by a shock to transition risk on average over the first 12 months after the shock.