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Climate risk and commodity currencies

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Climate Risk and Commodity Currencies*

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Abstract

The positive relationship between real exchange rates and natural resource income is well understood and studied. However, climate change and the transition to a lower-carbon economy now challenges this relationship. We document this by proposing a novel news media-based measure of climate change transition risk and show that when such risk is high, major commodity currencies experience a persistent depreciation and the relationship between commodity price fluctuations and currencies tends to become weaker.

JEL-codes: C11, C53, D83, D84, E13, E31, E37

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1 Introduction

In the autumn of 2020 one of the highest-profile climate change lawsuits cases was being processed by the Norwegian Supreme Court. The case, where environmental groups argue that new exploratory drilling licenses violate a constitutional right to a healthy environment, has attracted considerable attention both in Norway and internationally. The reason is that it is a test case taking on an industry that is key to a commodity exporter's economy. Regardless of outcome,[1] it directly challenges the right to further exploration and thereby implicitly argues for a structural transformation towards a lower-carbon economy. In this transition, fossil fuel commodity production has to be reduced. This creates climate change transition risk.[2]

Does climate change transition risk already affect prices? Recent experiences suggest this could be the case: Low fossil fuel commodity currency valuations and the apparent disconnection between commodity prices and currencies, starting around 2016, have been puzzling market analysts monitoring the exchange rate market closely. As Norges Bank hypothesized in 2019:

> *"The krone has been weaker for some time than projected in the Monetary Policy Report. [...] Prospects for lower activity in the petroleum sector and uncertainty about the need for restructuring in the Norwegian economy may also have weighed on the krone."(Norges Bank Monetary Policy Report 3/2019)*

In this article we formally investigate the pricing implications of climate change transition risk on commodity currency developments in Australia, Brazil, Canada, Malaysia, Mexico, Norway, Russia, and South Africa. In particular, we look upon climate change transition risk as *concerns about structural change and policies aimed at reducing environmental and climate impact* voiced in the public discourse, and use tools from the Natural Language Processing (NLP) literature, and a unique dataset of news coverage from the *Dow Jones Newswires Archive* (DJ), to construct measures of this type of climate risk. We then document that when climate risk is high, these commodity currencies experience a persistent depreciation and the relationship between commodity prices and currencies tends to become weaker.

[1] As of this writing, the verdict has still not been made public.

[2] Climate change risks are often decomposed into the following three components (Carney, 2015): *Physical risk* arising from climate- and weather-related events; *Liability risk* arising if losses due to climate change are insured and legally pursued with compensation demanded; *Transition risk* resulting from the process of adjustment towards a lower-carbon economy. In the following we will often denote *climate change transition risk* simply as *climate risk*, but make the distinction between the different climate change risks when it is important and to avoid confusion.

These results are all new in the literature, but their intuition can easily be understood using standard economic theory and acknowledging that expectations about the future matter for exchange rates today. First, the theory on structural transformation from changes in natural resource income predicts that decreased income from natural resources results in lower overall domestic demand (Corden and Neary (1982), Corden (1984)). Part of this lower demand is absorbed by lower demand for non-traded goods, which implies that labor and capital will flow to the traded sectors. A depreciation of the exchange rate facilitates the shift. This is just the basic "Dutch disease theory". Conventionally, the theory is often formulated under the assumption of an exogenous permanent fall in commodity prices. However, as documented empirically and theoretically in Bjørnland and Thorsrud (2016) and Bjørnland et al. (2019), the effect can also be formulated under the expectation of a permanently lower activity level in the commodity-producing sector of a country. Accordingly, when climate risk, i.e., concerns about structural transformation away from fossil fuel production, is high, the exchange rate should experience a persistent depreciation, as we find.[3]

Second, although modeling exchange rates is difficult (Meese and Rogoff, 1983), a vast empirical literature on commodity exporters has shown that including commodity prices in exchange rate models provides a substantially better fit to the data (see, e.g., Amano and van Norden (1995), Chen and Rogoff (2003), Akram (2004), Bodart et al. (2012), Ferraro et al. (2015), Zhang et al. (2016), Kohlscheen et al. (2017)). The reason is that commodity price fluctuations contain important exogenous terms-of-trade shocks. Thus, to the extent that prolonged periods of increasing climate risk make commodity currencies less dependent on commodity income, either because of lower global demand for fossil fuels in general, or because resource income has become a smaller share of total value creation in the commodity-exporting country, a weaker correlation between commodity price fluctuations and exchange rates is what one would expect.

The novelty of our analysis is how we use tools from the NLP literature and news media coverage to construct country-specific measures of climate change transition risk. While the scientific discussion about climate change and the statistical evidence documenting

[3]This does not rule out that high climate risk is associated with expectations of permanently lower commodity prices. As long as production technology has diminishing returns to scale, a long-run depreciation of the exchange rate is a common feature in theoretical models containing a reduction in natural resource income. Under the assumption of constant returns to scale in production, however, the equilibrium exchange rate will typically be determined only by the supply side of the economy, and commodity income does not matter (Rogoff and Obstfeld, 1996, Chap. 4). Still, even in this setting, transitional dynamics imply a real exchange rate depreciation, and the return to an equilibrium might take a very long time. Moreover, the real exchange rate might also be affected, even in the very long run, if domestic markups correlate positively with commodity income.

it dates back several decades (Arrhenius (1896), Keeling (1970), Nordhaus (1977)), the puzzle related to commodity prices and currencies, and the public awareness of climate risk and its potential economic consequences, seems to be of a much newer date. For this reason we share the view taken in, e.g, Nimark and Pitschner (2019), Larsen et al. (2020), and ter Ellen et al. (2020), where the media operates as "information intermediaries" between agents and the state of the world, and use news media coverage as a proxy for capturing changing perceptions of climate risk in the public discourse. This naturally includes changes in actual policies and investor and consumer behavior, but also more silent features related to systematic directional modification of ideas and narratives as they are spread in the public discourse (Shiller (2017), Hirshleifer (2020)).

Our underlying hypothesis is simple: When the association in media coverage between a given country and talk about structural change and policies aimed at reducing environmental and climate impact is high, it signals climate risk that might lead to a persistent depreciation of commodity currencies and weaken their relationship with commodity prices, due to the mechanisms discussed above.

We operationalize this hypothesis using a unique and large corpus, i.e., text from over 20 million articles, of international business news provided by DJ. This data is then partitioned into monthly blocks and a neural network is used to construct word embeddings for each month in the dataset. Word embeddings represent words in vector space, and have, following the seminal contributions of Mikolov et al. (2013) and Mikolov et al. (2013), become a much-used tool in the NLP and Machine Learning (ML) literature. The reason is that they densely encode many linguistic regularities and patterns, and allow for arithmetic operations capturing associative meaning. Accordingly, for each month in the sample, we derive the weighted sum of word vectors representing concerns about structural change and policies aimed at reducing environmental and climate impact, and regress these on word vectors for each country. The parameter estimates of these regressions measure how strong the association between a given country and climate risk is in each month.

Including the climate risk indexes in otherwise standard empirical exchange rate models increases the model fit by roughly 8 percent on average. Allowing for a non-linear relationship between climate risk and exchange rates suggests that climate risk has affected commodity currencies throughout the 2000s, but that the dominant effects are found after 2014. Moreover, although the relationship between commodity prices and currencies tends to become weaker when climate risk is high, this finding is not universal across the countries we study. For countries where the commodity basket contains a large share of gas exports, we actually find the opposite relationship. This indicates that climate risk is also associated with substitution effects between fossil fuel products.

Consuming gas, for example, emits less Green House Gas (GHG) than consuming coal, potentially benefiting exporters of the former commodity at the expense of the latter.

The negative relationship between climate change transition risk and commodity currency valuations is affirmed when we estimate Vector-Autoregressive (VAR) models. Taking into account the dynamic interactions between, e.g., commodity prices, asset prices, currencies, and climate risk, shows that climate change transition risk is generally not significantly affected by the other variables in the system, whereas exogenous climate risk innovations generally lead to a significant and persistent exchange rate depreciation. Because natural resource income is an important part of aggregate income creation in major commodity exporters, forward looking asset markets are naturally also affected by these effects. According to our estimates, an unexpected increase in climate change transition risk tends to cause persistently lower aggregate stock market valuations.

To the best of our knowledge, this is the first analysis providing evidence about how climate change transition risk affects the highly liquid foreign exchange market. Our results do not only have practical importance for policy makers, as highlighted by the quote above, but also contribute to three different growing strands of the economic literature.

First, our study speaks directly to a growing literature on the pricing implications of climate risk. Cha et al. (2020) analyze the responses of monthly U.S. dollar real exchange rates of 76 countries to global temperature shocks, i.e., physical climate risk, and find significant responses for roughly half of the countries in the sample, where increasing the relative size of the agricultural sector makes one more prone to a depreciation. Thus far, however, most of this literature has been concerned with pricing of firms and firm value. For example, Krueger et al. (2020) use a survey to document that institutional investors believe climate risks have financial implications for their portfolio firms and that these risks, particularly regulatory risks, have already begun to materialize.[4] In relation to commodity producers, the recent study by Atanasova and Schwartz (2019) is particularly relevant. They find that growth of commodity-producing firms' fossil fuel reserves now has a negative effect on firm value, suggesting that capital markets treat fossil fuel as "stranded assets" in the transition to a lower-carbon economy. Thus, just as stranded assets might affect firms' value negatively because of climate risk, our results imply that this risk also negatively affects the pricing of exchange rates and aggregate stock markets in countries where natural resource income is a large fraction of total income.

Second, this article speaks to a growing literature using tools from NLP and ML to address puzzles and improve measurement in economics and other social sciences. For example, Kozlowski et al. (2018) use word embeddings to produce richer insights into

[4]For other recent examples on the same topic, see, e.g., Bolton and Kacperczyk (2020), Hsu et al. (2020), Freeman et al. (2015), Daniel et al. (2019), Batten et al. (2016), Andersson et al. (2016), In et al. (2017).

cultural associations and categories than possible with existing methods in the field of sociology, while Thorsrud (2018), Larsen and Thorsrud (2019), Baker et al. (2016), and Hansen et al. (2018) use text as data to measure business cycle developments, uncertainty, and monetary policy. In particular, by focusing on climate change, this article relates to Engle et al. (2020) who propose a news-based climate risk measure for dynamically hedging climate change risk. However, their index essentially measures *how much* climate change is focused upon in the news, whereas our word embedding approach measures in *what context* it is focused upon. In terms of commodity currencies, the difference between *how much* and *what context* matters. Indeed, when using the climate risk index proposed by Engle et al. (2020) to explain exchange rate fluctuations, the estimated coefficients of climate risk are inconsistent regarding their sign and often insignificant.

Finally, our study relates more loosely to a growing literature studying information diffusion, belief formation, and the social processes that shape economic thinking and behavior (Gentzkow et al. (2011), King et al. (2017), Prat (2018), Shiller (2017), Hirshleifer (2020)). Consistent with studies finding that the news media channel matters in this context (Larsen et al. (2020), ter Ellen et al. (2020)), we find that alternative climate risk approximations, such as so-called Climate Change Performance Indexes or actual temperature change anomalies, tend to produce inconsistent results across countries in terms of explaining commodity currency developments. Thus, climate change transition risk, and how economic agents in the commodity currency market perceive this risk, does not seem to be measurable from climate change statistics or hard economic data alone.

The rest of this paper is organized as follows: Section 2 presents the textual data, the word embedding methodology, and the proposed climate risk measures. Section 3 describes the exchange rate modeling framework and presents the main results. In Section 4 we document that our results are robust to a number of different modeling choices. Section 5 concludes.

2 Climate risk and measurement

Below we describe the DJ corpus in greater detail, and then how we apply a word embedding model to construct quantitative and country-specific climate risk measures.

2.1 News coverage and word embeddings

The DJ corpus consists of roughly 23 million news articles, written in English, covering the period 2001 to 2019. The database covers a large range of Dow Jones' news services, including content from *The Wall Street Journal*. Arguably, the DJ does not fully reflect the public discourse. Still, news stories relevant for investors and agents in the international foreign exchange market are undoubtedly well covered by this type of business news. The *Dow Jones* company, and its flagship publication *The Wall Street Journal*, is also one of the largest newspapers in the U.S. in terms of circulation. This means that it has a large footprint in both the U.S. and global media landscape and that important ongoing stories and discussions are well covered by this type of news outlet.

The news corpus is cleaned prior to estimation. We remove all email and web addresses, numbers, and special characters, erase punctuation, set all letters to lowercase, and remove words containing fewer or more than two and ten letters, respectively. These feature selection steps reduce the size of the vocabulary to approximately 90000 unique terms. The dimension reduction facilitates estimation and is common in the literature. Finally, the corpus is partitioned into monthly blocks of articles. Each month of data contains between 42000 (2005M2) and 115000 (2013M3) articles.

To make the vast amount of text into quantifiable objects useful for statistical analysis, we use a word embedding model. Word embedding models represent words as relatively small and dense vectors. The famous and widely used word2vec algorithm (Mikolov et al. (2013), Mikolov et al. (2013)) is one of many algorithms to compute such vectors, and is often denoted as a skip-gram model with negative sampling. In essence, the method uses a binary classification problem, asking "is word *co* likely to show up near the word *ta*?", as a vehicle to compute the classifier weights which will be the actual word embeddings.

In our setting, this approach has two particularly appealing features. First, running text can be used as implicit supervised training. This avoids the need for any sort of hand-labeled supervision signal and makes the methodology flexible and user friendly in many different contexts. Second, and most importantly, the estimated word embeddings encode many linguistic regularities and patterns, and allow for arithmetic operations that can capture associative meaning. A famous example is "king" $-$ "man" $+$ "woman" $\approx$ "queen", where the word (vector) "king" and the difference between "woman" and "man" pulls the resulting vector in the royal and feminine directions, respectively. Thus, the resulting vector tends to end up close to the actual vector for the word "queen".

More formally, given a target word ta and a context word co, the probability that the word co is (is not) a real context word for ta is $P(+|ta, co)$ ($P(-|ta, co) = 1 - P(+|ta, co)$). The intuition for the skip-gram model is then that a word is likely to occur near the target if its embedding is similar to the target embedding, where similarity is approximated by the dot product of the word vectors for co and ta. The goal of the learning algorithm for the skip-gram model is then to maximize

$$L(\theta) = \sum_{(ta,co)\in +} P(+|ta, co) + \sum_{(ta,co)\in -} P(-|ta, co), \tag{1}$$

which for one word/context pair (ta, co) can be written as:

$$L(\theta) = log\frac{1}{1+e^{-co\cdot ta}} + \sum_{i=1}^{k} log\frac{1}{1+e^{n_i\cdot ta}}, \tag{2}$$

where k denotes the context window for which the co words occur relative to the target word ta, and the logistic (or sigmoid) function is used to turn the similarity measure between the word vectors for co and ta into probabilities. The last term in (2) relates to the negative sampling part of the skip-gram model name. As running text is used as input to the model, only positive examples are present and negative examples need to be generated and added to the data. These terms are commonly called noise terms (n_i). Thus, for each target word, it is common to add k noise words.

Maximizing (2) can be solved using different methods. Here we use a simple two-layered neural network. This method is fast, efficient to train, and easily available in many software packages. The context window $k = 5$, we restrict the word embedding length $d = 100$, and the network is trained for five epochs on every monthly partition of the data. Thus, for each month in the sample, the word2vec algorithm provides us with a large word embedding matrix, where each row represents a word in the vocabulary, and the column length equals d.

2.2 Word embeddings and climate risk

To construct our climate risk measures, i.e., concerns about structural change and policies aimed at reducing environmental and climate impact, we use the linguistic regularities and patterns encoded in the word vectors and arithmetic operations. The intuition for this approach is very much the same as in the royal example above.

More precisely, we first define five word-based categories representing the content of our definition, and then add these together to obtain an approximation of what we define as climate change transition risk. This is illustrated in Table 1. Accordingly, the sum of the *concern*, *fossil fuels*, and *economy* categories results in a vector intended to point in a direction encompassing "concerns about structural change in a fossil fuel exporting economy", whereas adding $climate^{+} - climate^{-}$ is intended to pull the vector in a more climate-friendly direction, encompassing "policies aimed at reducing environmental and climate impact". Finally, to capture the monthly association between countries and our definition of climate risk, we solve

$$CR_t \equiv \hat{\beta}_t = \arg\min S(\beta_t) \quad \text{and} \quad S(\beta_t) = \left\| country_{ct} - climate\ risk_t \times \beta_t \right\|^2, \tag{3}$$

where the word vector for $country_{ct}$ is given in Table 1, and β_t is the association between country c and climate risk. Although $\hat{\beta}_t$ is estimated using the OLS estimator on each

Table 1. Constructing climate risk indexes from word embeddings. The upper part of the table reports the core of the climate risk definition used in this article. Categories are printed in bold and the associated words (i.e., word vectors) are listed in the right side of the table. The lower part of the table reports the words (word vectors) used to define each country. To avoid associating climate risk with the African continent as a whole, we use words related to South Africa's two largest capitals when defining the South African country vector.

Definition and **categories**		Words
Climate risk $\approx$		
$\boldsymbol{concern}_t$	=	$\frac{1}{n_1}(concern_t + concerned_t + risk_t + risky_t + uncertain_t + worried_t + worrying_t)$
about structural change in a		
$\boldsymbol{fossil\ fuel}_t$	=	$\frac{1}{n_2}(extract_t + mine_t + fossil_t + fuels_t + fuel_t + oil_t + crude_t + petroleum_t + coal_t + lignite_t)$
exporting		
$\boldsymbol{economy}_t$	=	$\frac{1}{n_3}(economy_t + economic_t + economics_t + business_t + sector_t + sectors_t)$
due to more		
$\boldsymbol{climate}_t^+$	=	$\frac{1}{n_4}(climate_t + green_t + clean_t + renewable_t + oxygen_t + recycling_t + ecosystem_t + cooling_t + protect_t)$
relative to		
$\boldsymbol{climate}_t^-$	=	$\frac{1}{n_5}(emissions_t + dirty_t + fossil_t + dioxide_t + methane_t + pollution_t + warming_t + exploit_t)$
policies and actions		

$$Climate\ risk_t \approx concern_t + fossil\ fuel_t + economy_t + (climate_t^+ - climate_t^-)$$

Countries ($country_{ct}$)		
Norway	=	$\frac{1}{n}(norway_t + norwegian_t)$
Mexico	=	$\frac{1}{n}(mexico_t + mexican_t)$
Malaysia	=	$\frac{1}{n}(malaysia_t + malaysian_t)$
Canada	=	$\frac{1}{n}(canada_t + canadian_t)$
Australia	=	$\frac{1}{n}(australia_t + australian_t)$
South Africa	=	$\frac{1}{n}(pretoria_t + cape_t)$
Brazil	=	$\frac{1}{n}(brazil_t + brazilian_t)$
Russia	=	$\frac{1}{n}(russia_t + russian_t)$

monthly partition of the sample, the subscript t is used to highlight that this relationship potentially changes across time.

We emphasize three points about this construction. First, because of differences in policies, public perception, and consumer and investor behavior across countries, the degree of climate risk is not only time-varying, but also potentially country-specific. Second, the individual words in each category in Table 1 are averaged to construct one word vector for each category. This ensures that the methodology is robust to the exact words, and the number of words, allocated to each category.[5] Finally, the CR_t estimates contain both high- and low-frequency fluctuations. Part of the high-frequency fluctuations can

[5] Performing over 30000 random leave-one-word-out (of each category) permutations of the words listed in Table 1, and computing a climate risk measure for each unique combination of words, does not change the main conclusions presented in Section 3.2 (Figure B.1 in Appendix B).

be due to randomness in news coverage across months. To remove this high-frequency variation, the raw CR_t series are smoothed using moving averages with a window size of seven months.[6]

To construct confidence intervals for the CR_t estimates, we follow Kozlowski et al. (2018) and conduct subsampling (Politis and Romano, 1994). For 90% confidence intervals, the corpus (for any given month) is randomly partitioned into 20 subcorpura, and the word2vec algorithm is run to produce the word embedding matrix for each partition of the data. Then, the error of the projection statistic CR_t for each subsample s is $e^s = \sqrt{\tau_s}(CR_t^s - CR_t)$, where τ_s and CR_t^s are the number of texts and the solution to (3), respectively, in subsample s. Then, the 90% confidence interval spans the 5th and 95th percentile variances, defined by $CR_t + \frac{e^{s(19)}}{\sqrt{\tau}}$ and $CR_t - \frac{e^{s(2)}}{\sqrt{\tau}}$, where $e^{s(2)}$ and $e^{s(19)}$ denote the 2nd and 19th order statistic associated with the lower and upper bound of the confidence interval.

Figure 1 reports the country-specific climate risk measures together with the estimated uncertainty. As clearly seen in the graphs, the climate risk measures are very precisely estimated. It is also clear that there is large cross-country variation in the degree of climate risk across time. For Norway, for example, the degree of climate risk is substantially higher in the period after 2012 than in the preceding 10-year period, while the developments in Brazil are almost the opposite. However, for six of the eight countries we study, the peak of the climate risk estimates occur after 2014. For some of the countries, i.e., Norway, Mexico, Malaysia, and Canada, the climate risk measures also contain a small upward-drifting trend during this sample period.

In studies using text as data, it is common to annotate graphs like those in Figure 1 with historical events to informally validate how plausible the estimates are from a narrative perspective. Such an approach is less suited here. The reason is that CR_t measures the association between a country and climate risk, and not how much climate risk is talked about per se. In other words, whereas events likely affect *how much* different topics are talked about in the public discourse, the events might not change in *what context* these topics are talked about. Still, the annotations reported in Figure 1 suggest that there is some correlation between important climate events and our proposed climate risk indexes. In the case of Norway, for example, there has been a substantial increase in climate risk following the decision to stop further oil and gas exploration in the Arctic.

[6] As alternative strategies, one could have estimated the word2vec algorithm at a lower frequency, e.g., yearly partitions of the news data, and thereby obtained less volatile word embeddings, or estimated (3) using a more complex time-varying parameter model. We refrained from these alternatives to keep the methodology simple and to allow for the possibility of sudden, and potentially permanent, monthly shifts in CR_t. However, Figure B.2, in Appendix B, shows that the main results presented in Sections 3.2 and 3.3 are robust to working with the raw climate risk estimates as well as using larger smoothing windows.

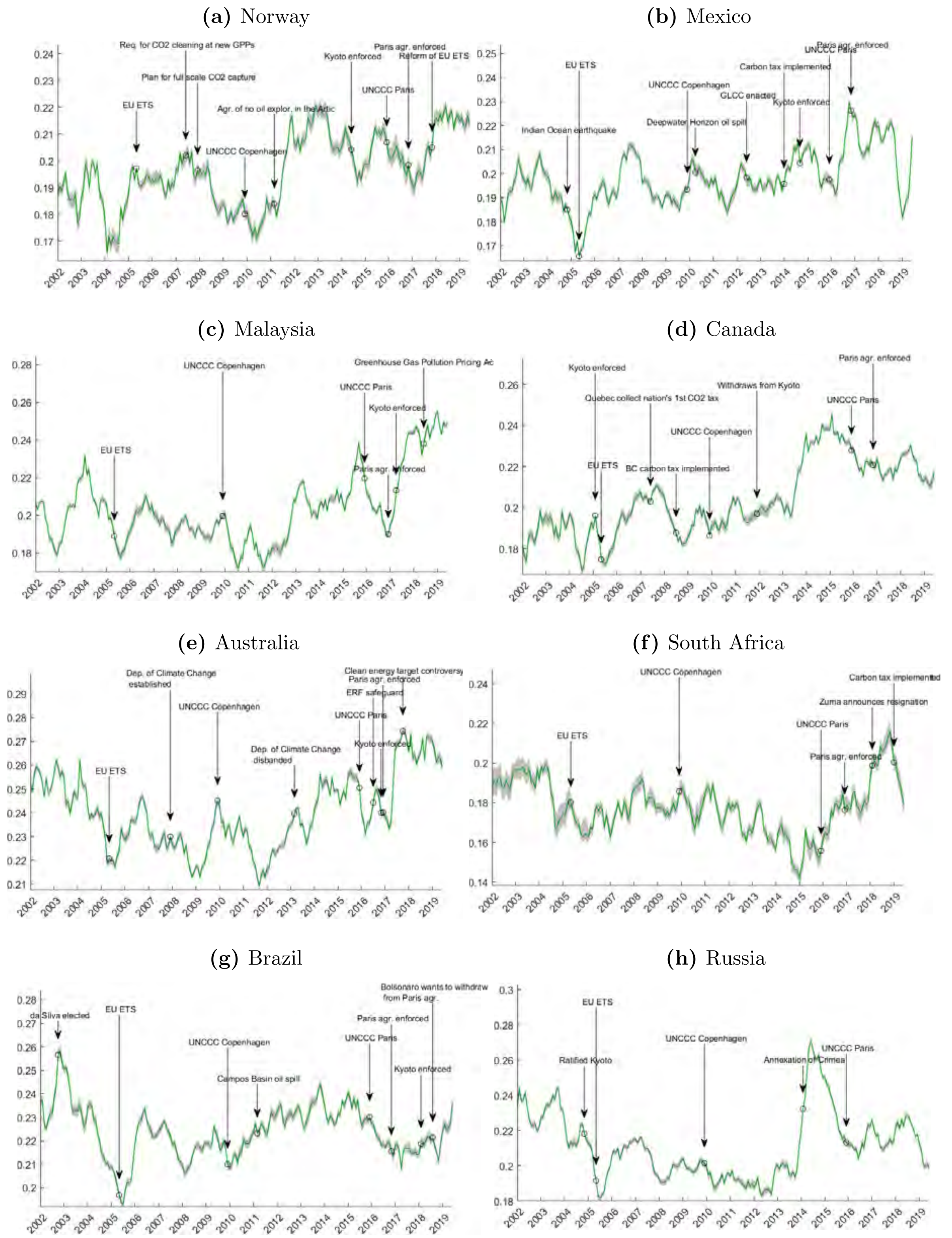


Figure 1. Climate change transition risk. The green lines show the mean estimates. The gray color shadings cover the 90% confidence intervals. The annotations report some important international and domestic climate change and political events. The ordering of countries follows from the fact that Norway, Mexico, Malaysia, and Canada produce primarily petroleum products, while the remaining countries produce a mix of commodities, including gas, oil, and coal (Figure B.6 in Appendix B).

Table 2. Climate risk and temperature anomaly correlations. The first row reports the correlation between the raw series. The second column reports the correlation when a Hodrick–Prescott filter (Hodrick and Prescott, 1997), with a smoothing parameter set to 1600, is used to extract the low-frequency fluctuations from the series. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Norway	*Mexico*	*Malaysia*	*Canada*	*Australia*	*SouthAfrica*	*Brazil*	*Russia*
Raw	0.31***	0.47***	0.45***	-0.13*	0.35***	-0.12*	-0.15**	-0.09
HP-filtered	0.60***	0.75***	0.64***	-0.22***	0.63***	-0.10	-0.15**	-0.09

Similarly, most countries experienced an increase in climate risk in the period after the Paris agreement and around the implementation of the EU Emissions Trading System (ETS).[7]

Another way to informally validate the constructed climate risk measures is to analyze how they correlate with one of the most direct and widely used measures of climate change, namely temperature change observations (see, e.g., Deschenes and Greenstone (2007) and Kumar et al. (2019) for applications in economics and finance). After all, it is reasonable to assume that media coverage of climate risk should bear at least some resemblance to actual climate change statistics. We therefore collect statistics from the GISS Surface Temperature Analysis and use the longitude and latitude resolution provided in that database to construct country-specific monthly time series of abnormal temperature fluctuations.[8] Table 2 shows that the correlations are high and significant for at least half of the countries in our sample, and particularly so when looking at the low-frequency movements in the series. Figure B.5, in Appendix B, visualizes these correlation patterns, and graphs the temperature anomaly series together with our measures of climate risk.

3 Commodity currencies

Can climate change transition risk explain commodity currency developments? In the following, we first present a simple single-equation benchmark model intended to capture

[7]Some climate risk spikes have a more ambiguous interpretation. The large increase in climate risk for Russia in 2014, for example, might be due to a large increase in the association between Russia and risks due to conflict, or alternatively, concerns about future Russian gas supply to continental Europe. Only the latter interpretation has a plausible relationship with our definition of climate risk. For these reasons we also control for alternative uncertainty measures in the exchange rate models used in the next section.

[8]GISTEMP Team, 2020: GISS Surface Temperature Analysis (GISTEMP), version 4. NASA Goddard Institute for Space Studies. Dataset accessed 2020-10-18 at https://data.giss.nasa.gov/gistemp/. See Lenssen et al. (2019) for details and the most recent description of the data. By definition, these time series measure deviations from the corresponding 1951-1980 means. It is common in the climate literature to remove high-frequency noise from the series, and here we do so using the same moving average filter as used for the news-based climate risk measures.

short- and long-run fluctuations in commodity currencies. We then document how it performs relative to an augmented version including climate risk. Next, we evaluate the relationship between commodity currencies and alternative climate risk approximations, including temperature anomalies, and present results from systems taking into account dynamic interactions between commodity prices, currencies, and climate risk.

3.1 The benchmark model and prediction failures?

The theoretical and empirical literature on exchange rate determination is vast. Here we take a somewhat reduced-form view and use a Behavioural Equilibrium Exchange Rate (BEER) modeling approach (Clark and MacDonald, 1999).[9]

The BEER model builds on the observed fact that real exchange rates (REER) are far from constant and takes as a starting point that the slow reversion to Purchasing Power Parity (PPP) observed in the data can be explained by fundamental variables explaining either short- or long-run fluctuations in real exchange rates. For commodity-exporting economies, and for data sampled at monthly frequency, commonly used explanatory variables include a commodity price index and short- and long-run interest rate differentials to capture deviations from Uncovered Interest rate Parity (UIP), differences in growth prospects, and potential forward guidance effects (Amano and van Norden (1995), Chen and Rogoff (2003), Akram (2004), Bodart et al. (2012), Ferraro et al. (2015), Zhang et al. (2016), Kohlscheen et al. (2017), Martinsen (2017)). Newer studies also often include some measures of uncertainty to capture "flight-to-quality" effects in times of trouble, such as financial crisis, wars, and geopolitical risks (Forbes and Warnock (2012), Rey (2015), Goldberg and Krogstrup (2018), Caldara and Iacoviello (2018), Akram (2020)). Thus, the simple benchmark model we consider can be written as

$$REER_t = \gamma_0 + \gamma_1 r_t^S + \gamma_2 r_t^L + \gamma_3 UNC_t + \gamma_4 GPR_t + \beta_1 ComX_t + u_t \tag{4}$$

where t denotes the time index, r_t^S and r_t^L are the respective short- and long-run real interest rate differentials, UNC_t is a (global) measure for financial uncertainty, GPR_t is a measure of (global) geopolitical risk, and $ComX_t$ is the real commodity price index.

Naturally, in later sections (4) is augmented with the proposed climate risk indexes. In the interest of conserving space, a detailed description of the traditional economic variables is relegated to Appendix A. In short, for a given country the REER measures the real effective exchange rate, and we construct the real interest rate differentials using

[9] While there are theoretical structural models of exchange rate determination, they are, as noted by Rossi (2013), "...typically too stylized to be literally taken to the data" and do not fit exchange rate data well. In contrast, BEER models are widely used in policy institutions and have proven to provide a reasonable historical fit to the data (Martinsen (2017), Mijakovic et al. (2020), Akram (2020)).

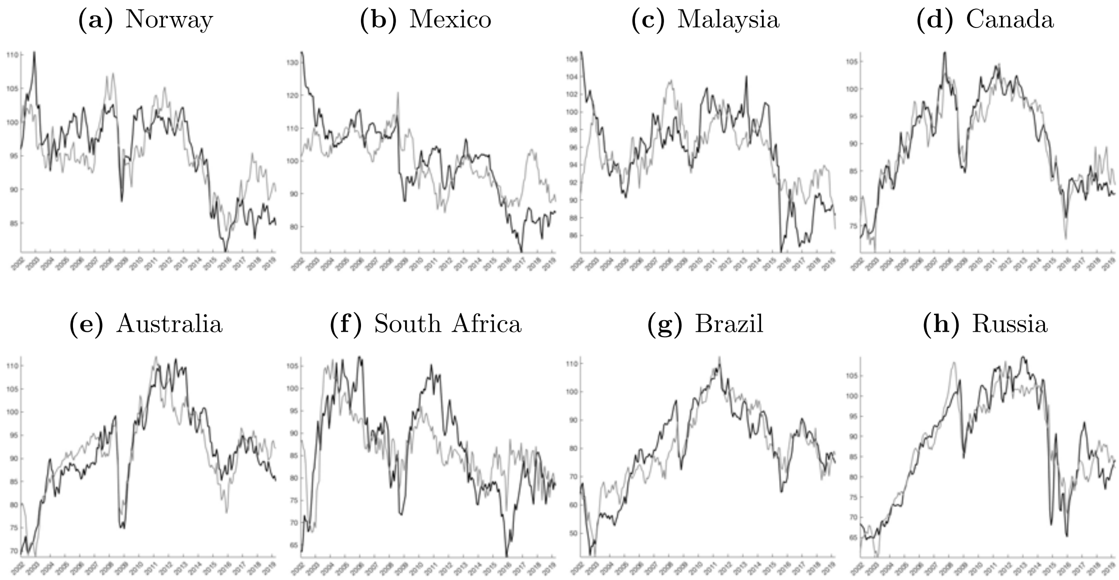


Figure 2. REER and benchmark model fit. The figure shows the real effective exchange rate indexes (black) and the in-sample fitted values (gray) from the benchmark regressions (equation (4)).

trade weights. The benchmark uncertainty measure is the VIX_t derived from implied volatility in the U.S. stock market, the GPR_t is obtained from Caldara and Iacoviello (2018), and $ComX_t$ is obtained from Gruss and Kebhaj (2019).[10]

The model in (4) is estimated separately for each country c, and later also as a panel regression, using data covering the period 2002M1 to 2019M6. This ensures that we have the same amount of data available for all the countries we study, and it is a period in which many of the countries in our sample either directly or indirectly have adopted a monetary policy regime associated with inflation targeting. To obtain parameter estimates, we use the Dynamic Ordinary Least Squares (DOLS) estimator (Stock and Watson, 1993), which takes into account the possible endogeneity of the right-hand side variables as well as potential omission of dynamic effects in models.[11]

Figure 2 graphs the REER for each country as well as the fitted values from (4). Figure 3 reports the adjusted R^2 statistics and parameter estimates. For visual clarity, we only

[10] $ComX_t$ takes into account the basket of commodities produced by country c, and is constructed using time-varying net-export shares. As discussed in Gruss and Kebhaj (2019), different findings across studies regarding the relationship between commodity prices and currencies might simply reflect differences in how the commodity price indexes are defined. As documented in Figure B.3, in Appendix B, our main results regarding climate risk and exchange rates (see Sections 3.2 and 3.3) are robust to using the alternative commodity price indexes suggested by Gruss and Kebhaj (2019).

[11] A battery of tests give inconsistent results across countries, regarding both the existence of variable unit roots and the degree of cointegration. Our qualitative conclusions are robust in estimating the long-run coefficients in (4), and (5) in the next section, using either the OLS estimator or Autoregressive Distributed Lag (ARDL) models (Pesaran and Shin, 1998). See also Section 3.5, where we estimate (5) as an endogenous system using VAR models.

report estimates associated with our main research question, i.e., $ComX$ and CR, noting that the remaining estimates are all generally consistent with economic theory, and can be obtained on request. Two broad patterns stand out. First, although simple, the model is able to explain the historical exchange rate developments for these eight commodity currencies fairly well. As seen from the gray entries in the last column in Figure 3, the adjusted R^2 statistics are as high as 0.85 and over 0.6 on average. Moreover, an increase in the commodity price index is associated with an appreciation of the REER for all commodity exporters, as expected. For most of the countries in the sample, the effect is also highly significant.

Second, towards the latter part of the sample, and especially after 2014, the model fit deteriorates for many of the countries. In particular, while there are earlier periods in the sample where the predicted and actual exchange rates differ considerably, it is only towards the end of the sample this finding is common for most of the countries.

3.2 Adding climate risk

To investigate the role played by climate risk, we augment (4) with the CR_t indexes, such that

$$\begin{aligned} REER_t = &\gamma_0 + \gamma_1 r_t^S + \gamma_2 r_t^L + \gamma_3 UNC_t + \gamma_4 GPR_t \\ &+ \beta_1 ComX_t + \beta_2 CR_t + \beta_3 (ComX_t \times CR_t) + u_t \end{aligned} \tag{5}$$

and z-score both the commodity price indexes and the climate risk measures prior to estimation (to make the interpretation of the parameter estimates easier).

In (5), β_2 captures the idea that higher values of climate risk should be associated with a lower REER because structural transformation away from fossil fuels implies that labor and capital will have to flow from the non-traded to the traded sectors in the economy. More short-run effects are captured by β_3, which measures how terms-of-trade shocks associated with the commodity market interact with climate risk. While the expected sign of β_2 is clear (negative), the expected sign of β_3 is more ambiguous.

We expect β_3 to be negative if prolonged periods of increasing climate risk make commodity countries less dependent on commodity income, or if rising climate risk is associated with (global) changes in preferences and public regulation and incentive schemes towards renewable energy sources. Both cases are plausible, and in both cases a simultaneous increase in commodity prices and climate risk will lead to smaller terms-of-trade effects than normal.

On the other hand, in the climate change debate, some fossil fuels are looked upon as "greener" than others. For example, consuming gas emits less GHG than consuming

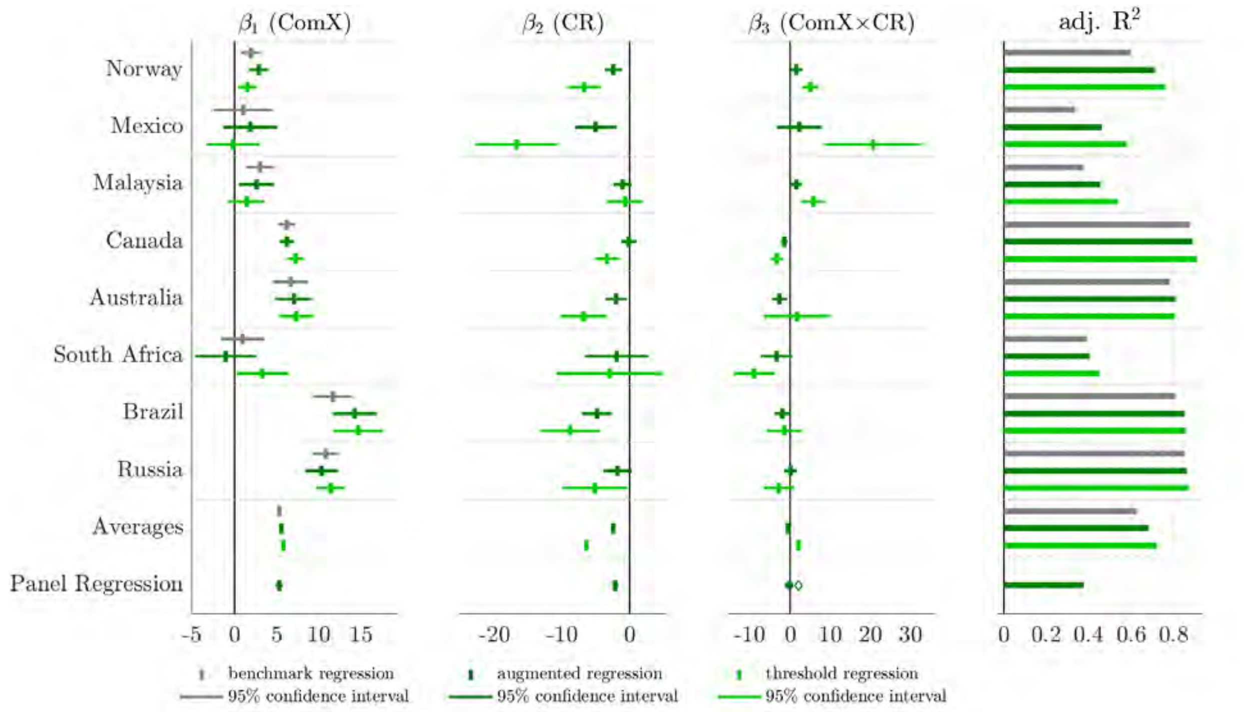


Figure 3. Exchange rates, commodity prices and climate risk estimates. The benchmark regression is defined in (4), the climate-augmented regression is defined in (5), and the threshold regression is defined in (6). The 95% confidence intervals are computed using HAC-corrected standard errors. The row labeled *Average* reports the average coefficient estimates across countries. The row labeled *Panel* reports the results from estimating a version of (5) using a fixed effect panel estimator with standard errors clustered at the country level. A separate interaction term between climate risk and commodity prices is estimated for countries producing (filled circles) and not producing (diamonds) coal.

coal.[12] Accordingly, as highlighted by some recent studies, substitution effects between fossil fuel products affect their relative demand (Bloch et al. (2015), Baffes et al. (2020)), potentially benefiting exporters of petroleum products at the expense of exporters of coal. If these effects are strong, a simultaneous increase in commodity prices and climate risk might actually lead to larger terms-of-trade effects than normal, i.e., a positive β_3 estimate.

The augmented regression results marked in dark green in Figure 3 summarize our main result. An increase in climate risk is without exception associated with a depreciation of the REER. The results for the three countries exporting primarily petroleum products, i.e., Norway, Mexico, and Malaysia, are particularly strong. Here, the β_2 estimates are significant at the 95% level (90% level for Malaysia), and the improvement in fit between the benchmark regression and the climate risk augmented version is between 16% (Norway) and 36% (Mexico). Although the improvement in model fit is less extreme

[12]Indeed, in the debate about climate change and what to do about it, an increase in gas consumption, at the expense of, e.g., oil and coal, is discussed as a solution by organizations such as the International Energy Agency (IEA, 2020).

for the other countries, the direct climate risk effect is predominantly negative, and very uncertain only for South Africa. On average across the countries, a one standard deviation increase in climate risk is associated with a real exchange rate depreciation of about 2.5 index points. Further, including climate risk in the models increases the adjusted R^2 by roughly 8% on average.

In terms of the interaction effects, the results are more mixed and less significant. However, in line with simple descriptive statistics on commodity production (Figure B.6 in Appendix B), we find a separation between commodity exporters producing coal and those that do not. For Norway, Mexico, and Malaysia, the β_3 estimates are positive, while the estimates for the remaining countries are negative (or zero). Together, these results are consistent with an interpretation where climate risk leads to substitution effects between fossil fuel products.

A logical consequence of this heterogeneity argument is that the country-specific climate risk measures share a non-trivial common (global) component, and that this common component, rather than the country-specific one, matters for the interaction term. That is, a substitution between fossil fuel products should only matter to the extent that climate risk matters for the commodity market as a whole, not for a single country. To investigate this more formally, we compute the risk component common to all countries in our sample, and include this component as well as one country-specific (idiosyncratic) risk measure in (5) and re-estimate the model. As seen from Figure B.7 in the appendix, the direct effect of both the common and idiosyncratic risk components tend to have a negative effect on the REERs, as before. Most importantly, however, the effect of interacting the commodity price index with idiosyncratic climate risk is largely insignificant, while the interaction term between the common component and commodity prices follows the same pattern as in Figure 3.[13]

The last row in Figure 3 formalizes these arguments further by showing the results from a fixed effects panel regression where a separate interaction term between climate risk and commodity prices is estimated for countries producing and not producing coal. As seen in the figure, the direct effect of climate risk is highly significant and negative,

[13] The common component is computed as the first principal component of the country-specific climate risk measures. The idiosyncratic climate risk measures for each country are then computed as the residuals from regressing the common component on the original country-specific risk measures. Figure B.4, in Appendix B, reports the common component. It explains roughly 40% of the cross-country variation. Another logical consequence of the substitution argument is that an increase in the common component of climate risk should be associated with less global consumption of coal as well as higher prices for coal relative to oil and gas in particular. I.e., coal prices should not simply increase because of higher demand for the commodity. A simple glance at the data suggests that both of these factors seem present (Table B.1 in Appendix B).

and the interaction terms have the expected signs: For countries not producing coal, a simultaneous increase in climate risk and commodity prices leads to a positive and significant terms-of-trade effect. In contrast, for coal producers, the effect is negative, although the parameter estimate is insignificant.

3.3 Allowing for non-linearities

To accommodate for the possibility that climate change and the introduction of climate risk represent a structural break in the relationship between commodity prices and currencies, we proceed by estimating simple threshold models (Hansen, 2000). In this setup, the real exchange rate can be described by the following model

$$REER_t = \begin{cases} \gamma_0 + \beta_1 ComX_t + \Gamma \boldsymbol{x}_t + u_t & \text{if } CR_t < z \\ (\gamma_0 + \beta_2) + (\beta_1 + \beta_3) ComX_t + \Gamma \boldsymbol{x}_t + u_t & \text{if } CR_t \geq z \end{cases} \tag{6}$$

with $\hat{z} = \arg\min_z SSR$, and where $\boldsymbol{x}_t$ is a vector containing the variables r_t^S, r_t^L, UNC_t, and GPR_t. Accordingly, we assume there are two regimes, and that the difference between them is driven by the climate risk index and the effect of commodity prices on REER. If the climate risk index is below the threshold value z, the model in (6) would be the same as the one in (4). In contrast, if the climate risk index is above the threshold value z, the intercept term changes to $\tilde{\gamma}_0 = (\gamma_0 + \beta_2)$, while the effects of commodity price fluctuations on REER are captured by $\tilde{\beta}_1 = (\beta_1 + \beta_3)$. In line with the discussion above, we expect high climate risk to be associated with a lower long-run REER value, i.e., $\tilde{\gamma}_0 < \gamma_0$, while the size of $\tilde{\beta}_1$ relative to β_1 is ambiguous.

The threshold regression results marked in light green in Figure 3 report the estimated β_1, β_2, and β_3 parameters from (6). Qualitatively, the main conclusions from the linear case continue to hold. However, the non-linear model naturally provides a better fit to the data, primarily for Norway, Mexico, and Malaysia, and the direct effect of climate risk on commodity currencies becomes stronger and more negative. While in a high climate risk regime, i.e., when $CR_t \geq z$, a one standard deviation increase in climate risk is associated with an average real exchange rate depreciation of 8 index points.

To probe deeper into the timing of the different regimes, Figure 4 reports the fitted values from (6) together with color shadings illustrating time periods with high climate risk regimes. We only report the results for countries where the β_2 estimates are significant, and for comparison report the actual REER and the benchmark results from estimating (4). As seen in the figure, the model suggests that the latter part of the sample, especially the period after 2014, is associated with periods of high climate risk for almost all countries. Perhaps more surprising is the fact that earlier periods, and in particular the start of the sample, seem to be associated with a high climate risk regime

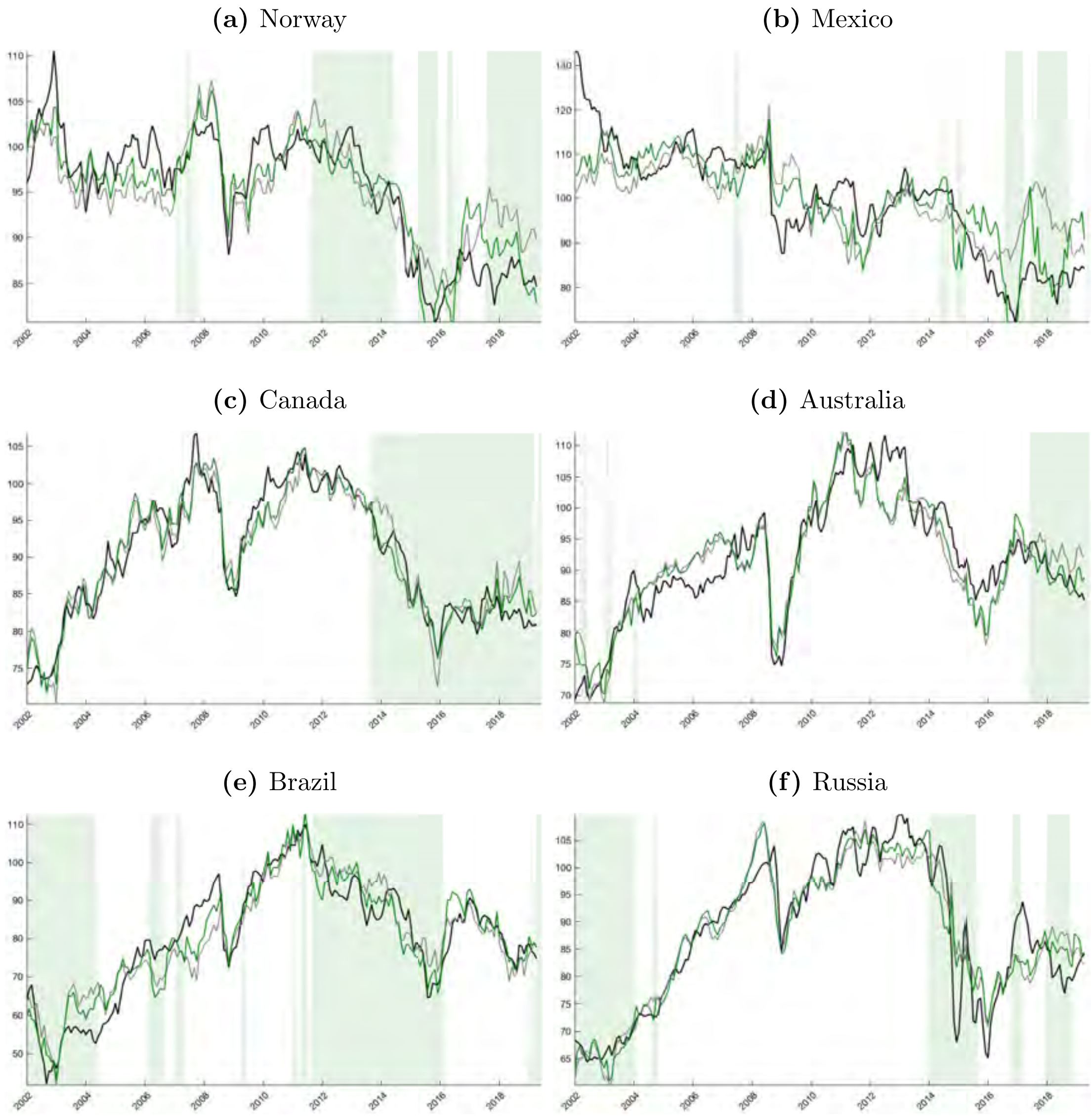


Figure 4. REER, benchmark and threshold model fit. The figure shows the REERs (black) and the in-sample fitted values from the benchmark model (gray: equation (4)) and the threshold model (green: equation (6)). The shaded areas indicate high climate risk regimes, i.e., when $CR_t \geq z$ in (6).

for at least some of the countries, i.e., Brazil and Russia. Still, it is a common theme for all countries that the biggest improvements in model fit are obtained after 2014. For Norway, for example, the benchmark model prediction is off by roughly 6 index points in 2019, whereas the prediction of the climate-augmented threshold regression is off by less than 2 index points.

Admittedly, the results in Figure 4 also echo our earlier findings that climate risk does not always matter a lot. Canada is a good example. Here, although climate risk has a negative effect on the exchange rate, augmenting the benchmark exchange rate model with this risk does not improve the model fit significantly. In the next section, we further validate our results by comparing them to using alternative climate risk approximations.

3.4 Alternative climate risk approximations

Because climate risk is not directly observed, the literature we speak to has used different approaches to approximate it based on either "soft" data such as text or "hard" data such as climate change statistics.

The recent news-based climate risk measure suggested by Engle et al. (2020) builds on a type of motivation similar to that of our measures, where the news media implicitly operate as information intermediaries between agents and the state of the world. However, they use their proposed climate risk measure to explore various ways of dynamically hedging climate change risk in the asset market, and their climate risk measure does not try to separate between the different forms of climate change risk. Moreover, their index can be looked upon as a common (global) risk measure, and builds on a frequency-based approach, measuring *how much* climate risk is focused upon in general. In contrast, our risk measures are country-specific and measure in *which context* climate risk is focused upon. Figure 5 shows that these differences matter for describing the relationship between climate risk and commodity currencies. In particular, by replacing our suggested climate risk measures with the one proposed by Engle et al. (2020), and re-estimating (5), one observes that the estimated coefficient of climate risk is inconsistent regarding the sign and often insignificant. With the exception of South Africa, however, the estimated signs of the interaction terms are more in line with ours. This is also logically consistent with our earlier discussion about how global (common) risk potentially affects the β_3 estimates.

Another proxy for climate risk used in the literature, see, e.g., Atanasova and Schwartz (2019), are so-called Climate Change Performance Indexes (CCPI). A well-known set of measures in this respect are produced by the non-governmental organization *Germanwatch* since 2005. Their CCPIs, see Figure B.8, in Appendix B, track countries' efforts to combat climate change, and evaluates and compares their climate protection performance based on indicators covering four categories: GHG Emissions (weighting 40%); Renewable Energy (weighting 20%); Energy Use (weighting 20%); Climate Policy (weighting 20%). Still, although the CCPIs measure many aspects of climate change transition risk, they do not provide theory-consistent results in terms of explaining commodity currency fluctuations. As seen from Figure 5, replacing our climate risk measures with the country-specific CCPIs gives a mix of significant and insignificant results with both positive and negative parameter estimates. One potential reason for these conflicting results might be that the CCPIs include scores correlated with economic activity, e.g., emissions and energy use. However, in unreported results we have also used the *Global Climate Risk* indexes produced by *Germanwatch*, capturing extreme weather-related events, reaching similar conclusions.

Finally, the results marked in red in Figure 5 report estimates from (5) when our

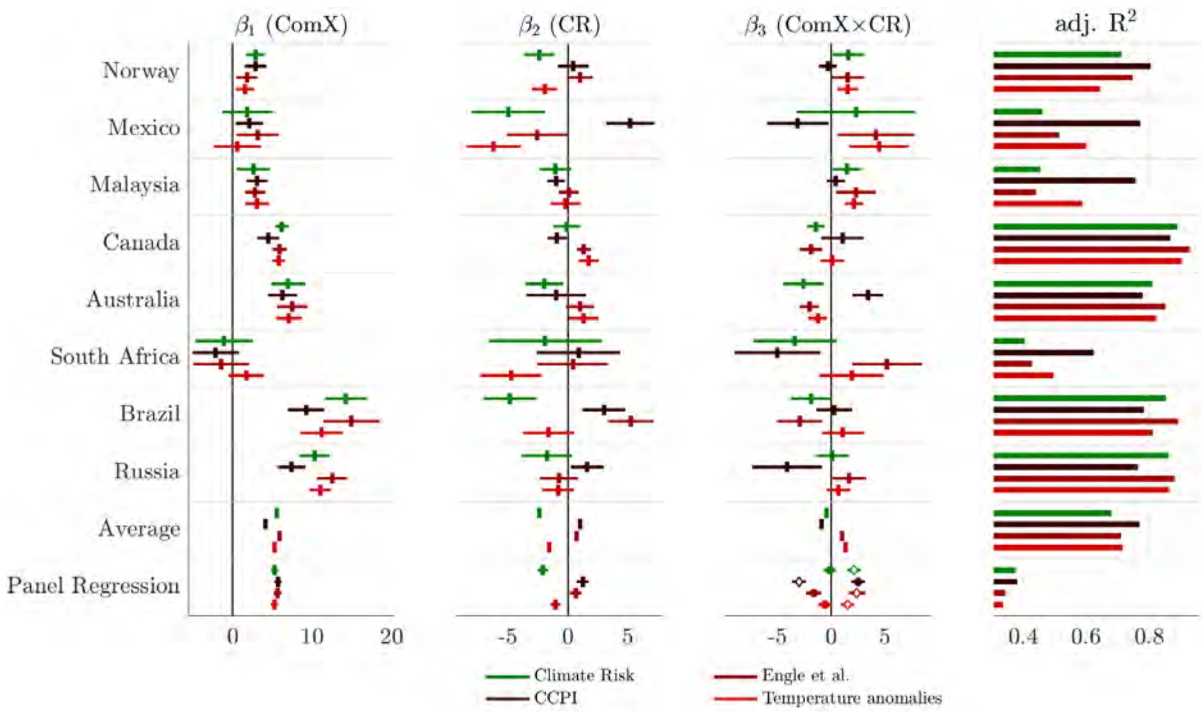


Figure 5. Exchange rates, commodity prices and climate risk estimates for alternative climate risk variables. For each country, the figure reports the results from estimating the climate-augmented regression in (5), using one of the following: our proposed measure of climate risk (*Climate risk*), the CCPIs (*CCPI*), the climate risk measure suggested by Engle et al. (2020) (*Engle et al.*), or abnormal temperature changes (*Temperature anomalies*). The 95% confidence intervals are computed using HAC-corrected standard errors. The row labeled *Average* reports the average coefficient estimates across countries. The row labeled *Panel* reports the results from estimating a version of (5) using a fixed effect panel estimator with standard errors clustered on the country level. A separate interaction term between climate risk and commodity prices is estimated for countries producing (filled circles) and not producing (diamonds) coal.

measure of climate risk is replaced by the temperature anomaly statistics described in Section 2.2. The use of temperature anomalies yields numerical results which are very similar to our climate risk indexes for Norway. The results are also similar to some extent for Mexico, Malaysia and Russia, while the results for other countries are more mixed. On average across all the countries, however, the direct effect (β_2) of using temperature anomalies as a measure of climate risk is very similar to our news-based risk approach.[14]

The panel data regressions reported in the last row in Figure 5 highlight these points further: Using the CCPIs gives results counter to theory; Using the Engle et al. (2020) climate risk index gives similar results to ours for the interaction terms, with one likely reason being that it captures climate risk common to many countries; Using temperature anomalies gives qualitative results similar to ours when considering average effects across

[14] Figure B.9, in Appendix B, shows that all these conclusions hold when considering the alternative climate risk measures together with the threshold model in (6).

all the countries, but not necessarily so when considering countries individually. In that respect, the news-media channel seems important. As stated by Shiller (2001): "significant market events generally occur only if there is similar thinking among large groups of people, and the news media are essential vehicles for the spread of ideas".

3.5 Allowing for dynamic interactions

The single equation framework adopted in (5) captures the long-run relationship between commodity currencies and economic fundamentals, but does not take into account the potential dynamic interaction between the right- and left-hand side variables. To do so, we estimate VAR models and identify exogenous climate risk innovations using a simple recursive ordering.

The VAR models can be written as

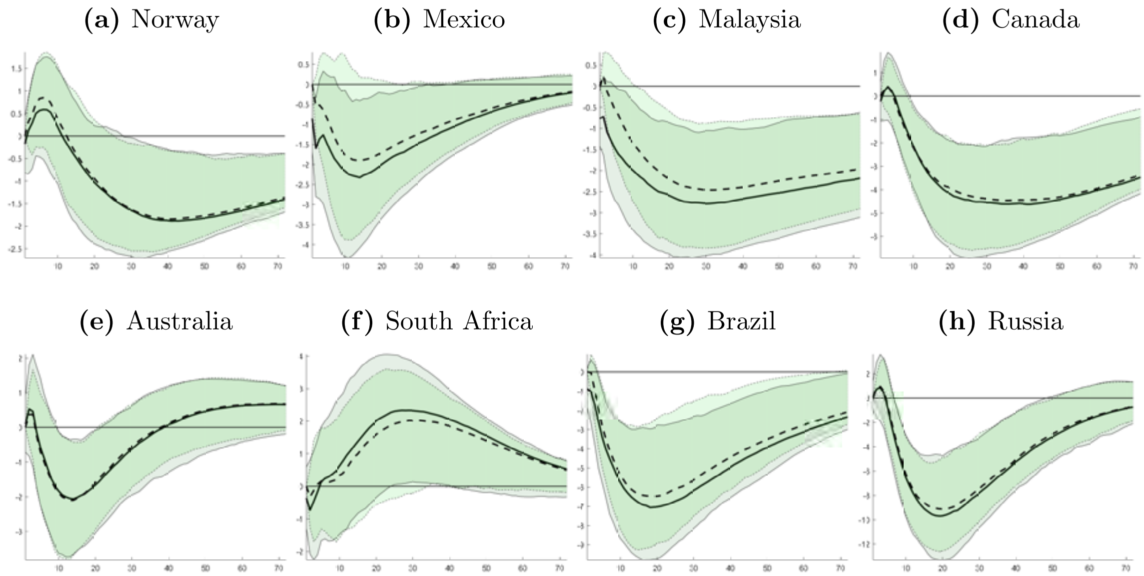
$$\boldsymbol{y}_t = \boldsymbol{c} + \boldsymbol{\beta}_1 \boldsymbol{y}_{t-1} + \dots \boldsymbol{\beta}_p \boldsymbol{y}_{t-p} + \boldsymbol{u}_t \quad \boldsymbol{u}_t \sim i.i.d.N(0, \boldsymbol{\Sigma}) \tag{7}$$

where $\boldsymbol{y}_t = [\boldsymbol{x}_t' \quad REER_t \quad CR_t]'$, and $\boldsymbol{c}$, $\boldsymbol{\beta}_1, \dots, \boldsymbol{\beta}_p$, and $\boldsymbol{\Sigma}$ are matrices of suitable dimensions containing the model's unknown parameters.[15] Exogenous innovations, $\boldsymbol{\varepsilon}_t$, are then identified through the relationship $\boldsymbol{\varepsilon}_t = \boldsymbol{P}\boldsymbol{u}_t$ where $\boldsymbol{P}$ is a lower triangular matrix derived from $\boldsymbol{P}\boldsymbol{P}' = \boldsymbol{\Sigma}$.

We do not take a strong stand on whether climate risk is contemporaneously unaffected by shocks to the other variables in the system, and therefore identify climate risk innovations by ordering climate risk either first or last in the system. The lag length is set according to the AIC. For most of the countries, a lag length of three or less is preferred, and all the roots of the processes' characteristic equations are found to be inside the unit circle. More elaborate prior beliefs about the model's short- and long-run relationships are entertained later in this section.

Figure 6 reports the response functions of the exchange rates following the climate risk innovations. The response paths are very similar irrespective of whether climate risk is ordered first or last in the system, and the climate risk response itself (not reported) is temporary and returns to its steady state after roughly 40 months (on average). Despite this, a one standard deviation increase in climate risk leads to a persistent and significant depreciation of the real exchange rate in Norway, Malaysia, Canada and Brazil. For Mexico, Australia and Russia, the responses are either barely significant or less persistent, but all have the same expected negative sign. Only for South Africa do we obtain results that run counter to our earlier analysis. However, for this country, the earlier estimates

[15] Since the VARs are highly parameterized models, and since the r_t^L variables are generally found to be the least important variables when estimating (5), the long-run interest rate differentials are dropped from the $\boldsymbol{x}_t$ vector here, i.e., $\boldsymbol{x}_t = [r_t^S \quad UNC_t \quad GPR_t \quad ComX_t]'$.



(a) Norway **(b)** Mexico **(c)** Malaysia **(d)** Canada

(e) Australia **(f)** South Africa **(g)** Brazil **(h)** Russia

Figure 6. VAR and REER responses. Each graph reports the REER response following a one standard deviation exogenous innovation to the climate risk variable. The innovations are computed from two different recursive orderings, where the climate risk variable is ordered either first (solid black) or last (dotted black) in the system. 95% confidence bands are constructed using a residual bootstrap.

were also associated with a large degree of uncertainty. It is also the case that climate change transition risk is generally not significantly affected by the other variables in the system. Figure B.10, in Appendix B, illustrates this, and reports the climate risk response following either an exogenous commodity price or REER innovation.

To alleviate the concern that climate change transition risk is driven solely by actual temperature change statistics, we augment the VAR with the temperature anomaly series. In this case as well, the conclusions from above remain robust (Figure 7). In fact, under the reasonable assumption that temperature anomalies are contemporaneously exogenous to the remaining variables in the system, we order the temperature statistics first in the system and find mostly insignificant REER responses following an exogenous temperature shock. In contrast, the REER responses following climate change transition risk shocks are mostly negative and significant, as before. Figure B.11, in Appendix B, reports the variance decomposition for the responses reported in Figure 7. At the two- and six-year horizons, the climate risk shocks explain between 15 and 25 percent of the average variation in the REERs across countries. Temperature innovations, on the other hand, hardly explain any of the observed commodity currency fluctuations.

To entertain the possibility that much larger lag lengths are needed to capture the dynamic interaction between temperature anomalies, climate risk, and commodity currencies, and to discipline the long-run behavior of the system, we have also estimated the VARs using the prior long-run distributions proposed by Giannone et al. (2019). In this

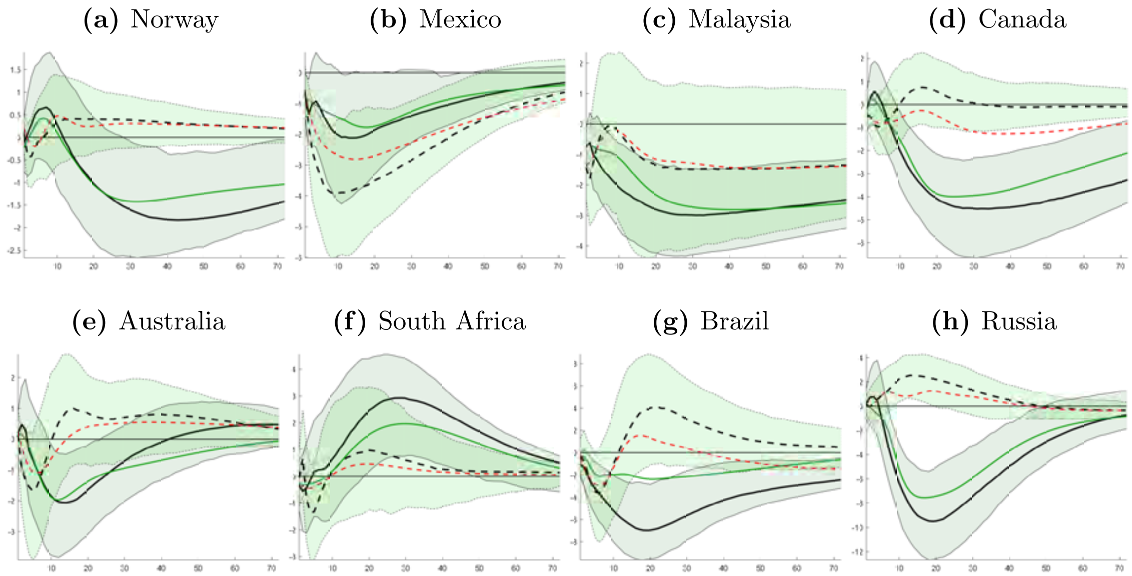


Figure 7. VAR and REER responses including temperature anomalies. Each graph reports the REER response following a one standard deviation exogenous innovation to either the climate risk variable (solid line) or the temperature anomaly series (dotted line). The impulse responses are computed using a recursive ordering, where the temperature anomalies and climate risk variable are ordered first and second in the system, respectively. 95% confidence bands are constructed using a residual bootstrap. The red and green lines report posterior mode estimates when using the prior long-run distributions proposed by Giannone et al. (2019) when estimating the model.

framework, prior views about common trends shared by the variables within the system can be elicited, and over-fitting is avoided by efficiently shrinking the VAR coefficients towards zero. Accordingly, the VARs are specified by up to 12 lags, and we (apriori) allow temperature anomalies and climate risk to share a common stochastic trend, and assume that their difference is stationary. Likewise, we impose a prior view consistent with (5), where a linear combination of r_t^S, $ComX_t$, CR_t, and temperature anomalies captures the long-run behavior of the REER. However, as seen from the red and green lines in Figure 7, which report the posterior modes of the estimates, our earlier qualitative conclusions are unaffected by this alternative modeling strategy.

Finally, in terms of the pricing implications of climate risk, existing studies in the literature have primarily been concerned with firms and firm value (see, e.g., In et al. (2017), Atanasova and Schwartz (2019), Bolton and Kacperczyk (2020), Hsu et al. (2020), Engle et al. (2020)). Because natural resource income is an important part of aggregate income creation in major commodity exporters, the mechanisms that give rise to a persistent exchange rate depreciation might also affect forward looking asset markets at the national level. To address this linkage we therefore include the countries' (log) real stock market indexes in the VAR model, and analyze their responses following exogenous climate

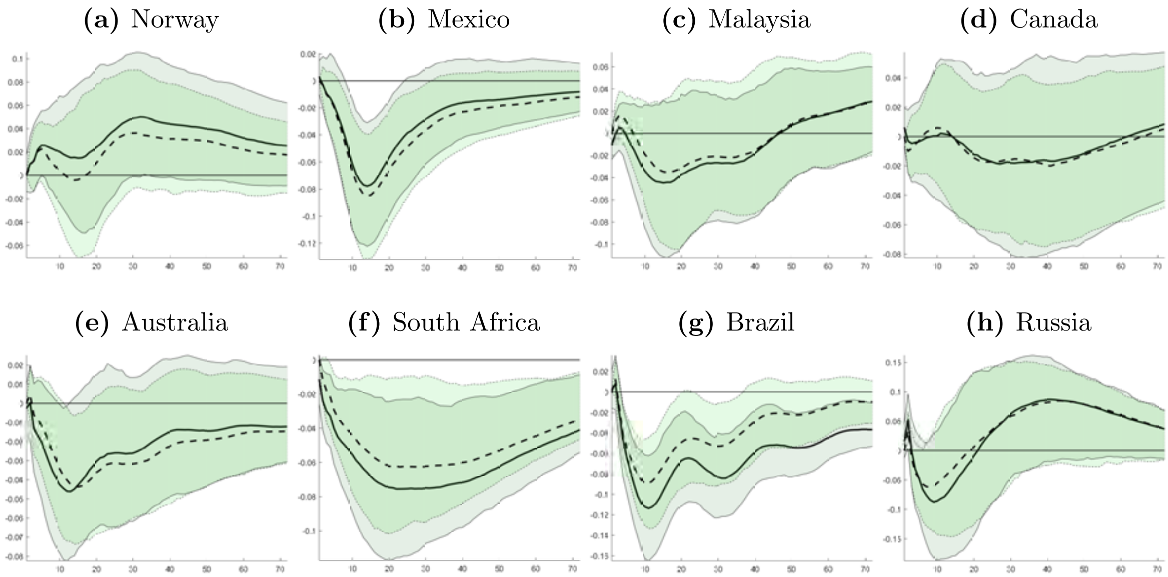


Figure 8. VAR and stock market responses. Each graph reports the aggregate stock market response following a one standard deviation exogenous innovation to the climate risk variable. The innovations are computed from two different recursive orderings, where the climate risk variable is ordered either first (solid black) or last (dotted black) in the system. 95% confidence bands are constructed using a residual bootstrap. To reduce the dimensionality of the augmented VAR system, the UNC_t and GPR_t variables are excluded from the $\boldsymbol{y}_t$ vector when estimating the VARs. The y-axis are in log scale.

change transition risk innovations.[16] As seen in Figure 8, a one standard deviation increase in climate risk leads to persistent and significantly lower stock market valuations in Mexico, Australia, South Africa, and Brazil. For Norway, Malaysia, Canada, and Russia the response paths are not significantly different from zero, but still tend to be negative for Malaysia and Canada. At the same time, the REER responses from this augmented system are qualitatively the same as before (Figure B.12 in Appendix B).[17]

4 Additional results and robustness

As described in Section 2.2, our main conclusions are robust in a number of different modeling choices related to how the climate risk indexes are constructed. Below we discuss how our main results are robust along three other dimensions as well.

First, our qualitative conclusions are unlikely to be driven by other important developments in the commodity market during the last decade(s), such as the depletion of

[16] The stock market variables are sourced from *Macrobond* and are the MSCI IMI Total Return indexes in local currency. The series are deflated by domestic CPI values.

[17] Even within major commodity exporters some sectors might benefit at the expense of others when faced with climate change transition risk. Indeed, the theoretical mechanism we build on predicts that this will happen. In the case of Norway, we explore this theme further in Appendix C which reports how changes in climate risk correlates with returns in 10 different (value weighted) industry portfolios over time.

remaining reserves and the technological advances in shale-oil extraction. In particular, as remaining reserves are drawn down, commodity production inevitably has to slow down. Similarly, the growth in shale-oil production has likely increased the supply elasticities in the (global) market for oil (Bjørnland et al., 2020). In turn, this potentially reduces the price impact of (demand-driven) commodity market shocks. Still, augmenting (5) and (6) with remaining reserves, or the growth in shale-oil production (see Appendix A), has very little effect on our main estimates (Figure B.13 in Appendix B).

Second, we have performed a more data-driven variable selection approach, allowing for potentially up to 13 different "control" variables when estimating (5). The variables, in addition to the ones already in $\boldsymbol{x}_t$, are: The remaining reserves and shale-oil production variables discussed above; The CCPIs and temperature anomalies; Alternative (global) uncertainty measures denoted VIX^{Com} and VIX^{ER}; Country-specific and total OECD composite leading indicators (see Appendix A). All variables are allowed to affect the REER contemporaneously, and with up to three period lags. Accordingly, the augmented $\tilde{\boldsymbol{x}}_t$ vector consists of 50 elements. To still favor a small model size, and reduce noise and potential biases, a double selection procedure for selecting the relevant variables is implemented (Belloni et al., 2014). Naturally, the model fit increases with this more flexible modeling approach. The estimated climate risk and interaction term coefficients also become somewhat more uncertain, but the sign of the coefficients still aligns well with our main results (Figure B.14 in Appendix B).

Third, we have estimated the VAR models from Section 3.5, augmented with the extra variables in the $\tilde{\boldsymbol{x}}_t$ vector. In none of these alternative specifications, where the extra variables are added one at a time, do our qualitative conclusions change (Figure B.15 in Appendix B).

5 Conclusion

In this article we relate climate change transition risk to concerns about structural changes away from fossil fuel production voiced in the public discourse, and use news media coverage and word embedding models to derive news-based and country-specific measures of such risk. We then use these risk indexes to explain recent exchange rate developments in eight major commodity exporters.

In line with economic theory on structural transformation due to changes in natural resource income, and standard terms-of-trade arguments, we document that when climate risk is high, these commodity currencies experience a persistent depreciation and the relationship between commodity prices and currencies tends to become weaker. In addition, our results indicate that climate risk is associated with substitution effects between fossil fuel products, potentially benefiting exporters of, e.g., petroleum products at the expense of exporters of, e.g., coal.

A growing literature investigates how climate change is affecting economic outcomes. Still, in terms of pricing implications, existing studies have primarily been concerned with firms and firm value. Our study contributes by showing how climate change transition risk matters at the national level by affecting commodity currencies. In line with this finding, however, we also document that unexpected increases in climate change transition risk tend to cause persistently lower aggregate stock market valuations.

The novelty of our study is related to how we derive the risk indexes. Indeed, we show that using alternative climate risk approximations based on already established hard climate change or economic data does not provide theory consistent results, whereas our news-based risk measures do. Thus, although our application is specific to commodity currencies, the methodology we propose is applicable in a wide range of settings where information diffusion, belief formation, and the social processes that shape economic thinking and behavior are potentially important.

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Appendices

Appendix A Data Description

Exchange rates and weights. The real effective exchange rates indices $REER_{tc}$ are obtained from the Bank for International Settlements. They are constructed for each country through trade weighting its exchange rates with up to 39 of its trading partner countries (with the Eurozone considered as one entity). We also obtain the Bank for International Settlement's used trade weights w_{tci} of country c for its trading partner i at time t to construct interest rate differentials. The weights are available for three-year periods: 1999-2002, 2003-2005, and 2014-2016. As trade weights for the period 2017-2019 were not yet available, we simply assumed the trade weights of the previous period.

Interest rates and inflation. Average values of 3-month Treasury rates and 10-year government bonds serve as *nominal* short-term and long-term interest rates respectively. These are obtained for 29 countries (one of the 'countries' is the Eurozone) that together make up 87.6% of global GDP according to the IMF World Economic Outlook 2019. Hence, we do not consider all trading partners of a country but only the bulk. The majority of 3-month Treasury and 10-year government bond series are obtained from the Global Financial Data database and all remaining missing series are obtained from Macrobond and the OECD database. The last required short-term interest rate for the analysis (for the country China) is available from January 2002 on. *Real* short-term interest rates r^{S*}_{tc} and long-term interest rates r^{L}_{tc} for country c are created through subtracting year-on-year inflation from nominal interest rates. For consistency reasons, the inflation series for all countries are obtained from the Bank of International Settlements, with the exception of Taiwan and Colombia, which were not available. These two variables are therefore obtained from Global Financial Data.

Interest rate differentials. The real short-term interest rate *differential* for country c is created by taking the difference between the real short-term interest rate and the trade-weighted real short-term interest rates of its trading 28 partners: $r^{S}_{tc} = r^{S*}_{tc} - \sum_{i=1}^{28} w_{tci} * r^{S*}_{ti}$, The long-term interest rate differentials r^{L*}_{tc} are created analogously to the short-term interest rate differentials. We hope to capture the forward guidance of central banks by adding the long-term interest rate differentials to the regressions. As forward guidance began to play a role only since the financial crisis, we multiply the real interest differential by a dummy that takes the value one from January 2009 on and zero before that.

Commodity price indices. We use three different series of commodity price indices, for each country, from Gruss and Kebhaj (2019): The commodity price indices weighted by time-varying weights of the net export share relative to GDP, which serves as $ComX_{ct}$

in the main analysis. The same measure constructed with fixed weights as well as the commodity price indices are weighted by time-varying weights of the export share relative to GDP serve as $ComX_{ct}$ in a robustness tests.

Commodity price. Commodity prices and indices of oil, gas and coal are obtained from the IMF Commodity Data Portal. The price (index) of oil is calculated as the average of the WTI (40 API), Brent light blend (38 API) and Dubai Fateh (32 API). The price (index) of gas is calculated as the average of the U.S. Henry Hub Terminal in Louisiana, the Netherlands TTF Natural Gas Forward Day Ahead and the Indonesian Liquefied Natural Gas in Japan. The price (index) of coal is calculated as the average of the Australian Thermal Coal and the South African Export Price.

Growth of the share of tight oil supply. The U.S. tight oil production and the global crude oil production (including lease condensates) is obtained from the U.S. Energy Information Administration. The growth of the tight oil production as a share of global oil production is calculated through the month-to-month difference of the log of this share.

Uncertainty measures. We obtained two different measures. The volatility index for financial markets UNC_t is obtained from the Chicago Board Options Exchange, which retrieves the constant 30-day expected volatility from call and put options on the S&P500. The (global) geopolitical risk index GPR_t is obtained from Caldara and Iacoviello (2018). In addition, we obtained the Equity Market Volatility Tracker for Commodity Markets VIX_t^{Com} as well as the Equity Market Volatility Tracker for Exchange Rates VIX_t^{ER} from the FRED database. Both series are constructed by Baker et al. (2019).

Fuel net export shares. Exported fuels by country are obtained from the World Integrated Trade Solution for the years 1998 until 2019. The term 'fuels' describes all products classified in section 27 of the HS code list. The Subsection 01 to 16 of section 27 are further assigned by us to either oil, gas, coal or none of these fossil fuels based on its closeness of the class of products.

Reserves, production and consumption of fossil fuels. Reserves, consumption and production of oil, gas and coal are obtained from the BP Statistical Review of World Energy from 2002 until 2020.

Composite leading indicators. The leading indicators are obtained from the OECD, and are the amplitude-adjusted CLI series. The common component is taken as the OECD average. For Malaysia, we use the CLI series for the five biggest economies in Asia, as a country-specific index is not included in the database.

Appendix B Additional results

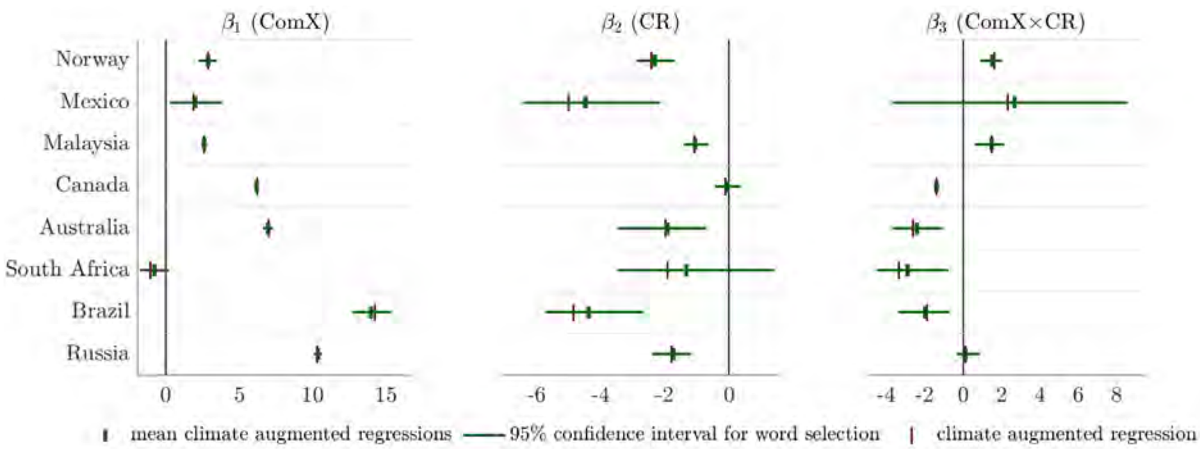


Figure B.1. Climate risk and word selection robustness. The red markers report the mean estimate from using the main climate risk indexes and the baseline climate-augmented regression described in Section 3.2. The green markers report the mean estimate, in addition to the lower and upper 2.5 and 97.5 percentile, from over 30000 random leave-one-out simulations of the underlying climate risk indexes.

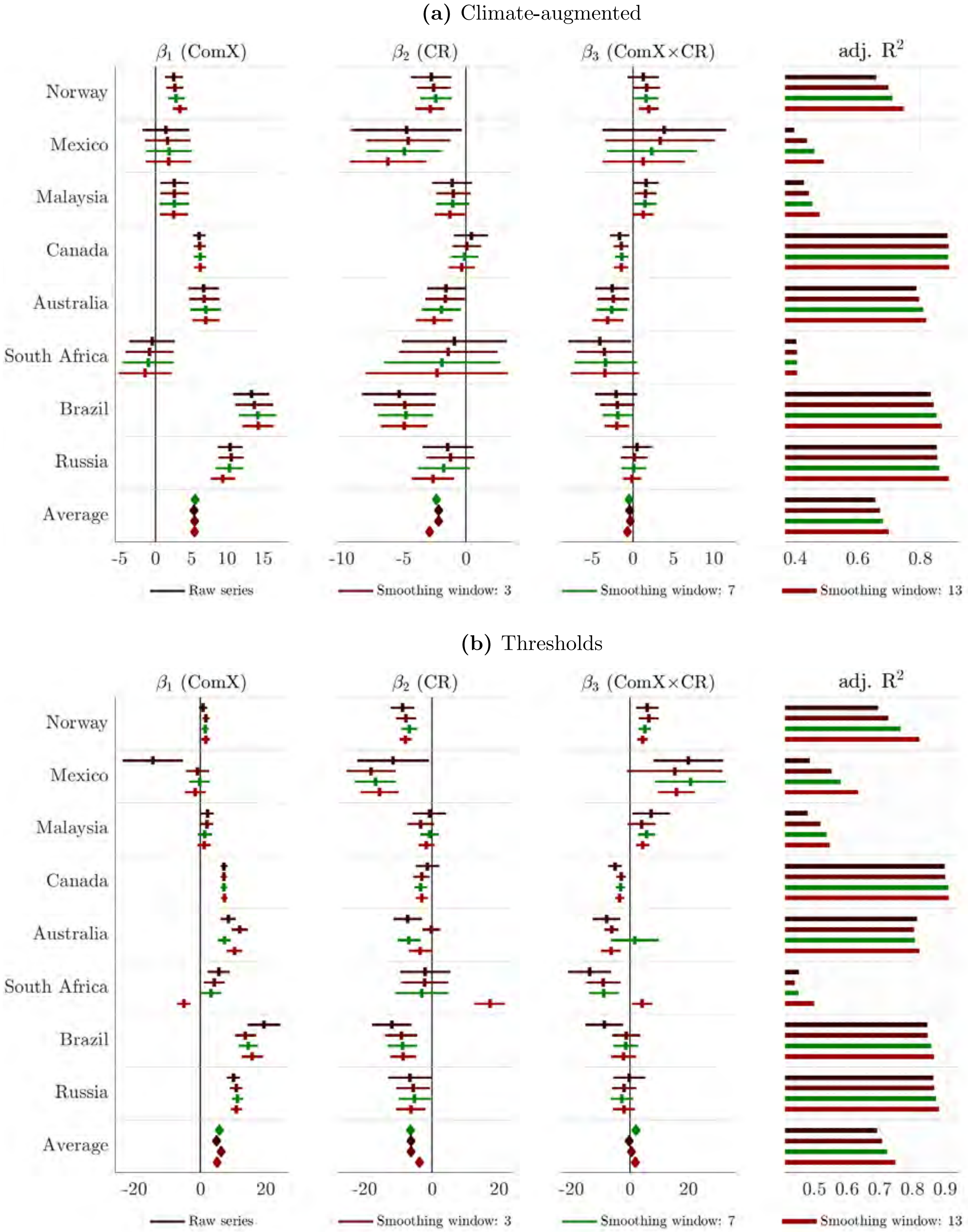


Figure B.2. Climate risk and smoothing robustness. For each country the figures report the estimated climate risk coefficients from (5) and (6) using different degrees of smoothing when constructing CR. The main results are produced using seven-month moving average (Smoothing window: 7). The 95% confidence intervals are computed using HAC-corrected standard errors.

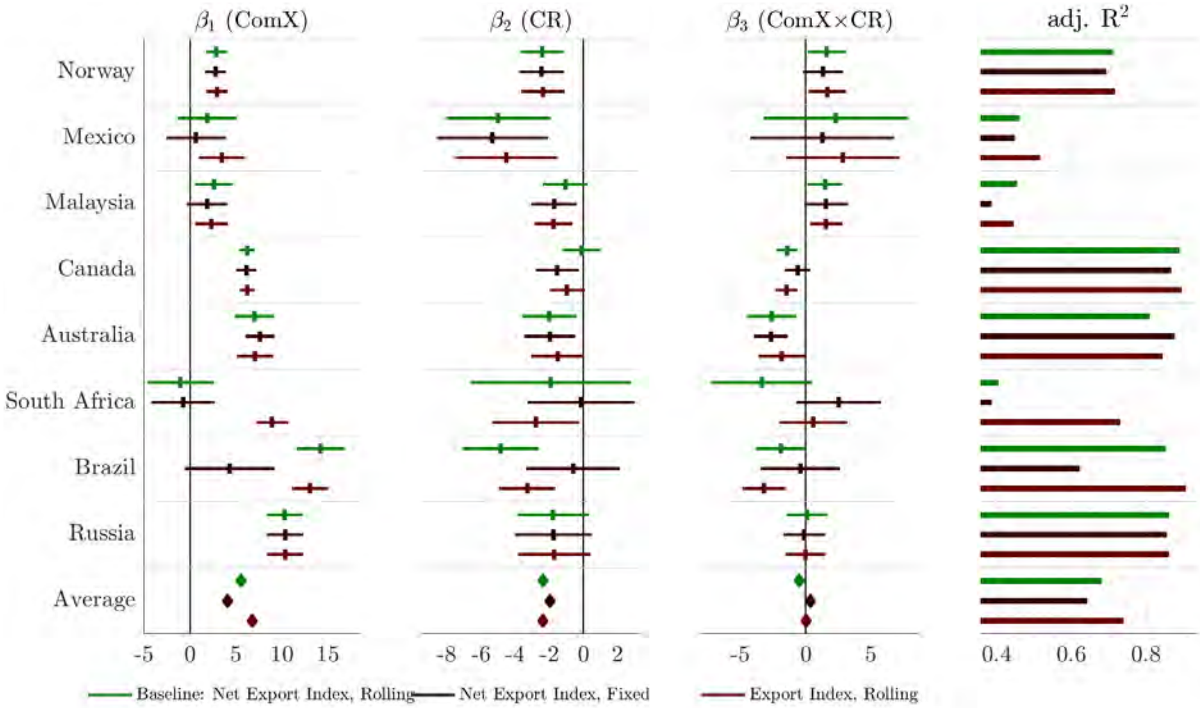


Figure B.3. Climate risk and commodity price index robustness. For each country the figures report the estimated climate risk coefficients from (5) and (6) using three different definitions of the commodity price index provided by Gruss and Kebhaj (2019). The main results are produced using net-export shares and a rolling window for the weights (Net Export Index, Rolling). The 95% confidence intervals are computed using HAC-corrected standard errors.

Figure B.4. Common components. The figure reports the first principal component estimate from the cross-sectional residuals from (4) (black) and from the individual climate risk indexes (green). The common residual and climate risk components explain 28 and 42 percent of the variation in the data, respectively.

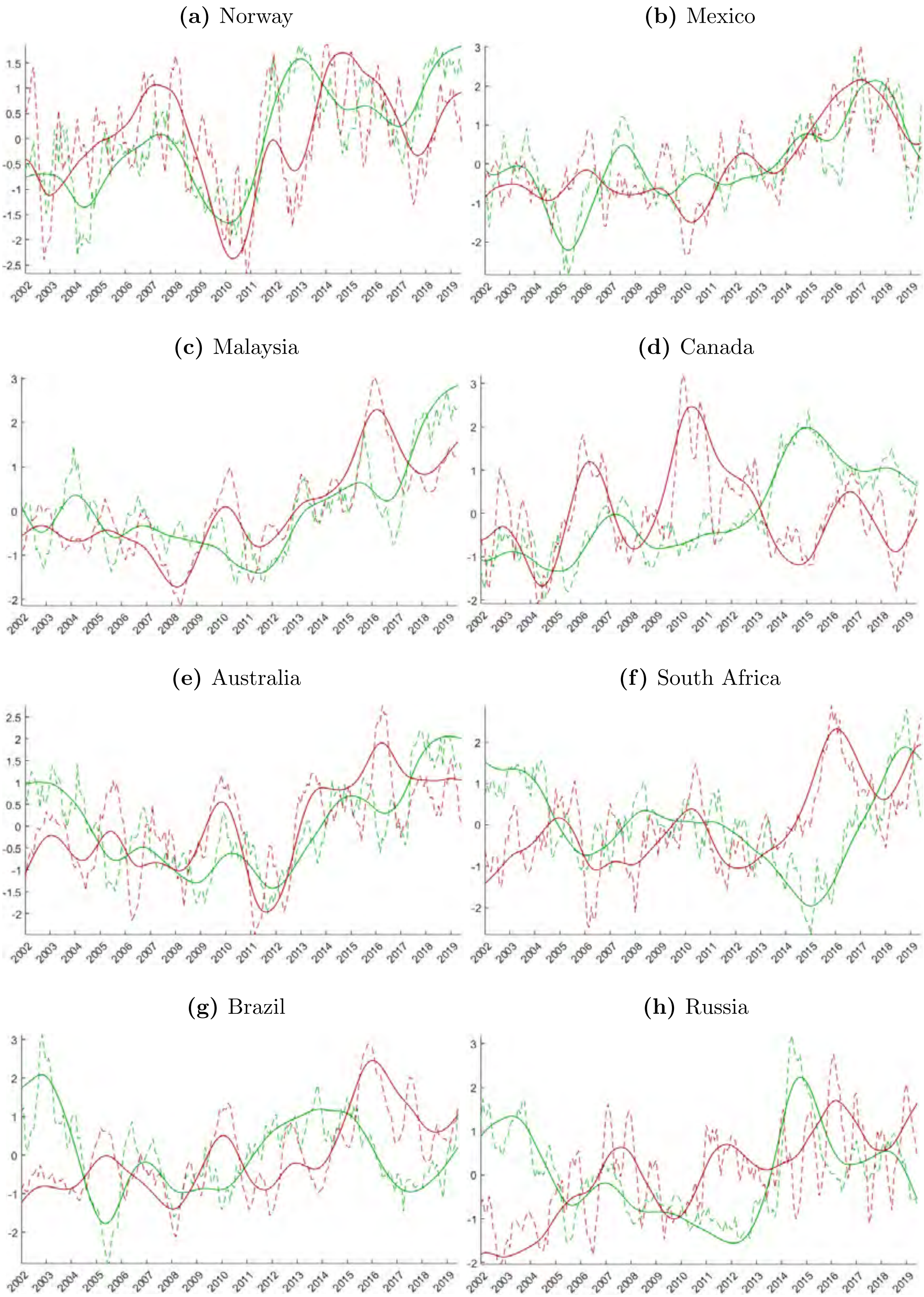


Figure B.5. Climate risk (green) and temperature anomalies (red). The dotted lines report the raw series. The solid lines report the data when a Hodrick–Prescott filter (Hodrick and Prescott (1997)), with a smoothing parameter set to 1600, is used to extract the low-frequency fluctuations from the series.

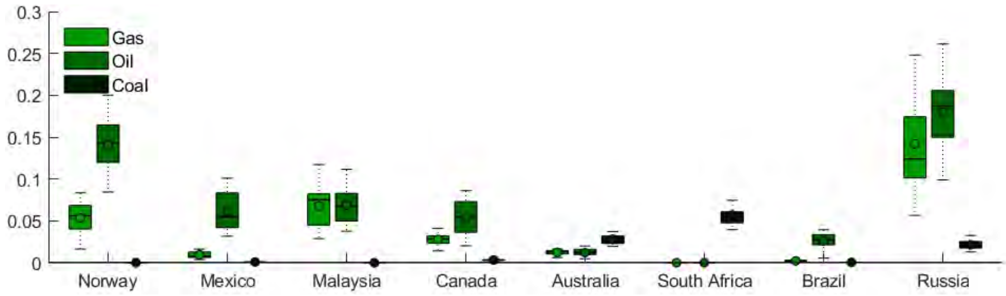


Figure B.6. Gas, oil, and coal production relative to GDP. For each country, the figure reports a standard box plot of the production shares for the period 2002 to 2019. The underlying data is sourced from British Petroleum Company (2020).

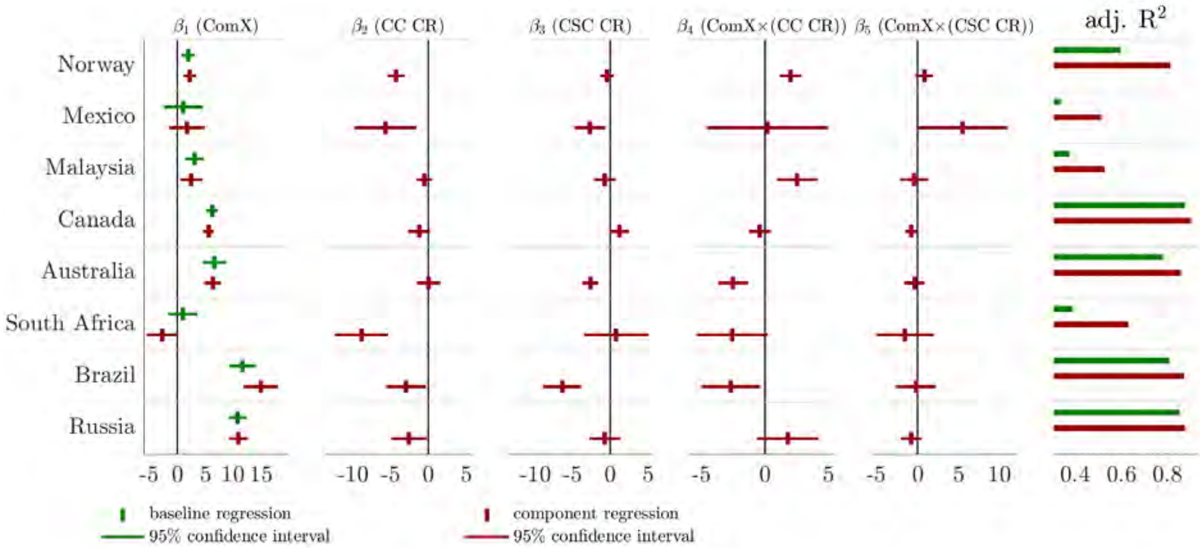


Figure B.7. Exchange rates, commodity prices and common and idiosyncratic climate risk estimates. The figure reports the results from estimating (5) using both the common (CC CR) and idiosyncratic (CSC CR) climate risk variables. The 95% confidence intervals are computed using HAC-corrected standard errors.

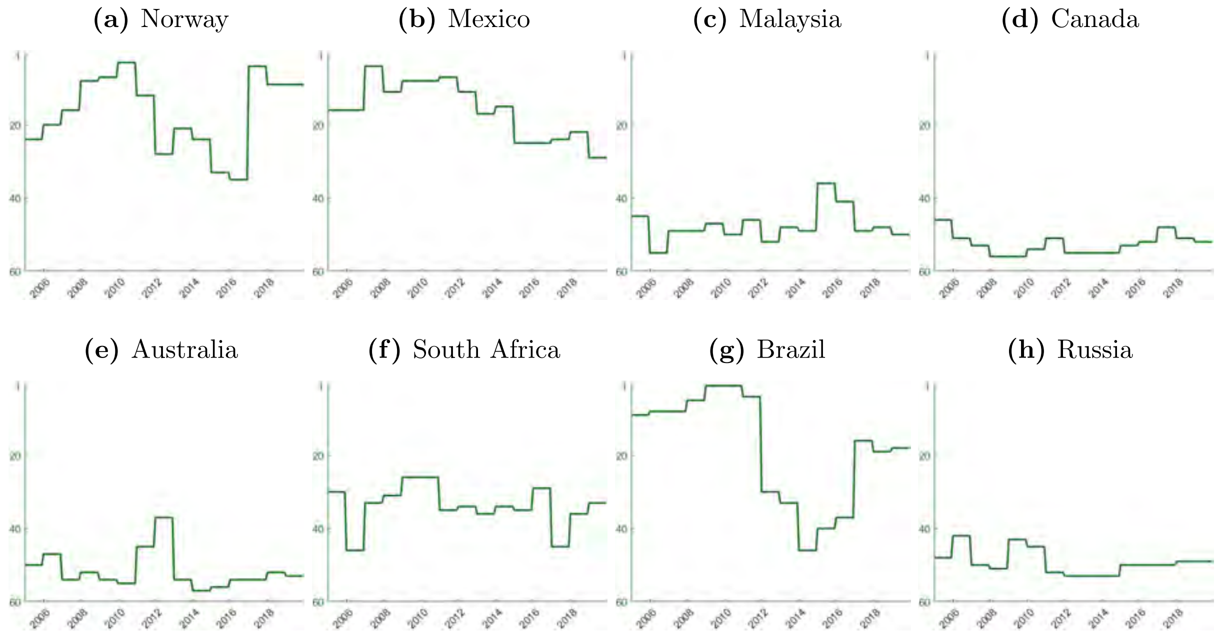


Figure B.8. Climate Change Performance Indexes (CCPI). The CCPIs report each country's rank and are produced by *Germanwatch* since 2005. The statistics are sampled on a yearly frequency, and we assume that the rank stays the same within each year.

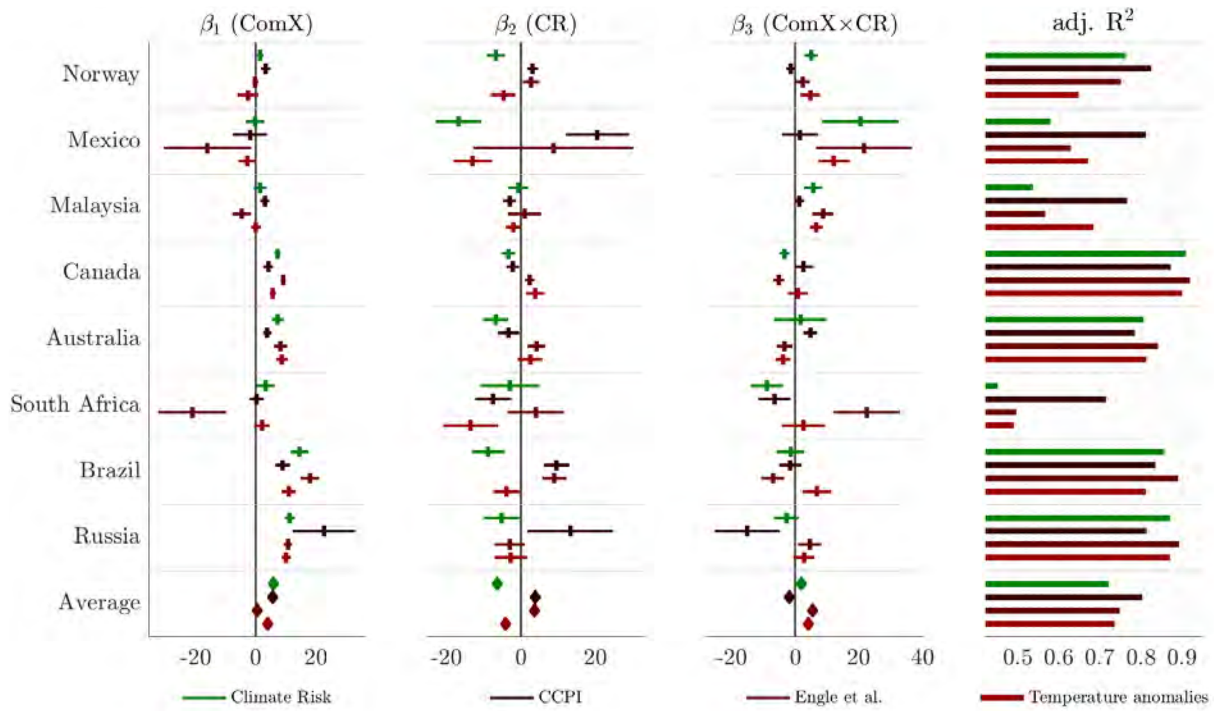


Figure B.9. Exchange rates, commodity prices and climate risk estimates for alternative climate risk variables. For each country, the figure reports the results from estimating the threshold regression in (6), using one of the following: our proposed measure of climate risk (*Climate risk*), the CCPIs (*CCPI*), the climate risk measure suggested by Engle et al. (2020) (*Engle et al.*), or abnormal temperature changes (*Temperature anomalies*). The 95% confidence intervals are computed using HAC-corrected standard errors.

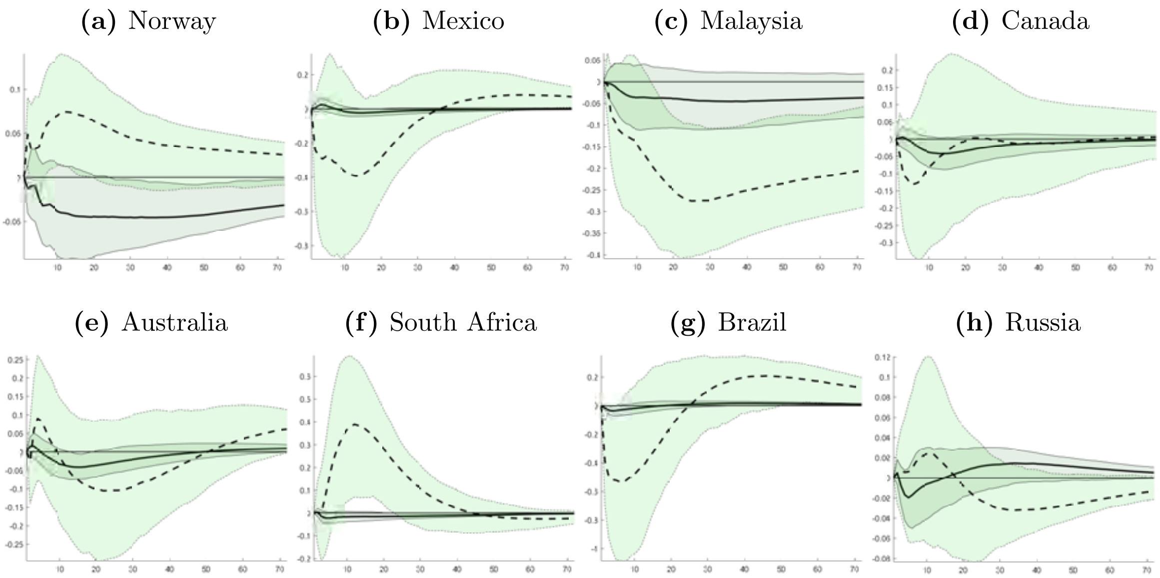


Figure B.10. VAR and climate risk responses. Each graph reports the CR response following a one standard deviation exogenous innovation to either the REER (solid line) or commodity prices (dotted line). The innovations are computed from a system where the climate risk variable is ordered first in the system. 95% confidence bands are constructed using a residual bootstrap.

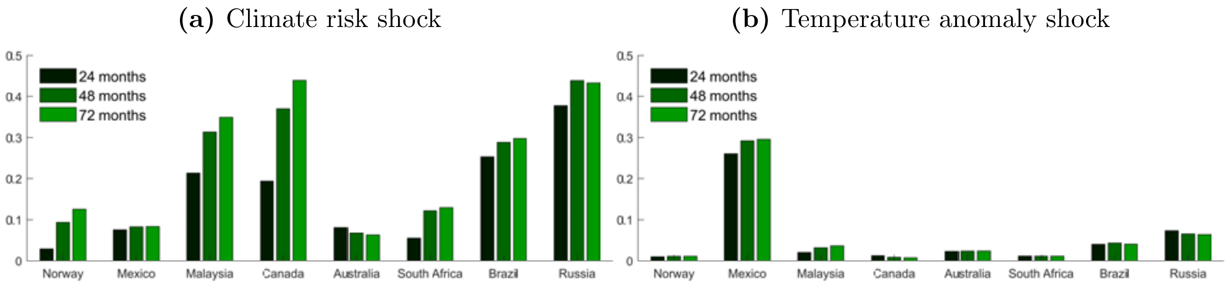


Figure B.11. VAR and REER variance decompositions. Each graph reports how much of the variance in the REER is explained by a one standard deviation exogenous innovation to either the climate risk variable or the temperature anomaly series. The results are computed using a recursive ordering, where the temperature anomalies and climate risk variable are ordered first and second in the system, respectively.

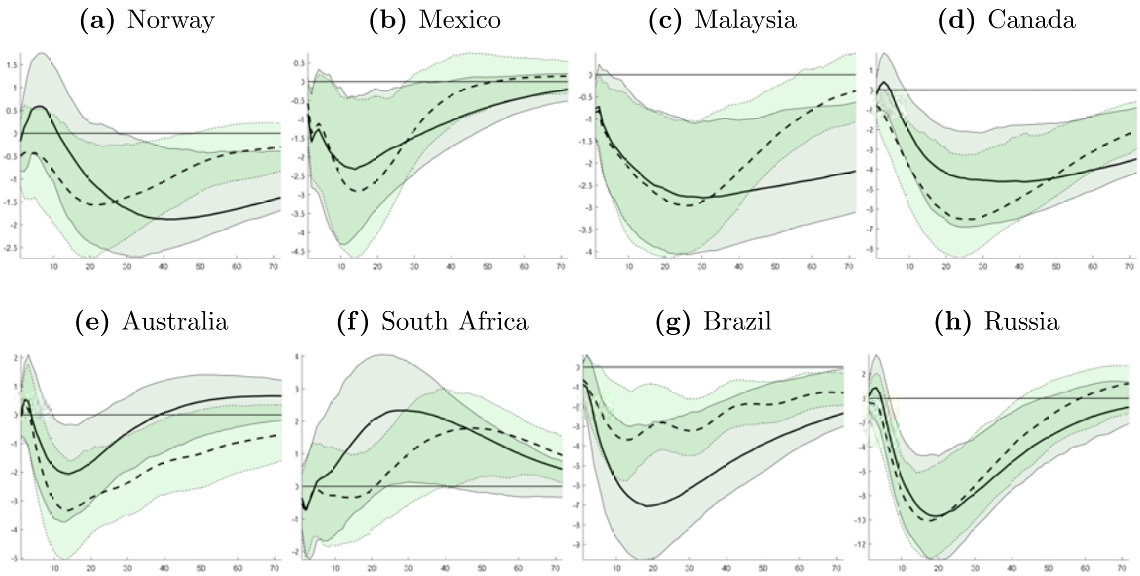
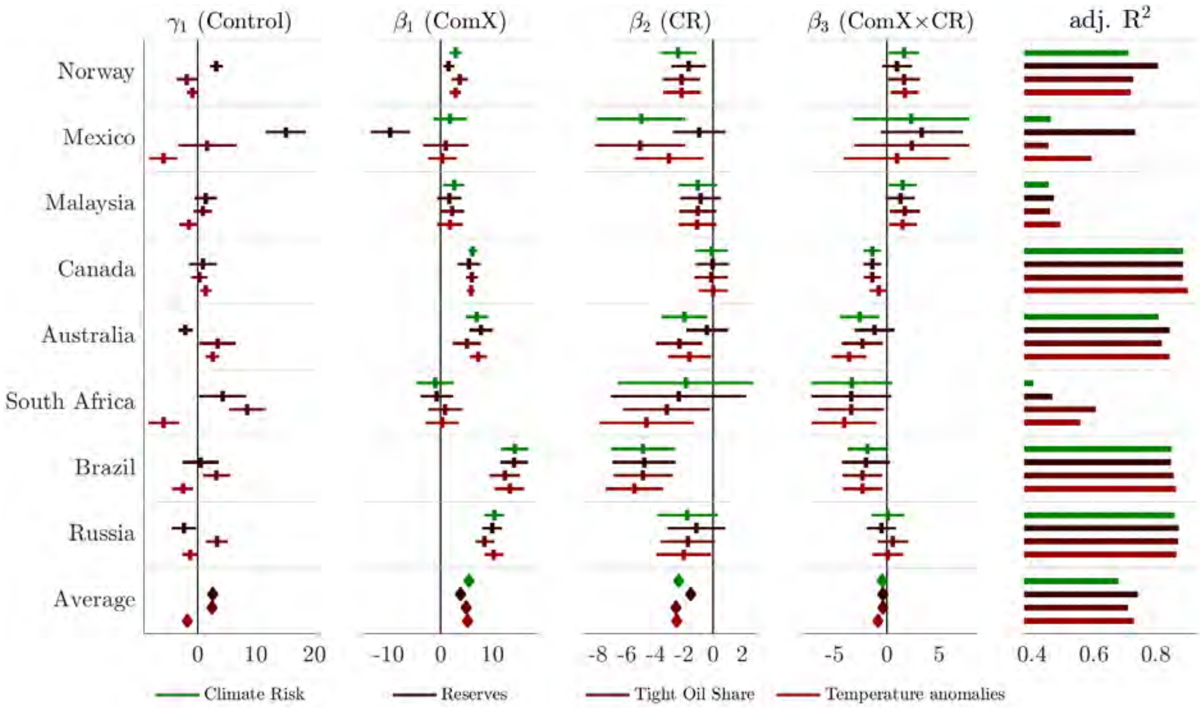


Figure B.12. VAR and REER responses, controlling for the stock market. Each graph reports the REER response following a one standard deviation exogenous innovation to the climate risk variable. The innovations are computed from the same VAR as used in Figure 8, with the climate risk variable ordered first in the system. The mean response paths are reported with a dotted line. 95% confidence bands are constructed using a residual bootstrap. For comparison the benchmark responses, from Figure 6, are reported with a solid line.

(a) Climate-augmented



(b) Threshold

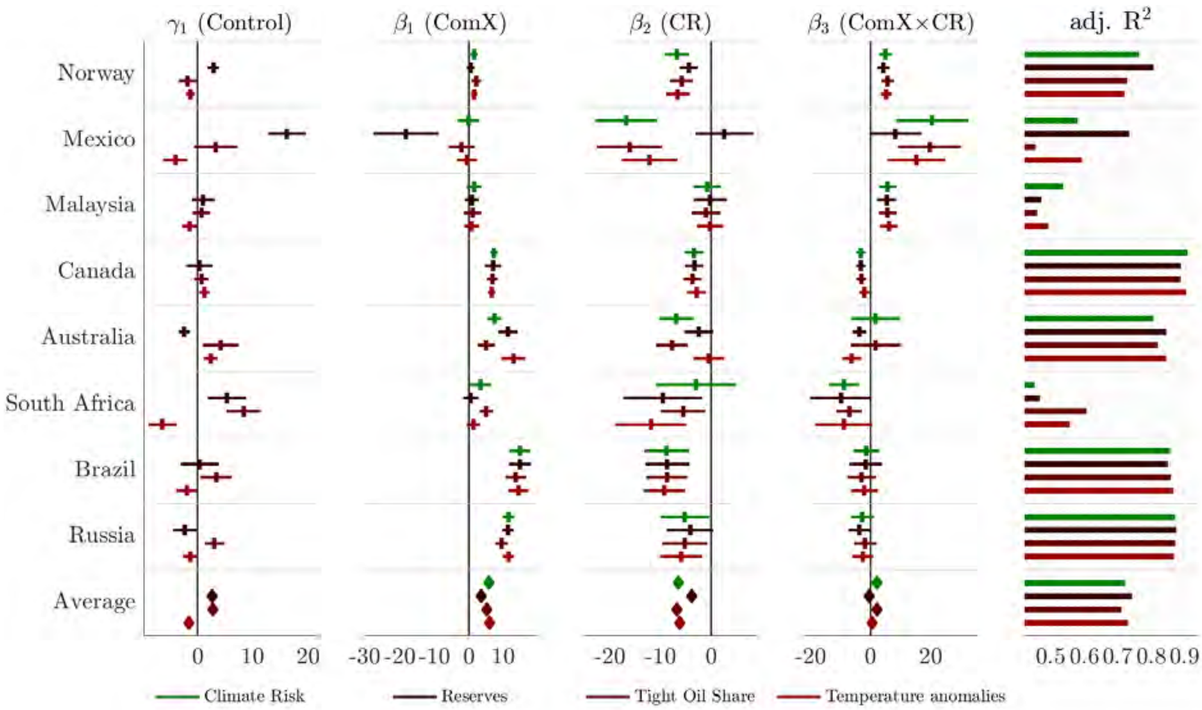


Figure B.13. Exchange rates, commodity prices and climate risk estimates with additional controls. For each country, the figure reports the results from estimating the climate-augmented regressions in (5) or (6), augmented with either remaining reserves, shale-oil growth, or temperature anomalies. The 95% confidence intervals are computed using HAC-corrected standard errors.

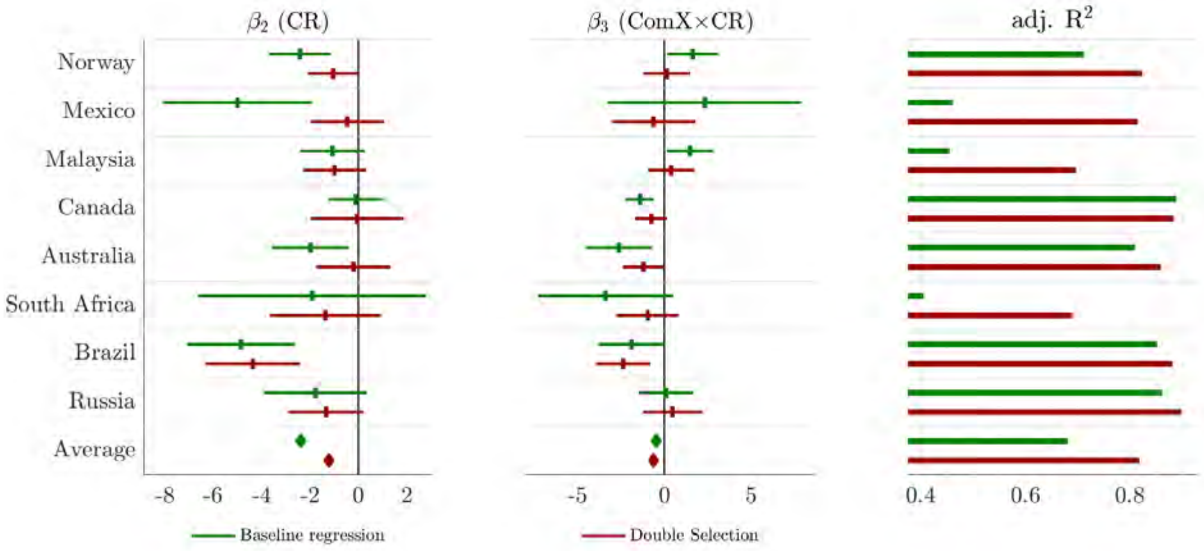


Figure B.14. Exchange rates, commodity prices and climate risk estimates. Baseline regression (equation (5)) and double selection results. The 95% confidence intervals are computed using HAC-corrected standard errors. The double selection is computed as follows: First, the REER, CR, and $ComX \times CR$ variables are regressed separately on all the variables in the augmented $\tilde{\boldsymbol{X}}_{ct}$ vector using the LASSO estimator (Tibshirani (1996)). 100 different penalization parameters together with the BIC are used to tune the amount of regularization. Next, after these three penalized regressions, the REERs are regressed on (using OLS) CR, $ComX \times CR$, and the union of the control variables selected in step one.

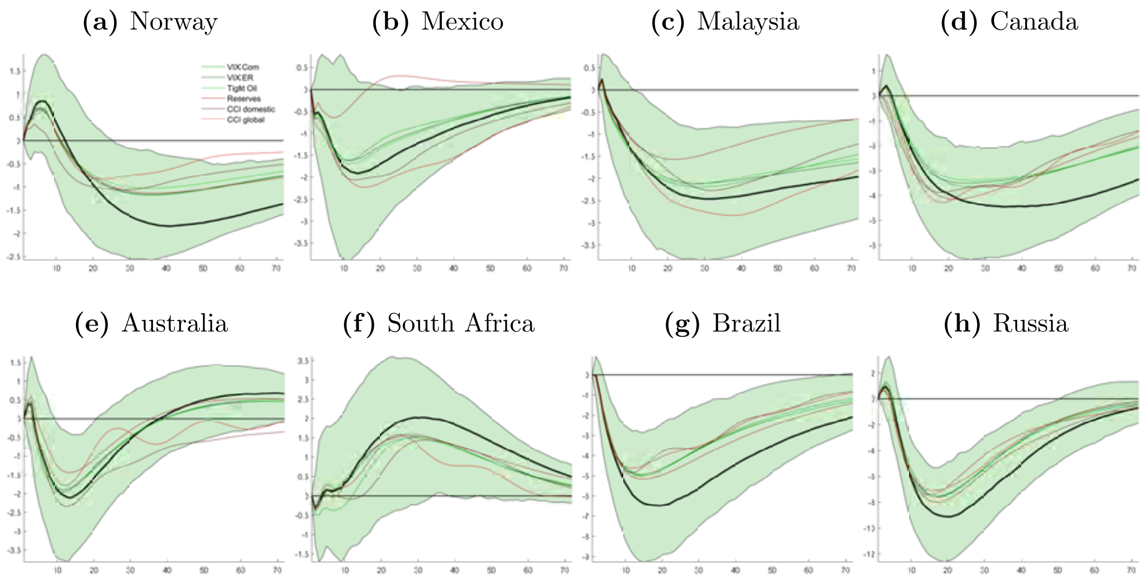


Figure B.15. VAR estimates with extra control variables and REER responses. Each graph reports the REER response following a one standard deviation exogenous innovation to the climate risk variable. The climate risk variable is ordered last in the system. The VAR includes the variables in $\boldsymbol{y}_t$ in addition to one of the following: remaining reserves, shale-oil production growth, (global) uncertainty measures denoted VIX^{Com} and VIX^{ER}, country-specific and total OECD composite leading indicators. The dotted black line and 95% confidence bands represent the "benchmark" results presented in Figure 6. The other lines represent the mean REER response path from each of the alternative model specifications.

Table B.1. Climate risk and commodity market correlations. The table reports the correlation between the common component of climate risk and relative prices of gas, oil, and coal, and the global consumption of the same commodities. The correlations between climate risk and prices are computed using monthly time series. The global consumption growth statistics are collected from British Petroleum Company (2020), and are sampled on a yearly frequency and measured in Exajoules. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Relative prices			Relative global consumption		
	Gas – Oil	*Gas – Coal*	*Oil – Coal*	*Gas – Oil*	*Gas – Coal*	*Oil – Coal*
Common climate risk component	-0.09	-0.13*	-0.11	0.59***	0.66***	-0.01

Appendix C The Norwegian stock market and climate risk

Even within major commodity exporters some sectors might benefit at the expense of others when faced with climate change transition risk. Indeed, the theoretical mechanism we build on predicts that this will happen. In the case of Norway, Figure C.1 reports how changes in climate risk correlates with returns in 10 different (value weighted) industry portfolios over time. In each of the regressions we control for the traditional risk factors and changes in commodity prices, and use a 5-year rolling estimation window. Thus, parameter estimates are obtained for the period 2007 to 2019. For most of the sectors, changes in climate risk have an insignificant loading on average. Consistent with our earlier results for the foreign exchange market, however, we observe that the climate change transition risk loading on returns in the *Energy* sector has a strong negative drift, starting before 2014. Towards the latter part of the sample, the loading becomes negative and significant. Conversely, returns in the *Telecommunication* and *Consumer Discretionary* sectors, and to some extent also the *IT* and *Material* sectors, become more positively correlated with changes in climate risk over time.

Figure C.2 shows the cumulative returns of a simple zero-cost trading strategy utilizing the regression results from above. At each point in time, the strategy goes one NOK long and short in the industry portfolios having a significant positive and negative climate risk factor loading, respectively. The portfolio is re-balanced each month, and for a trade to take place at least one sector needs to be on each side. As seen in the figure, a clear break occurs roughly midway in the sample. However, for the latter part of the sample, the strategy creates risk-adjusted returns. The estimated *alpha* suggest that an investment strategy that purchases shares in industries with a positive climate change transition risk exposure and sells shares in industries with a negative exposure earns abnormal returns of roughly 12 basis points per year.

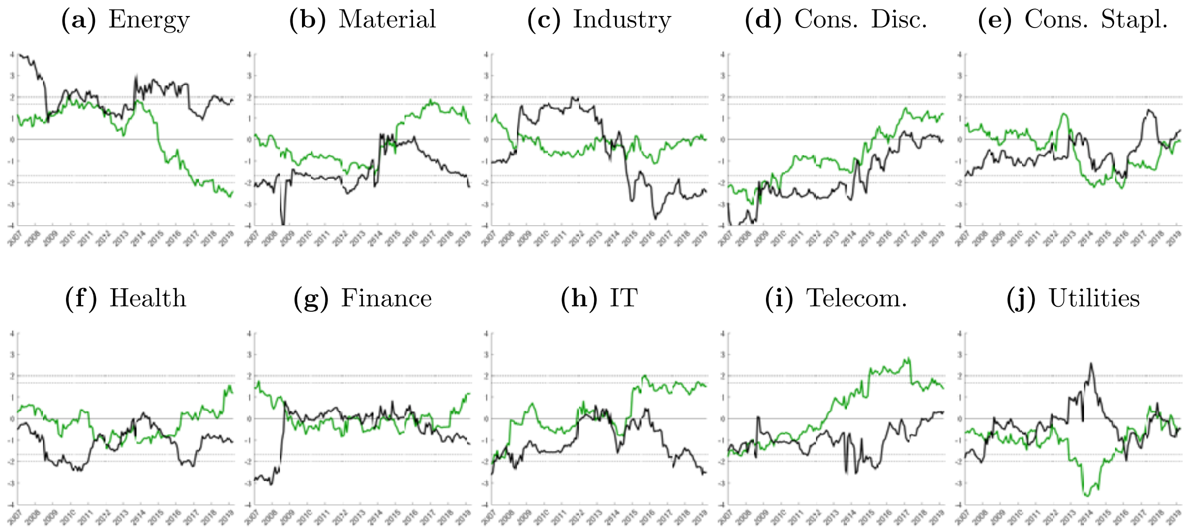
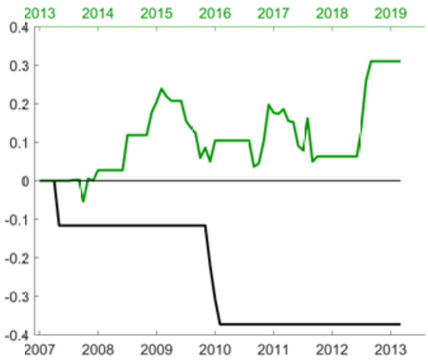


Figure C.1. Industry returns and factor loadings. The change in climate change transition risk ΔCR_t is related to the return (minus the risk free rate) of industry portfolio j by:

$$r_{tj} = \mu_j + \beta_{1j}MR_t + \beta_{2j}SMB_t + \beta_{3j}HML_t + \beta_{4j}UMD_t + \beta_{5j}LIQ_t + \beta_{6j}\Delta ComX_t + \beta_{7j}\Delta CR_t + u_{tj}$$

where MR_t, SMB_t, HML_t, MON_t, and LIQ_t are the traditional market (MR), size (SMB), book-to-market (HML), momentum (UMD), and liquidity (LIQ) risk factors (Fama and French (1993), Jegadeesh and Titman (1993), Carhart (1997), and Pastor and Stambaugh (2003). See Odegaard (2017) for the construction of these for the Norwegian market.) The equation is estimated using a 5-year rolling window. I.e., the estimates reported in, e.g., 2007, reflect the average relationship in the period 2002 to 2007. The graphs reports the evolution of the t-statistic for $\hat{\beta}_{6j}$ (black) and $\hat{\beta}_{7j}$ (green). The dotted lines represent the 95% and 90% critical values.

Although simple, these results speak to a growing literature in finance investigating the pricing implications of different forms of climate risk (see, e.g., In et al. (2017), Atanasova and Schwartz (2019), Bolton and Kacperczyk (2020), Hsu et al. (2020), Engle et al. (2020)). Thus far, however, the literature has produced conflicting results regarding the relationship between such risk and prices. Potential reasons for the conflicting results might be the time period used in the analysis, how climate risk is defined, e.g., transitional or physical climate risk, or the market being studied. Our abnormal return estimate for the 2014 to 2019 period is very small but statistically significant, and questions whether there is a premium related to sectors with a direct (negative) exposure towards climate change transition risk in the Norwegian stock market for this time period.



	Evaluation sample		
	2007 - 2019	2007-2013	2014-2019
alpha	0.00	-0.00	0.01**
MR	-0.07	-0.02	-0.29*
SMB	-0.33***	-0.14	-0.57***
HML	0.03	0.01	-0.02
LIQ	0.24**	0.12	0.28*
UMD	-0.03	-0.05	-0.03
N	149	74	76
R^2	0.10	0.05	0.20

Figure C.2. Cumulative and risk-adjusted returns. The figure graphs the cumulative returns from a zero-cost investment strategy that goes long and short in the industry portfolios having a significant positive and negative climate risk factor loading, respectively. The cumulative returns for the period 2007-2013 (2014-2019) are reported in black (green). The table reports the risk-adjusted returns (alpha) from the investment strategy. Three different evaluation periods are considered. MR_t, SMB_t, HML_t, MON_t, and LIQ_t are the traditional market (MR), size (SMB), book-to-market (HML), momentum (UMD), and liquidity (LIQ) risk factors (Fama and French (1993), Jegadeesh and Titman (1993), Carhart (1997), and Pastor and Stambaugh (2003). See Odegaard (2017) for the construction of these for the Norwegian market.). *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.