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ESSAYS IN MACRO-FINANCE & APPLIED ECONOMETRICS

Berthold Brendan

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT D'ÉCONOMIE

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THÈSE DE DOCTORAT

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pour l'obtention du grade de
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par

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Lausanne, le 24.08.2023

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and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
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Contents

INTRODUCTION

Risk is a fascinating concept which pervades economic decisions that firms and individuals face on a daily basis. On the one hand, risk-taking lies at the heart of entrepreneurship and drives innovation. Economic prosperity often results from individuals believing in their ideas and taking calculated risks to achieve their visions. However, risk can also generate volatility and uncertainty, and excessive risk-taking can lead to catastrophic consequences. The Great Financial Crisis of 2008 serves as a poignant reminder of the economic costs of poorly managed risk-taking. In addition, the crisis has underscored the central role played by financial intermediaries and made it clear that developments in the financial markets matter for the macroeconomy. Looking ahead, climate change appears as one of the most pressing challenges facing humanity, and the transition towards a greener economy is likely to lead to increased risks and volatility.

The aim of this thesis is to better understand the interplay between financial markets and the real economy. Chapter 1 focuses on the macro-financial effects of financial volatility, while Chapter 2 and Chapter 3 investigate the macro-financial risks associated with the implementation of climate policies. Finally, Chapter 4 examines the impact of risk on the behaviour of safe-haven currencies. Overall, the results from this thesis provide insights on the macro-financial effects of different types of economic risks which are relevant to policymakers, investors, and academics.

In the first chapter (single-authored), I delve into the concept of financial volatility and use creative econometric techniques to distinguish uncertainty from risk aversion shocks. Intuitively, financial measures of volatility reflect both physical risk (referred to as uncertainty in the academic literature) and a risk-premium component. Conceptually, the distinction is important because uncertainty captures the agents' expectations or beliefs regarding the future whereas the risk-premium component relates to the marginal investor's ability to bear the risk (risk aversion). Furthermore, the academic literature has highlighted different channels through which uncertainty and risk aversion can have macroeconomic implications.

In terms of econometrics, however, the separate identification of uncertainty and risk aversion shocks is challenging because both variables are greatly correlated. To tackle this issue, I postulate that risk aversion shocks are related to the net worth of financial intermediaries, and impose narrative restrictions around events which coincided with policy interventions aimed at reducing financial stress, and at the same time took place in an environment characterized by high uncertainty.

My results highlight the differing nature of uncertainty and risk aversion, and show that they have distinct macro-financial effects. In particular, I find that uncertainty shocks have large negative effects on output, while risk aversion shocks are particularly damaging to asset prices. Furthermore, I show that the Great Financial Crisis is best characterised by a combination of uncertainty and risk aversion shocks, while uncertainty shocks played a significantly larger role than risk aversion shocks during the COVID pandemic. The results highlight the importance of the risk perception of financial intermediaries in driving equity returns, and can be used to quantify the macro-financial benefits of policies aimed at stabilizing risk aversion during periods of heightened uncertainty.

The second chapter, joint with Ambrogio Cesa-Bianchi, Federico di Pace, and Alex Haberis from the Bank of England, provides evidence on the heterogeneous macro-financial effects of carbon pricing policies, and develops a theoretical model with green and brown firms to explore the underlying economic channels. In light of the climate crisis, it is increasingly clear that additional climate policies will be implemented in Europe. Yet, there is limited evidence about the associated macroeconomic risks, and in particular from an international perspective.

We investigate these questions for a panel of 14 advanced European economies and document that carbon pricing shocks are contractionary, inflationary, and lead to a significant tightening of financial conditions. We further document that browner countries and firms (as measured by their CO2 intensity) are disproportionately more affected by carbon pricing shocks. In our economic model, we highlight theoretically the key role played by the degree of substitutability between firms in determining the magnitude of the economic effects. The results have important policy implications in terms of international cooperation, and uncover dimensions of hetereogeneity which may be particularly important.

In the third chapter, I investigate the macro-financial effects of the risks surrounding climate policies in Switzerland. To do so, I develop a new index of Climate Policy Risk (CPR) using text-analysis techniques on a large dataset of newspaper articles. The index spikes around a number of international and domestic events related to climate policies, and credibly captures the public awareness to a wide array of risks related to climate policies.

In terms of econometrics, the key novelty is to identify and quantify the effect of exogenous CPR shocks by leveraging on narrative restrictions around events which are likely to have coincided with an increase in the probability of adopting tighter climate policies. In addition to its high flexibility, this approach has the advantage of mapping directly with the theoretical definition of climate transition risk shocks from recent literature.

The results suggest that CPR shocks have macroeconomic effects as they lead to a significant drop in real GDP, and are associated with lower firm-level CO2 emissions. Furthermore, I find evidence that equity prices increasingly reflect concerns about climate policies, both using regression analyses and an event-study approach. In particular, the stock prices of firms with relatively low within-sector CO2 emissions tend to outperform that of browner firms when climate policy risk rises unexpectedly. Overall, the results highlight the macro-financial relevance of climate policy risk and may be particularly relevant going forward for investors willing to hedge that type of risk when forming their portfolios.

The fourth chapter, joint with Philippe Bacchetta and Kenza Benhima from the University of Lausanne, investigates the opportunity cost of foreign exchange interventions for safe-haven currencies. Recent literature suggests that what matters are deviations from the Covered Interest rate Parity (CIP). However, foreign exchange interventions are typically unhedged, which suggests that deviations from the Uncovered Interest rate Parity (UIP) should also play a role. This distinction between CIP and UIP appears particularly relevant for safe haven countries, as we show that the deviations have been of different signs for Switzerland and Japan since the Great Financial Crisis.

To clarify these questions, we consider a small open economy which receives capital flows through risk averse (global) financial intermediaries. Because the constrained financial intermediaries face exchange rate risk, UIP and CIP deviations differ and may be of different signs. We show that, for a country like Switzerland, there may be an opportunity benefit (rather than a cost) of performing foreign exchange interventions by documenting empirically that the safe-haven properties of the Swiss franc appear to be more valued by international financial intermediaries than by domestic households. We further show that this opportunity benefit is higher in high-risk environment. Our results provide a new perspective on the safe-haven properties of the Swiss franc by relying on insights from the literature on intermediary asset pricing.

CHAPTER 1

THE MACROECONOMIC EFFECTS OF UNCERTAINTY AND RISK AVERSION SHOCKS

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Abstract

This paper identifies two types of volatility shocks, namely *quantity* and *price* of risk shocks, which can intuitively be interpreted as uncertainty and risk aversion shocks, respectively. Identification is achieved in a shock-restricted SVAR framework using a combination of narrative and external variable restrictions. We find that uncertainty shocks have large negative effects on output, while risk aversion shocks are particularly damaging to asset prices and are deflationary. We also quantify to which extent the endogenous response of risk aversion can exacerbate the effects of uncertainty shocks, thereby providing an estimate of the quantitative relevance of the risk-premium channel of uncertainty shocks. A historical contribution exercise suggests that the GFC is best characterized by a combination of uncertainty and risk aversion shocks, while uncertainty shocks were more important than risk aversion shocks during the COVID pandemic.

Keywords: Volatility, Uncertainty, Risk Aversion, Shock-Restricted SVAR, Set Identification

JEL: E44, E32, D80, G1

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1 Introduction

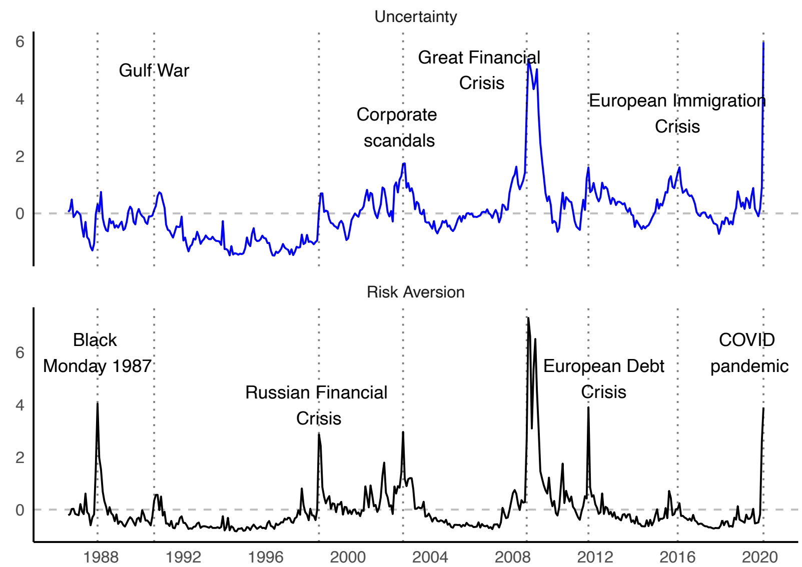
Risk-neutral measures of financial volatility such as the VIX depend on both a *physical risk* (quantity of risk) and a *risk-premium* (price of risk) component. In the macroeconomic literature, the physical risk component is referred to as "uncertainty" (see e.g. Bloom (2014)), while the risk-premium component is often associated with risk aversion (see e.g. Bekaert et al. (2013); Drechsler and Yaron (2011); Bekaert et al. (2021)). Interestingly, the literature highlights distinct potential mechanisms through which each variable can affect the economy. For instance, uncertainty shocks can operate through a real-option channel and so-called wait-and-see effects (Bernanke (1983); Bloom (2009)). For risk aversion shocks, the channels are generally more financial in nature, as they can affect the external finance premium and operate through a financial accelerator mechanism (Bernanke et al. (1999); Smets and Wouters (2007); Christiano et al. (2014)). Furthermore, uncertainty can also endogenously increase risk premia, thereby also (indirectly) operating through a risk-premium channel (Gilchrist et al. (2014); Bretscher et al. (2022)). Building on these observations, this paper aims i) to separately identify uncertainty and risk aversion shocks, ii) quantify their respective macroeconomic effects, and iii) estimate the empirical relevance of the risk-premium channel of uncertainty shocks.

By separating between uncertainty and risk aversion shocks, this paper aims to answer the following question: how much of the effect of financial volatility on the economy reflects variations in physical risk (uncertainty), and how much of it can be attributed to variations in the risk bearing capacity of the financial sector (risk aversion)? The answer to this question is relevant for policy makers because policies to address either uncertainty or risk aversion differ. Ex-ante, uncertainty-reducing policies could focus on improving the institutional framework, for example through the clear spelling-out of economic plans, a sound fiscal position and a credible central bank. For risk aversion, the policies are likely to be more financial in nature, for example through the preventive usage of macro-prudential policies, or more generally effective financial regulation. Furthermore, policies aimed at restoring liquidity during periods of financial stress can be particularly effective at reducing risk aversion, while having a more limited effect on uncertainty. At a general level, the distinction between uncertainty and risk aversion can also considerably help with financial stability monitoring (ECB (2018)). It is therefore important for policy makers to understand how each type of shock affects the economy. Our results allow for example to assess the quantitative relevance of the risk premium channel of uncertainty shocks. These results can be used to estimate the economic benefits of a policy that would mitigate the increase in risk aversion following an uncertainty shock. As noted in Bekaert et al. (2013), existing literature often blurs the distinction between the two types of shocks by using some common measures of volatility. In this paper, we explicitly distinguish between the two concepts.

Figure 1.1 plots the uncertainty and risk aversion variable from Bekaert et al. (2021) that we use in this paper. As we can see, the two variables clearly co-move, with a correlation of 0.81. This is consistent with the existence of feedback effects between uncertainty and risk aversion. For this reason, the separate identification of uncertainty and risk aversion shocks is challenging from an econometric perspective. Because of these feedback effects, identification schemes relying on external instruments or so-called proxy SVARs (Stock and Watson (2018)) are difficult to motivate. Similarly, recursive identification schemes are not particularly convincing because of the fast moving nature of both uncertainty and risk aversion.

In this paper, we propose to adopt a shock-restricted SVAR approach in the spirit of Ludvigson et al. (2021). In a nutshell, rather than imposing restrictions on the im-

Figure 1.1 Uncertainty and Risk Aversion measures from Bekaert et al. (2021)



Note. This Figure displays the Uncertainty and Risk Aversion variables from Bekaert et al. (2021) as well as the likely sources of the different spikes. While the raw correlation between the two series is high (0.81), there are also periods with distinctly different behaviour.

pact matrix as is common in the literature, we impose restrictions on the behaviour of identified shocks around certain key events. To separately identify uncertainty and risk aversion shocks, we rely on three principles. First, we restrict uncertainty and risk aversion shocks to behave in a way broadly consistent with a historical reading of a few key economic events which likely coincided with large variations in uncertainty or risk aversion. Second, following the literature on intermediary asset pricing (He and Krishnamurthy (2013)); Brunnermeier and Sannikov (2014)) and risk premium shocks (Smets and Wouters (2007); Bernanke et al. (1999)), we postulate that risk aversion shocks are related to the net worth of financial intermediaries, and particularly so during periods when it is dangerously low. The underlying argument is that a low capital ratio may cause non-linear changes in global risk perceptions, resulting for example from regulatory constraints. Third, we consider historical events that likely generated different behaviours for uncertainty and risk aversion. In practice, we focus on periods characterized by high uncertainty, which coincided with the implementation of policies specifically targeted at reducing the stress in the financial sector. We argue that these events are particularly effective to separate uncertainty from risk aversion shocks.

To reduce potential "event-mining" concerns, a novelty of this paper is to transparently look for events that are likely to provide useful identifying information. Around these events, we propose an intuitive type of "historical contribution" restriction (in the spirit of Antolin-Diaz and Rubio-Ramirez (2018)) which reduces the set of models considered to those that feature shocks that have a meaningful contribution to the unexpected variation in the variable of interest. In line with Antolin-Diaz and Rubio-Ramirez (2018), our narrative restrictions do not prevent other shocks to also play an important role. We further refine the set identification using external variables restrictions, which importantly don't need to satisfy an exclusion restriction. The separate identification of the two shocks is finally made possible by the recent development of measures that are precisely aimed to distinguish between uncertainty and risk aversion (Bekaert et al. (2021)). To take into account the non Gaussianity of the identified shocks, we conduct inference in a frequentist setting by proposing a simple extension of the wild-bootstrap procedure developed in Gonçalves and Kilian (2004).

Conceptually, we define uncertainty shocks as sudden changes in the agents' expectations or beliefs regarding future physical risk in the economy.[1] On the other hand,

[1] An example would be the outcome of the Brexit referendum which increased uncertainty by increasing the probability of extreme events (such as a No-Deal Brexit), independently of its actual effect on present and future economic conditions.

risk aversion shocks are defined as exogenous variations in the marginal investor's ability to bear (or appetite towards) risk. We remain agnostic about the fundamental sources of these shocks, but postulate that they could reflect unmodelled (regulatory) risk constraints faced by marginal investors, or shifts in risk preferences induced by certain types of news. In this framework, financial volatility can arise either because the physical risk in the economy increased, or because financial intermediaries see their risk-bearing capacities impaired.[2]

In terms of results, we find that the average dynamic effects of uncertainty and risk aversion shocks differ. In particular, uncertainty shocks are associated with significant and persistent declines in output and asset prices but have no significant effect on consumer prices. On the other hand, risk aversion shocks do not appear to affect output significantly, but lead to large and contemporaneous decline in asset prices and consumer prices. The response of the policy rate is also different, as the central bank tends to significantly loosen its stance in face of uncertainty shocks, while it essentially looks through risk aversion shocks. Quantitatively, a one standard-deviation uncertainty shock leads to a decline of output of around 0.7% and a decline of around 1.5% in asset prices. On the other hand, a risk aversion shock decreases asset prices by more than 2% and the consumer price index by 0.15%. The results suggest feedback effects between uncertainty and risk aversion shocks, as the increase in one variable causes the other to increase as well. We further find that uncertainty and risk aversion shocks are important drivers of macroeconomic fluctuations, as they can jointly explain significant shares of the variation in stock prices, output, consumer prices and the policy rate.

Armed with these results, we run a historical decomposition exercise to shed light

[2] In line with this, Lansing and LeRoy (2014) show theoretically how higher risk aversion leads to larger stock price volatility.

on the different nature of shocks depending on the period considered. We find that risk aversion shocks were important drivers of fluctuations during the Great Financial Crisis but were of more limited importance during the COVID period. Additionally, we find that uncertainty shocks have played an important role in impeding the recovery in the years following the GFC, and were the main drivers of the drop in output during the COVID recession. In other words, our results suggest that all volatility shocks are not alike.

Finally, to better understand the interplay between uncertainty and risk aversion, we investigate the dynamic effects of uncertainty shocks by running a counterfactual exercise in which we simulate the dynamic effects of an uncertainty shock keeping the risk aversion variable at its pre-shock level. The results provide an estimate of the "risk aversion version" of the finance uncertainty multiplier (Alfaro et al. (2018)), that is the role played by the endogenous response of risk aversion in magnifying the effect of uncertainty shocks. This provides a way to quantify the economic relevance of the risk premium channel of uncertainty shocks recently put forward in the litterature (Bretscher et al. (2022)). We find this multiplier to be between 2 and 3 for asset prices, that is the endogenous response of risk aversion to uncertainty shocks multiplies by 2 to 3 times the effect of uncertainty shocks on equity prices. On the other hand, the multiplier for output is only slightly above 1, thereby suggesting that the risk-premium channel is quantitatively limited for output. This suggests that policies aimed at stabilising risk aversion following uncertainty shocks may be effective at stabilising asset markets, but may be more limited at containing output losses.

This paper is structured as follows. Section 2 reviews some related literature. Section 3 details the identification approach and the empirical restrictions. Section 4 investigates the dynamic effects and the business cycle importance of uncertainty and risk aversion shocks, and quantifies the risk aversion uncertainty multiplier. Section

7 concludes.

2 Related Literature

Our paper is related to the literature that investigates the macroeconomic effects of uncertainty. Bloom (2009) and Bloom et al. (2018) investigate the real-option channel of uncertainty shocks in a framework characterized by irreversible investment. Basu and Bundick (2017) analyse the precautionary-saving channel of uncertainty shocks in a model with nominal rigidities. Other papers highlight the role of financial frictions in exacerbating the effects of uncertainty shocks (Gilchrist et al. (2014); Christiano et al. (2014)). Bretscher et al. (2022) explicitly investigate the risk-premium channel of uncertainty shocks in a DSGE model with stochastic volatility in productivity. Fernández-Villaverde et al. (2011) investigate the effects of volatility shocks in small open economies.

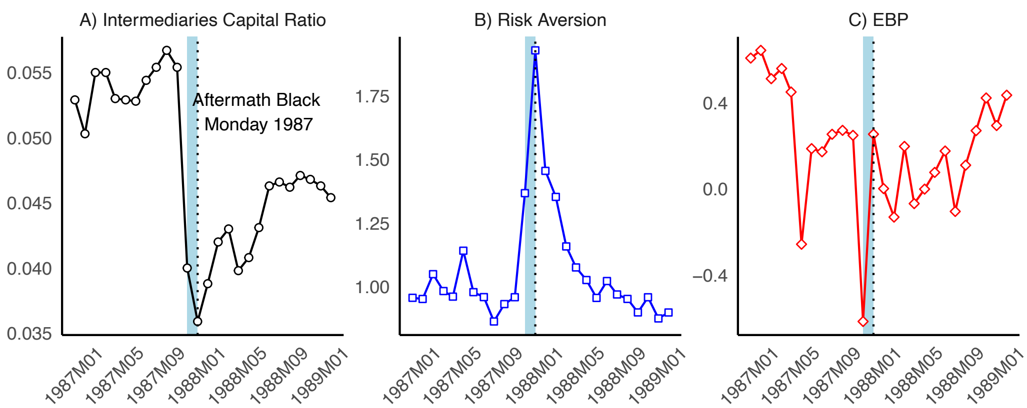
Our paper also connects with an emerging literature aiming to distinguish between uncertainty and other types of (financial) shocks (e.g. Caldara et al. (2016); Furlanetto et al. (2019)). De Santis et al. (2022) distinguish between uncertainty and financial shocks in a Bayesian SVAR using narrative restrictions similar to Antolin-Diaz and Rubio-Ramirez (2018). They find that financial shocks are deflationary, while uncertainty shocks are inflationary. Brianti (2021) separately identifies uncertainty and financial shocks, and investigates their respective monetary policy implications.

A paper particularly close to ours in spirit and method is Caggiano et al. (2021) which separately identifies uncertainty and credit supply shocks using narrative restrictions in a set-identified VAR. In particular, the credit supply shocks are recovered using the Excess Bond Premium (EBP) series from Gilchrist and Zakrajšek (2012). We see our work as complementary to this study but also highlight a number of important differences. First, conceptually, our focus is on the identification of different sources of volatility, namely uncertainty and risk aversion shocks because they connect well with the theoretical literature on uncertainty and risk premium shocks, respectively. Furthermore, the distinction allows to investigate the risk-premium channel of uncertainty shocks. By considering the EBP series, the interpretation in Caggiano et al. (2021) is that of a credit supply shock. In this paper, the focus is different in the sense that we interpret risk aversion shocks as shocks to the *risk-bearing capacity* of the marginal investor, with the intuitive characteristic to be related with the net worth of financial intermediaries.

Figure 2.1 illustrates the difference between the two approaches by looking at the period following the 1987 Black Monday crash and plotting the EBP, the risk aversion measure used in this paper and the capital ratio of large US financial intermediaries taken from He et al. (2017). In Caggiano et al. (2021), the authors use this event to impose a narrative restriction on the identified shock by arguing that, despite the stock market crash, overall financial conditions–as proxied by the EBP–remained stable, notably thanks to a rapid and effective intervention of the Federal Reserve. As a result, they argue that the 1987 Black Monday crash is unlikely to coincide with a large credit supply shock. This interpretation is crucial in their identification because it significantly helps to disentangle uncertainty shocks from credit supply shocks. Although their argumentation is sensible in their context, it does not connect well with the interpretation of risk aversion shocks as net worth shocks that we consider in this paper.

As we can see on the graph, the aftermath of the 1987 Black Monday crash coincided with a severe deterioration of the capital ratios of large US financial intermediaries, a development which is expected to coincide with an impairment of the risk bearing capacity of the economy. Consistent with this, our risk aversion measure rises significantly, and we impose this event to coincide with a risk aversion shock in the empirical

Figure 2.1 DYNAMICS AROUND THE 1987 BLACK MONDAY CRASH



NOTE. This Figure displays the behaviour of the Intermediaries' Capital Ratio measures from He et al. (2017), the Risk Aversion measure from Bekaert et al. (2021) and the EBP series from Gilchrist et al. (2012) around the Black Monday Stock Market Crash on October 19th 1987. As we can see, the month following the crash coincides with a local low of the capital ratio (going from around 5.5% to 3.5% in a matter of months) as well as a spike in the Risk Aversion measure. On the other hand, the EBP series remains at moderate levels, and even decreases in October 1987.

part. On the other hand, the EBP series remains relatively stable and even improves. In other words, the different interpretation of the 1987 Black Monday Crash is a key feature that distinguishes our risk aversion shocks from the credit supply shocks considered in Caggiano et al. (2021).

This paper also directly connects with a literature aiming at decomposing the drivers of financial volatility. Chiu et al. (2018) decompose financial volatility in a long-run persistent component and a short-run transitory component. They assume that the long-term component of volatility is associated with macroeconomic fundamentals, while the short-run component is related to the transitory determinants of volatility, such as investor sentiment. Bekaert et al. (2013) decompose the VIX index into two components, namely an "expected volatility" term which they interpret as a measure of uncertainty (physical risk) and a residual term–defined as the variance risk premium–which they interpret as a proxy for risk aversion. Their focus is on the feedback effects between uncertainty, risk aversion and monetary policy. Bekaert and Hoerova (2014) find that the variance risk premium is a reliable predictor of stock returns while the uncertainty term (conditional volatility) is a better predictor of economic activity.

Finally, we connect with the literature on time-varying risk-aversion. Gordon and St-Amour (2000) show that stochastic risk aversion in the form of preference shocks can successfully explain empirical variations in the price of risk. In the same vein, Bekaert et al. (2009) and Bekaert et al. (2010) model risk aversion as a stochastic process and interpret shocks to risk aversion as preference shocks. More recently, evidence from Martin (2017) and Bekaert et al. (2021) imply that risk aversion is much more rapidly mean reverting than implied by standard habit models (such as Campbell and Cochrane (1999)), thereby emphasizing the empirical relevance of (high-frequency) exogenous variations. The literature on intermediary asset pricing argues that the balance sheet of financial intermediaries is directly related to the stochastic discount factor (and thus risk aversion) of the marginal investor (see e.g. Krishnamurthy and Vissing-Jorgensen (2012)). Finally, risk premium shocks in the form of preference shocks are important drivers of macroeconomic fluctuations in Smets and Wouters (2007).

3 Identification and Empirical Approach

3.1 Identification Problem

We consider a monthly US VAR consisting of $n = 6$ endogenous variables and a sample running from 1986M6 to 2020M2. The beginning of the sample is restricted by the availability of the economic uncertainty and risk aversion measures from Bekaert et al. (2021). For the end of the sample, we do not include the COVID observations following Lenza and Primiceri (2022) who argue that dropping these observations is sensible when it comes to parameter estimation and inference. However, we view the COVID pandemic as an important volatility shock and as such wish to use some of the information contained in this event. To do so and as will be explained below, we propose a way to estimate structural shocks "out-of-sample" by treating the one-step ahead forecast error as the out-of-sample reduced form residual and check that the implied structural shocks are coherent with a historical reading of the COVID pandemic.

Formally, we consider the following notation for our SVAR. Let $\boldsymbol{Y}_t$ be a $n \times 1$ vector of endogenous variables :

$$\boldsymbol{Y}_t = \boldsymbol{\Phi}(L)\boldsymbol{Y}_{t-1} + \boldsymbol{B}\boldsymbol{\varepsilon}_t \tag{3.1}$$

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

$$\boldsymbol{u_t} = \boldsymbol{B}\boldsymbol{\varepsilon}_t \tag{3.2}$$

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

$$\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u_t} \tag{3.3}$$

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

$$\Sigma_{uu} = \boldsymbol{C}\boldsymbol{C}' = \boldsymbol{C}\boldsymbol{Q}\boldsymbol{Q}'\boldsymbol{C} \tag{3.4}$$

In this paper, we consider a "shock-based" identification scheme à la Ludvigson et al. (2021). Rather than imposing restrictions on the impact matrix as is common, the idea is to restrict *structural shocks* to behave in a certain way during some carefully selected economic events. In a second step, we sharpen the identification using the information contained in external variables, without requiring a potentially controversial exogeneity assumption.

In practice, we draw K (a large number) of $\boldsymbol{Q}$ matrices and recover structural shocks according to (E.3), and check that they fulfil our set of restrictions.[3] In our bootstrap replications, we work with $K = 1$ million. We collect each of these matrices in a set that we denote by $\mathcal{B} = \{\boldsymbol{B} = \boldsymbol{C}\boldsymbol{Q}, \boldsymbol{Q} \in \mathcal{O}_n, diag(\boldsymbol{B}) \geq 0, \boldsymbol{B}\boldsymbol{B}' = \boldsymbol{\Sigma_{uu}}\}$ where $\mathcal{O}_n$ is the set of $n \times n$ random orthonormal matrices. The restriction $diag(\boldsymbol{B})$ is for convenience and ensures that a positive structural shock implies an increase in the variable of interest. We refer to $\mathcal{B}$ as the "unconstrained set". For each K elements of the set $\mathcal{B}$, we can retrieve the related structural shocks $\boldsymbol{\varepsilon}_t$ using $\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t$. We denote the set of unconstrained structural shocks $\mathcal{E} = \{\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t, \boldsymbol{B} \in \mathcal{B}\}$. Note that, for notational convenience, the dependence of $\boldsymbol{B}$ and $\boldsymbol{\varepsilon}_t$ on the draw k is dropped, but we keep in mind that they correspond to a particular draw $k \in \{1, ..., K\}$. Identification

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

is then achieved by only keeping models (defined by a particular draw of the $\boldsymbol{B}$ matrix) which satisfy our narrative and "external variable" restrictions. Obviously, if the restrictions are too strict or incompatible with the data, the constrained set (denoted by $\tilde{\mathcal{B}}$) is empty. On the other hand, if restrictions are too lax, the unconstrained set is very similar to the constrained one and thus does not provide any identification gains.

Dealing with COVID observations

As mentioned, the estimation sample ends in February 2020 and thus does not include the COVID period. The reason is that including the period of the COVID is likely to interfere with parameter estimations (see Lenza and Primiceri (2022)). However, we still want to use the information contained in the COVID period, as it is likely to be a large and informative volatility shock. To do so, our approach is to use the estimated VAR parameters in-sample to produce out-of-sample forecast. We then interpret the one-step ahead forecast errors as the reduced form residual and invert it using the $\boldsymbol{B}$ matrix. Formally, let T be the last period of observation (February 2020 in our case). The forecast errors can be recovered recursively using the observed data and the estimated VAR as follows:

$$\boldsymbol{u}_{T+h} = \boldsymbol{Y}_{T+h} - \mathbb{E}_T(\boldsymbol{Y}_{T+h}|\boldsymbol{Y}_{t+h-1}) \tag{3.5}$$

Where T is 2020M2 and $h \geq 0$ is expressed in months. The “out-of-sample” structural shocks are then recovered iteratively according to:

$$\boldsymbol{\varepsilon}_{T+h} = \boldsymbol{B}^{-1}\boldsymbol{u}_{T+h} \tag{3.6}$$

Intuitively, restrictions on the behaviour of ε_{T+h} is the out-of-sample equivalent of in-sample restrictions on ε_t for $t \leq T$.

3.2 VAR Data

For the VAR, we consider four standard macroeconomic variables (CPI, stock prices, industrial production, and the shadow-policy rate from Wu and Xia (2016)) to take into account the Zero Lower Bound (ZLB) period) which we complement with measures of uncertainty and risk aversion from Bekaert et al. (2021). At a general level, the two measures appear particularly suited because the approach in Bekaert et al. (2021) explicitly separates the price of risk from its quantity within a common framework. The uncertainty variable is recovered by extracting macro risk factors from US monthly industrial production. To derive the risk aversion variable, the starting point is a habit formation framework à la Campbell and Cochrane (1999) and a utility function that depends on both a consumption (or "fundamentals") and a non-fundamentals factor. Risk aversion shocks are then defined as a second factor in the pricing kernel that is not exclusively driven by fundamentals. We refer the reader to the original paper for more information. Figure 1.1 plots the two variables.

3.3 Empirical Restrictions

Our identification restrictions rely on three pillars. The first is that we impose restrictions on the historical contribution of certain shocks around key economic events that are likely to have coincided with either large uncertainty or risk aversion shocks. The underlying idea is that any reasonable solution should be in line with a broad historical reading of a few key economic events. We refer to this as a "*large shocks*" type of restriction. Second, we exploit a number of policy interventions that i) have taken place in an environment characterized by high uncertainty and ii) appear to have been effective at keeping risk aversion at moderate levels. Around such events, we impose that a positive (but not necessarily very large) uncertainty shock took place, and that the corresponding risk aversion shock has been small or negative. To the extent that measures of uncertainty and risk aversion are generally greatly correlated, exploiting such events is likely to provide significant identifying power. We refer to these restrictions as "*different behaviours*" restrictions. Finally, we use information from outside the VAR in the form of "*external variable*" restrictions to sharpen identification. For example, in line with the literature on intermediary asset pricing and risk premium shocks, we postulate that risk aversion shocks are related to the time variation in the ability of financial intermediaries to bear risk, as proxied by unexpected variations in their net wealth.[4]

Large Shocks Restrictions

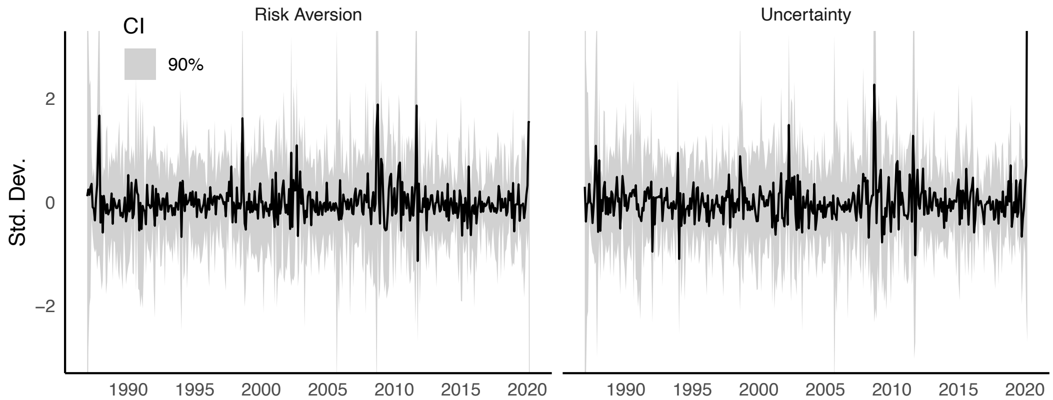
To identify events which are likely to coincide with large shocks, we "let the data speak" and compute the cross-sectional median uncertainty and risk aversion shocks for each date in the unconstrained set of structural shocks ($\mathcal{E}$). The resulting series of uncertainty and risk aversion shocks (as well as the 90th percentiles) are displayed in Figure 3.1.

This procedure turns out to be effective at identifying major economic events which are likely to have generated important variations in uncertainty and risk aversion.[5] Table D1 in Appendix C displays the 5 largest median shocks in the uncertainty and

[4]An additional reason that makes the risk aversion measure particularly well suited for our exercise is its high correlation with the intermediary capital risk factor (a measure of changes in net worth of financial intermediaries) from He, Kelly, and Manela (2017). The raw correlation between the two series is equal to 0.33. For comparison, the correlation with the EBP is 0.18, and 0.22 with the uncertainty series.

[5]It should be noted that our approach to identify relevant events differs from the one adopted in Ludvigson et al. (2021). In their paper, the authors look for dates which feature the most maxima for the unconstrained set of structural shocks, and use the resulting dates to impose "event constraints". In this paper, we rely on the distributional properties (i.e. percentiles) of the unconstrained shocks.

Figure 3.1 UNCONSTRAINTED UNCERTAINTY AND RISK AVERSION SHOCKS

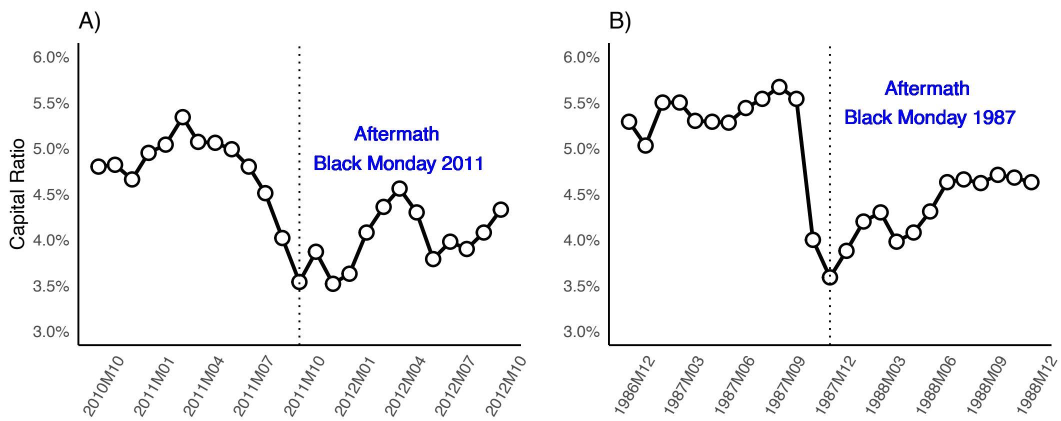


NOTE. This Figure displays the structural shocks recovered using equation (E.4) from the unconstrained set of solutions $\mathcal{E}$. The solid black line corresponds to the median shock while the shaded area corresponds to the 90th percentiles.

risk aversion variable, as well as a short historical labelling. Interestingly, the largest shocks for the two variables generally differ, suggesting that the data alone can provide useful information. We use this table as a basis to select 4 "large shocks" restrictions.

For restrictions on large uncertainty shocks, we consider 2020M3 and 2008M9, which respectively coincide with the declaration of the COVID pandemic by the World Health Organisation, and the failure of Lehman Brothers. For large risk aversion shocks, we consider 2011M9 and 1987M11, which coincide with the aftermath of the 2011 and 1987 Black Monday stock market crashes, respectively. While 2008M10 turns out to be the largest risk aversion shock, we decide not to include it as a restriction because of its proximity with the uncertainty shock that is likely to have taken place during the failure of Lehman Brothers in 2008M9. In this context, it is not clear to which extent the risk aversion shock in 2008M10 reflects an *endogenous* response, rather than a true exogenous shock. For this reason, we feel more comfortable not imposing a narrative restriction on this date. Another reason that supports our choice to consider 2011M9 and 1987M11 as large risk aversion shocks is that both dates coincide with a local low in the capital ratio as can be seen in Figure 3.2. Such a situation may generate some non-linear adjustments in the marginal risk appetite, for example due to regulatory constraints. We provide some further historical context in Appendix B.1 to motivate our "large shocks" restrictions.

Figure 3.2 INTERMEDIARY CAPITAL RATIOS AROUND LARGE RISK AVERSION SHOCKS



NOTE. This Figure plots the Intermediary Capital Ratio measure from He et al. (2017) around the two events which we interpret as "large risk aversion shocks".

Around the 4 selected events, we impose that the structural shock can explain at least a quarter of the reduced form innovation in the variable of interest. For example, we impose that the uncertainty shock that took place in 2020M3 can explain at least 25% of the unexplained variation of the uncertainty variable during this month.[6] Panel A) of Table 3.1 summarises the four "large shocks" restrictions. Each restriction reduces

[6]It should be noted that our type of "historical contribution" restriction is similar to the narrative restrictions considered in Antolin-Diaz and Rubio-Ramirez (2018) but differ in one key aspect. In particular, the narrative restrictions from Antolin-Diaz and Rubio-Ramirez (2018) generally assume that a given shock is the largest contributor to the unexpected variation of a given variable. With our type of restriction, other shocks could explain more than 25% of the unexpected variation.

the set of admissible solutions by roughly 70%. Taken together, only 6.22% of models satisfy jointly the 4 restrictions. This suggests that they are quite effective at reducing the set of potential solutions. Appendix A.1 provides additional information regarding the computation of the "historical contribution" restrictions that we consider.

Table 3.1 IDENTIFYING RESTRICTIONS

A) Large Shocks Restrictions

		Historical Contribution	
Date	Event	Uncertainty	Risk Aversion
2020M3	Declaration of the COVID Pandemic by the WHO	>25%	Ø
2008M9	Failure Lehman Brothers	>25%	Ø
2011M9	Aftermath Black Monday 2011	Ø	>25%
1987M11	Aftermath Black Monday 1987	Ø	>25%

B) Different Behaviours Restrictions

		Historical Contribution	
Date	Event	Uncertainty	Risk Aversion
2011M2	Concerns about EU debt / Liquidity injections by CB	$> 10\%$	$< 10\%$
2008M12	Pres. Bush facilitates TARP interventions during GFC	$> 10\%$	$< 10\%$

C) External Variables Restrictions

Proxy	Description	Source	Restrictions
Unc. (Z_t^U)	Intraday gold price variations	Piffer and Podstawski (2017)	$cov(\varepsilon_t^U, Z_t^U) > cov(\varepsilon_t^{RA}, Z_t^U)$
RA (Z_t^{RA})	Intermediary capital risk factor	He et al. (2017)	$cov(\varepsilon_t^{RA}, Z_t^{RA}) > cov(\varepsilon_t^U, Z_t^{RA})$

NOTES. This table summarises the restrictions used in the baseline identification scheme. The historical contribution restrictions define the minimum share of the unexpected variation of variable i with $i \in \{UNC, RA\}$ that can be explained by the respective (positive) structural shock ε_t^i at the time of the event. For example, we require that the uncertainty shock explains at least 25% of the reduced form residual increase in the uncertainty variable in 2020M3. Table D1 displays the dates of the 5 largest uncertainty and risk aversion shocks resulting from the data-driven algorithm described in the text. Table C2 displays the dates featuring different median behaviours for uncertainty and risk aversion.

Different Behaviours Restrictions

To identify events which display different behaviours in terms of uncertainty and risk aversion shocks, we again try to let the data speak as much as possible. In particular, we first impose that one of the two (median) shock from the unconstrained set ranks above the 80th percentile of median shocks. This ensures that at least one of the two shock can credibly be considered as being large. At the same time, we impose that the two median shocks are of different signs. This procedure identifies a number of possible dates which meet those criteria. Table C2 in Appendix C displays such dates as well as a short historical labelling. 2011M12 (Liquidity injections by central banks in the context of the European sovereign debt crisis) and 2008M12 (President Bush facilitates TARP interventions during the GFC) stand out as being especially suitable for our restrictions, as they coincided with policy interventions that likely kept risk aversion at a moderate level, while taking place in a context of significant uncertainty. Around these two events, we impose that the uncertainty shock was positive and contributed more than 10% to the unexpected increase in the uncertainty variable, while the contribution of the risk aversion shock to the risk aversion variable was small and below 10%. In words, we require that the contribution of the uncertainty shock was positive and potentially large, while we restrict the contribution of the risk aversion shock to be small, and possibly negative. Panel B) of Table 3.1 summarises the two "different behaviours" restrictions. Each of these restrictions reduces the set of admissible solutions by around 75%. Taken together, 10.5% of all models satisfy jointly these "different behaviours" restrictions. Appendix B.2 provides additional historical context to further motivate the restrictions.

External Variable Restrictions

To further sharpen our identification, we propose to add two external variables restrictions. The idea is to use information from outside the VAR, but critically and as opposed to standard proxy SVAR approaches, we do not require the external proxies to be valid instruments, but merely that they are correlated in a meaningful fashion with our shocks of interest.

To improve the identification of uncertainty shocks, we use the (updated) uncertainty proxy developed in Piffer and Podstawski (2017). The proxy is built by looking at intraday price variation of gold around uncertainty events that are unexpected and arguably exogenous with regards to other macroeconomic development. By focusing on the price of gold, the idea is that the resulting series should be positively correlated with "true" uncertainty shocks, thereby forming the basis to work as an instrument. In our context, using the uncertainty proxy as an *external* instrument would likely not be convincing: by using the variation of an asset price like gold, it is very likely that the resulting shock at least partly reflects risk premia shocks, thereby making a strict exclusion restriction unconvincing. This highlights the great difficulty to find exogenous instruments in our context.

We sharpen the identification of risk aversion shocks using the measure of capital risk developed in He et al. (2017). In doing so, we rely on insights from the literature on intermediary asset pricing which postulates that financial intermediaries behave as marginal investors in a large number of markets. As such, variations in their net wealth–proxied by the capital ratio–can affect the aggregate pricing kernel and thus aggregate risk aversion. We thus expect our risk aversion shocks to be positively correlated with such measures. As in He et al. (2017), we run an AR(1) on the measure of the capital ratio and then divide the resulting residual by the lagged capital ratio. This gives us the so-called "intermediary capital risk factor" which we use as our risk aversion proxy. Importantly, we do not argue that this constitutes a valid instrument, but merely that it should be positively correlated with the true risk aversion shocks.

In practice, we require the uncertainty (risk aversion) shock to be more correlated with the uncertainty (risk aversion) proxy than with the other proxy. Panel C) of Table 3.1 summarises the two "external variables" restrictions. Each external variable restriction reduces by roughly 50% the set of potential solutions. Considering all restrictions, we find that the narrative restrictions are remarkably effective at reducing the set of potential solutions, as only 0.11% satisfy jointly the "large shocks" and "different behaviours" restrictions. Adding the external variable restrictions further reduces this number to 0.06%.

3.4 Inference

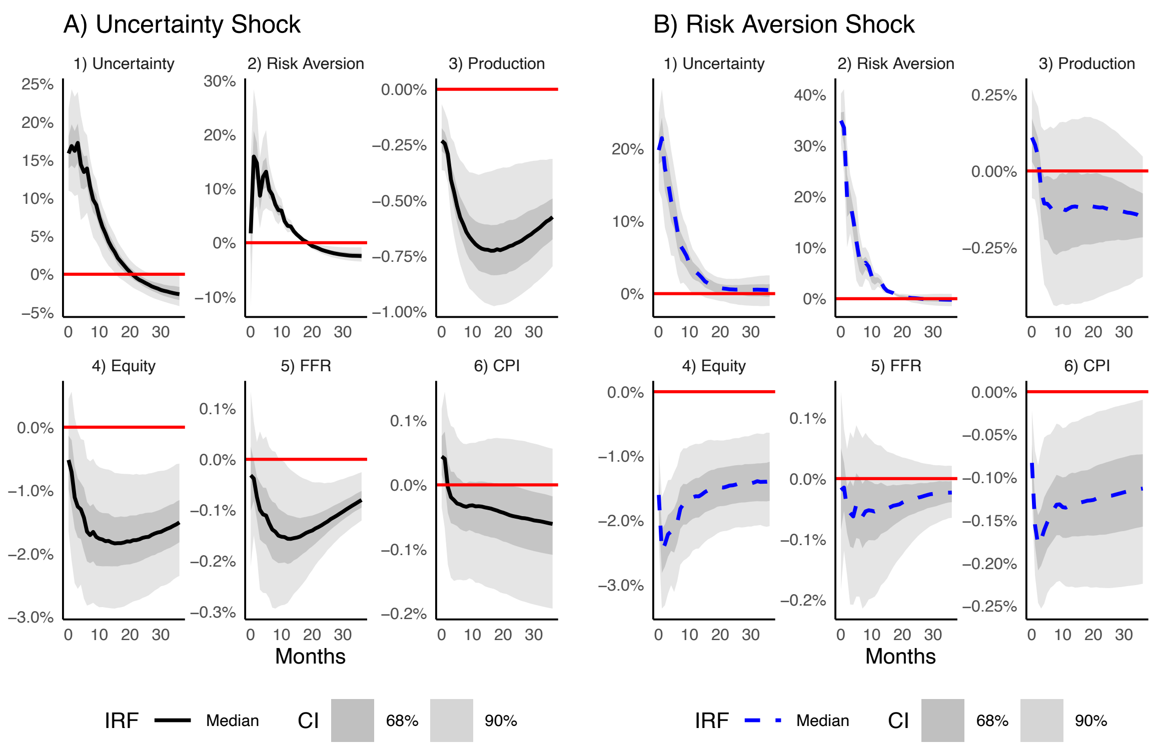
To conduct inference, we follow Mertens and Ravn (2013) and Gertler and Karadi (2015) in using the wild bootstrap method developed in Gonçalves and Kilian (2004), and extend it to our setting. Standard wild bootstrap re-samples the reduced form residuals by switching the sign of the reduced form vector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

4 Results

4.1 Average Dynamic Responses

We compute the dynamic response of the 6 endogenous variables in our VAR following an uncertainty and risk aversion shock set-identified with the narrative and external variable restrictions, and using $p = 6$ lags. Figure 4.1 plots the results. We find that the average dynamic effects of uncertainty and risk aversion differ. In particular, uncertainty shocks are associated with persistent declines in production and equity prices. On the other hand, risk aversion shocks do not appear to affect output significantly, but coincide with a large and contemporaneous decline in equity prices. Furthermore, while the effect of uncertainty shocks on consumer prices is not significant, we find that risk aversion shocks are deflationary, even though the effect is quantitatively limited. The response of the policy rate is also different, as the central bank tends to significantly loosen its stance in face of uncertainty shocks, while it essentially looks through risk aversion shocks. We also find that the increase in one variable causes the other to increase as well, consistent with the existence of important feedback effects between uncertainty and risk aversion. Quantitatively, a one standard-deviation uncertainty shock leads to a decline of output of around 0.7% and a decline of around 1.5% in asset prices. On the other hand, a risk aversion shock decreases asset prices by more than 2% and the consumer price index by 0.15%. Figure C1 in the appendix shows the power of the identification restrictions by comparing the IRFs resulting from the unconstrained set of models to those obtained using our narrative and external variable restrictions restrictions.

Figure 4.1 IDENTIFIED IRFS



NOTE. Impulse Response Functions correspond to a one standard-deviation shock to the reduced form residual of the uncertainty and risk aversion variable, respectively. Shocks are set-identified using the narrative and external variable restrictions discussed in Section 3.3. Confidence intervals and median response are obtained using the extension of the wild bootstrap procedure discussed in Section E.3. We consider 1,000 bootstrap replications. The uncertainty and risk aversion variables are normalized to have a unit mean, so that the y-axis can be interpreted as the percentage deviations from the mean. The policy rate is expressed in percent. All the other variables are in log-levels.

Robustness

A potential concern of our identification scheme is that it relies on a number of "large shocks" restrictions such as the failure of Lehman Brothers or the declaration of the COVID pandemic. Such extreme events can involve a number of non-linearities which may distort the average results.[7] More generally, it is important to understand how each type of restriction affects the results. Appendix C (Figure C2) investigates this

[7]We thank a referee for pointing this out.

issue by considering identification schemes relying only on one type of restrictions ("large shocks" (LS), "different behaviours" (DB), or "external variables" (EXT)), and any combination of two types of restrictions. For uncertainty shocks, we find that the average dynamic responses are remarkably similar across the types of identification restrictions (even though confidence intervals tend to be wider). For risk aversion shocks, results remain qualitatively similar across all specifications, but the negative response of equity prices is somewhat less pronounced without the "large shocks" type of restrictions. Overall, the results suggest that our main results are not overly influenced by one type of restriction in particular. We also reestimate the VAR using $p = 12$ lags instead of 6 as in the baseline specification. Results turn out to be similar as well (see Figure C3).

4.2 Contribution to Business Fluctuations

Since at least Kydland and Prescott (1982), the question of the source of macroeconomic fluctuations has been at the centre of macroeconomic analysis. Because our identification scheme is based on restrictions regarding the behaviour of shocks around certain key events, it is natural to rely on historical decomposition exercises to get a sense of the respective and overall macroeconomic importance of uncertainty and risk aversion shocks in driving business cycle fluctuations. Formally, one can rewrite equation (3.1) as the sum of structural shocks (once again ignoring the constant/trend for simplicity):

$$\boldsymbol{Y}_t = \boldsymbol{\Phi}(L)^{t-1}\boldsymbol{Y}_1 + \sum_{j=0}^{t-2} \boldsymbol{\Phi}(L)^j \boldsymbol{B}\boldsymbol{\varepsilon}_{t-j} \tag{4.1}$$

The path of any variables in the absence of certain structural shocks can then be retrieved by setting certain columns of the impact matrix ($\boldsymbol{B}$) to zero. Similarly, one can easily retrieve the *historical contribution* of each structural shock. Figure 4.2 plots the (yearly average) historical contributions of uncertainty and risk aversion shocks to the variables contained in our VAR for the last 20 years of our sample (2000-2020). This allows to better understand which type of shock mattered when.

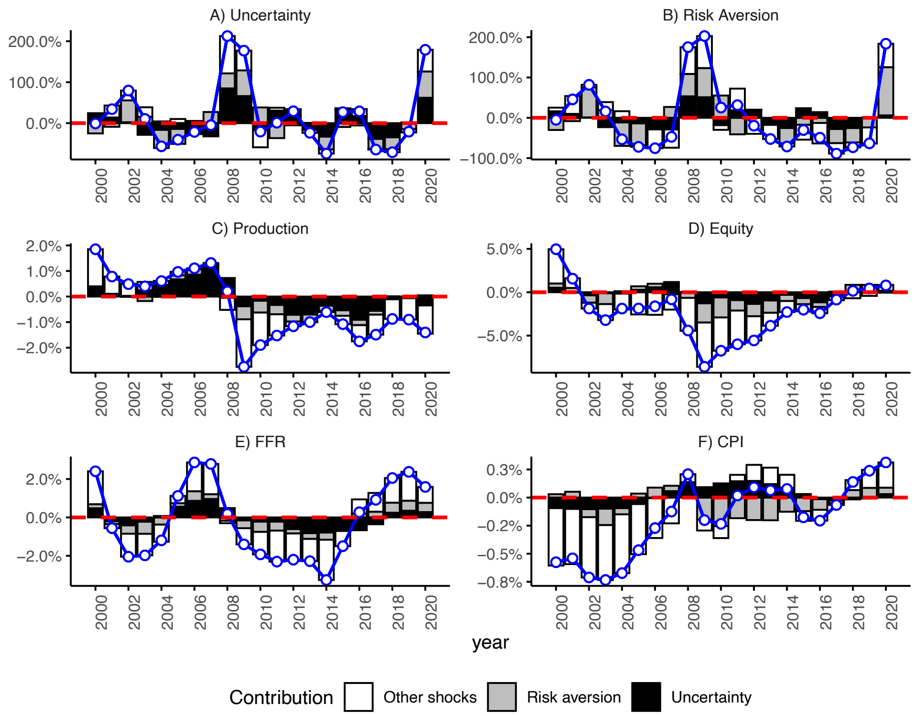
The results highlight how different crises feature different types of shocks. For example, the contribution of uncertainty shocks to the initial decline in production following the GFC (2009 to 2011) has been relatively small. However, uncertainty shocks appear to have significantly impeded the subsequent economic recovery (large negative contribution starting in 2012). For equity prices, we find that risk aversion shocks have significantly contributed to the poor performance following the GFC, while the importance of uncertainty shocks is smaller. For the COVID period (2020), we can see that uncertainty shocks contributed negatively to output, while the contribution of risk aversion is negligible. In Appendix D, we investigate in more details the respective role of uncertainty and risk aversion shocks for the GFC and COVID periods.

In Table 4.1, we report the average (across all models satisfying the restrictions) percentage contribution of each type of shock to the residual variation of the variables from the VAR. We find that uncertainty shocks can account for close to 40% of unexpected variations in production, while the contribution of risk aversion is significantly smaller and equal to 10%. Taken together, uncertainty and risk aversion shocks can almost account for 50% of the variations in equity prices, and 66.6% and 63.2% of variations in the uncertainty and risk aversion variables, respectively. We take this as evidence of the macroeconomic relevance of the two types of identified shocks.

4.3 Risk Aversion Uncertainty Multiplier

In this section, we quantify to which extent the endogenous response of risk aversion can exacerbate the effects of uncertainty shocks. To do so, we adopt an approach

Figure 4.2 HISTORICAL CONTRIBUTIONS OF UNCERTAINTY AND RISK AVERSION SHOCKS



NOTE. This figure plots the average yearly historical contributions of uncertainty, risk aversion, and the other types of shocks to the unexplained variations for each variable from the VAR. For all variables except the policy rate which is kept in levels, the historical contributions are expressed as the percentage deviation from the sample mean of the given variable. Historical contributions are retrieved using (4.1) equation iteratively.

similar to Caggiano et al. (2021) and compare the unconstrained impulse response function to an uncertainty shock to a counterfactual impulse response which shuts down the endogenous response of risk aversion. In practice, this is achieved by adding a series of risk aversion shocks which exactly offset the effect of uncertainty shocks on risk aversion, such that the risk aversion variable stays at its pre-shock level. We argue that this exercise allows to quantify the risk-premium channel of uncertainty shocks recently put forward in the literature (see Bretscher, Hsu, and Tamoni (2022)).

Formally, we denote the counterfactual IRF of variable j as: $\left[\frac{\partial j_{t+h}}{\partial \epsilon_t^{UNC}} \middle| \frac{\partial RA_{t+h}}{\partial \epsilon_t^{UNC}} = 0\right]$. In the spirit of Caggiano et al. (2020), we define the Risk Aversion Uncertainty Multi-

Table 4.1 AVERAGE HISTORICAL CONTRIBUTIONS

	Shock		
Variable	Unc.	RA	Other
Uncertainty	36.3%	30.3%	33.4%
Risk Aversion	26.8%	36.4%	36.8%
Equity	22.2%	22.3%	55.56%
FFR	30.0%	15.6%	54.3%
Production	39.7%	10.8%	49.5%
CPI	22.7%	27.2%	50.1%

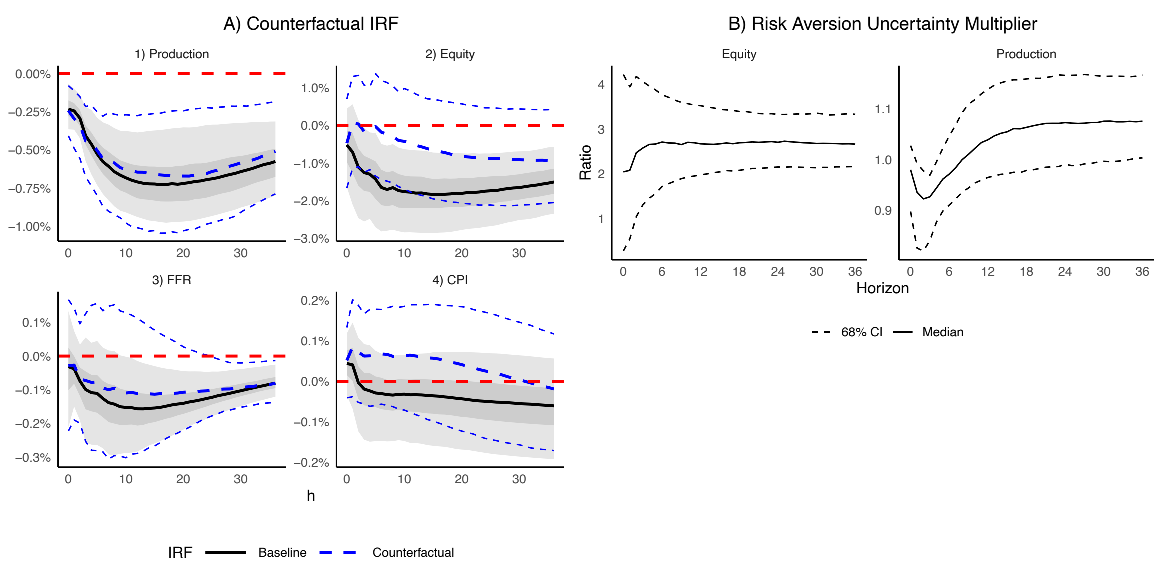
Note:
This table reports the average historical contribution of three types of shocks on the 6 endogenous variables of the VAR.

plier (RAUM) as the ratio of the cumulated unconstrained impulse response to the counterfactual one at a given horizon H. Formally, the RAUM is defined as:

$$RAUM_{j,H} = \frac{\sum_{h=0}^{H} \left[\frac{\partial j_{t+h}}{\partial \epsilon_t^{UNC}} \right]}{\sum_{h=0}^{H} \left[\frac{\partial j_{t+h}}{\partial \epsilon_t^{UNC}} \middle| \frac{\partial RA_{t+h}}{\partial \epsilon_t^{UNC}} = 0 \right]} \tag{4.2}$$

Figure 4.3 plots the results. Panel A) displays both the unconstrained (grey shaded area) and the counterfactual (blue) impulse responses for production, equity, the policy rate, and the consumer price index. As we can already see, absent the endogenous response of risk aversion, the effect of uncertainty shocks on equity prices would be significantly smaller. On the other hand, the response of output remains roughly the same in both situations. Panel B) computes the RAUM using equation (4.2) for $H = 1, ..., 36$ for production and equity prices. In line with the results from Panel A), we find the multiplier associated with equity prices to be large and significant as it is comprised between 2 and 3, depending on the horizon considered. In other words, the endogenous response of risk aversion multiplies by 2 to 3 the cumulated effect of uncertainty shocks on equity prices. On the other hand, the multiplier associated with output is only slightly above 1, which suggests that the multiplier for output is not as quantitatively important than for equity prices. In terms of policy implications, the results suggest that policies aimed at stabilising risk aversion following uncertainty shocks can be effective at stabilising asset markets (by reducing the drop in equity prices), but may be more limited at containing output losses.

Figure 4.3 THE RISK AVERSION MULTIPLIER



NOTE. Panel A) compares the unconstrained IRF to an uncertainty shock (shaded grey and solid line) to the counterfactual IRF which shuts off the endogenous response of risk aversion (blue dashed line). The difference between the "Baseline" and "Counterfactual" line can be interpreted as the risk-premium channel of uncertainty. Panel B) computes the Risk Aversion Uncertainty Multiplier using equation (4.2) for different (cumulated) horizons h. For instance, the ratio at $h = 36$ indicates by how much the cumulated response of a given variable after 36 months is magnified by the endogenous response of risk aversion. Percentiles are obtained cross-sectionally across all models satisfying the restrictions (from the wild-bootstrap procedure detailled in the text).

5 Conclusion

This paper identifies uncertainty and risk aversion shocks within a shock-based SVAR identification framework in the spirit of Ludvigson et al. (2021). Identification is achieved using a combination of narrative and external variable restrictions. To separate uncertainty from risk aversion shocks, we postulate that risk aversion shocks are related to the net worth of financial intermediaries and exploit a number of events which coincided with policy interventions aimed at reducing financial stress, and at the same time took place in an environment characterized by high uncertainty. The results suggest that uncertainty shocks are particularly damaging for output while risk aversion shocks are particularly bad for equity prices. Consistent with this, we find that the central bank only significantly loosens the policy stance in the face of uncertainty shocks. A historical contribution exercise suggests that the GFC is best characterized by a combination of uncertainty and risk aversion shocks, while uncertainty shocks were more important than risk aversion shocks during the COVID pandemic. Our results further allow to quantify the risk-premium channel of uncertainty shocks. We find the risk aversion uncertainty multiplier to be large for equity prices, but more quantitatively limited for output.

While the study and identification of uncertainty shocks is now extensive, a small (but growing) literature tries to distinguish between different types of shocks. To the best of our knowledge, this paper is the first to use a shock-based SVAR identification scheme to distinguish between uncertainty and risk aversion shocks. We see work on better understanding how different policies can optimally react to each type of shock each as being fruitful avenues for future research.

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Appendix to Chapter 1

A Notes on the Types of Restrictions

A.1 Historical Contribution Restrictions

Historical contribution restrictions are defined as restrictions on the share of the unexplained variation in a given variable that can be explained by a certain variable. Formally, we define the absolute contribution of the structural shocks at time t from a given draw (k) as follows:

$$\boldsymbol{C}_t = \boldsymbol{B}' \odot \boldsymbol{\varepsilon}_t \tag{A.1}$$

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

$$\boldsymbol{S}_t = \boldsymbol{B} \oslash \boldsymbol{u}_t' \tag{A.2}$$

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

$$g(i, j, t, \lambda) = S_{i,j,t} \geq \lambda \in \{0, 1\} \tag{A.3}$$

In words, the restriction $g(i, j, t, \lambda)$ requires that the contribution of the structural shock of variable i to the unexplained variation in variable j at time t is greater or equal to λ, with λ being between 0 and 1. Intuitively, an example would be $g(UNC, UNC, 2020M3, 0.3)$ which imply that we restrict the set of models considered to those that feature a structural uncertainty shock that can explain at least 30% of the unexpected rise in uncertainty in March 2020, that is when the COVID has been declared a pandemic. We highlight the fact that this type of restriction does not rule out that other structural shocks were important. Rather, it merely restricts that a given shock has occurred, and has contributed meaningfully to the unexpected variation of our variable of interest. It should be noted that this type of restriction is similar to the narrative restrictions considered in Antolin-Diaz and Rubio-Ramirez (2018) but differ in one key aspect. In particular, the narrative restrictions from Antolin-Diaz and Rubio-Ramirez (2018) generally assume that a given shock is the *largest* contributor to the unexpected variation of a given variable. In that sense, we see our historical importance restrictions as less restrictive, as it could very well be the case that another shock contributes more.

A.2 External Variable Restrictions

The second set of restrictions that we consider are "external variables restrictions." Rather than imposing potentially controversial exclusion restrictions, this type of restriction only requires that the identified shocks correlate in a meaningful way with a few selected external variables. Formally, we define an external variable restriction for variable k as :

$$g(k, \bar{Z}^k, \lambda) : cor(\varepsilon_k, Z^k) \geq \lambda \tag{A.4}$$

Where Z^k is the external proxy for variable $k \in \{UNC, RA\}$ and λ is between 0 and 1. In our setting, we set $\lambda = \max\{corr(\varepsilon_i, Z^k), 0\}$ for $i \in UNC, RA$. In words, we require that the structural uncertainty (risk aversion) shock is positively correlated with the uncertainty (risk aversion) proxy, and this correlation is larger than with the risk aversion (uncertainty) shock.

B Historical Context to Narrative Restrictions

In this section, we provide some historical context for each of the narrative restriction.

B.1 Large Shocks Restrictions

2020M3 - COVID is declared a pandemic

In March 2020, the World Health Organisation declared the COVID a pandemic. In the same month, California became the first US state to introduced a partial lockdown on its residents. Clearly, this once-in-a-century pandemic has massively impacted the daily lives of millions of people and generated a great deal of uncertainty, not only regarding the virus in itself, but also with regards to the economic risks induced by different policy responses. As such, 2020M3 appears as a turning point in the emergence of the virus and as such is likely to coincide with a sizeable uncertainty shock.

2008M9 - Failure of Lehman Brothers

The second largest uncertainty shock happens in September 2008. September 2008 is the month during which Lehman Brothers filled for bankruptcy. The fact that it was "allowed to go down" by financial authorities is a defining moment of the Great Financial Crisis and has generated a massive amount of uncertainty, notably with regards to the survival of certain financial institutions, future bailout decisions, or other (fiscal) policies of federal authorities. In this context, it appears reasonable to impose that the (exogenous) uncertainty shock that took place in September 2008 can at least explain 25% of the unexpected increase in uncertainty in that month.

2011M9 - Aftermath Black Monday 2011

The first narrative restriction for risk aversion that we consider coincides with the month following the Black Monday crash in 2011. The crash followed the downgrading of the US credit rating score by Standard & Poors on Friday August 9th, and happened in a context of wide-ranging concerns about debt sustainability, be it related to the US debt ceiling or the European sovereign debt crisis. Panel A) of Figure 3.2 displays the measure of the capital ratio of US financial intermediaries from He, Kelly, and Manela (2017) around the event. Interestingly, it turns out that 2011M9 coincides with a local low in the capital ratio. This, combined with large stock market volatility is likely to have contributed to an important increase in risk aversion.

1987M11 - Aftermath Black Monday 1987

The last "large shock" restriction that we consider is 1987M11, that is one month after the Black Monday crash of October 1987. Looking at Panel B) of Figure 3.2, we can see that the 1987 Black Monday Crash and its aftermath coincides with a massive decrease and a local low in the capital ratio, going from around 5.5% to around 3.5% in the matter of two months. We take this evidence that a risk aversion shock is likely to have taken place. Another potential rationale is that the 1987 stock market crash is also often considered to be a turning point in terms of risk management, something that could also well impact risk aversion preferences.

B.2 Different Behaviours Restrictions

2011M12 - Liquidty Injections by the ECB: In December 2011, concerns about the EU sovereign debt situation and the potential of a contagion and a financial crisis were at high levels. In its Tealbook report, the Fed notes that "[t]he most important factor is our more pessimistic view about the European situation and its implications for the U.S. economy." At the same time, December 2011 coincided with a number of measures taken by the ECB in order to reduce financial distress, notably liquidity-provision through the Long Term Refinancing Operations (LTRO) which loaned €489 billions to 523 banks at unusually advantageous conditions as well as measures aimed at strengthening the capital position of European banks. Furthermore, a number of central banks including the Fed, the ECB, the SNB, and the BoJ agreed to lower the cost of dollar currency swaps in order to support overall liquidity. According to Table C2, these measures were effective at reducing risk aversion, while at the same time coincided with a relatively large uncertainty shock, in line with a historical reading of the environment prevailing.

2008M12 - President Bush facilitates TARP interventions The last narrative restriction that we consider is on the behaviour of the uncertainty and risk aversion shock in December 2008. In a context of ongoing concerns about the implications of the financial crisis, the Fed lowered its policy rate to 0bp, formally entering the ZLB. At the same time, President Bush extended the flexibility regarding the Target Asset Purchase Programs (TARP) in order to prevent liquidity crises. The program provided a financial bailout package to banks, insurers, and other institutions that were deemed "too big to fail." This program was intended to restore confidence in the financial system and reduce risk aversion. Table C2 suggests that these policies were helpful at containing, and even reducing risk aversion, while at the same time were taken in a context of high uncertainty.

C Additional Results and Robustness

Table C1 LARGEST UNCERTAINTY AND RISK AVERSION SHOCKS

Date	Median	Rank	Percentile	Description of the event
Uncertainty shock				
2020M3	5.6	1	100.00	COVID Pandemic Declaration
2008M9	2.3	2	99.75	Failure of Lehman Brothers.
2002M4	1.5	3	99.50	Stock market downturn of 2002
2011M8	1.3	4	99.25	Black Monday 2011 / US Debt Ceiling / EU Soveregeind Debt Crisis
2008M10	1.3	5	99.00	'Intensification' of the financial crisis / Fed reduces rates by 50 bp.
Risk aversion shock				
2008M10	1.9	1	100.00	'Intensification' of the financial crisis / Fed reduces rates by 50 bp.
2011M9	1.9	2	99.75	Aftermath Black Monday 2011. Increasing concerns about sovereign debt.
1987M11	1.7	3	99.50	One month after Black Monday 1987 crash
2020M3	1.6	4	99.25	COVID Pandemic Declaration
1998M8	1.6	5	99.00	Russian financial crisis

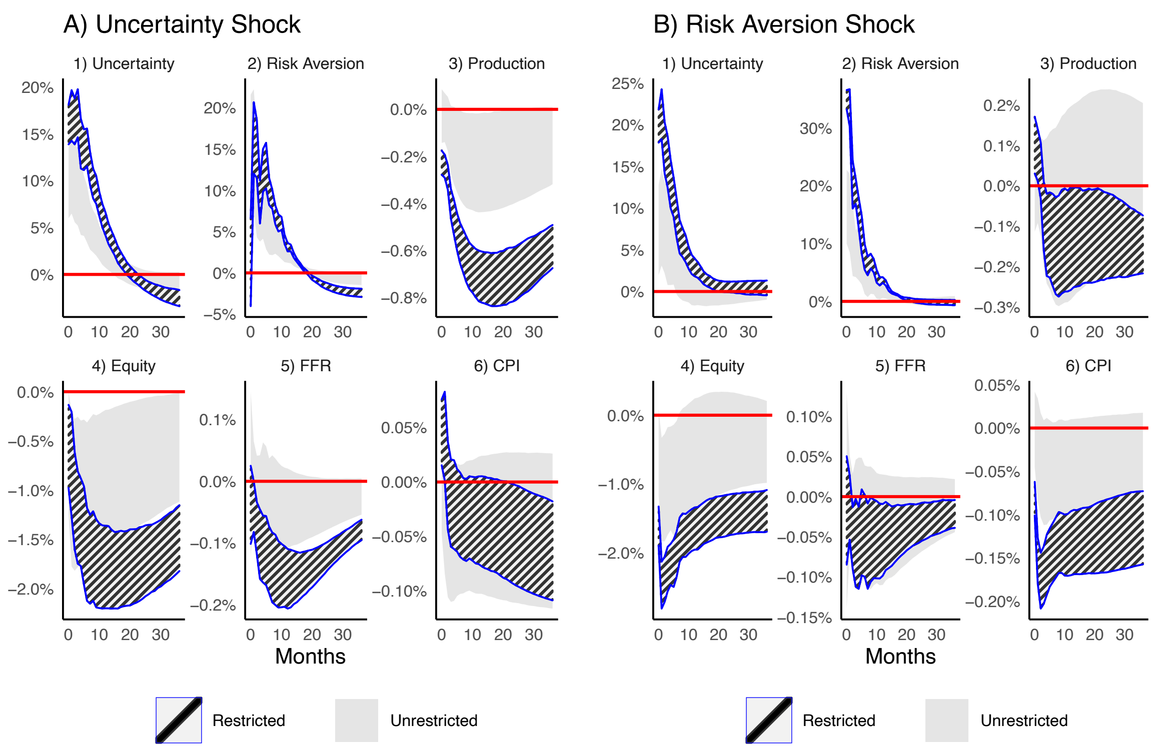
Notes:
This table reports the 5 largest identified median uncertainty and risk aversion shocks for the unconstrained set $\mathcal{E}$. After 2020M2, structural shocks are recovered 'out-of-sample'. Percentiles are computed with regards to the distribution of the median shocks over all dates in the sample.

Table C2 EVENTS WITH DIFFERENT BEHAVIOURS

		Median Shock		Percentiles		
Date	Δ	Unc.	RA	Unc.	RA	Description of the event
2011M12	0.8	0.6	-0.2	96.00	27.25	Concerns about EU sovereign debt / Liquidity injections by central banks
1999M12	-0.7	-0.4	0.3	10.50	90.00	Concerns about the dotcom bubble
1998M10	0.7	0.3	-0.4	86.25	7.50	IMF and World Bank meet to discuss the global economic crisis
2008M12	0.7	0.2	-0.4	81.50	6.50	President Bush facilitates TARP interventions
1989M11	0.6	0.3	-0.4	84.50	8.75	Fall of the Berlin wall

Notes:
This table reports the 5 events which feature the largest difference between the median uncertainty and risk aversion shocks, and at the same time display a positive shock above the 80th percentile for one of the variable, and a negative shock in the other, considering the unconstrained set $\mathcal{E}$. Percentiles are computed with regards to the distribution of the median shocks over all dates in the sample.

Figure C1 UNCONSTRAINED VERSUS BASELINE IRFS



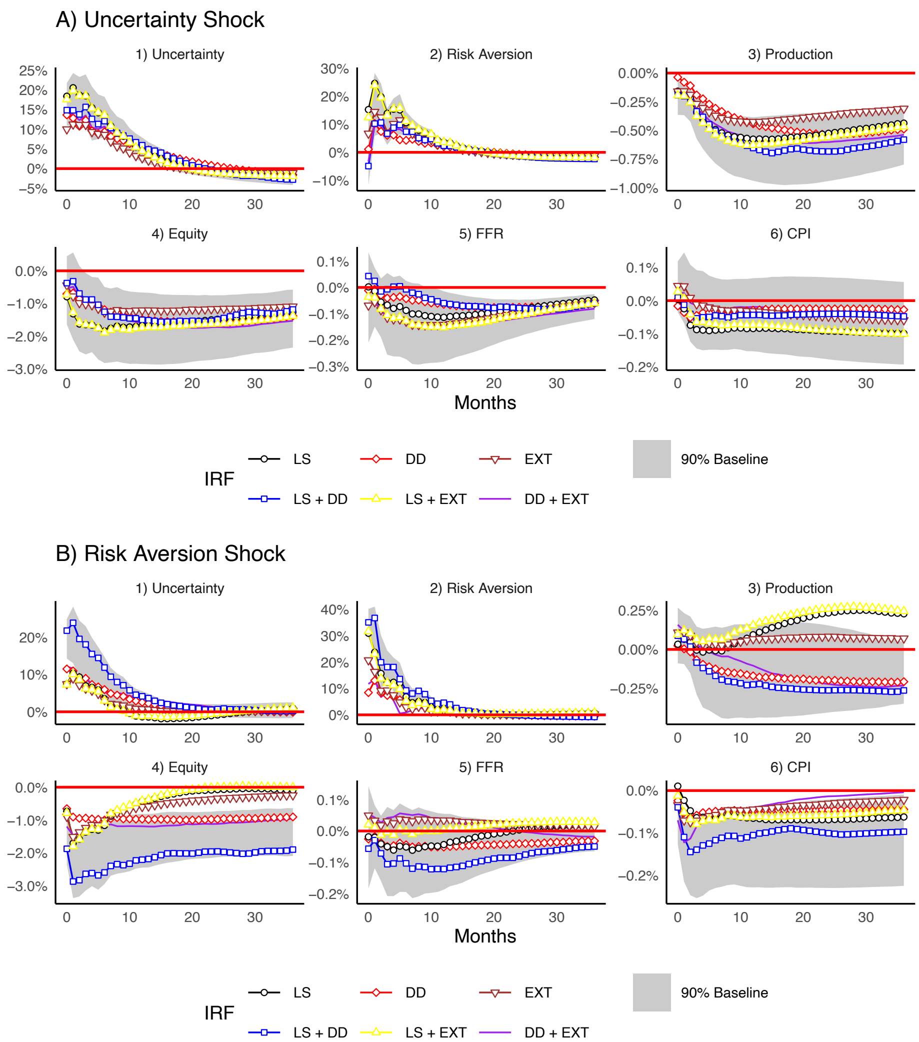
NOTE. This figure compares the impulse response from the unconstrained set $\mathcal{E}$ with those from the baseline (narrative + external variable restrictions). The confidence bands are 68%.

D Investigating the GFC and COVID Periods

D.1 Analysis of the Great Financial Crisis

Panel A) of Figure D1 plots the dynamics of industrial production, equity prices, risk aversion and uncertainty during the Great Financial Crisis (GFC). The solid line plots the actual data while the dashed line represents the counterfactual dynamics in the absence of both uncertainty and risk aversion shocks. All variables are expressed in percentage change from the initial date on the plot (taken to be 6 months before the collapse of Lehman Brothers in September 2008). As we can see, it is clear that the Great Financial Crisis coincided with massive uncertainty and risk aversion shocks, as both variables would have risen significantly less in their absence. These shocks appear to also have had large effects on stock prices and output. In particular, we find that, absent uncertainty and risk aversion shocks, the drop in equity prices would have been around 3%, whereas it was close to 8% in the data. For output, the drop would have approximately reached minus 3% at the maximum, whereas it reached 4% in the

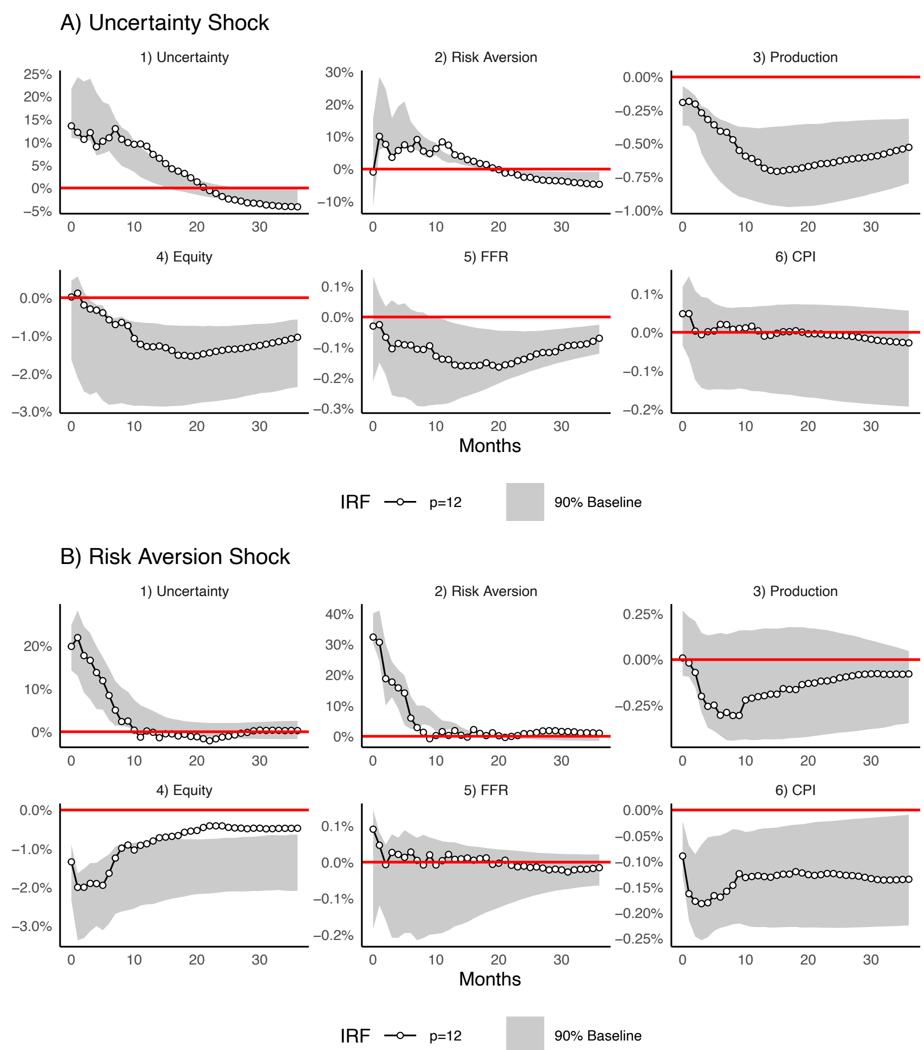
Figure C2 Robustness Checks : Different Identifying Restrictions



Note. This Figure displays the effect of each type of restrictions on the identified IRFs to an uncertainty and risk aversion shocks. LS stands for "large shocks" restrictions. DB stands for "different behaviours" restrictions. EXT stands for external variable restrictions. Each line represents the median response using an identification scheme using only one or two types of restrictions. The grey area corresponds to the 90% confidence intervals from the baseline model ("LS + DD + EXT").

data. To get a finer analysis of both types of shocks, Panel B) of Figure D1 displays the historical (mean) contribution of the two shocks for the four endogenous variables. For equity prices, we find that risk aversion shocks were the largest contributors, accounting for roughly two thirds of the total decline that can be attributed to the two types of shocks. For output, risk aversion and uncertainty shocks contributed

Figure C3 Robustness Checks : Changing the Lags



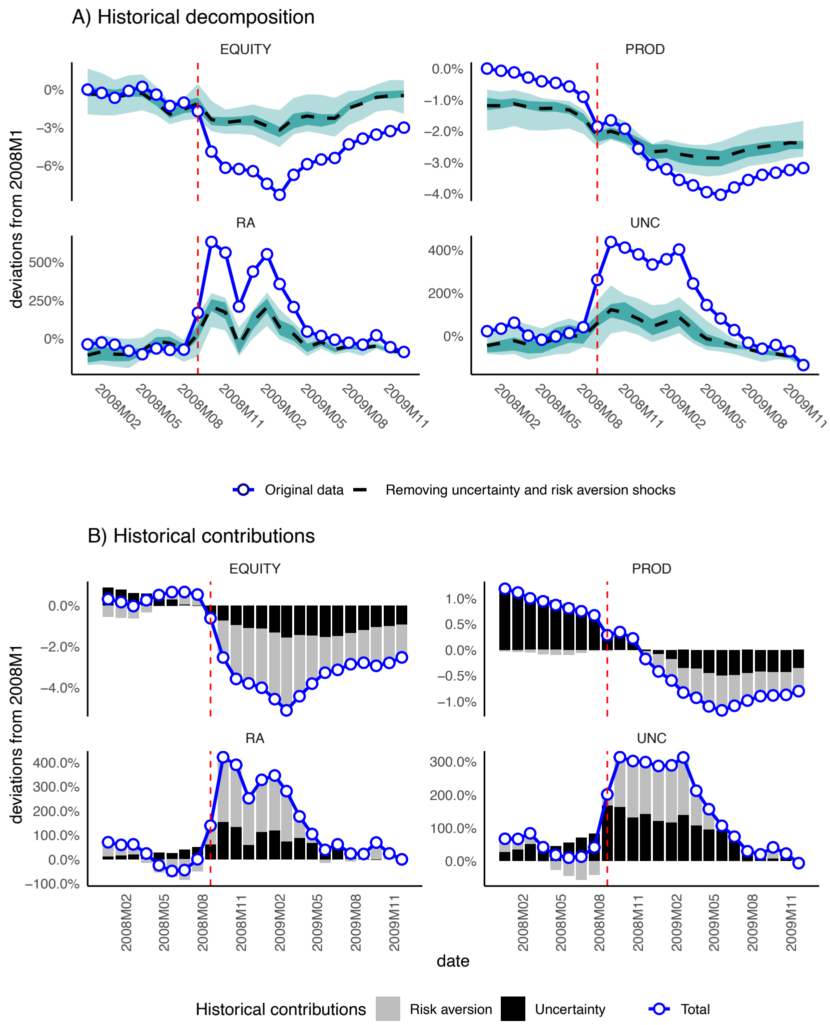
Note. This figure reestimates the baseline VAR using $p = 12$ lags instead of $p = 6$.

roughly in equal parts to the decline. Overall, we interpret the results as suggesting that risk aversion shocks have played an important role in the dynamics of asset prices and output around the GFC.

D.2 Analysis of the COVID pandemic

Panel A) of Figure D2 plots the behaviour of four endogenous variables with and without the contribution of uncertainty and risk aversion shocks during the COVID pandemic. The vertical line indicates the date at which the World Health Organisation

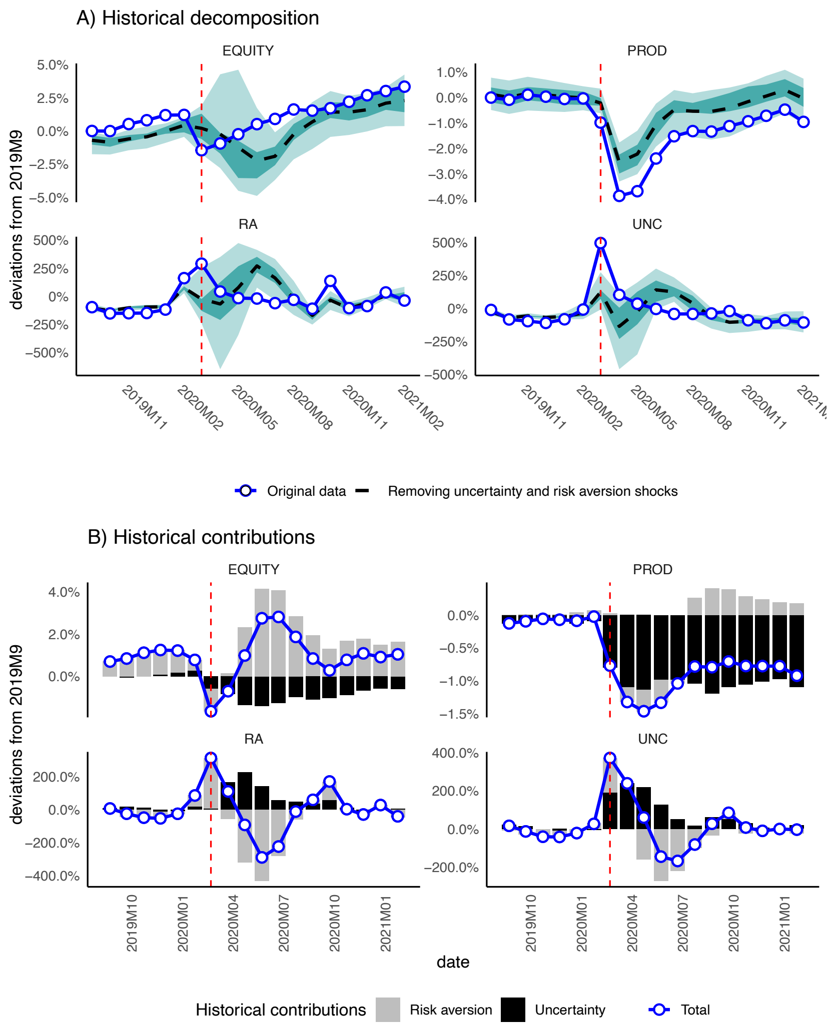
Figure D1 Analysis of the Great Financial Crisis



Note. Panel A) displays the historical decomposition of four endogenous variables, namely the log of equity prices and industrial production, the risk aversion, and uncertainty variable. The counterfactuals are obtained by setting the first two columns of $\boldsymbol{B}$ to zero and estimating equation (4.1) for each impact matrices satisfying our identification restrictions (that is matrices which are part of the constrained set $\tilde{\boldsymbol{B}}$). Error bands correspond to the cross-sectional 68% and 90% percentiles of the historical decompositions. The dashed line corresponds to the cross-sectional mean. Panel B) plots the respective (mean) historical contributions of uncertainty and risk aversion shocks to the four endogenous variables. The vertical dashed line corresponds to 2008M9, that is the month in which Lehman Brothers filled for bankrupcty.

declared the COVID a pandemic. Clearly, 2020M2 and 2020M3 appear to coincide with large uncertainty and risk aversion shocks for the uncertainty and risk aversion variables. Interestingly, the following months exhibit a different pattern. In particular, in the months following 2020M2, we find that risk aversion shocks were negative, and actually contributed positively to the rebound following the initial decline in stock prices. One interpretation of this result is that policies that were put in place after the initial shock in March 2020 were effective at containing risk aversion. On the other hand, the contribution of uncertainty shocks remains negative throughout the period. It is particularly clear for production, as the vast majority of the negative contribution can be attributed to uncertainty shocks. Without uncertainty shocks, the drop in output would have been around 1% less negative. This suggests that uncertainty shocks played a significantly more important role than risk aversion shocks for the dynamics of output. Overall, the results highlight the heterogeneous dynamics and effects of uncertainty and risk aversion shocks, depending on the type of crisis considered.

Figure D2 ANALYSIS OF THE COVID PANDEMIC



NOTE. The vertical dashed line corresponds to 2020M3, that is the month in which the COVID was declared a pandemic by the World Health Organisation. For additional notes, refer to Figure D1.

CHAPTER 2

THE HETEROGENEOUS EFFECTS OF CARBON PRICING: MACRO AND MICRO EVIDENCE

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Abstract

This paper investigates the economic effects of carbon pricing policies using a panel of countries that are members of the EU Emissions Trading System. Carbon pricing shocks lead, on average across countries, to a decline in economic activity, higher inflation, and tighter financial conditions. These average responses mask a large degree of heterogeneity: the effects are larger for higher carbon-emitting countries. To sharpen identification, we exploit granular firm-level data and document that firms with higher carbon emissions are the most responsive to carbon pricing shocks. We develop a theoretical model with green and brown firms that accounts for these empirical patterns and sheds light on the transmission mechanisms at play.

Keywords: Business Cycles, Carbon Pricing Shocks, Heterogeneity, Asset Prices

JEL: E32, E50, E60, H23, Q54

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1 Introduction

In order to achieve the objectives of the Paris Agreement, governments around the world need to increase the ambition and implementation of climate change mitigation policies.[1] Cap-and-trade schemes, which set overall limits on the quantities of emissions of greenhouse gases (GHGs) and allow their price to be determined by market forces, are likely to (continue to) be an important part of the climate policy mix necessary to meet objectives on climate change mitigation. The European Union Emissions Trading System (EU ETS), introduced in 2005 under the Kyoto Protocol, is one such scheme and has reduced emissions in relevant sectors in the EU by over 40 percent. Moreover, in July 2021 the European Commission announced that the emissions limits defined by the ETS would be made stricter in order to reduce GHG emissions in the EU by at least 55 percent relative to 1990 levels by 2030. While cap-and-trade schemes have long been part of the economic analysis of pollution mitigation, evidence on their wider economic and macroeconomic effects remains relatively limited.

The aim of this paper is, therefore, to provide empirical evidence on the economic effects of carbon pricing shocks and to understand their transmission mechanism. Our key innovation is to document the heterogeneous effects of carbon policies on macroeconomic and firm-level outcomes based on CO_2 intensity, and to exploit such heterogeneity to learn about the transmission mechanisms at play. This analysis is an important step towards understanding the macroeconomic and microeconomic implications of policies that governments would need to implement during the transition to a low-carbon economy.

Our analysis consists of three steps. First, we document the macroeconomic effects of carbon pricing shocks for a panel of 15 euro area countries. We define carbon pricing shocks as exogenous variations of the carbon futures prices in the EU ETS following Känzig (2023). We use the resulting carbon policy surprise (CPS) series in a panel structural VAR, and show that carbon pricing shocks are contractionary, inflationary, and lead to a significant tightening of

[1]For example, see the 2022 G7 Leaders' Communiqué.

financial conditions. A one standard deviation carbon pricing shock leads to a contraction in real GDP of about 0.2 percent and an increase in consumer prices of about 0.05 percent. The shock also leads to a fall in equity prices of more than 2 percent, and an increase in credit spreads of about 10 basis points. The cross-country dimension of our analysis allows us to investigate whether carbon pricing shocks have heterogeneous effects depending on a country's CO_2 emissions intensity. The results suggest that countries with higher CO_2 intensity tend to suffer relatively more from carbon pricing shocks, with larger falls in output and equity prices.

Second, we exploit granular firm-level data to sharpen the identification of the role of CO_2 emissions intensity for the transmission of carbon pricing shocks. In particular, we use the CPS series in a firm-level panel local projection to investigate the differential response of equity prices of high-emissions firms. The results suggest that firms with relatively higher CO_2 emissions within a sector tend to suffer significantly more than their greener counterparts. This differential effect is quantitatively significant and persistent: following a one-standard deviation carbon pricing shock, browner firms see their equity prices decrease by around 1 percent more than green firms 15 months after the initial shock.

Third, and finally, we develop a two-good model with an environmental externality and climate policies to shed light on the transmission mechanism of carbon pricing shocks. Because our empirical analysis highlights the role of asset prices for the transmission of carbon pricing shocks, we extend the production technology proposed by Copeland and Taylor (2004) and Shapiro and Walker (2018) to allow for physical capital and embed this technology into a DSGE model. In addition, we generalize the production function to a CES (rather than to a Cobb-Douglas) that combines emissions, labor and physical capital as inputs. In such a setting, brown producers—those that use emissions as an input—can optimally choose to abate part of their production to limit emissions, depending on their price. The price of emissions is subject to shocks, comparable to those we employ in our empirical analysis. The model's climate block is similar to that in the DICE model proposed by Nordhaus (2008), and adopted by Heutel (2012) and Annicchiarico and Di Dio (2015), among others, in that firm emissions increase the level of atmospheric carbon in the atmosphere, causing damages which harm aggregate productivity. The model features nominal and real rigidities in order to assess the impact of carbon pricing shocks on aggregate activity, inflation and asset prices at the business cycle frequency.

In line with our empirical evidence, in the model, positive carbon pricing shocks are recessionary, inflationary, and reduce asset valuations. For brown firms, the increase in the price of carbon emissions represents, in effect, an increase in input costs, leading them to reduce output and raise prices. The fall in brown output drives the fall in aggregate output. While green output rises, as consumers shift their demand to the now relatively cheaper green goods, this is insufficient to offset the fall in brown output. Brown goods inflation contributes largely to the rise in aggregate inflation. There is a very small pickup in green goods inflation, reflecting the increase in demand for green goods.

Equity prices for both brown and green firms decline, consistent with a decline in current and expected profits, leading to a decline in aggregate equity prices. In agreement with the firm-level empirical results, asset prices fall more for brown firms than for green firms. Brown firms experience a larger fall in asset prices primarily because they are hit directly by the increase in costs resulting from a higher cost of emissions. Firms cannot easily substitute towards other inputs without incurring further costs (in terms of adjustment costs of through bidding up factor prices). The fall in green firms' asset prices reflects the squeeze on their profits in real terms (i.e. in terms of the composite consumption good), which results from the large increase in aggregate consumer prices (due to the increase in brown goods' prices).

Related literature

Our paper contributes to a recent but growing literature on the macroeconomic implications of climate change mitigation policies. Känzig (2023) study of surprises in the EU ETS market similarly finds that positive carbon pricing shocks lead to a rise in consumer price inflation, a fall in aggregate economic activity, and a drop in the stock market. Using data on 25 OECD countries, Moessner (2022) investigates the effect of carbon pricing shocks on inflation. He finds an important pass through to energy prices but a more limited effect on core inflation. Konradt and di Mauro (2021) document that carbon taxes have only a limited effect on inflation, and may even be deflationary. Metcalf (2019) provide evidence that carbon taxes are effective at reducing GHG emissions in Europe and British Columbia. Metcalf and Stock (2020) rely on local projections to measure the macroeconomic impact of carbon taxes on output and employment, and find quantitatively limited effects. Using a VAR framework, Bernard et al. (2018) come to the same conclusions in British Columbia. Ciccarelli and Marotta (2021) use a panel of 24 OECD countries to investigate the macroeconomic effect of climate change, environmental policies as well as environment-related technologies. They find that the effect of climate change and climate policies is significant but quantitatively limited. Känzig and Konradt (2023) study the differential effects of carbon pricing and carbon taxes in a unified empirical framework, and find that the former have more severe macroeconomic consequences.

By looking at firm-level equity price responses and focusing on the financial channel of climate policies, our paper is also connected to the rapidly growing climate finance literature (see Giglio et al., 2021, for a survey). Investigating the cross-section of over 14,400 firms in 77 countries, Bolton and Kacperczyk (2021) document the existence of a wide-spread carbon premium, whereby firms with higher exposure to transition risk tend to have higher expected returns. Hsu et al. (2022) show that high polluting firms have smaller average returns, and link this to uncertainty about environmental policy. Choi et al. (2020) find that stock prices of carbon intensive firms tend to under-perform the market when the weather is abnormally warm. Barnett (2020) uses an event-study framework and finds that increases in the likelihood of future climate policy action leads to decline in the stock prices of firms with larger exposure to climate policy risk. In the options markets, Ilhan et al. (2021) show that the cost of protection against extreme climate risks is larger for firms with more carbon-intensive business models. Using data on more than $2,000$ publicly listed European firms, Hengge et al. (2023) show that carbon pricing shocks lead to negative abnormal stock returns which increase with a firm's carbon intensity.

We also contribute to the literature incorporating the carbon cycle and climate policies into workhorse macroeconomic models. This literature typically examines the influence on business cycle dynamics of alternative climate policy regimes, particularly cap-and-trade schemes and carbon taxes, in response to productivity (or other economic) shocks (see Annicchiarico et al., 2022, for a survey). In doing so, it seeks to shed light on differences in climate policy regimes from positive and normative perspectives. From a positive standpoint, cap-and-trade policies tend to deliver lower output volatility than a carbon tax (for example, Fischer and Springborn, 2011). From a normative perspective, Heutel (2012) shows that the Ramsey-optimal emissions cap and carbon tax are both pro-cyclical (i.e. so that the cap-and-trade scheme is more stringent in expansions, while the carbon tax is more stringent in recessions, and vice versa). In addition, Angelopoulos et al. (2013) find that optimal environmental tax is pro-cyclical after an economic shock, and counter-cyclical after environmental shocks. As such, the focus of this literature differs from the approach that we take, which is instead to shed light on the transmission mechanism of climate policy by considering the impact of exogenous changes in the policy itself.

The paper is structured as follows. Section 2 describes the data sources. Section 3 reports the results from the panel VAR country-level exercise. Section 4 reports the results from the panel firm-level local projection exercise. Section 5 rationalizes our empirical findings with a theoretical model with a climate block and brown and greens firms. Section 6 concludes.

2 Data

We compile our data set by combining several sources: settlement prices of the European Union Allowance carbon futures contracts around a selected list of regulatory events that affected the supply of emission allowances (as in Känzig, 2023) from Datastream; macroeconomic and financial data from National Statistical Offices and corporate bond spreads data from ICE BoAML for a panel of countries that are member of the EU ETS carbon market; and firm-level data on equity prices and emissions for all the firms included in the major equity indices of each country in our sample from Datastream. Below, we briefly describe each data source, while additional details and summary statistics of the data are provided in Appendix A.

Identification of Carbon Pricing Shocks

A key challenge in measuring carbon pricing shocks is that most of the variation in carbon prices is driven by their endogenous response to aggregate economic conditions. To address this challenge, we rely on the methodology developed by Känzig (2023), which exploits high-frequency variation in futures prices in the EU ETS carbon market around a selected list of regulatory events that affected the supply of emission allowances.[2]

Specifically, we compute a set of carbon policy surprises (CPS) as the percentage price variation of the European Union Allowance (EUA) futures prices around 113 regulatory events about the supply allowances of carbon emissions within the EU. More formally, letting $F_{t,d}$ be the (log) settlement price of the EUA futures contract in month t on day d, we compute:

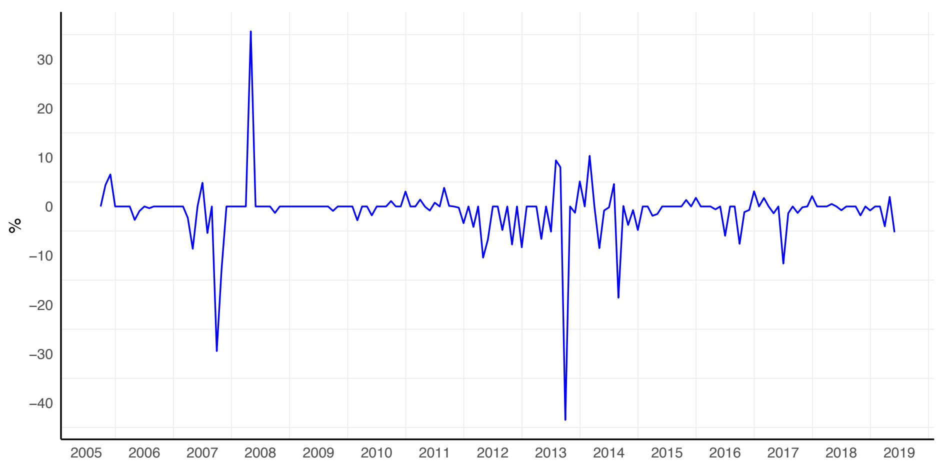
$$CPS_{t,d} = F_{t,d} - F_{t,d-1}. \tag{2.1}$$

As the EUA futures market is liquid, futures prices are likely to incorporate all relevant information available to investors. Thus, the identified surprise in carbon futures prices captures the unexpected component of the information released in the regulatory event. Of course, it is crucial that the events do not coincide with other economic announcements, such as the demand of emission allowances or variations in economic activity in the EU. To address these concerns, Känzig (2023) select only regulatory events that were specifically about changes to

[2]The EU ETS market is a perfect laboratory for our empirical exercise. It is the largest carbon market in the world, covering roughly 40 percent of the EU greenhouse gases emissions.

the supply of emission allowances in the European carbon market, and do not include broader events such as outcomes of Conference of the Parties (COP) meetings or other international conferences.[3]

Figure 2.1 THE CARBON POLICY SURPRISES SERIES



NOTE. Replication of the high frequency carbon policy surprises of Känzig (2023). The price change around regulatory events is defined as percentage changes at daily frequency.

As it is common in the high-frequency identification literature, we then aggregate the daily series at the monthly frequency by taking the sum of the daily surprises within a given month. In months without events, the series takes the value of zero. Figure 2.1 shows the resulting series of carbon policy surprises. As shown in Känzig (2023), the series is not serially correlated, is not Granger caused by other variables, and is not significantly correlated with other measures of structural shocks from the literature (including oil, uncertainty, financial, fiscal and monetary policy shocks).

[3] For robustness, we also consider a different definition of the CPS series. Specifically, we compute nominal futures price changes (as opposed to percentage changes as in our baseline) and divide them by the wholesale energy price (see Känzig, 2023).

Country-level Aggregate Data

We collect macroeconomic and financial data at the monthly frequency for a panel of 15 advanced economies that are members of the EU Carbon ETS, namely Austria, Belgium, Denmark, Finland, France, Germany, Greece, United Kingdom, Italy, Ireland, The Netherlands, Norway, Portugal, Spain, and Sweden.[4] Specifically, we collect data from Datastream on (a monthly measure of) real GDP ($RGDP_{i,t}$); consumer prices (CPI_t); policy interest rates ($IR_{i,t}$); and equity prices ($EQUITY_{i,t}$).[5] We complement this set of macroeconomic and financial variables with a measure of (option and maturity adjusted) corporate bond spreads ($CS_{i,t}$) from ICE Bank of America Merrill Lynch. All variables except the short-term rate (in percentage points) and corporate bond spreads (in basis points) are in log-levels. Table A1 in Appendix A provides a summary of data coverage.

Firm-level Data

We collect equity price data for firm j in country i at monthly frequency (which we denote by $EQUITY_{ij,t}$) for the constituents of the main equity indices of the countries in our sample. We complement the equity price data with firm-level proxies for 'carbon intensity', which we denote by $CO2_{ij,t}$. Specifically, we consider both Scope 1 and Scope 2 CO_2 emissions at the firm-level from Datastream, which are available at the annual frequency. Scope 1 emissions include greenhouse gases (GHG) emissions that emanate from the operation of capital directly owned by the firms. Scope 2 emissions are indirect emissions associated with the purchase of electricity, steam, heat, or cooling. As the two measures are complementary, we consider a measure that sums Scope 1 and Scope 2 emissions. Finally, we consider a vector $Z_{ij,t}$ constituted by a number of firm-level controls available at the quarterly frequency from Datastream, namely a measure of leverage (measured as the ratio of total debt to assets),

[4]In robustness analysis, we also consider an extended sample of all of the 29 countries member of the EU ETS.

[5]The monthly GDP measure is obtained by interpolating quarterly level data using a shape-preserving piecewise cubic interpolation, as in Miranda-Agrippino and Rey (2020). In robustness analyses, we also consider monthly industrial production as an alternative measure of economic activity.

a measure of profitability (sales growth), and a measure of size (total assets). Table A2 in Appendix A provides summary statistics by country as well as additional information about the data coverage.

Final sample

Our final data set runs from January 1997 to December 2019, covers 113 regulatory events about the supply allowances of carbon emissions within the EU, includes country-level macroeconomic data for 15 countries, and has firm-level information on equity prices, balance sheet data, and CO_2 emissions for 521 unique firms. Our sample period is restricted by the availability of corporate bond spreads, which are available from 1997 onward. To avoid the large shocks associated with the Covid-19 pandemic, we stop our sample in December 2019.

3 Evidence from Aggregate Data: Panel VAR

In this section we provide evidence on the macroeconomic effect of carbon pricing shocks using aggregate data for the countries in our data set. We proceed in two steps. First, we estimate the impact of carbon pricing shocks on selected macroeconomic variables and asset prices using a panel vector autoregressive model (PVAR). The PVAR allows us to investigate both the behavior of the 'average' economy in response to the shock and the cross-country differences in its transmission. In the second step, we provide evidence on the heterogeneous effects of carbon pricing shocks across countries depending on their CO_2 intensity.

To identify carbon pricing shocks, we rely on the internal instrument approach proposed in Plagborg-Møller and Wolf (2021). In practice, we augment our vector of endogenous regressors by the CPS series, which we order first, and impose recursive zero contemporaneous restrictions by means of a Cholesky decomposition of the VAR's reduced-form variance-covariance matrix. The identifying assumption is that the CPS series is orthogonal to the other shocks. In our baseline specification we consider 9 lags of the endogenous variables, as suggested by the Akaike criterion.

We define define the vector of endogenous variables for country i in month-year t as $\boldsymbol{Y}_{i,t} = [CPS_t, RGDP_{i,t}, CPI_{i,t}, IR_{i,t}, EQUITY_{i,t}, CS_{i,t}]'$ and specify the following panel VAR:

$$\boldsymbol{Y_{i,t}} = \boldsymbol{C}_i + \boldsymbol{\Phi}_i(L)\boldsymbol{Y_{i,t-1}} + \boldsymbol{B}_i\boldsymbol{\varepsilon}_{i,t}, \tag{3.1}$$

where the vector C includes a constant and a deterministic trend; $\boldsymbol{\Phi}(L)$ is the distributed lag matrix in companion form; $\boldsymbol{B}$ is the structural impact matrix; and $\boldsymbol{\varepsilon}_{i,t}$ is the vector of structural shocks, whose first element is thus the carbon pricing shock. For the estimation of (3.1) and the construction of confidence intervals, we rely on the mean group estimator (see Pesaran and Smith, 1995; Pesaran et al., 1999).

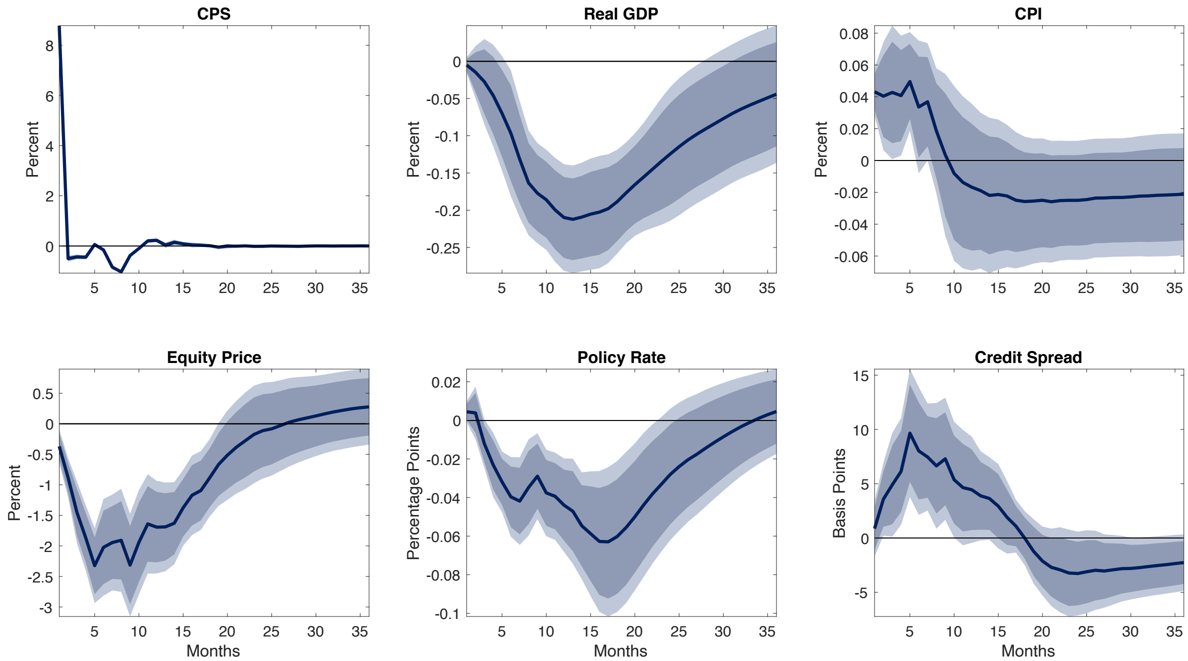
Response of the 'Average' Economy

Figure 3.1 plots the dynamic response of $\boldsymbol{Y_{i,t}}$ to a recursively identified one standard deviation shock to the CPS series. The impulse responses show that carbon pricing shocks resemble negative supply shocks, as they lead to a decrease in real GDP and an increase in consumer prices. Specifically, real GDP decreases by around 0.2 percent at the peak, while prices increase by about 0.05 percent. Carbon pricing shocks also lead to tighter financial conditions, as measured by a drop in equity prices (of about 2 percent) and a widening of corporate bond spreads, which increase by about 10 basis points; and to a loosening of the monetary policy stance, with policy rates falling by about 0.06 percentage points.

Figure 3.2 reports the mean group estimate of the forecast error variance decomposition for the variables in the VAR. Carbon pricing shocks explain a sizable portion of the variance of real and financial variables. For example, they account for almost 10 percent forecast error variance of real GDP at an horizon of about 18 months; and up to 5 percent of the forecast error variance of equity prices. The importance of the shocks for consumer prices is instead more limited—with only 2.5 percent of the forecast error variance explained by the carbon pricing shocks.

In sum, Figures 3.1 and 3.2 show that carbon pricing shocks have sizable effects on macroe-

Figure 3.1 THE EFFECT OF CARBON PRICING SHOCKS: AVERAGE ECONOMY



NOTE. Mean group estimate of the impulse responses to a one standard deviation (8.8 percent) increase in the carbon policy surprise (CPS) series. The carbon pricing shock is identified using the CPS series as an internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals.

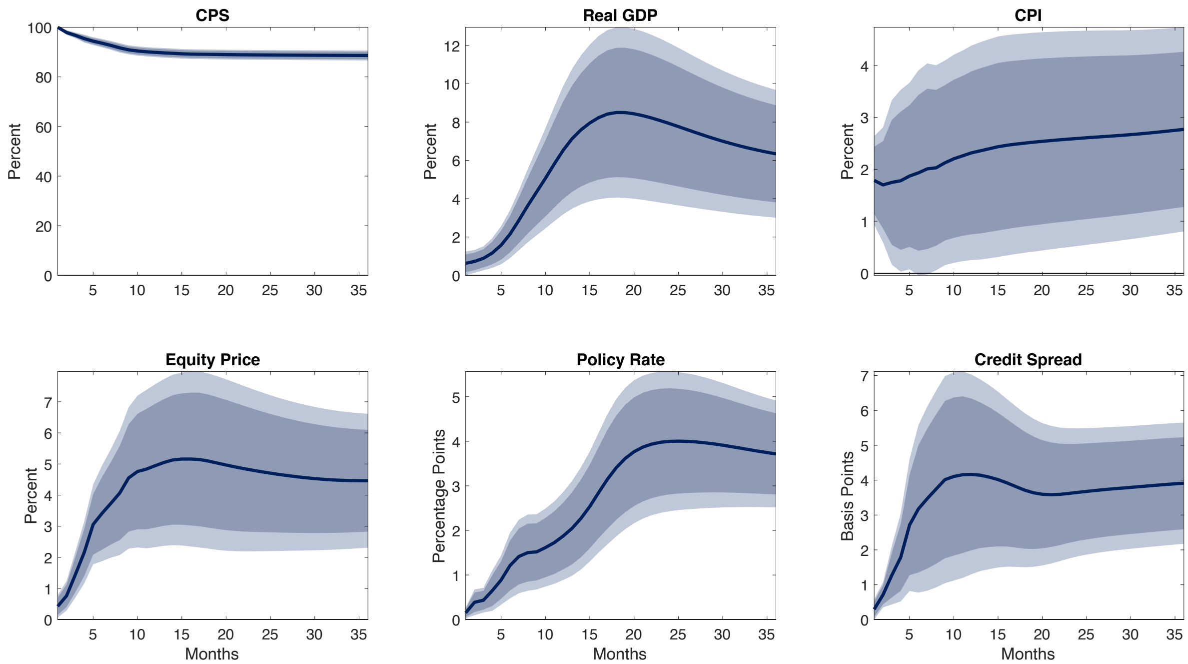
conomic and financial variables, and smaller but non-negligible effects on consumer prices.

Cross-country Heterogeneity

The error bands in Figure 3.1 and 3.2 are relatively wide, reflecting significant differences across countries. We now investigate whether this heterogeneity follows specific patterns. In particular, we ask whether countries that are more 'CO_2 intensive' tend to suffer more from carbon pricing shocks. The underlying idea is that, if carbon pricing shocks lead to a reallocation of resources away from more polluting activities, this may prove to be particularly costly for countries where more reallocation is required. To proxy for CO_2 intensiveness, we rely on the CO_2 intensity measure from the OECD Green Growth Indicators, which is defined as the amount of CO_2 required per unit of GDP.[6]

[6]Table A3 in Appendix A provides summary statistics at the country-level.

Figure 3.2 The Effect of Carbon Pricing Shocks: Variance Decompositions

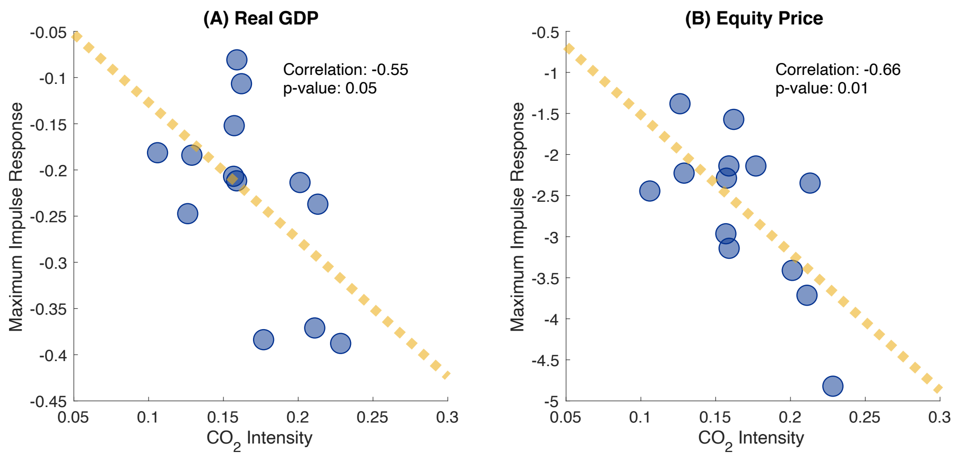


Note. Mean group estimate of the forecast error variance decomposition to carbon pricing shocks. The carbon pricing shock is identified using the CPS series as an internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals, respectively.

Figure 3.3 display a scatter plot of the country-specific peak impulse response of real GDP (panel A) and equity prices (panel B) against the country's CO_2 intensity. The panels also report the correlation coefficient between the peak IRFs and the CO_2 intensity, together with the corresponding p-value. This simple exercise suggests that countries with higher CO_2 intensity indeed tend to experience larger drop in output and equity prices.[7] The results reported in Figure 3.3 are robust to using the peak share of the forecast error variance of explained by the carbon pricing shocks—if anything the results are stronger, as they show a statistically significant correlation for credit spreads and policy rates, too (see Figure B9 in Appendix B). Overall, the results suggest that, following a carbon pricing shock, 'browner countries' tend to suffer more in terms of output and financial conditions.

[7]The correlations for the remaining variables are not statistically significant. Figure B8 Appendix B reports the full set of scatter plots for all the variables in the VAR.

Figure 3.3 HETEROGENEITY: COUNTRY-SPECIFIC RESPONSES AND CO_2 INTENSITY



NOTE. Country-specific country-specific CO_2 intensity (Horizontal axis, *CO_2 Intensity*) and peak impulse response to the carbon pricing shock (vertical axis, *Maximum Impulse Response*) of real GDP (panel A) and equity prices (panel B). The dotted lines plot the fitted values from a linear regression model. Each panel reports the implied correlation coefficient and associated p-value.

The patterns we document in this section are suggestive of a significant degree of heterogeneity. However, the granularity of our analysis (which is constrained at the country level given our panel VAR framework) raises a number of identification challenges. For example, the CO_2 intensity variable may correlate with other country-specific characteristics that affect the strength of the transmission of carbon pricing shocks. It is therefore difficult to establish whether more CO_2-intensive economies suffer more from carbon pricing shocks. In section 4, we tackle these limitations by leveraging on granular firm-level data that allow us to sharpen substantially the identification. Before doing that, however, we report a set of additional exercises that show the robustness of the results presented in this section.

Robustness

We run a battery of robustness checks. A first potential concern relates to the specification of the carbon policy surprise series. As the price of carbon futures has been volatile and close to zero at some point in our sample, computing percentage change variation could lead to identify certain events as leading to large price variations, even though the *nominal* price change remains modest. For this reason, we re-run our panel VAR using a “energy price specification" of the CPS series by computing absolute price change (rather than the log-price change, as in equation (2.1)) and dividing by the wholesale energy price as in Känzig (2023). The resulting CPS series is displayed in Figure B1. Figure B2 compares the IRFs from the panel VAR for the two specifications. The responses of GDP, the short-term rate, equity prices and bond spreads are remarkably similar to our baseline. On the other hand, the response of CPI is slightly smaller and less persistent. Second, we check that our results are robust to a different choice of countries in the panel VAR. Specifically, Figure B3 reports the results we obtain from a specification that uses data from the sample of all the 29 countries that are members of the EU ETS carbon market for which we have macroeconomic and financial data. Third, given the relatively small sample period, we check that our results are robust to a more conservative specification that uses only 6 lags (Figure B4). Fourth, we consider a shorter sample period that starts when the first CPS shock is observed (Figure B5), and thus covers the 2005-2019 period. Fifth, we consider an alternative measure of economic activity, namely industrial production instead of real GDP (Figure B6). Finally, we consider a specification that excludes the deterministic trend (Figure B7).

4 Evidence from Firm-level Data: Panel Local Projections

Motivated by the suggestive cross-sectional evidence from the VAR’s impulse responses, this section use a more tightly identified set up to investigate whether the effect of carbon pricing shocks varies with CO_2 intensity. In particular, we exploit granular firm-level data on equity prices and emissions to document that firms with higher CO_2 emissions experience larger drops in their equity prices following a carbon pricing shock.

We employ a panel local projections approach. Let $EQUITY_{ij,t}$ denote the log equity price of firm j in country i in period t. CPS_t is the futures price variation in the EU ETS carbon market described in the previous section. We define $\Delta EQUITY_{ij,t+h} = EQUITY_{ij,t+h} -$

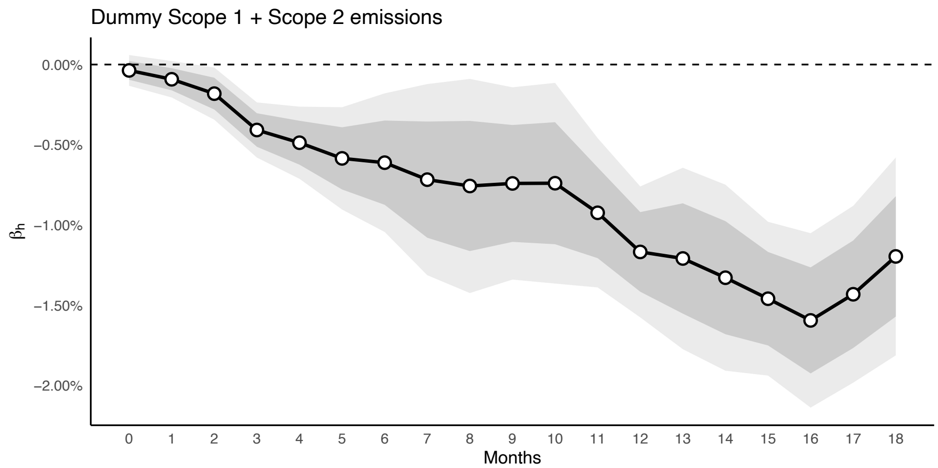
$EQUITY_{ij,t-1}$ as the cumulative change in equity prices at horizon $t+h$. Finally, we define $CO2_{ij}$ as a (time-invariant) firm-level carbon intensity variable. In our baseline specification, it takes the form of a 'brown dummy' variable that takes the value 1 if a given firm's CO_2 emissions (average over time) are above the median CO_2 emissions in a given sector and country. As a result, in each sector within each country, half of the firms are considered as relatively brown, while the other half is considered as relatively green. We further define $Z_{ij,t}$ as a vector of firm-level controls. We consider variants of the following regression:

$$\Delta EQUITY_{ij,t+h} = \alpha_j^h + \alpha_{t,i,s}^h + \beta^h (CPS_t \times CO2_{ij}) + \Gamma^h Z_{ij,t} + u_{ij,t+h}. \tag{4.1}$$

We control for firm fixed-effects (α_j) to capture permanent differences across firms. We further add a triple interacted fixed-effect ($\alpha_{t,i,s}$) with time (t), country (i), and sector (s) to control for any country and sectoral time-varying factors that may affect firms' equity prices. We further add firm-level controls which may affect the response of the firm over time ($Z_{ij,t}$). In particular, we consider quarterly sales growth, total assets and a measure of leverage (debt divided by assets) in the vector $Z_{ij,t}$. The coefficient of interest β^h captures the marginal effect of being a brown firm in a given sector (i.e. $CO2_{ij} = 1$) following a carbon pricing shock at horizon h, relative to a comparable firm in the same sector and country for which $CO2_{ij} = 0$, after controlling for firm-specific variables $Z_{ij,t}$ and a number of fixed-effects.

Figure 4.1 plots the estimate of β_h from equation (4.1) at horizons $h = \{0, 1, ..., 18\}$ and using total CO_2 emissions (Scope 1 + Scope 2) to define the within-sector brown dummy variable $CO2_{ij}$. We obtain 68 and 90 percent confidence bands by clustering standard errors two-ways (by firm and month). The figure shows that, following a one standard deviation carbon pricing shock, a brown firm sees its equity price decrease by close to 1.5 percent more than a comparable green firm within the same sector and country. In Appendix B, Figure B11 shows the results from the same regressions but with the brown firm dummy variable defined based on either Scope 1 (Panel A) or Scope 2 (Panel B) CO_2 emissions. Results are qualitatively similar, and quantitatively larger when defining the dummy variable using Scope 1 emissions

Figure 4.1 FIRM-LEVEL EQUITY PRICE RESPONSE TO A CARBON PRICING SHOCK



NOTE. Impulse response of equity prices (β_h) from equation (4.1) for horizons $h \in \{0, 1, ..., 12\}$. Standard errors are clustered two-way, at the firm and time level. Shaded areas display 68 percent and 90 percent confidence intervals. The CPS and the carbon intensity series are normalized to have zero mean and unit standard deviation. The total number of observations is $71,584$.

only.

Robustness and Additional Results

We run a number of robustness exercises. In the first, we re-estimate equation (4.1) using all the countries that are members of the EU ETS carbon market. In the second, we consider the CPS series in absolute changes divided by the wholesale energy price rather than in percentage changes (energy price specification). In the third, we compute the brown firm dummy by country (rather than by country sector), that is, firms with emissions above the median emission in the country have the dummy equal to 1. In the fourth, we normalize the CO_2 variable by total assets (instead of taking CO_2 emissions in levels) before computing the dummy variable. Figure B11 plots the response of each of these exercises. As we can see, all results are robust to these different specification choices. We take this as evidence that CO_2 emissions are strongly linked to the sensitivity of firms' equity price responses following carbon pricing shocks.

In Appendix B, we also compare the firm-level results with the panel VAR evidence. The idea is to check whether the firm-level specification is consistent with the aggregate results, and as such depicts dynamics that are relevant at the macro level. Figure B12 displays the average firm-level response following a carbon pricing shock. Furthermore, we investigate whether the average firm operating in a browner country (as proxied by the country CO2 intensity) tends to suffer more from carbon pricing shocks (Figure B13). Overall, the firm-level results are consistent with the aggregate ones.

5 Making Sense of the Evidence

In this section, we rationalize the empirical results using a two-good DSGE model with climate policies. First, we outline the features of the model. We then discuss its responses to changes in climate policy in order to shed light on the mechanisms underpinning our empirical results.

5.1 Model

Our model has two types of firm—"brown" and "green"—which are distinguished by the extent to which they pollute, consistent with Copeland and Taylor (2004) and Shapiro and Walker (2018). We assume that emissions are associated with firms' production, that firms are subject to environmental policies that make polluting costly, and, as a result, they undertake abatement activities to limit their pollution. Whether firms are brown or green is determined by the value of one parameter; i.e., the share of pollution is positive for brown firms and zero for green firms. This way of modelling heterogeneity is consistent with the empirical approach described in Section 4, where we estimate the differences in firm responses depending on emissions, while controlling for other factors, including time-by-sector fixed effects. The model has an endogenous carbon cycle, in which atmospheric pollution feeds back onto aggregate productivity, as well as a number of more standard real and nominal rigidities. The rest of this section outlines the model in more detail.

5.1.1 Households

Households, denoted by the index $\omega \in [0,1]$, make consumption and investment (savings) decisions, and supply labor and capital services to producing firms. We assume that households can insure themselves against idiosyncratic changes in their wage incomes. Households hold government bonds, make investment decisions in physical capital and buy/sell stocks in mutual funds. Households maximize their life-time utility:

$$\mathcal{V}_0(\omega) = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \mathcal{U}(C_t(\omega), N_t(\omega)),$$

where the period utility is given by:

$$\mathcal{U}(C_t(\omega), N_t(\omega)) = \frac{(C_t(\omega) - \phi C_{t-1}(\omega))^{1-\sigma} - 1}{1-\sigma} - \chi \frac{(L_t(\omega))^{1+\varphi}}{1+\varphi}.$$

Here $C_t(\omega)$ denotes consumption, $N_t(\omega)$ hours worked, σ is the inverse of inter-temporal elasticity of substitution, ϕ the degree of external habit formation, and φ the inverse of the Frisch elasticity of labor supply. Consumption is a CES composite that combines consumption of goods produced by brown firms, C_t^B, with consumption of goods produced by green firms, C_t^G:

$$C_t(\omega) = \left\{ \nu^{\frac{1}{\eta}} \left(C_t^B(\omega)\right)^{\frac{\eta-1}{\eta}} + (1-\nu)^{\frac{1}{\eta}} \left(C_t^G(\omega)\right)^{\frac{\eta-1}{\eta}} \right\}^{\frac{\eta}{\eta-1}}, \tag{5.1}$$

where η denotes the intra-temporal elasticity of substitution and ν the share of brown goods in the aggregator. Each household minimizes consumption expenditure by choosing C_t^B and C_t^G. The optimality conditions are given by:

$$C_t^B(\omega) = \nu \left(\frac{P_t^B}{P_t}\right)^{-\eta} C_t(\omega), \tag{5.2}$$

$$C_t^G(\omega) = (1-\nu) \left(\frac{P_t^G}{P_t}\right)^{-\eta} C_t(\omega), \tag{5.3}$$

where P_t^G, P_t^B and P_t denote the nominal prices of brown, green and aggregate goods, respectively. Substituting (5.2) and (5.3) into equation (5.1) gives an expression for the aggregate price index:

$$P_t = \left\{ \nu \left(P_t^B\right)^{1-\eta} + (1-\nu)\left(P_t^G\right)^{1-\eta} \right\}^{\frac{1}{1-\eta}},$$

where P_t^j denotes the price of good $j = \{B, G\}$.

There are investment packers, who combine investment from firms to produce aggregate investment into an aggregate investment good. The intra-period problem of investment packers is similar to that of consumers and is detailed in the Appendix C. The evolution of capital is however specific to each firm type and household face costs when adjusting firm-specific investment. This means that the physical capital used by firms to produce output is made out of a mixture of brown and green goods.

The budget constraint is given by:

$$\begin{aligned} C_t(\omega) + \sum_{j=\{B,G\}} \mathcal{I}_t^j(\omega) + B_t(\omega) + \sum_{j=\{B,G\}} S_{t+1}^j(\omega) V_t^j &= R_{t-1} \frac{B_{t-1}(\omega)}{\Pi_t} \\ + w_t(\omega) N_t(\omega) + \sum_{j=\{B,G\}} \left\{ r_{K,t}^j K_{t-1}^j + S_t^j(\omega)\left(V_t^j + \Phi_t^j / P_t\right) \right\} &- T_t(\omega)/P_t. \end{aligned}$$

where P_t is the aggregate consumer price level, $\mathcal{I}_t^j(\omega)$ denotes investment by firm of type $j \in \{B, G\}$, $S_t^j(\omega)$ the stock holdings in mutual fund of firm-type j, V_t^j the price of shares of firm of type j in the mutual fund in units of consumption, $w_t(\omega)$ the real wage rate, $K_t^j(\omega)$ is physical capital of firms of type j, $r_{K,t}^j$ real rental rate of capital for firm of type j, $T_t(\omega)$ nominal lump sum transfers and $\Phi_t^j(\omega)$ nominal profits. The law of motion of investment of type j is given by:

$$K_t^j(\omega) = (1-\delta_K) K_{t-1}^j(\omega) + \left(1 - \frac{\psi_j}{2}\left(\frac{\mathcal{I}_t^j(\omega)}{\mathcal{I}_{t-1}^j(\omega)} - 1\right)^2\right) \mathcal{I}_t^j(\omega). \tag{5.4}$$

The household maximizes life-time utility subject to a series of budget constraints and the two laws of motion of capital. From here onwards, we drop the index ω for brevity. The first order conditions with respect to C_t, K_t^B, K_t^G, $\mathcal{I}_t^B$, $\mathcal{I}_t^G$ and B_t are given by:

$$\Lambda_t = \left(C_t - \phi C_{t-1}\right)^{-\sigma} - \beta\phi\mathbb{E}_t\left(C_{t+1} - \phi C_t\right)^{-\sigma}, \tag{5.5}$$

$$\Lambda_t = \beta\mathbb{E}_t\left\{\frac{R_t}{\Pi_{t+1}}\Lambda_{t+1}\right\}, \tag{5.6}$$

$$Q_t^j = \beta\mathbb{E}_t\frac{\Lambda_{t+1}}{\Lambda_t}\left\{r_{K,t+1}^j + \left(1-\delta_K\right)Q_{t+1}^j\right\} \quad \text{for} \quad j = \{B, G\}, \tag{5.7}$$

$$\begin{aligned} 1 =& Q_t^j\left[1 - \frac{\psi_I^j}{2}\left(\frac{\mathcal{I}_t^j}{\mathcal{I}_{t-1}^j} - 1\right)^2 - \psi_I^j\left(\frac{\mathcal{I}_t^j}{\mathcal{I}_{t-1}^j} - 1\right)\frac{\mathcal{I}_t^j}{\mathcal{I}_{t-1}^j}\right] + \\ &+ \beta\mathbb{E}_t\left\{Q_{t+1}^j\frac{\Lambda_{t+1}}{\Lambda_t}\psi_I^j\left(\frac{\mathcal{I}_t^j}{\mathcal{I}_{t-1}^j} - 1\right)\left(\frac{\mathcal{I}_t^j}{\mathcal{I}_{t-1}^j}\right)^2\right\} \quad \text{for} \quad j = \{B, G\}, \end{aligned} \tag{5.8}$$

In addition, asset prices for j-type firms (V_t^j) can be written as:

$$V_t^j = \beta\mathbb{E}_t\frac{\Lambda_{t+1}}{\Lambda_t}\left\{\frac{\Phi_{t+1}^j}{P_{t+1}} + V_{t+1}^j\right\}. \tag{5.9}$$

5.1.2 Firms

Firms are indexed by $i \in [0, 1]$ and produce goods of type $j = \{B, G\}$. They face a production technology given by:

$$Y_t^j(i) = Z_t\left(1 - A_t^j(i)\right)\left(N_t^j(i)\right)^{1-\alpha_j}\left(K_{t-1}^j(i)\right)^{\alpha_j}, \tag{5.10}$$

where $Z_t = 1 - \Gamma\left(\mathcal{CO}_t\right)$ denotes aggregate productivity and $\Gamma\left(\mathcal{CO}_t\right)$ is damage function in line with Nordhaus (2008), $A_t^j(i)$ is the fraction of output devoted to abatement of pollution and α_j is the capital share in production. The damage function $\Gamma\left(\mathcal{CO}_t\right)$ captures the adverse impact of the physical damages associated with climate change on aggregate productivity. These damages represent an externality imposed by polluting firms on others.

Following Copeland and Taylor (2004) and Shapiro and Walker (2018), firms produce pollution emissions according to a technology in which pollution is an increasing function of output and a decreasing function of abatement:

$$\xi_t(i) = \mu_j Z_t \left[\frac{\left(1 - A_t^j(i)\right)^{\frac{\zeta-1}{\zeta}} - (1-\gamma_j)}{\gamma_j} \right]^{\frac{\zeta}{\zeta-1}} \left(N_t^j(i)\right)^{1-\alpha_j} \left(K_{t-1}^j(i)\right)^{\alpha_j}, \tag{5.11}$$

with $\left(1 - A_t^j(i)\right)^{\frac{\zeta-1}{\zeta}} > (1-\gamma_j)$. Here μ_j is a scaling factor, γ_j captures the firms' pollution emissions intensity (pollution emitted per unit of output) with respect to their pollution abatement intensity (abatement expenditures divided by total factor costs) and ζ is the elasticity of substitution between emissions and value added.

As discussed in Copeland and Taylor (2004) and Shapiro and Walker (2018), under this formulation, emissions can be interpreted as an output of production or an input into it. They show that substituting for abatement into the production function gives rise to a Cobb-Douglas production technology that uses emissions, capital, labor, and damages to produce output. We show here that using a more general firm emission's function, equation (5.11), gives rise to a more general CES production function. Under this representation, γ_j will determine the degree to which brown firms will respond to exogenous changes in the price of carbon and ζ will change the effectiveness with which abatement reduces emissions. The production function of gross output of polluting firms is given by:

$$Y_t^j(i) = \left[\gamma_j \left(\frac{\xi_t(i)}{\mu_j} \right)^{\frac{\zeta-1}{\zeta}} + (1-\gamma_j) \left\{ Z_t \left(N_t^j(i)\right)^{1-\alpha_j} \left(K_{t-1}^j(i)\right)^{\alpha_j} \right\}^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}}. \tag{5.12}$$

Intuitively, the γ_j measures the "dirtiness" of a firms' production and ζ how easy or difficult it is to substitute between factors of production. When the value of ζ is lower than 1, emissions and value added are gross complements, whereas, when it is greater than 1, they are gross substitutes. As discussed below, we assume pollution regulations are sufficiently stringent for firms to engage in some form of abatement. We also assume that the only abatement cost is that of the associated diverted production.[8] This formulation of pollution and abatement implies that abatement is an effective way to cut back on pollution.

Firms are monopolistically competitive, facing downward sloping demands. Each firm chooses prices $P_t^j(i)$ and abatement investment $A_t^j(i)$, $N_t^j(i)$, and $K_{t-1}^j(i)$ to maximize profits:

$$\Phi_t^j(i) = P_t^j(i)\, Y_t^j(i) - P_t w_t(\omega)\, N_t^j(i) - P_t r_{K,t}^j K_{t-1}^j(i) - \tau P_t \theta_t \xi_t^j(i)\,.$$

The profit function involves several terms. A consumer or investor pays price $P_t^j(i)$ for good i. Each firm receives nominal revenue $P_t^j(i)\, Y_t^j(i)$. Firms' nominal costs comprise of the nominal wage bill $P_t w_t N_t^j(i)$, the nominal cost of renting physical capital $P_t r_{K,t}^j K_{t-1}^j(i)$, and the nominal cost of emissions $\tau P_t \theta_t \xi_t^j(i)$, where τ is a tax paid on emissions and θ_t the price of emissions (e.g. per ton of carbon).

The first order conditions for brown firms (type B) are given by:

$$mc_t^B(i) = \frac{\left(1 - A_t^j(i)\right)^{\frac{\zeta-1}{\zeta}} w_t N_t^B(i)}{(1-\gamma_B)\, p_t^B\, (1-\alpha_B)\, Y_t^B(i)}, \tag{5.13}$$

$$mc_t^B(i) = \frac{\left(1 - A_t^j(i)\right)^{\frac{\zeta-1}{\zeta}} r_{K,t}^j K_{t-1}^B(i)}{(1-\gamma_B)\, \alpha_B p_t^B Y_t^B(i)}, \tag{5.14}$$

$$1 - \gamma_B = \left(1 - A_t^j(i)\right)^{\frac{\zeta-1}{\zeta}} \left[1 - \gamma_B \left(\frac{p_t^B mc_t^B(i)}{\tau \theta_t \mu_B}\right)^{\zeta-1}\right]. \tag{5.15}$$

In Appendix C we show that the marginal cost of brown firms is the same across all brown firms. We assume that only brown firms pollute and green firms do not; i.e. $0 < \gamma_B < 1$ and $\gamma_G = 0$. The problem of a green firm i collapses to the standard problem where firms choose

[8] The results are robust to the introduction of quadratic abatement costs, which reduce net production.

prices, labor and physical capital. The first order conditions for green firms (type G) are:

$$mc_t^G(i) = \frac{w_t N_t^G(i)}{p_t^G(1-\alpha_G)Y_t^G(i)}, \tag{5.16}$$

$$mc_t^G(i) = \frac{r_{K,t}^G K_{t-1}^G(i)}{p_t^G \alpha_G Y_t^G(i)}. \tag{5.17}$$

We introduce price rigidities à la Calvo. Details can be found in Appendix C.

5.1.3 Aggregate Pollution

Aggregate atmospheric carbon ($\mathcal{CO}_t$) evolves according to the following exogenous law of motion,

$$\mathcal{CO}_t = (1-\varpi)\mathcal{CO}_{t-1} + \int_0^1 \xi_t(i)\,di. \tag{5.18}$$

where ϖ is the depreciation of atmospheric carbon. There is no explicit choice of atmospheric carbon. Rather, brown firms decide on the level of emissions, which in turn affects the stock of atmospheric carbon. Aggregate emissions are:

$$\xi_t = \int_0^1 \xi_t^B(i)\,di.$$

$$\xi_t = \mu_B Z_t \left[\frac{\left(1-A_t^B\right)^{\frac{\zeta-1}{\zeta}} - (1-\gamma_B)}{\gamma_B}\right]^{\frac{\zeta}{\zeta-1}} \left(N_t^B\right)^{1-\alpha_B}\left(K_{t-1}^B\right)^{\alpha_B}. \tag{5.19}$$

5.1.4 Market Clearing

Labor market clearing is such that:

$$N_t = N_t^B + N_t^G. \tag{5.20}$$

Aggregate investment is defined in the same vein as aggregate output:

$$I_t = \mathcal{I}_t^B + \mathcal{I}_t^G. \tag{5.21}$$

Goods market clearing requires:

$$Y_t^G = C_t^G + \mathcal{G}^G + I_t^G \tag{5.22}$$

and:

$$Y_t^B = C_t^B + \mathcal{G}^B + I_t^B. \tag{5.23}$$

Aggregate output is given by:

$$Y_t = p_t^B Y_t^B + p_t^G Y_t^G, \tag{5.24}$$

where p_t^B and p_t^G are the relative price of brown and green goods. Finally, price inflation of brown and green goods is:

$$\Pi_t^j = \frac{p_t^j}{p_{t-1}^j}\Pi_t \text{ for } j = \{G, B\}, \tag{5.25}$$

and wage inflation:

$$\frac{\Pi_{w,t}}{\Pi_t} = \frac{w_t}{w_{t-1}}. \tag{5.26}$$

5.1.5 Climate Policy

We assume climate policy is exogenous and can be summarized by the carbon price, θ_t. Although the policy regime that we have in mind is a quantity-based cap-and-trade scheme like the EU ETS, in line with our empirical analysis, shifts in climate policy are modelled as exogenous changes in the carbon price. In particular, we assume carbon prices follow the following AR(1) process:

$$\log\left(\frac{\theta_t}{\theta}\right) = \varrho_\theta \log\left(\frac{\theta_{t-1}}{\theta}\right) + \varepsilon_{\theta t}, \quad \varepsilon_{\theta t} \sim N\left(0, \varsigma_\theta\right), \tag{5.27}$$

where ϱ_θ and ς_θ denote the persistence and dispersion of the shock.

5.1.6 Fiscal and Monetary Authority

The monetary authority sets policy according to the Taylor rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{r_r} \left[\left(\frac{\Pi_t}{\Pi}\right)^{r_\pi} \left(\frac{Y_t}{Y_t^f}\right)^{r_y}\right]^{1-r_r} \exp\left(\varepsilon_{rt}\right), \quad \varepsilon_{rt} \sim N\left(0, \varsigma_r\right), \tag{5.28}$$

where r_r denotes the interest rate inertia, r_π and r_y capture the degree to which monetary policy responds to inflation and the output gap. The variable Y_t^f is aggregate output in the absence of nominal rigidities.

We assume that pollution tax revenues are used to finance government expenditure ($\mathcal{G}_t$). The government runs a balanced budget:

$$\tau \theta_t \xi_t + \frac{T_t}{P_t} = \mathcal{G}_t. \tag{5.29}$$

5.1.7 Calibration

We summarize in this section the parametrization of the model. We choose a quarterly calibration of the model in line with the literature. As is common practice, we calibrate the model to match some features of the observed data. The parameters related to the New Keynesian structure of the model are standard and in line with those estimated in Smets and Wouters (2007). The scale parameter χ measuring labor disutility is calibrated so that steady state hours worked are normalized to 1. Public consumption to GDP ratio g/y is set at 0.2. As is standard in these models, the steady-state target inflation is equal to zero ($\Pi = 1$). We set adjustment costs in brown and green investment to 5 ($\psi_B = \psi_G$). Note that the calibration of the price rigidity parameters and elasticity of substitution are symmetric across brown and green firms. We introduce nominal rigidities to investigate the short-term responses of key macroeconomic variables to carbon pricing shocks. The only dimension along which firms differs is in their technology.

Turning to the calibration of the climate block, we set the depreciation of atmospheric carbon (ϖ) to 0.0021 as in Heutel (2012). In line with Annicchiarico and Di Dio (2015), the steady state atmospheric carbon dioxide ($\mathcal{CO}$) is set consistent with a carbon mass of about 800 gigatons in 2005. The steady state value of abatement is taken from Annicchiarico and Di Dio (2015), and set to 0.1. Conditional on the value of ϖ, the steady state level of atmospheric carbon ($\mathcal{CO}$) pins down the steady state value of emissions (ξ). The implied parameters that pin down these targets are μ_B and τ. We borrow the elasticity of substitution from Integrated Assessment Models (IAMs) literature (see for example Luderer et al. (2020)). Consistently with this literature, we assume that ζ is 0.25. Following Shapiro and Walker (2018), we set the share of emissions in brown production to $\gamma_B = 0.03$.

In line with our within-sector brown dummy specification in the empirical part, we set the share of brown consumption/investment to 0.5, and the elasticity of substitution between brown and green goods to 1.5 as proposed by Ferrari and Pagliari (2021). We are interested here in the within-sector heterogeneity rather than sectoral heterogeneity. Note that substitution and labor mobility is likely to be higher across firms than across sectors. Unlike Ferrari and Pagliari (2021), we assume free labor mobility across brown and green firms. We normalize the carbon pricing shock to 1 and derive the implied carbon tax (τ). The persistence (ϱ_θ) and dispersion of the shock (ς_θ) are chosen to match the trough response of aggregate output in quarter 6 ($\varrho_\theta = 0.85$ and $\varsigma_\theta = 0.07$).

The damage function $\Gamma\left(\mathcal{CO}_t\right)$ is assumed to be quadratic:

$$\Gamma\left(\mathcal{CO}_t\right) = d_3\left(d_0 + d_1\mathcal{CO}_t + d_2\mathcal{CO}_t^2\right). \tag{5.30}$$

Since the model is calibrated so as to yield pollution stock in gigatons, we borrow the damage function parameters from Heutel (2012). Table 5.1 summarizes the model parametrization.

5.2 Rationalizing the results

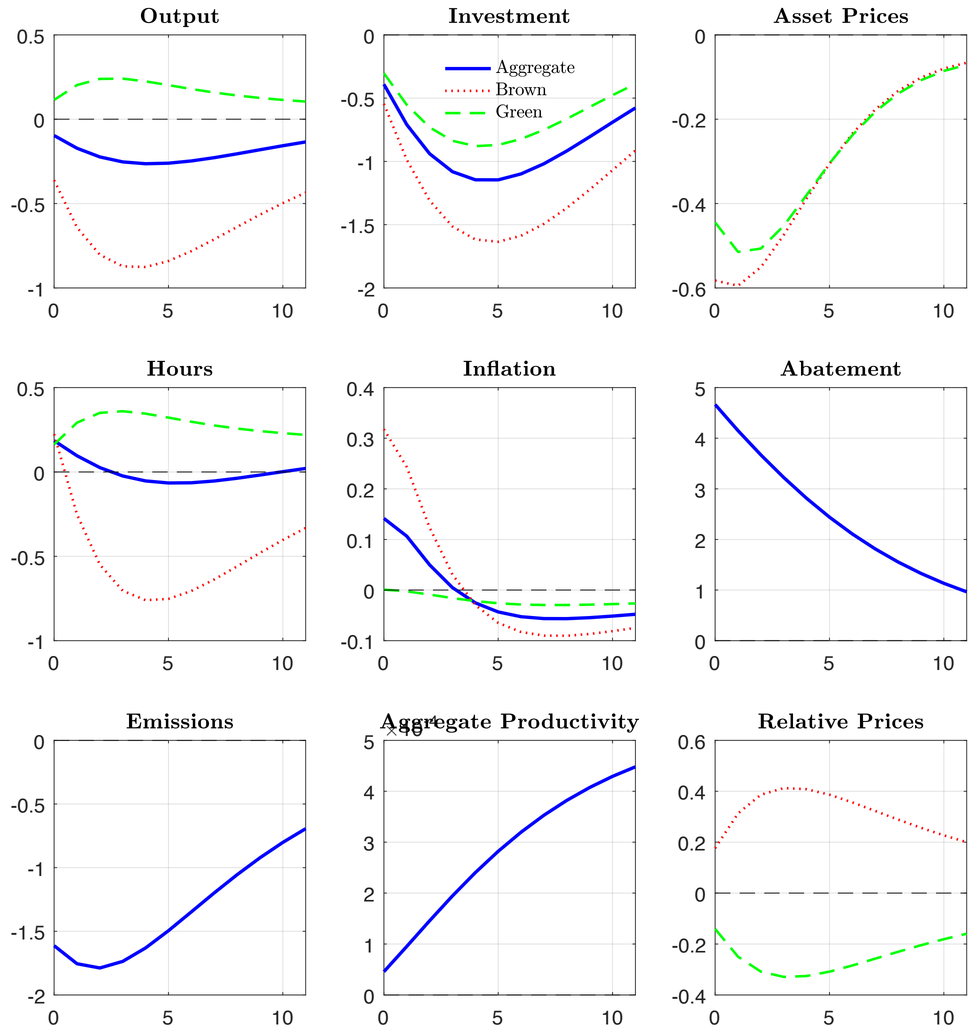
In this section, we consider the impact of an exogenous increase in the price of emissions in the model. As described in Section 5.1.5, this experiment is the model counterpart to the shock that we consider in our empirical analysis. In line with the empirical evidence, we show that the model generates a rise in aggregate inflation, a contraction in aggregate output and heterogeneous responses in asset prices across firms within a given sector after a carbon pricing shock. Figure 5.1 plots the responses to the shock for a selection of aggregate and good-specific variables.

The immediate and direct impact of the increase in the price of emissions is to raise costs for brown firms. This squeezes their margins, leading them to raise their prices, pushing up on brown inflation. This is associated with an increase in their price relative to green goods, so demand for brown goods falls. To the extent that output is demand determined in the short run, as a result of price stickiness, brown output falls. Although brown firms are able to switch their inputs away from higher-cost emissions, particularly towards labor, which is now relatively cheaper and easier to adjust than capital, profits overall decline. In turn, the persistent decline in profits pulls down on brown firms' equity prices through a standard asset-pricing channel (in which equity prices reflect the discounted sum of expected future profits). Furthermore, the reduced expected profitability of brown firms leads to a persistent reduction in investment.[9]

Although the shock's direct effects are on brown firms, it has spillover effects to green firms via good and factor markets. The demand for green goods rises, reflecting the fall in their relative price (and the fact that brown and green goods are substitutes for consumers and investors). In turn, green output rises. In order to support the increase in output, labor demand by the green firms must go up. Aggregate green firms' profits are squeezed, primarily as a result of the drop in relative green prices, which more than offsets the rise in green output. The

[9] These results hold true when introducing quadratic adjustment costs in abatement.

Figure 5.1 IMPULSE RESPONSES TO A CARBON PRICING SHOCK



NOTE. Impulse responses of the model variables to a carbon pricing shock. Solid blue lines report the response of aggregate variables; dashed green lines report the responses of green firms; and red dotted lines report the responses of brown firms. Apart from inflation, responses are expressed in percentage deviations from steady state values.

fall in relative green prices helps boosting consumption in the short-run but, since the drop in relative green prices is persistent, investment demand contracts. An implication of the decline in green profits is a fall in their equity prices, via a similar dividend-discount mechanism as described above. The reduced profitability of green firms triggers a reduction in investment.[10]

[10]Note that the responses for Tobin's Q are aligned with the responses of asset prices.

The relative impact of the shock on green and brown firms is qualitatively consistent with the empirical evidence. In particular, brown firms see on impact a bigger drop in their equity prices relative to green firms. Quantitatively, however, there is a divergence between the model responses and what we see in the data. In particular, in the model, asset prices of brown firms drop by two and a half times aggregate output, whereas the equivalent response is tenfold in the data. It is known that this class of models have a hard time matching quantitatively the response of asset prices.[11] The aggregate responses also broadly match the empirical results. In particular, aggregate output contracts, inflation rises, and asset prices drop.

Another way in which the carbon price shock affects dynamics is through its indirect impact on productivity, via the damage function (5.30). The increase in the cost of emissions induces brown firms to abate strongly, reducing the extent to which their production contributes to emissions. The fall in emissions in turn boosts productivity of brown and green firms. However, since these productivity gains are relatively small (and cumulate only slowly over time), the offsetting forces are not strong enough to undo the overall increase in the real marginal cost of production of brown firms over the short-term. If anything, the fall in damages helps to counter the negative impact on output and the positive impact on inflation. In addition, due to the fact that the emissions stay in the environment for extended periods of time, the impulse responses are longer lasting than in more conventional DSGE models. So, whilst the interaction between the climate and the macroeconomy does not affect by much the responses over the short-run, they introduce more persistence in the medium to long run. This is clear from the responses that only return to their steady state values after a very prolonged period of time.

To understand how climate block alters dynamics, we discuss impulse responses both aggregate and firm-specific inflation. Figure 5.1 shows that aggregate inflation increases immedi-

[11]One way to generate greater responses in asset prices is to modify the household's preference specifications. Alternatively, financial frictions can be introduced. This can potentially help matching the response of the bond spreads. We leave this for future research.

ately after the shock but, once the shock dissipates, the slow and continuous rise in aggregate productivity (due to lower atmospheric carbon), starts to exert downward pressure on (green, brown and aggregate) prices. This means that the carbon pricing shock is inflationary in the short-run but deflationary over the medium to longer run. It also means that the rise in aggregate productivity is deflationary on impact but quantitatively small. The longer run deflationary pressures are evidence of this channel further down the line. The overall inflation responses is indeed aligned with empirical results.

There are a number of climate-related parameters that influence the quantitative response of the model to the shock. The combination of three key parameters has the potential to help explain the heterogeneity observed in the data. In particular, the model can explain why some countries (and firms within a given country) are affected more than others after carbon pricing shocks but also why we observe differences in asset price valuations between green and brown firms.

First, we note that in a greener economy (low share of brown firms, ν), carbon pricing shocks in principle become quantitatively less important. Second, the carbon pricing shock becomes more important quantitatively for economic activity the higher the value of carbon intensity (captured by γ_B). Third, as the carbon price increases, firms would always want to, to the extent that is possible, substitute emissions for other inputs of production. Because physical capital is a slow moving variable, and investment is subject to adjustment costs, firms will have an incentive to adjust the labor margin in response to the shock. The degree of substitution across factors of production in brown output depends on the value of ζ. When emissions and value added as gross complements ($\zeta < 1$) is lower than 1, the demand for emissions will fall alongside the demand of other inputs and, as a result, brown output will respond sharply. When emissions and value added are substitutes ($\zeta > 1$), an exogenous rise in carbon prices will increase sharply the demand for labor, and brown output will contract by little. This will inevitably affect the profitability of brown firms relative to green firms. A lower value of ζ will increase the real marginal cost of brown production and reduce brown firms' asset valuations. Fourth, the degree of substitutability between green and brown goods for consumers (captured by η) determines both relative demand for brown and green goods and how aggregate demand responds to the shock. The higher the degree of substitution across goods, the lower the aggregate impact but the higher the differences between relative prices. A larger response in relative green prices (when $\eta < 1$) results in lower profitability of green firms, as relative green prices respond more strongly.

6 Conclusion

We provide empirical evidence on the heterogeneous effects of carbon pricing shocks. At the macro level, we find that countries with higher CO_2 intensity are more severely affected by the shocks. At the micro level, we find that firms with high within-sector levels of CO_2 emissions see their equity prices fall more than comparable firms with lower emissions.

To rationalize the empirical results we develop a theoretical framework with brown firms (which pollute) and green firms (which do not) and climate policy. We consider the effects of a carbon pricing shock in the model and demonstrate that we can broadly match the aggregate and firm level dynamics. In particular, in response to an increase in carbon prices, brown firms' asset prices decline by more than those of green firms. This reflects that carbon policy affects brown firms directly and that they are unable to substitute into other inputs sufficiently to offset the increase in costs from the increase in the carbon price.

Our results are important to understand the macroeconomic costs and economic channels associated with the transition towards a greener economy. Moreover, by highlighting the heterogeneous effects of environmental policies across countries, our results have potentially important implications for international coordination and the implementation of such policies.

Table 5.1 MODEL CALIBRATION

Parameter	Description	Value
β	Subjective discount factor	0.99
σ	Inverse of inter-temporal elast. of subst.	2
ϕ	Degree of consumption habits	0.75
φ	Inverse of Frisch elast.	2
χ	Disutility of labor (implied)	2.15
δ	Capital depreciation	0.025
α_j	Capital share in j	0.33
ψ_j	Investment adj. cost in j	5
$\frac{g}{y}$	Government to output ratio	0.2
ϵ_j	Elast. of subs. between goods	6
ϵ_w	Elast. of subs. between labor	11
ϑ_j	Calvo price in j	0.75
ϑ_w	Calvo wage	0.85
ι_j	Price indexation	0.25
ι_w	Wage indexation	0.25
r_r	Taylor rule inertia	0.75
r_π	Taylor rule parameter	1
r_π	Taylor rule parameter	0.15
	Climate parameters	
η	Elast. of subs. between B and G	1.5
ν	Consumption brown share	0.5
γ_B	Emission's share in B	0.03
A^B	Steady state abatement in B	0.1
ζ	Elast. of subs. between emissions and value added	0.25
μ_B	Emission's scale parameter (implied)	5.11
τ	Carbon tax rate (implied)	0.13
ϖ	Depreciation of atmospheric carbon	0.0021
d_0	Constant in damage function	$1.3950e-3$
d_1	1st order coeff. in damage function	$-6.6722e-6$
d_2	2nd order coeff. in damage function	$1.4647e-8$
d_3	Damage function shifter	1
ρ_θ	Persistence of the shock	0.85
ς_θ	Dispersion of the shock	0.07

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Appendix to Chapter 2

A Data

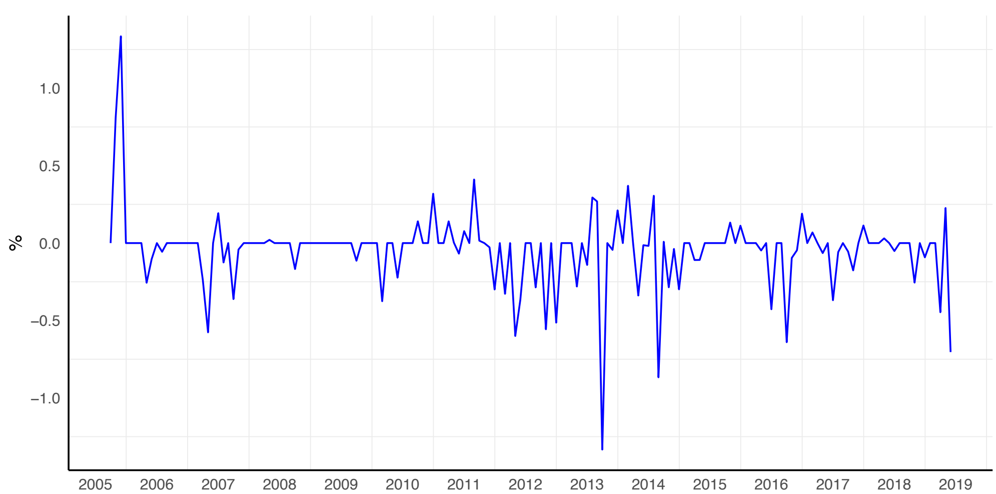
The source of the macroeconomic and financial data at the country level is as follows:

- $RGDP_{i,t}$: real GDP (index). Source: Datastream.
- $CPI_{i,t}$: consumer price index (index). Source: Datastream.
- $IR_{i,t}$: 3-month rate (monthly average). Source: Datastream.
- $EQUITY_{i,t}$: equity price index of the largest firms within each country (monthly average).Table A2 details how many firms we consider for each country. Source: Datastream.
- $CS_{i,t}$: option and maturity adjusted corporate bond spreads (monthly average). Source: ICE BofA ML.

B Additional Results & Robustness

B.1 Alternative Specification of the Carbon Policy Surprises

Figure B1 CARBON POLICY SURPRISE SERIES: ENERGY PRICE SPECIFICATION



NOTE. Replication of the high frequency carbon policy surprises of Känzig (2023). The price change around regulatory events is defined as the absolute price change in equation divided by the wholesale energy price (at daily frequency).

Table A1 Data coverage (PVAR)

Country	Sample	Included	N
AUT	1997M1 to 2019M12	Yes (baseline)	1
BEL	1997M1 to 2019M12	Yes (baseline)	2
DEU	1997M1 to 2019M12	Yes (baseline)	3
DNK	1997M1 to 2019M12	Yes (baseline)	4
ESP	1997M1 to 2019M12	Yes (baseline)	5
FIN	1997M1 to 2019M12	Yes (baseline)	6
FRA	1997M1 to 2019M12	Yes (baseline)	7
GRC	2011M12 to 2019M12	Yes (baseline)	8
GBR	1997M1 to 2019M12	Yes (baseline)	9
ITA	1997M1 to 2019M12	Yes (baseline)	10
IRL	1997M1 to 2019M12	Yes (baseline)	11
NLD	1997M1 to 2019M12	Yes (baseline)	12
NOR	1997M1 to 2019M12	Yes (baseline)	13
PRT	2011M12 to 2019M12	Yes (baseline)	14
SWE	1997M1 to 2019M12	Yes (baseline)	15
BGR	2013M12 to 2019M12	Yes (robustness)	16
CZE	1997M1 to 2019M12	Yes (robustness)	17
HRV	2004M7 to 2019M12	Yes (robustness)	18
LUX	1997M1 to 2019M12	Yes (robustness)	19
POL	1997M1 to 2019M12	Yes (robustness)	20
SVK	2013M8 to 2019M12	Yes (robustness)	21
ISL	2015M4 to 2019M12	Yes (robustness)	22
LTU	2017M8 to 2019M12	Yes (robustness)	23
CYP	Insufficient data	No	24
EST	Insufficient data	No	25
LVA	Insufficient data	No	26
MLT	Insufficient data	No	27
ROM	Insufficient data	No	28
SVN	Insufficient data	No	29

Note: This table displays the 29 countries which constitute the EU Carbon ETS as of 2019M12 (Liechtenstein excluded). The baseline Panel VAR is constituted of 15 countries. In the robustness exercise, we further add 8 countries. For most countries, data is available for the whole sample we consider (1997M12-2019M12). 7 countries are not included because insufficient data was available.

Table A2 Summary stats and coverage (Firm-level)

Country	Firms	Obs.	Scope 1 CO2 Mean	Scope 1 CO2 Median	Scope 1 CO2 p95	Scope 1 CO2 SD	Scope 2 CO2 Mean	Scope 2 CO2 Median	Scope 2 CO2 p95	Scope 2 CO2 SD	Coverage CO2
AUT	19	4009	306	50	1290	472	29	8	110	37	89.5%
BEL	20	4220	154	5	1040	319	62	6	300	114	75%
DEU	39	8229	1103	37	9170	3356	178	43	602	293	97.4%
DNK	43	5275	490	4	3702	1253	14	4	46	20	83.7%
ESP	14	2954	823	30	3546	1352	79	33	285	124	100%
FIN	38	5275	208	7	1060	628	48	10	267	89	84.2%
FRA	40	8440	1004	21	5705	3105	157	28	800	351	100%
GBR	94	19834	376	8	2380	1235	94	11	700	259	96.8%
GRC	25	5275	382	3	3257	1027	32	6	134	53	76%
ITA	71	8440	707	16	5826	2193	44	11	204	79	70.4%
IRL	33	6963	476	7	3240	905	48	2	260	78	100%
NLD	25	5275	1355	6	10500	3922	174	20	1100	416	100%
NOR	44	9284	256	8	1560	507	42	1	215	123	88.6%
PRT	15	3165	274	6	1805	573	30	13	103	40	93.3%
SWE	29	6119	27	3	87	79	22	12	71	31	96.6%

Note: This table provides summary statistics and coverage information on firm-level CO2 data for the 15 countries included in the baseline specification. The CO2 variable is expressed in 1,000 tonnes. Data is from Datastream.

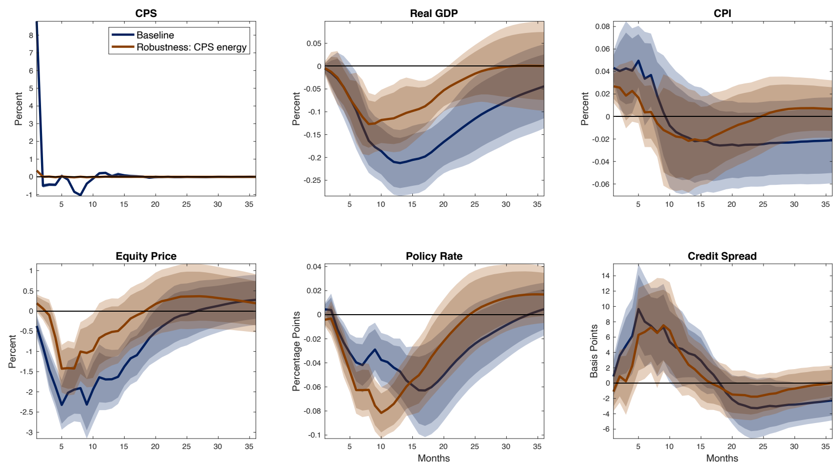
Table A3 SUMMARY STATISTICS CO2 INTENSITY

Country	CO2 intensity
AUT	0.16
BEL	0.21
DEU	0.21
DNK	0.16
ESP	0.16
FIN	0.23
FRA	0.13
GBR	0.18
GRC	0.24
IRL	0.16
ITA	0.16
NLD	0.20
NOR	0.13
PRT	0.15
SWE	0.11

NOTE: This table provides summary statistics of the CO2 intensity variable from the OECD Green Growth Indicators for the 15 baseline countries.

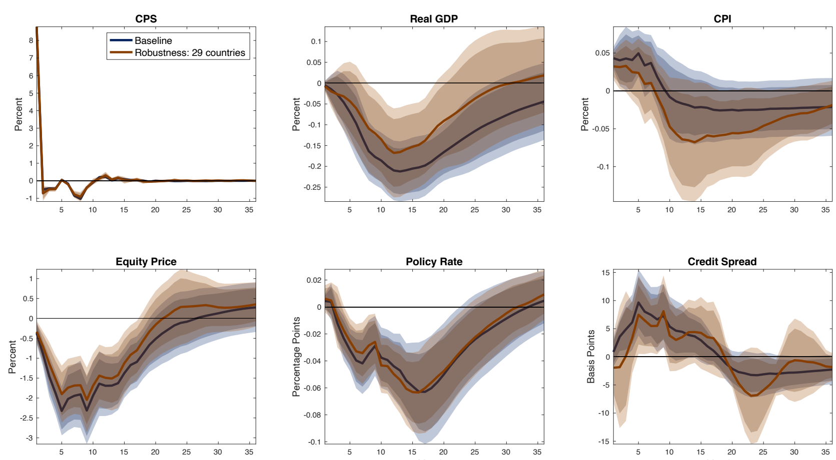
B.2 Robustness: Panel VAR

Figure B2 ROBUSTNESS PANEL VAR: ENERGY PRICE CPS



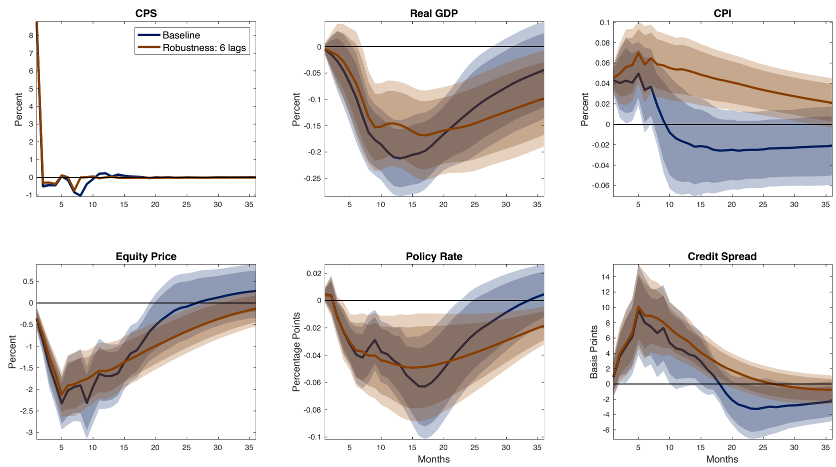
NOTE. Mean group estimate of the impulse responses to a one standard deviation (8.8 percent) increase in the carbon policy surprise (CPS) series. The carbon pricing shock is identified using the CPS series as internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals.

Figure B3 ROBUSTNESS PANEL VAR: FULL SET OF COUNTRIES



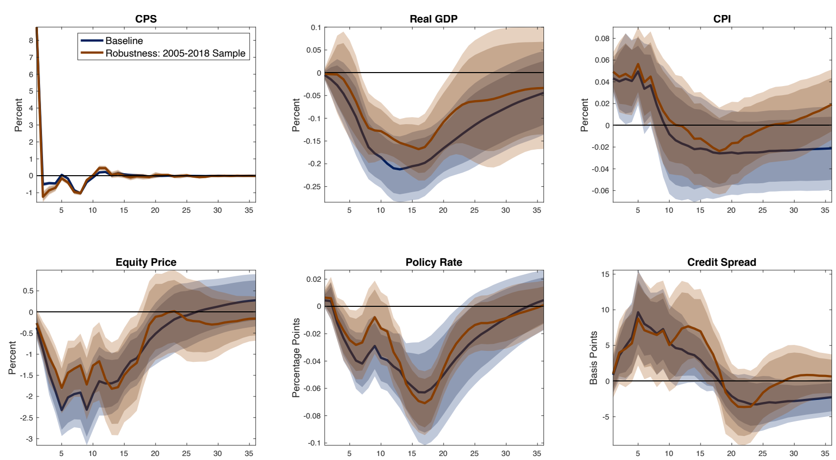
NOTE. Mean group estimate of the impulse responses to a one standard deviation (8.8 percent) increase in the carbon policy surprise (CPS) series. The carbon pricing shock is identified using the CPS series as internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals.

Figure B4 ROBUSTNESS PANEL VAR: DIFFERENT LAG SPECIFICATION



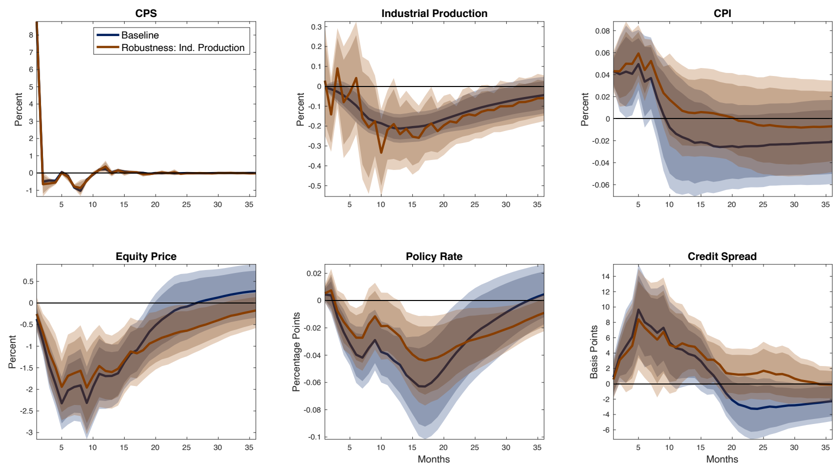
NOTE. Mean group estimate of the impulse responses to a one standard deviation (8.8 percent) increase in the carbon policy surprise (CPS) series. The carbon pricing shock is identified using the CPS series as internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals.

Figure B5 ROBUSTNESS PANEL VAR: SHORTER SAMPLE



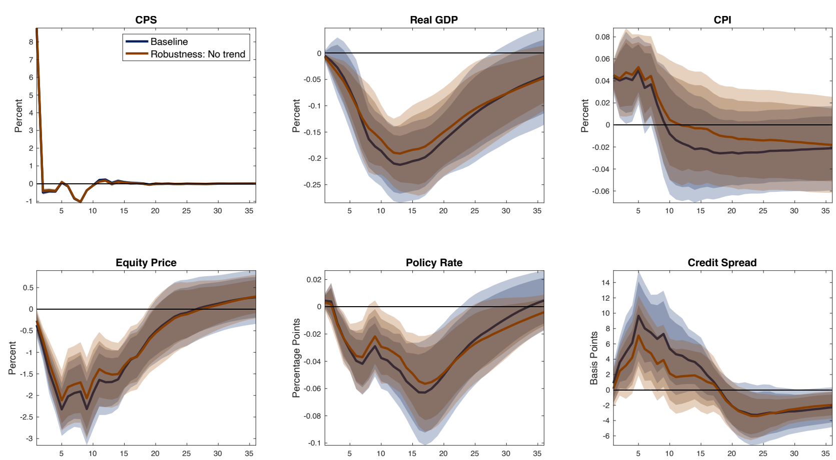
NOTE. Mean group estimate of the impulse responses to a one standard deviation (8.8 percent) increase in the carbon policy surprise (CPS) series. The carbon pricing shock is identified using the CPS series as internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals.

Figure B6 Robustness Panel VAR: Industrial Production



Note. Mean group estimate of the impulse responses to a one standard deviation (8.8 percent) increase in the carbon policy surprise (CPS) series. The carbon pricing shock is identified using the CPS series as internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals.

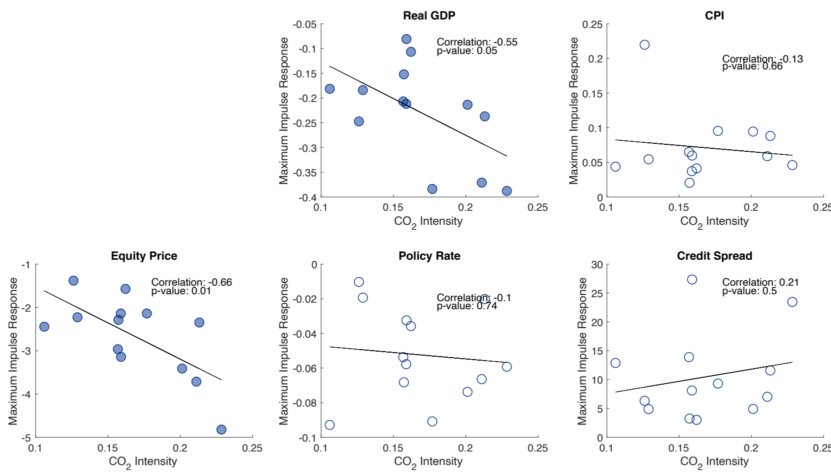
Figure B7 Robustness Panel VAR: No Trend



Note. Mean group estimate of the impulse responses to a one standard deviation (8.8 percent) increase in the carbon policy surprise (CPS) series. The carbon pricing shock is identified using the CPS series as internal instrument in the VAR (3.1). Shaded areas display 95 percent and 99 percent confidence intervals.

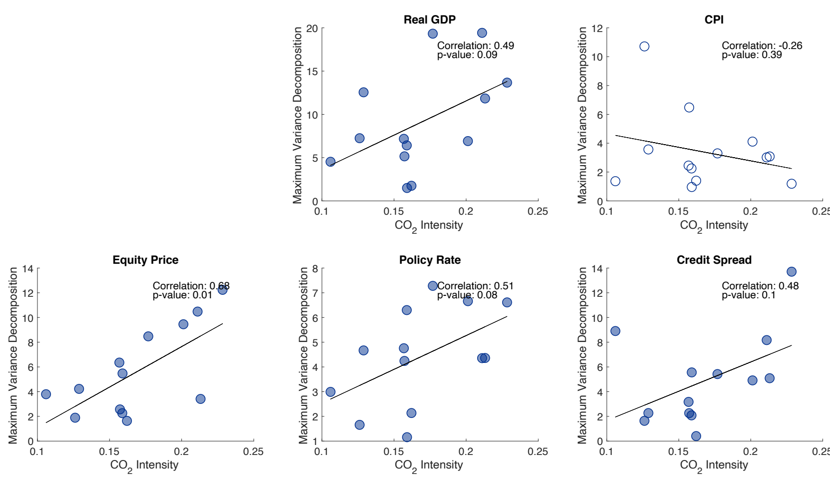
B.3 Cross-sectional Scatter Plots

Figure B8 Heterogeneity: Country-specific Impulse Responses and CO_2 Intensity



Note. Country-specific country-specific CO_2 intensity (Horizontal axis, *CO_2 Intensity*) and peak impulse response to the carbon pricing shock (vertical axis, *Maximum Impulse Response*) of all variables in the baseline VAR (3.1). Each panel reports the implied correlation coefficient and associated p-value.

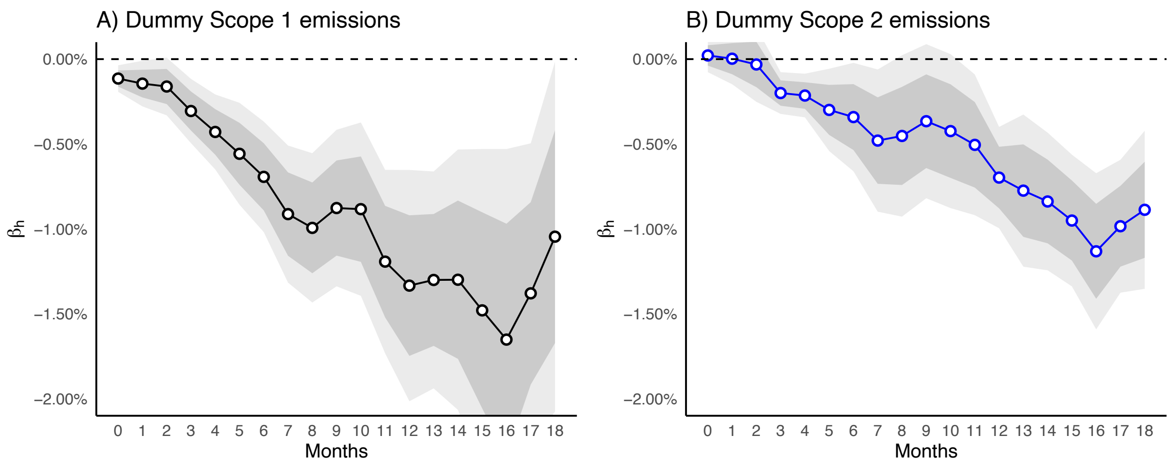
Figure B9 Heterogeneity: Country-specific Forecast Error Variance Decomposition and CO_2 Intensity



Note. Country-specific country-specific CO_2 intensity (Horizontal axis, *CO_2 Intensity*) and peak impulse response to the carbon pricing shock (vertical axis, *Maximum Impulse Response*) of all variables in the baseline VAR (3.1). Each panel reports the implied correlation coefficient and associated p-value.

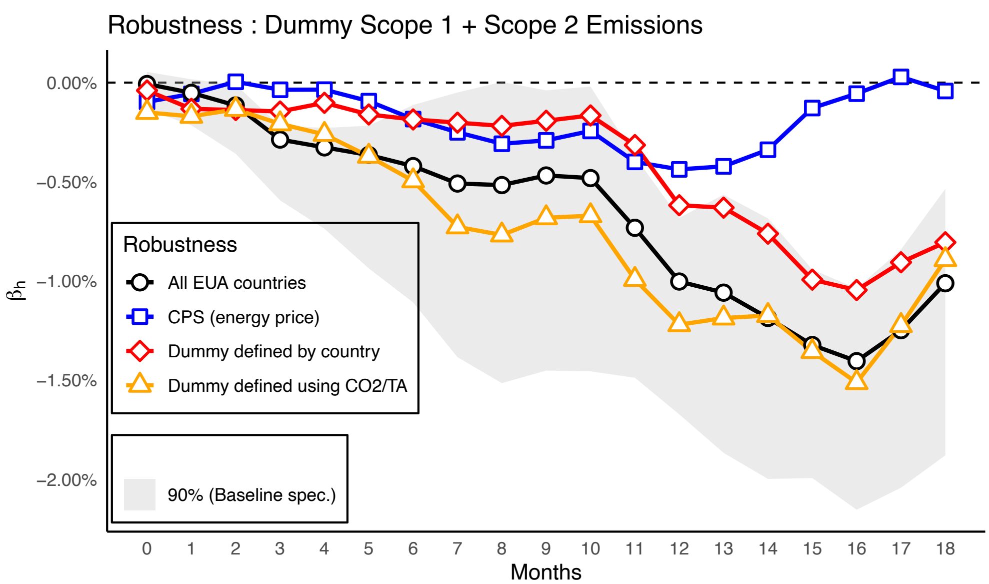
B.4 Robustness: Local Projections

Figure B10 Robustness: Dummy Scope 1 and Scope 2



Note. This Figure re-estimates equation (4.1) by defining the brown dummy firm ($CO2_i$) variable using only Scope 1 (Panel A)) or Scope 2 (Panel B)) CO2 emissions (instead of the sum of Scope 1 and 2 as in the baseline).

Figure B11 Robustness: Alternative Specifications



Note. This Figure re-estimates equation (4.1) for alternative specifications which are detailed in the text (Section 4). The shaded area represents the 90% confidence interval from Figure 4.1.

B.5 Comparison Between Local Projections & Panel VAR Evidence

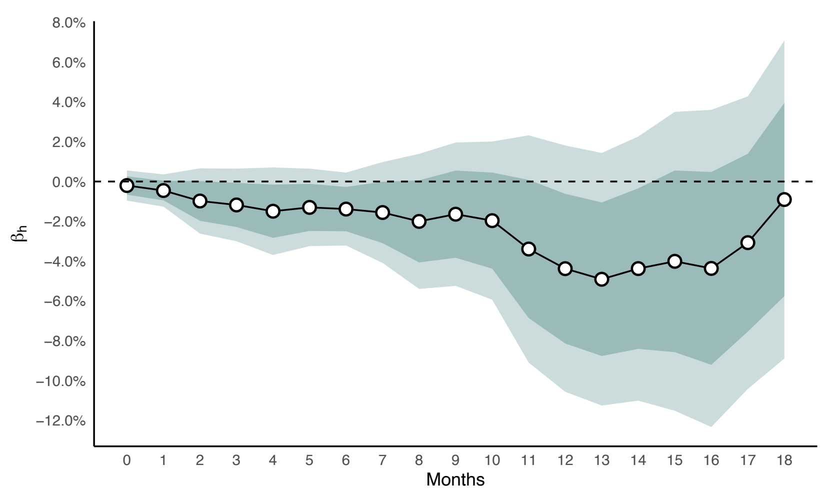
Average price response

To estimate the average firm response to a carbon pricing shock, we run:

$$\Delta p_{i,t+h} = \alpha_i + \bar{\beta}_h CPS_t + \Gamma Z_{i,t} + u_{i,t+h} \tag{B.1}$$

This formulation is obtained by removing the triple interacted fixed effect to the baseline equation (4.1). $\bar{\beta}_h$ captures the average firm-level price response at horizon h (across all countries and sectors) following a carbon pricing shock. Figure B12 plots the results of this regression. As we can see, the estimated $\bar{\beta}_h$ is at least qualitatively in line with the panel VAR evidence but fail to be significant at the 10% confidence level, presumably because of the conservative two-way clustering that we use.

Figure B12 THE EFFECT OF CARBON PRICING SHOCKS ON EQUITY PRICES: AVERAGE EFFECT ACROSS FIRMS



NOTE. This Figure displays the average firm-level dynamic price response (across all countries and sectors) to a carbon pricing shock.

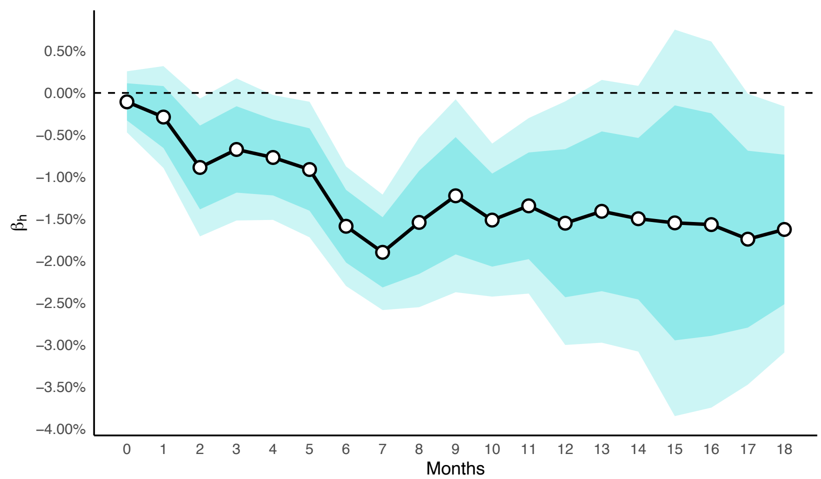
Country CO2 intensity

The cross-sectional evidence suggests that the drop in equity prices is larger in countries with higher CO2 intensity. Do we find a similar pattern when using the firm-level data? To investigate this, we define $CO2_c$ as a country-specific CO2 intensity variable taken from the OECD Green Growth Indicators Database. To help with the interpretation, we standardize the CO2 intensity variable to have zero mean and a unit standard deviation. We run the following regression:

$$\Delta p_{i,t+h} = \alpha_i + \alpha_h + \hat{\beta}_h (CPS_t \times CO2_c) + \Gamma Z_{i,t} + u_{i,t+h} \tag{B.2}$$

Where α_h is a horizon fixed effect and $Z_{i,t}$ is a vector of firm specific variables that may affect the price response over time. The coefficient of interest $\hat{\beta}_h$ thus captures the marginal effect of higher country CO2 intensity on the price response of an average firm within that country to a carbon pricing shock, relative to an average firm in a less polluting country. Figure B13 plots the results from running regression (B.2). As we can see, higher carbon intensity at the country level tends to be associated with a larger than average drop in equity prices. Quantitatively, firms operating in a country with a one-standard deviation higher carbon intensity tend to see their equity price decline by around 1.5 percent more than the equivalent firm in a country with average carbon intensity. These results echo our motivating PVAR evidence depicted in Figure 3.3 and suggest that browner countries may suffer relatively more from the introduction of carbon pricing policies

Figure B13 THE EFFECT OF CARBON PRICING SHOCKS ON EQUITY PRICES: HETEROGENEOUS EFFECT FOR HIGH-EMISSION COUNTRIES



NOTE. Average effect of higher country CO2 intensity on the average firm-level price response following a carbon pricing shock.

C Model

C.1 Labor Unions

Aggregate labor demand is given by:

$$N_t^d = \left[\int_0^1 N_t(\omega)^{\frac{\epsilon_w - 1}{\epsilon_w}} d\omega \right]^{\frac{\epsilon_w}{\epsilon_w - 1}},$$

where ϵ_w is the elasticity of substitution across labor varieties. The labor union maximizes

$$\max_{w_t^*} \mathbb{E}_t \sum_{s=t}^{\infty} (\beta \vartheta_w)^{s-t} \left\{ -\chi \frac{N_s(\omega)^{1+\varphi}}{1+\varphi} + \Lambda_s \prod_{s=1}^{j} \left(\frac{\Pi_{s-1}^{\iota_w} \Pi^{1-\iota_w}}{\Pi_s} \right) w_s(\omega) N_s(\omega) \right\},$$

subject to the following demand schedule:

$$N_s(\omega) = \left(\prod_{k=1}^{s} \frac{w_s(\omega)}{w_s} \frac{\Pi_{s-1}^{\iota_w} \Pi^{1-\iota_w}}{\Pi_s} \right)^{-\epsilon_w} N_s^d.$$

The problem of the union is to maximize profits,

$$\max_{w_t^*} \mathbb{E}_t \sum_{s=t}^{\infty} (\beta \vartheta_w)^{s-t} \left\{ -\chi \frac{\left[\left(\frac{w_t(\omega)}{w_s} \prod_{k=1}^{s} \frac{\Pi_{s-1}^{\iota_w} \Pi^{1-\iota_w}}{\Pi_s} \right)^{-\epsilon_w} N_s^d \right]^{1+\varphi}}{1+\varphi} + \right.$$
$$\left. + \Lambda_s w_s \left(\frac{w_t(\omega)}{w_s} \prod_{k=1}^{s} \frac{\Pi_{w,s-1}^{\iota_w} \Pi^{1-\iota_w}}{\Pi_s} \right)^{1-\epsilon_w} N_s^d \right\}.$$

The first order condition with respect to w_t^* can be expressed in recursive form by separating the LHS from the RHS of the first order condition.

$$\mathcal{F}_t^w = \epsilon_w \chi (\tilde{w}_t)^{-\epsilon_w(1+\varphi)} \left(N_t^d \right)^{1+\varphi} + \beta \vartheta_w \mathbb{E}_t \left(\frac{\Pi_t^{\iota_w} \Pi^{1-\iota_w}}{\Pi_{t+1}} \right)^{-\epsilon_w(1+\varphi)} \left(\frac{\tilde{w}_{t+1}}{\tilde{w}_t} \right)^{\epsilon_w(1+\varphi)} \mathcal{F}_{t+1}^w, \quad \text{(C.1)}$$

$$\mathcal{J}_t^w = (\epsilon_w - 1) \Lambda_t (\tilde{w}_t)^{1-\epsilon_w} w_t N_t^d + \beta \vartheta_w \mathbb{E}_t \left(\frac{\Pi_t^{\iota_w} \Pi^{1-\iota_w}}{\Pi_{t+1}} \right)^{1-\epsilon_w} \left(\frac{\tilde{w}_{t+1}}{\tilde{w}_t} \right)^{\epsilon_w - 1} \mathcal{J}_{t+1}^w, \quad \text{(C.2)}$$

$$\mathcal{J}_t^w = \mathcal{F}_t^w, \quad \text{(C.3)}$$

where $\tilde{w}_t = \frac{w_t^*}{w_t}$ is the optimal wage divided by the aggregate wage rate. The aggregate law of motion for wages is therefore equal to:

$$w_t^{1-\epsilon_w} = \vartheta_w \left(\frac{\Pi_{t-1}^{\iota_w} \Pi^{1-\iota_w}}{\Pi_t} w_{t-1} \right)^{1-\epsilon_w} + (1-\vartheta_w) (w_t^*)^{1-\epsilon_w}. \quad \text{(C.4)}$$

C.2 Capital Producers

Capital producers provide investment goods to brown and green firms by combining green and brown investment. Aggregate investment is

$$I_t = \left\{ \nu^{\frac{1}{\eta}} \left(I_t^B\right)^{\frac{\eta-1}{\eta}} + (1-\nu)^{\frac{1}{\eta}} \left(I_t^G\right)^{\frac{\eta-1}{\eta}} \right\}^{\frac{\eta}{\eta-1}}.$$

Profits are:

$$\Pi_t = I_t - p_t^B I_t^B - p_t^G I_t^G.$$

and the demand schedules are given by

$$I_t^B = \nu \left(p_t^B\right)^{-\eta} I_t, \tag{C.5}$$

$$I_t^G = (1-\nu) \left(p_t^G\right)^{-\eta} I_t. \tag{C.6}$$

C.3 Firms

Solving for $1 - A_t^j(i)$ and substituting into the production function, we can write a CES function combining pollution emissions and productive factors:

$$Y_t^j(i) = \left[\gamma_j \left(\frac{\xi_t(i)}{\mu_j} \right)^{\frac{\zeta-1}{\zeta}} + (1-\gamma_j) \left[Z_t \left(N_t^j(i)\right)^{1-\alpha_j} \left(K_{t-1}^j(i)\right)^{\alpha_j} \right]^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}}.$$

In this interpretation, γ_j is the share for pollution emissions and ζ_j the elasticity of substitution between emissions and value added. Theory and evidence do not give clear guidance on how to think about pollution emissions in the firm's environmental decisions. Is pollution a second output on which firms are taxed via environmental regulation? Or is pollution best thought of an input to production, which has a price due to environmental regulation? Or alternatively, should we think of firms as optimizing standard production decisions subject to a constraint on pollution emissions? An advantage of this framework is that it does not require choosing one of these interpretations as correct and the others as incorrect, since these interpretations are equivalent. For the operating firm, pollution emissions decline when firms reallocates productive factors to abatement investment. The model accounts for several ways in which firms and consumer behavior affect pollution emissions: consumption, investment and production all respond to environmental regulation, and all of these forces can interact to determine pollution emissions.

One concept that is commonly discussed is that the number of workers per unit of output, $\frac{Y_t^B(i)}{N_t^B(i)} = \left(1 - A_t^B(i)\right) \left(N_t^j(i)\right)^{-\alpha_B} \left(K_{t-1}^j(i)\right)^{\alpha_B}$ respond to environmental regulation. This depends on environmental regulation since it increases the shares allocated to abatement rather than producing output.

Firm i of type j solves the following problem,

$$\min_{A_t^B(i), N_t^B(i), K_{t-1}^B(i)} P_t w_t N_t^B(i) + P_t r_{K,t}^B K_{t-1}^B(i) + \tau P_t \theta_t^B \xi_t(i)$$

subject to equation (5.10). The first order conditions of brown firms are given by:

$$mc_t^B(i) = \frac{\tau\theta_t\mu_B}{p_t^B\gamma_B}\left[\frac{\left(1-A_t^j(i)\right)^{\frac{\zeta-1}{\zeta}}-(1-\gamma_B)}{\gamma_B}\right]^{\frac{\zeta}{\zeta-1}-1}\left(1-A_t^j(i)\right)^{\frac{\zeta-1}{\zeta}-1},$$

$$mc_t^B(i) = \frac{w_tN_t^B(i)}{(1-\alpha_B)\,p_t^BY_t^B(i)} + \frac{\tau\theta_t^B}{p_t^B}\mu_B\left[\frac{\left(1-A_t^B(i)\right)^{\frac{\zeta-1}{\zeta}}-(1-\gamma_B)}{\gamma_B}\right]^{\frac{\zeta}{\zeta-1}}\frac{1}{1-A_t^B(i)},$$

$$mc_t^B(i) = \frac{r_{K,t}^BK_{t-1}(i)}{\alpha_Bp_t^BY_t^B(i)} + \frac{\tau\theta_t^B}{p_t^B}\mu_B\left[\frac{\left(1-A_t^B(i)\right)^{\frac{\zeta-1}{\zeta}}-(1-\gamma_B)}{\gamma_B}\right]^{\frac{\zeta}{\zeta-1}}\frac{1}{1-A_t^B(i)},$$

where $mc_t^B(i)$ is the real marginal cost of firm i of type B. The real marginal cost of brown firms is therefore,

$$mc_t^B(i) = mc_t^B = \frac{1}{p_t^B}\left[(\gamma_B)^\zeta(\tau\theta_t\mu_B)^{1-\zeta}+(1-\gamma_B)^\zeta Z_t^{\zeta-1}\left[\left(\frac{w_t}{1-\alpha_B}\right)^{1-\alpha_j}\left(\frac{r_{K,t}^j}{\alpha_B}\right)^{\alpha_j}\right]^{1-\zeta}\right]^{\frac{1}{1-\zeta}}.$$

Equally, the real marginal cost of production of green firms can be obtained by substituting the first order conditions into the production function,

$$mc_t^G = \frac{1}{Z_tp_t^G}\left[\frac{w_t}{(1-\alpha_G)}\right]^{1-\alpha_G}\left(\frac{r_{K,t}^G}{\alpha_G}\right)^{\alpha_G}. \tag{C.7}$$

The Phillips curve for type-j firms is given by the following set of equations,

$$\mathcal{J}_t^j = \Lambda_t mc_t^jY_t^j + \beta\vartheta_j\mathbb{E}_t\frac{\Pi_{t+1}^j}{\Pi_{t+1}}\left(\frac{\Pi_{t+1}^j}{\left(\Pi_t^j\right)^{\iota_j}\Pi^{1-\iota_j}}\right)^{\epsilon_j}\mathcal{J}_{t+1}^j, \tag{C.8}$$

$$\mathcal{F}_t^j = \Lambda_t\tilde{p}_t^jY_t^j + \beta\vartheta_j\mathbb{E}_t\frac{\Pi_{t+1}^j}{\Pi_{t+1}}\left(\frac{\Pi_{t+1}^j}{\left(\Pi_t^j\right)^{\iota_j}\Pi^{1-\iota_j}}\right)^{\epsilon_j-1}\mathcal{F}_{t+1}^j, \tag{C.9}$$

$$\mathcal{J}_t^j = \tilde{p}_t^j\frac{\epsilon_j-1}{\epsilon_j}\mathcal{F}_t^j, \tag{C.10}$$

$$1 = \vartheta_j\left(\frac{\Pi_t^j}{\left(\Pi_{t-1}^j\right)^{\iota_j}\Pi^{1-\iota_j}}\right)^{\epsilon_j-1} + (1-\vartheta_j)\left(\tilde{p}_t^j\right)^{1-\epsilon_j}. \tag{C.11}$$

C.4 Market Clearing

Labor market clearing is such that:

$$N_t = \Delta_{w,t} \left(N_t^B + N_t^G \right). \tag{C.12}$$

where $\Delta_{w,t}$ denotes the wage dispersion, which evolves according to:

$$\Delta_{w,t} = (1-\vartheta_w) \left(\tilde{w}_t \right)^{-\epsilon_w} + \vartheta_w \left(\frac{\Pi_{t-1}^{\iota_w} \Pi^{1-\iota_w}}{\Pi_t} \right)^{-\epsilon_w} \left(\frac{w_{t-1}}{w_t} \right)^{-\epsilon_w} \Delta_{w,t-1}. \tag{C.13}$$

The price dispersion for firms of j type evolves as follows:

$$\Delta_t^j = (1-\vartheta_j) \left(\tilde{p}_t^j \right)^{-\epsilon_j} + \vartheta_j \left(\frac{\Pi_t^j}{\left(\Pi_{t-1}^j \right)^{\iota_j} \Pi^{1-\iota_j}} \right)^{\epsilon_j} \Delta_{t-1}^j \quad \text{for} j = \{B, G\}. \tag{C.14}$$

Market clearing in the investment market is:

$$I_t = \mathcal{I}_t^B + \mathcal{I}_t^G, \tag{C.15}$$

Goods market clearing requires:

$$Y_t^G = C_t^G + \mathcal{G}_t^G + I_t^G \tag{C.16}$$

and

$$Y_t^B = C_t^B + \mathcal{G}_t^B + I_t^B. \tag{C.17}$$

Finally, price inflation is:

$$\Pi_t^j = \frac{p_t^j}{p_{t-1}^j} \Pi_t \text{ for } j = \{G, B\}, \tag{C.18}$$

and wage inflation:

$$\frac{\Pi_{w,t}}{\Pi_t} = \frac{w_t}{w_{t-1}}. \tag{C.19}$$

C.5 Model aggregation

Market clearing. Integrating over ω gives:

$$C_t + \sum_{j=\{B,G\}} \mathcal{I}_t^j = w_t N_t + \sum_{j=\{B,G\}} \left\{ r_{K,t}^j K_{t-1}^j + \frac{\Phi_t^j}{P} \right\} - T_t.$$

Aggregate profits of brown firms are given by:

$$\frac{\Phi_t^B}{P_t} = \frac{P_t^B}{P_t}\int_0^1 \frac{P_t^B(i)}{P_t^B} Y_t^j(i)\,di - w_t N_t^B - r_{K,t}^B K_{t-1}^B - \tau\theta_t \xi_t^B,$$
$$\frac{\Phi_t^B}{P_t} = p_t^B Y_t^B - w_t N_t^B - r_{K,t}^B K_{t-1}^B - \tau\theta_t \xi_t^B.$$

Equally, aggregate profits of green firms are:

$$\frac{\Phi_t^G}{P_t} = p_t^G Y_t^G - w_t N_t^G - r_{K,t}^G K_{t-1}^G.$$

Substituting aggregate profits into the budget constraint yields:

$$C_t + I_t = p_t^B Y_t^B + p_t^G Y_t^G - \tau\theta_t\xi_t^B - T_t,$$
$$C_t + I_t = p_t^B Y_t^B + p_t^G Y_t^G - \tau\theta_t\xi_t^B - \mathcal{G}_t + \tau\theta_t\xi_t^B,$$
$$C_t + I_t + \mathcal{G}_t = p_t^B Y_t^B + p_t^G Y_t^G.$$

Aggregate production. Using the CES production function, we can derive aggregate output for green firms,

$$\int_0^1 Z_t \left(N_t^G(i)\right)^{1-\alpha_G} \left(K_{t-1}^G(i)\right)^{\alpha_G} di = \int_0^1 \left(\frac{P_t^G(i)}{P_t^G}\right)^{-\epsilon} Y_t^G di,$$
$$N_t^G \int_0^1 Z_t \left(\frac{K_{t-1}^G}{N_t^G}\right)^{\alpha_G} di = Y_t^G \int_0^1 \left(\frac{P_t^G(i)}{P_t^G}\right)^{-\epsilon} di,$$
$$Z_t \left(N_t^G\right)^{1-\alpha_G} \left(K_{t-1}^G\right)^{\alpha_G} = \Delta_t^G Y_t^G.$$

Aggregation across green firms is obtained using the first order condition with respect to abatement, which is not specific to brown firms. Equation (C.7) entails that real marginal cost and, therefore, abatement are the same across brown firms. This in turn implies that:

$$\int_0^1 Z_t \left(1 - A_t^B(i)\right) \left(N_t^B(i)\right)^{1-\alpha_B} \left(K_{t-1}^B(i)\right)^{\alpha_B} di = \int_0^1 \left(\frac{P_t^B(i)}{P_t^B}\right)^{-\epsilon} Y_t^B di,$$
$$Z_t \left(1 - A_t^B\right) \int_0^1 \left(N_t^B(i)\right)^{1-\alpha_B} \left(K_{t-1}^B(i)\right)^{\alpha_B} di = \int_0^1 \left(\frac{P_t^B(i)}{P_t^B}\right)^{-\epsilon} Y_t^B di,$$
$$Z_t \left(1 - A_t^B\right) N_t^B \int_0^1 \left(\frac{K_{t-1}^B}{N_t^B}\right)^{\alpha_B} di = \int_0^1 \left(\frac{P_t^B(i)}{P_t^B}\right)^{-\epsilon} Y_t^B di,$$
$$Z_t \left(1 - A_t^B\right) \left(N_t^B\right)^{1-\alpha_B} \left(K_{t-1}^B\right)^{\alpha_B} = \Delta_t^B Y_t^B.$$

D Dynamic equations

The system of equations is given by:

$$\Lambda_t = \left(C_t - \phi C_{t-1}\right)^{-\sigma} - \beta\phi\mathbb{E}_t\left(C_{t+1} - \phi C_t\right)^{-\sigma}, \tag{D.1}$$

$$\Lambda_t = \beta \mathbb{E}_t \left\{ \frac{R_t}{\Pi_{t+1}} \Lambda_{t+1} \right\}, \tag{D.2}$$

$$Q_t^B = \beta \mathbb{E}_t \frac{\Lambda_{t+1}}{\Lambda_t} \left\{ r_{K,t+1}^B + (1-\delta_K) Q_{t+1}^B \right\}, \tag{D.3}$$

$$Q_t^G = \beta \mathbb{E}_t \frac{\Lambda_{t+1}}{\Lambda_t} \left\{ r_{K,t+1}^G + (1-\delta_K) Q_{t+1}^G \right\}, \tag{D.4}$$

$$\begin{aligned} 1 = Q_t^B & \left[1 - \frac{\psi_I^B}{2} \left(\frac{\mathcal{I}_t^B}{\mathcal{I}_{t-1}^B} - 1 \right)^2 - \psi_I^B \left(\frac{\mathcal{I}_t^B}{\mathcal{I}_{t-1}^B} - 1 \right) \frac{\mathcal{I}_t^B}{\mathcal{I}_{t-1}^B} \right] + \\ & + \beta \mathbb{E}_t \left\{ Q_{t+1}^B \frac{\Lambda_{t+1}}{\Lambda_t} \psi_I^B \left(\frac{\mathcal{I}_t^B}{\mathcal{I}_{t-1}^B} - 1 \right) \left(\frac{\mathcal{I}_t^B}{\mathcal{I}_{t-1}^B} \right)^2 \right\}, \end{aligned} \tag{D.5}$$

$$\begin{aligned} 1 = Q_t^G & \left[1 - \frac{\psi_I^G}{2} \left(\frac{\mathcal{I}_t^G}{\mathcal{I}_{t-1}^G} - 1 \right)^2 - \psi_I^B \left(\frac{\mathcal{I}_t^G}{\mathcal{I}_{t-1}^G} - 1 \right) \frac{\mathcal{I}_t^G}{\mathcal{I}_{t-1}^G} \right] + \\ & + \beta \mathbb{E}_t \left\{ Q_{t+1}^G \frac{\Lambda_{t+1}}{\Lambda_t} \psi_I^G \left(\frac{\mathcal{I}_t^G}{\mathcal{I}_{t-1}^G} - 1 \right) \left(\frac{\mathcal{I}_t^G}{\mathcal{I}_{t-1}^G} \right)^2 \right\}, \end{aligned} \tag{D.6}$$

$$K_t^B = (1-\delta_K) K_{t-1}^B + \left(1 - \frac{\psi_B}{2} \left(\frac{\mathcal{I}_t^B}{\mathcal{I}_{t-1}^B} - 1 \right)^2 \right) \mathcal{I}_t^B, \tag{D.7}$$

$$K_t^G = (1-\delta_K) K_{t-1}^G + \left(1 - \frac{\psi_G}{2} \left(\frac{\mathcal{I}_t^G}{\mathcal{I}_{t-1}^G} - 1 \right)^2 \right) \mathcal{I}_t^G, \tag{D.8}$$

$$\mathcal{F}_t^w = \epsilon_w \chi \left(\tilde{w}_t \right)^{-\epsilon_w (1+\varphi)} \left(\frac{N_t}{\Delta_t^w} \right)^{1+\varphi} + \beta \vartheta_w \mathbb{E}_t \left(\frac{\Pi_t^{\iota_w} \Pi^{1-\iota_w}}{\Pi_{t+1}} \right)^{-\epsilon_w (1+\varphi)} \left(\frac{\tilde{w}_{t+1}}{\tilde{w}_t} \right)^{\epsilon_w (1+\varphi)} \mathcal{F}_{t+1}^w, \tag{D.9}$$

$$\mathcal{J}_t^w = (\epsilon_w - 1) \Lambda_t \left(\tilde{w}_t \right)^{1-\epsilon_w} w_t \frac{N_t}{\Delta_t^w} + \beta \vartheta_w \mathbb{E}_t \left(\frac{\Pi_t^{\iota_w} \Pi^{1-\iota_w}}{\Pi_{t+1}} \right)^{1-\epsilon_w} \left(\frac{\tilde{w}_{t+1}}{\tilde{w}_t} \right)^{\epsilon_w - 1} \mathcal{J}_{t+1}^w, \tag{D.10}$$

$$\mathcal{J}_t^w = \mathcal{F}_t^w, \tag{D.11}$$

$$1 = \vartheta_w \left(\frac{\Pi_{t-1}^{\iota_w} \Pi^{1-\iota_w}}{\Pi_t} \frac{w_{t-1}}{w_t} \right)^{1-\epsilon_w} + (1-\vartheta_w) \left(\tilde{w}_t \right)^{1-\epsilon_w}, \tag{D.12}$$

$$\Delta_t^w = (1-\vartheta_w) \left(\tilde{w}_t \right)^{-\epsilon_W} + \vartheta_w \left(\frac{\Pi_t^{\iota_w} \Pi^{1-\iota_w}}{\Pi_{t+1}} \right)^{-\epsilon_w} \left(\frac{w_{t-1}}{w_t} \right)^{-\epsilon_w} \Delta_{t-1}^w, \tag{D.13}$$

$$\frac{\Pi_{w,t}}{\Pi_t} = \frac{w_t}{w_{t-1}}, \tag{D.14}$$

$$1 = \left\{ \nu \left(p_t^B\right)^{1-\eta} + (1-\nu)\left(p_t^G\right)^{1-\eta} \right\}^{\frac{1}{1-\eta}}, \tag{D.15}$$

$$\Delta_t^B Y_t^B = Z_t \left(1 - A_t^B\right) \left(N_t^B\right)^{1-\alpha_B} \left(K_{t-1}^B\right)^{\alpha_B}, \tag{D.16}$$

$$\Delta_t^G Y_t^G = Z_t \left(N_t^G\right)^{1-\alpha_G} \left(K_{t-1}^G\right)^{\alpha_G}, \tag{D.17}$$

$$mc_t^B = \frac{\left(1 - A^B\right)^{\frac{\zeta-1}{\zeta}} w_t N_t^B}{(1-\gamma_B)(1-\alpha_B) p_t^B Y_t^B}, \tag{D.18}$$

$$mc_t^B = \frac{\left(1 - A_t^B\right)^{\frac{\zeta-1}{\zeta}} r_{K,t}^j K_{t-1}^B}{(1-\gamma_B)\alpha_B p_t^B Y_t^B}, \tag{D.19}$$

$$1 - \gamma_B = \left(1 - A_t^B\right)^{\frac{\zeta-1}{\zeta}} \left[1 - \gamma_B \left(\frac{p_t^B mc_t^B}{\tau \theta_t \mu_B}\right)^{\zeta-1}\right], \tag{D.20}$$

$$mc_t^G = \frac{w_t N_t^G}{p_t^G (1-\alpha_G) Y_t^G}, \tag{D.21}$$

$$mc_t^G = \frac{r_{K,t}^G K_{t-1}^G}{p_t^G \alpha_G Y_t^G}, \tag{D.22}$$

$$\xi_t = \mu_B Z_t \left[\frac{\left(1 - A_t^B\right)^{\frac{\zeta-1}{\zeta}} - (1-\gamma_B)}{\gamma_B}\right]^{\frac{\zeta}{\zeta-1}} \left(N_t^B\right)^{1-\alpha_B} \left(K_{t-1}^B\right)^{\alpha_B}, \tag{D.23}$$

$$\mathcal{CO}_t = (1-\varpi)\mathcal{CO}_{t-1} + \xi_t, \tag{D.24}$$

$$Z_t = \left[1 - d_3\left(d_0 + d_1 \mathcal{CO}_t + d_2 \mathcal{CO}_t^2\right)\right], \tag{D.25}$$

$$\mathcal{J}_t^B = \Lambda_t mc_t^B \frac{Y_t^B}{\Delta_t^B} + \beta \vartheta_B \mathbb{E}_t \left(\frac{\Pi_{t+1}^B}{\left(\Pi_t^B\right)^{\iota_B} \Pi^{1-\iota_B}}\right)^{\epsilon_B} \mathcal{J}_{t+1}^B, \tag{D.26}$$

$$\mathcal{F}_t^B = \Lambda_t \tilde{p}_t^B \frac{Y_t^B}{\Delta_t^B} + \beta \vartheta_B \mathbb{E}_t \left(\frac{\Pi_{t+1}^B}{\left(\Pi_t^B\right)^{\iota_B} \Pi^{1-\iota_B}}\right)^{\epsilon_B - 1} \frac{\tilde{p}_t^B}{\tilde{p}_{t+1}^B} \mathcal{F}_{t+1}^B, \tag{D.27}$$

$$\mathcal{J}_t^B = \frac{\epsilon_B - 1}{\epsilon_B} \mathcal{F}_t^B, \tag{D.28}$$

$$1 = \vartheta_B \left(\frac{\Pi_t^B}{\left(\Pi_{t-1}^B\right)^{\iota_B} \Pi^{1-\iota_B}}\right)^{\epsilon_B - 1} + (1-\vartheta_B)\left(\tilde{p}_t^B\right)^{1-\epsilon_B}, \tag{D.29}$$

$$\Delta_t^B = (1-\vartheta_B)\left(\tilde{p}_t^B\right)^{-\epsilon_B} + \vartheta_B \left(\frac{\Pi_t^B}{\left(\Pi_{t-1}^B\right)^{\iota_B} \Pi^{1-\iota_B}}\right)^{\epsilon_B} \Delta_{t-1}^B, \tag{D.30}$$

$$\Pi_t^B = \frac{p_t^B}{p_{t-1}^B} \Pi_t, \tag{D.31}$$

$$\mathcal{J}_t^G = \Lambda_t mc_t^G Y_t^G + \beta\vartheta_G \mathbb{E}_t \left(\frac{\Pi_{t+1}^G}{\left(\Pi_t^G\right)^{\iota_G} \Pi^{1-\iota_G}} \right)^{\epsilon_G} \mathcal{J}_{t+1}^G, \tag{D.32}$$

$$\mathcal{F}_t^G = \Lambda_t \tilde{p}_t^G Y_t^G + \beta\vartheta_G \mathbb{E}_t \left(\frac{\Pi_{t+1}^G}{\left(\Pi_t^G\right)^{\iota_G} \Pi^{1-\iota_G}} \right)^{\epsilon_G - 1} \frac{\tilde{p}_t^G}{\tilde{p}_{t+1}^G} \mathcal{F}_{t+1}^G, \tag{D.33}$$

$$\mathcal{J}_t^G = \frac{\epsilon_G - 1}{\epsilon_G} \mathcal{F}_t^G, \tag{D.34}$$

$$1 = \vartheta_G \left(\frac{\Pi_t^G}{\left(\Pi_{t-1}^G\right)^{\iota_G} \Pi^{1-\iota_G}} \right)^{\epsilon_G - 1} + (1-\vartheta_G) \left(\tilde{p}_t^G\right)^{1-\epsilon_G}, \tag{D.35}$$

$$\Delta_t^G = (1-\vartheta_G) \left(\tilde{p}_t^G\right)^{-\epsilon_G} + \vartheta_G \left(\frac{\Pi_t^G}{\left(\Pi_{t-1}^G\right)^{\iota_G} \Pi^{1-\iota_G}} \right)^{\epsilon_G} \Delta_{t-1}^G, \tag{D.36}$$

$$\Pi_t^G = \frac{p_t^G}{p_{t-1}^G} \Pi_t, \tag{D.37}$$

$$N_t = N_t^B + N_t^G, \tag{D.38}$$

$$I_t = \mathcal{I}_t^B + \mathcal{I}_t^G, \tag{D.39}$$

$$Y_t^G = (1-\nu) \left(p_t^G\right)^{-\eta} \left(C_t + \mathcal{G}_t + I_t\right), \tag{D.40}$$

$$Y_t^B = \nu \left(p_t^B\right)^{-\eta} \left(C_t + \mathcal{G}_t + I_t\right), \tag{D.41}$$

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{r_r} \left[\left(\frac{\Pi_t}{\Pi}\right)^{r_\pi} \left(\frac{Y_t}{Y}\right)^{r_y} \right]^{1-r_r} \exp\left(\varepsilon_{rt}\right), \tag{D.42}$$

$$Y_t = p_t^B Y_t^B + p_t^G Y_t^G, \tag{D.43}$$

$$\log\left(\frac{\xi_t}{\xi}\right) = \varrho_\xi \log\left(\frac{\xi_{t-1}}{\xi}\right) + \varepsilon_{\xi t}, \quad \varepsilon_{\xi t} \sim N\left(0, \varsigma_\xi\right), \tag{D.44}$$

This system of equations solves for the following variables, Λ_t, C_t, $\mathcal{I}_t^B$, $\mathcal{I}_t^G$, I_t, Y_t^B, Y_t^G ,Y_t, Π_t, R_t, Q_t^B, Q_t^G, p_t^B, p_t^G, $\mathcal{J}_t^B$, $\mathcal{J}_t^G$, $\mathcal{J}_t^w$, $\mathcal{F}_t^B$, $\mathcal{F}_t^G$, $\mathcal{F}_t^w$, Δ_t^B, Δ_t^G, Δ_t^w, mc_t^B, mc_t^G, $\tilde{w}_t$, $\tilde{p}_t^B$, $\tilde{p}_t^G$, Π_t^B, Π_t^G,, Π_t^w, ξ_t, Z_t, $\mathcal{CO}_t$, A_t^B, N_t^B, N_t^G, N_t, K_t^B, K_t^G, w_t, θ_t, $r_{K,t}^B$, $r_{K,t}^G$ and the shock process ξ_t. Note in addition that there is a block including flexible price variables.

D.1 Steady State

The steady state is given by the following equations,

$$\Lambda_t = \left((1-\phi) C\right)^{-\sigma} (1-\phi\beta), \tag{D.45}$$

$$R = \frac{1}{\beta}, \tag{D.46}$$

$$r_K^B = \frac{1}{\beta} - (1-\delta_K), \tag{D.47}$$

$$r_K^G = \frac{1}{\beta} - (1 - \delta_K), \tag{D.48}$$

$$\mathcal{G} = \frac{\mathcal{G}}{Y} Y, \tag{D.49}$$

$$Q^B = 1, \tag{D.50}$$

$$Q^G = 1, \tag{D.51}$$

$$\mathcal{I}^B = \delta_K K^B, \tag{D.52}$$

$$\mathcal{I}^G = \delta_K K^G, \tag{D.53}$$

$$\tilde{w} = 1 \tag{D.54}$$

$$\tilde{p}^B = 1 \tag{D.55}$$

$$\tilde{p}^G = 1 \tag{D.56}$$

$$\Delta^w = 1, \tag{D.57}$$

$$\Delta^B = 1, \tag{D.58}$$

$$\Delta^G = 1, \tag{D.59}$$

$$\Pi^w = \Pi, \tag{D.60}$$

$$\Pi^B = \Pi, \tag{D.61}$$

$$\Pi^G = \Pi, \tag{D.62}$$

$$mc^B = \frac{\epsilon_B - 1}{\epsilon_B}, \tag{D.63}$$

$$mc^G = \frac{\epsilon_G - 1}{\epsilon_G}, \tag{D.64}$$

$$1 = \left\{ \nu \left(p^B \right)^{1-\eta} + (1 - \nu) \left(p^G \right)^{1-\eta} \right\}^{\frac{1}{1-\eta}}, \tag{D.65}$$

$$Y^B = Z \left(1 - A^B \right) \left(N^B \right)^{1-\alpha_B} \left(K^B \right)^{\alpha_B}, \tag{D.66}$$

$$Y^G = Z \left(N^G \right)^{1-\alpha_G} \left(K^G \right)^{\alpha_G}, \tag{D.67}$$

$$mc^B = \frac{\left(1 - A^B \right)^{\frac{\zeta-1}{\zeta}} w N^B}{(1 - \gamma_B)(1 - \alpha_B) p^B Y^B}, \tag{D.68}$$

$$mc^B = \frac{\left(1 - A^B \right)^{\frac{\zeta-1}{\zeta}} r_K^B K^B}{(1 - \gamma_B) \alpha_B p^B Y^B}, \tag{D.69}$$

$$1 - \gamma_B = \left(1 - A^B \right)^{\frac{\zeta-1}{\zeta}} \left[1 - \gamma_B \left(\frac{p^B mc^B}{\tau \mu_B} \right)^{\zeta-1} \right], \tag{D.70}$$

$$mc^G = \frac{w N^G}{p^G (1 - \alpha_G) Y^G}, \tag{D.71}$$

$$mc^G = \frac{r_K^G K^G}{p^G \alpha_G Y^G}, \tag{D.72}$$

$$\xi = \mu_B Z \left[\frac{\left(1 - A^B\right)^{\frac{\zeta-1}{\zeta}} - (1 - \gamma_B)}{\gamma_B} \right]^{\frac{\zeta}{\zeta-1}} \left(N^B\right)^{1-\alpha_B} \left(K^B\right)^{\alpha_B}, \tag{D.73}$$

$$\mathcal{CO} = \frac{\xi}{(1 - \varpi)}, \tag{D.74}$$

$$Z_t = \left[1 - d_3 \left(d_0 + d_1 \frac{\xi}{(1 - \varpi)} + d_2 \left(\frac{\xi}{(1 - \varpi)} \right)^2 \right) \right], \tag{D.75}$$

$$\mathcal{J}^w = \mathcal{F}^w, \tag{D.76}$$

$$\mathcal{F}^w = \frac{\epsilon_w \chi \left(N\right)^{1+\varphi}}{1 - \beta \vartheta_w}, \tag{D.77}$$

$$\mathcal{J}^w = \frac{(\epsilon_w - 1) \Lambda w N}{1 - \beta \vartheta_w}, \tag{D.78}$$

$$\mathcal{J}^G = \frac{\Lambda mc^G Y^G}{1 - \beta \vartheta_G}, \tag{D.79}$$

$$\mathcal{F}^G = \frac{\Lambda Y^G}{1 - \beta \vartheta_G}, \tag{D.80}$$

$$\mathcal{J}^G = \frac{\epsilon_G - 1}{\epsilon_G} \mathcal{F}^G, \tag{D.81}$$

$$\mathcal{J}_t^B = \frac{\Lambda mc^B Y^B}{1 - \beta \vartheta_B}, \tag{D.82}$$

$$\mathcal{F}_t^B = \frac{\Lambda Y^G}{1 - \beta \vartheta_B}, \tag{D.83}$$

$$\mathcal{J}^B = \frac{\epsilon_B - 1}{\epsilon_B} \mathcal{F}^B, \tag{D.84}$$

$$N = N^B + N^G, \tag{D.85}$$

$$I = \delta K^B + \delta K^B, \tag{D.86}$$

$$Y^B = \nu \left(p^B\right)^{-\eta} \left(C + \mathcal{G} + I\right), \tag{D.87}$$

$$Y^G = (1 - \nu) \left(p^G\right)^{-\eta} \left(C + \mathcal{G} + I\right), \tag{D.88}$$

$$Y = p^B Y^B + p^G Y^G. \tag{D.89}$$

CHAPTER 3

THE MACRO-FINANCIAL EFFECTS OF CLIMATE POLICY RISK: EVIDENCE FROM SWITZERLAND

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Abstract

This paper quantifies empirically the macroeconomic and financial effects of climate policy risk in Switzerland. To do so, we develop a new index of Climate Policy Risk (CPR) using text-analysis techniques on a large dataset of Swiss media articles. The identification of CPR shocks is achieved by using narrative restrictions around events which are likely to have coincided with an increase in the probability of adopting tighter climate policies. We find that CPR shocks lead to a significant decline in real GDP and are associated with a decline in firm-level CO2 emissions. Using firm-level equity price data and rolling linear panel regressions, we document that climate policy risk is increasingly reflected in asset prices. We further find that CO2-intensive firms perform significantly worse than their greener counterparts following events which increased transition risk. Our results are in line with recent theoretical contributions.

Keywords: Business Cycles, Carbon Pricing Shocks, Heterogeneity, Asset Prices

JEL: E32, E50, E60, H23, Q54

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1 Introduction

Climate change concerns, and in particular so-called transition risks arising from a possible transition to a low-carbon economy are becoming increasingly relevant for central banks (see e.g. Rudebusch et al. (2019); Batten et al. (2020); Maechler and Moser (2019)). For example, a mispricing of climate-related risks could have important implications for financial stability in the case of a sudden implementation of stringent climate policies (Battiston et al. (2021)). Furthermore, the uncertainty surrounding the transition path can also have important macro-financial implications. Fried et al. (2022) develop a dynamic general equilibrium model to quantify the macroeconomic impacts of climate policy transition risk. They show that transition risk (defined as the future probability of adopting a carbon tax) can affect the composition of capital and reduce output. Climate considerations are also becoming increasingly relevant for investors. Krueger et al. (2020) survey active investment managers and find that a large proportion of investors believe that climate change can have important implications for their portfolios. Pástor et al. (2021) develop a general equilibrium model of sustainable investing and show that green assets can outperform brown ones when concerns about climate change rise unexpectedly, and link this to the investors' preference for sustainability.

Against this backdrop, the aim of this paper is to empirically quantify the macroeconomic and financial effects of climate policy risk in a small open economy like Switzerland. A key novelty of this paper is to identify Climate Policy Risk (CPR) shocks using narrative restrictions around events which are likely to have coincided with an increase in the probability of adopting tighter climate policies. At the macroeconomic level, we find that CPR shocks lead to a significant decline in real GDP and are associated with lower firm-level CO2 emissions. In terms of financial response, we document that the equity price of firms with low within-sector CO2 has outperformed that of browner firms when climate policy risk rises unexpectedly over the last decade, both using linear panel regressions and a better identified event-study approach.

To quantify risks related to climate policies, we develop a new index of Climate Policy Risk (CPR) for Switzerland using text-analysis techniques on a large number of Swiss media articles. The focus on Switzerland differs from most of the existing literature but seems particularly relevant as Switzerland systematically ranks among the countries with the highest Environmental Policy Stringency index,[1] which suggests that transition risk may be particularly important there (See Figure G1). To build our index, we adopt an approach similar to that of Baker et al. (2016) in the context Economic Policy Uncertainty, and recently applied to US Climate Policy Uncertainty (US CPU) in Gavriilidis (2021). The resulting index rises around a number of important climate policy-related events such as international climate agreements, IPCC and other scientific reports, or development related to the introduction or revocation of climate policies. While being largely correlated with the US CPU index from Gavriilidis (2021), our Swiss index also displays distinct behaviours, notably related to domestic developments in Switzerland. Furthermore, the index is available at the daily frequency. We argue that the CPR index is a reasonable measure capturing the public awareness to a wide array of risks related to climate policies which are particularly relevant for Switzerland.

In Fried et al. (2022), an increase in climate transition risk corresponds to an increase in the probability of adopting a higher carbon tax. As the empirical equivalent to this

[1]The Environment Policy Stringency index is developed by the OECD and "measures the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour." More information here: https://www.oecd-ilibrary.org/environment/data/oecd-environment-statistics/environmental-policy-stringency-index_2bc0bb80-en

concept is challenging to find, we propose to use our daily CPR to narratively identify a number of events which are likely to have coincided with an increase in the probability of adopting stricter climate policies (for example the so-called "green wave" at the Swiss federal elections), and at the same time received an important media coverage. Our approach is then to leverage on these so-called "climate transition risk events" to empirically test the theoretical predictions from Fried et al. (2022).

At the macroeconomic level, we estimate a monthly VAR for Switzerland over the period 2000M1 to 2020M2, and adopt a shock-based identification scheme à la Ludvigson et al. (2021) using narrative restrictions around the transition risk events. In more details, CPR shocks are identified by restricting that they contribute meaningfully to the unexpected variations in the CPR index around the transition risk events. In line with Fried et al. (2022), we find that the narratively identified CPR shocks lead to a significant drop in real GDP, and find suggestive evidence that a higher CPR coincides with lower subsequent CO2 emissions at the firm-level. These results are robust to different sample specifications and identification schemes.

Regarding the financial response, our VAR exercise finds little average effects of CPR shocks on equity prices, and no significant heterogeneous effects on green versus brown equity indices. We conjecture that this lack of result may be driven by the fact that investors have only recently started to incorporate climate-related considerations in their portfolio decisions. To investigate this time dimension, we first define a green minus brown (GMB) portfolio which goes long (short) in firms with relatively low (high) within-sector CO2 emissions. The underlying argument is that, if climate policy risk is priced, the GMB portfolio should rise in value when climate policy risk increases, as green firms are expected to fare better than browner ones. Using rolling panel linear regressions, we find that, over the last 10 years, this portfolio is associated with significantly higher returns when climate policy risk rises unexpectedly, in line with the predictions from Pástor et al. (2021). However, such a portfolio does not provide higher returns in the beginning of our sample (2000-2012). We interpret this as suggestive evidence that climate policy risks have only recently started to be systematically integrated in asset prices in Switzerland.

We further confirm the relevance of transition risk events for asset prices by using an event-study approach combined with Jordà (2005)-type local projections. We find that, following events which arguably increased the probability of adopting stricter policies, the equity prices of firms with relatively high CO2 emissions drop significantly more than their greener counterparts 6 days after the events, which provides direct evidence that investors pay attention to news about climate transition risk. The monthly results suggest that the drop is persistent, as the equity price of brown firms is around 4 percent smaller 12 months after the event. Overall, our results suggest that transition risk has macroeconomic implications, and that asset prices (increasingly) reflect climate policy risk considerations, as predicted theoretically in Fried et al. (2022), and Pástor et al. (2021).

This paper is structured as follows. Section 2 surveys related literature. Section 3 describes the data sources. Section 4 details and discusses the construction of the CPR index. Section 5 reports the macroeconomic effects of CPR shocks. Section 6 focuses on the financial response of asset prices. Section 7 concludes.

2 Related literature

This paper is related to the growing literature investigating the macroeconomic implications of risks related to climate change, and in particular those related to the transition towards a greener economy (so-called transition risks). Känzig (2021) focuses on the economic effects of carbon pricing policies in the EU Exchange Traded System while Konradt and di Mauro (2021), Metcalf (2019), and Metcalf and Stock

(2020) focus on carbon taxes. Fried et al. (2022) develop a dynamic general equilibrium model to quantify the macroeconomic impacts of climate policy transition risk. They show that transition risk reduces emissions by reducing the expected returns of fossil capital, but also lead to lower output overall. Ferrari and Pagliari (2021) develop a two-country two-sector (brown and green) DSGE model and explore the cross-country implications of climate-related policies. At a general level, our work is related to the recent effort of central banks to incorporate climate considerations to help foster macroeconomic and financial stability (e.g. Rudebusch et al. (2019); Batten et al. (2020)).

By focusing on the financial effects of climate policy risk, this paper is also related to the climate finance literature (see Giglio et al. (2021) for a survey). Bolton and Kacperczyk (2021a) investigate investors' attention to carbon risk and find that higher carbon emissions are associated with higher expected returns in the US stock market. Bolton and Kacperczyk (2021b) confirm these results more globally by documenting the existence of carbon premium in all sectors over three continents, namely Asia, Europe, and North America. They further argue that the premium has increased in importance since the Paris agreement. In line with this, Alessi et al. (2021) find the existence of a greenium (a negative risk premium) for firms which are more environmentally friendly and transparent. Choi et al. (2020) document that the stock price of low-emission firms tend to outperform when the weather is abnormally warm. On the other hand, Hong et al. (2019) find that stock prices tend to underreact to physical climate risks. Theoretically, Pástor et al. (2021) propose an equilibrium model of sustainable investing. Their key result is that, in equilibrium, green assets have lower expected returns because investors value their (non-pecuniary) environment, social, and governance (ESG) characteristics. However, green assets outperform when there are positive shocks to the ESG factor. Ardia et al. (2022) confirm this empirically by showing that US green firms tend to outperform brown firms when climate change concerns change unexpectedly.

On the methodological front, the construction of our index connects with a literature which uses text-analysis methods to produce new proxies of economic concepts. For instance, Baker et al. (2016) develop an index of economic policy uncertainty using 10 leading U.S. newspapers. Other examples of text-based indices include Gentzkow and Shapiro (2010), Hoberg and Phillips (2010), and Boudoukh et al. (2013). Finally, Gavriilidis (2021) adapts the approach from Baker et al. (2016) to construct an index of climate policy uncertainty.

3 Data

3.1 Newspapers data

We rely on a novel database called Swissdox to construct the index of Climate Policy Risk. The database is comprehensive and essentially covers the universe of published articles.[2] We focus on the the main Swiss outlets in French and German. German-written newspapers include the *Neue Zürcher Zeitung, Tages Anzeiger, Blick,* and *20 Minuten.* French-written newspapers include *Le Temps, 24 heures, Tribune de Genève, 20 minutes,* and *Le Matin.* The sample starts in January 2000 and ends in October 2022. For all newspapers, we focus on printed articles. The final dataset is made of close to 4 millions articles, out of which 69.7% are in German and 30.3% are in French, roughly in line with the language repartition of the country. Table B1 in Appendix B provide the number of articles by media outlets. Figure B2 displays the time-series of the number of articles by year and language.

[2]The media data is made available through Swissdox@LiRI by the Linguistic Research Infrastructure of the University of Zurich (see https://t.uzh.ch/1hI for more information). We thank the Swiss Institute of Applied Economics of the University of Lausanne (CREA) for giving us access to this data.

3.2 Macroeconomic Data

We collect macroeconomic data at the monthly frequency on real GDP, equity prices, the consumer price index, and the policy rate data for Switzerland using Datastream. Our monthly sample is restricted by the availability of the CPR index and runs from 2000M1 to 2020M2. Monthly real GDP is obtained by interpolating quarterly level data using a shape-preserving piecewise cubic interpolation as in Miranda-Agrippino and Rey (2020). Figure B1 in Appendix B provides a graphical representation of the data.

3.3 Firm-level data

We collect firm-level equity price data from Datastream at the daily frequency for all public firms in Switzerland. We complement the equity price data with firm-level measures for CO2 emissions, denoted by $CO2_{i,t}$. Specifically, we consider both scope 1 and scope 2 CO2 emissions at the firm-level from Datastream and available at the annual frequency. Scope 1 emissions include greenhouse gases (GHG) emissions that emanate from the operation of capital directly owned by the firms. Scope 2 emissions are indirect emissions associated with the purchase of electricity, steam, heat, or cooling. As the two measures are complementary, our main measure of interest is the sum of scope 1 and scope 2 emissions. Finally, we consider a vector $X_{i,t}$ constituted by a number of firm-level controls available at the quarterly frequency from Datastream, namely a measure of leverage (measured as the ratio of total debt to assets), a measure of profitability (sales growth), and a measure of size (total assets). In the full sample, there are 217 unique firms and 1,024,967 observations. The coverage of CO2 data is equal to 45.2% of the 217 public firms in the SPI index. Table B2 provides summary statistics at the sector level.

4 An Index of Climate Policy Risk

4.1 Methodology

To build our Climate Policy Risk (CPR) index, we adopt an approach similar to that of Baker et al. (2016) in the context of Economic Policy Uncertainty, and recently applied to US Climate Policy Uncertainty in Gavriilidis (2021). In particular, we search for articles which contain keywords related to climate change (such as climate, CO2, greenhouse gases, renewable energy, etc). We then refine the search by adding terms related to policy (such as government, law, parliament, regulation, federal, Bern, etc). Finally, we add keywords related to risk and uncertainty (risk, uncertainty, doubt, unanticipated, unstable, etc). In Appendix A, we provide the list of keywords that we use. We then divide the number of articles that contain keywords related to climate, policy, and risk by the total number of articles in each month or day. The resulting CPR index is available at both the daily and monthly frequency.

4.2 Validation of the index

The resulting monthly CPR index is displayed in Figure D1. The index rises around a number of important climate policy-related events such as international climate agreements, IPCC and other scientific reports, or development related to the introduction or revocation of climate policies. As climate change is a global phenomenon, our index captures a number of international developments. By relying on Swiss newspapers, our conjecture is that we capture these developments from a point of view which is most relevant for the Swiss economy. The index also spikes around a number of domestic events, such as the proposal of a new CO2 law by the Swiss Federal council in 2022M9, the rejection of the CO2 law by Swiss people in 2021M6, or in 2019M10, a period that coincides with a "green wave" at the Swiss federal elections.

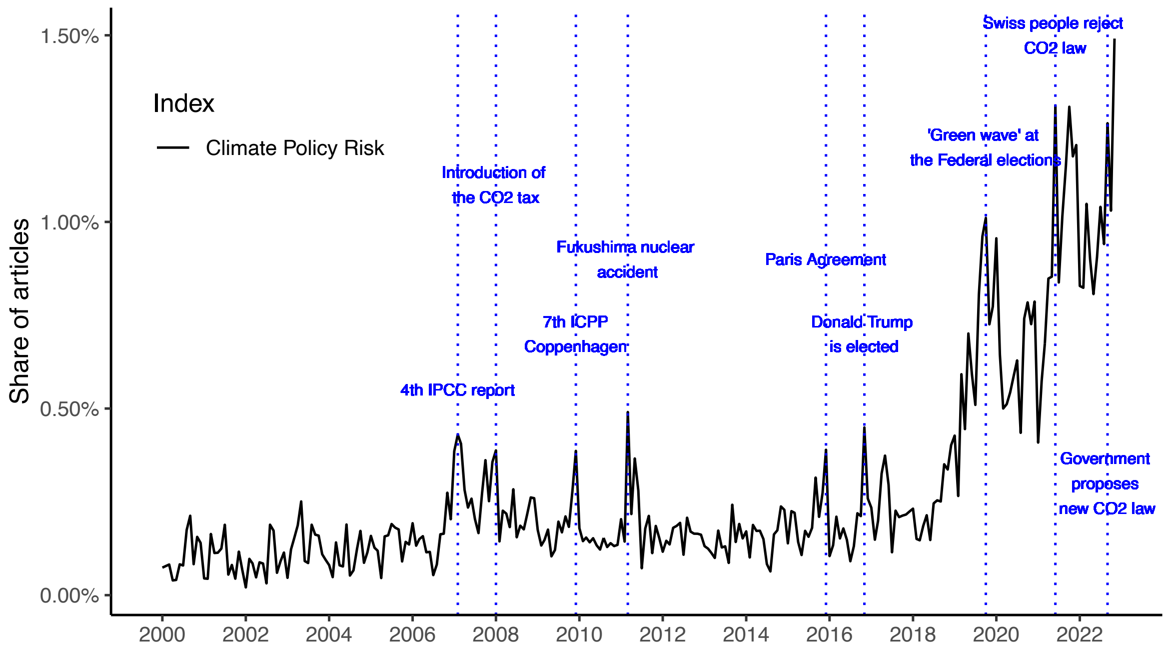
Interestingly, it is in general always possible to link a spike to a climate-related event, which suggests that the index does not identify false positives and that the keywords considered are suitable for our exercise. Generally speaking, the index appears to be effective at identifying a wide array of climate-related risks as well as periods which are likely to have coincided with increases in transition risk.

In Figure G2 of the Appendix, we compare the (scaled) CPR with the US Climate Policy Uncertainty (US CPU) index from Gavriilidis (2021). The two series turn out to be closely related with a correlation of 0.74, as can be expected as climate change is a global phenomenon. However, they also diverge during certain periods, for example around the election of Donald Trump which appears to be a significantly larger shock for the US CPU. Similarly, the spike related to the rejection of the CO2 law is virtually absent from the US CPU. We interpret this as evidence that our index captures transition risk that is most relevant to Switzerland.

4.3 Discussion

We now discuss the interpretation of our CPR index. Broadly defined, climate policy risks include the economic risks induced by the transition towards a greener economy. As a result, this does not only include the risks stemming from the discussion or the implementation of stricter climate policies (e.g. the "green wave" at the federal elections or the introduction of a CO2 tax), but also the uncertainty created by the (possible) revocation or loosening of existing climate policies (e.g. the election of Donald Trump or the rejection of a CO2 law). Similarly to the economic policy uncertainty (EPU) index from Baker et al. (2016), our media-based index captures variations in the *public awareness* of climate-related policy risks. This notably allows to capture a large number of events, not only restricted to the discussion, implementation or revocation of climate policies. For example, we capture the nuclear accident

Figure D1 THE CLIMATE POLICY RISK INDEX IN SWITZERLAND



NOTE. This Figure displays the Climate Policy Risk Index for Switzerland over the period 2000-2020. The frequency here is monthly but the index is available also at the daily frequency.

in Fukushima in 2011M3, or the release of the 4th IPCC report. Given that transition risk is a multi-faceted concept with no single and comprehensive definition, we view the flexibility granted by the keyword-based approach as a great advantage. Furthermore, focusing on newspapers is in line with Nimark and Pitschner (2019) who highlight the importance of the media in updating consumers and investors' view on the state of the world. Several studies have also confirmed the importance of media in increasing public awareness regarding environmental issues (see e.g. Boykoff and Rajan (2007); Sampei and Aoyagi-Usui (2009)).

In Fried et al. (2022), transition risk shocks are defined as an exogenous increase in the probability of adopting a stricter carbon tax policy. How does this compare with our CPR index? Figure D1 suggests that a number of spikes can credibly be mapped to an increase in the probability of adopting stricter carbon policies. For example, this includes the introduction of the CO2 tax in 2007M6, the "green wave" at the Federal election in 2019M10 or the government proposal of a new CO2 tax in 2022M9. In Figure G3, we further show that our CPR index is positively correlated to the Environmental Policy Stringency index from the OECD, thereby suggesting that our index is generally associated with a tightening of climate policies.

On the other hand, our approach also captures a number of events which appear to coincide with a weakening of existing climate policies. Examples include the election of Donald Trump or the rejection of the Swiss CO2 law in the ballot box. While these events likely generated uncertainty and risks regarding the transition towards a greener economy, and, as such, fit into our definition of climate policy risks, they may nevertheless not map directly with the definition of transition risk shocks from Fried et al. (2022).[3] In the next section, we leverage on our daily CPR index to manually identify a number of events that can be more directly interpreted as an increase in the probability of adopting stricter climate policies. We refer to these events as "transition risk events".

[3]This being said, there is anecdotal evidence that such events are not always effectively interpreted as a loosening of existing policies by economic agents. For example, Holden (2019) argue that many large automakers such as Ford, Honda, Volkswagen or BMW decided to adopt stricter fuel economy standards than those proposed by the Trump administration, out of fear that "years of regulatory uncertainty [...] could end with judges deciding against Trump." Furthermore, around one year following the narrow rejection of the Swiss CO2 law (51.59% to 48.41%), the Federal Council proposed a new CO2 law, clearly stating that the climate objectives remained the same. More generally, even a weakening of climate policies today can increase transition risk. The reason is that delaying climate action today can lead to a more abrupt adoption of additional climate policies in the future, for example because inaction increases physical risk (Adrian et al. (2022)).

4.4 Identifying transition risk events

To identify transition risk events, we consider the daily version of our CPR index, and identify days during which the share of articles containing keywords related to climate, policy and risk is particularly high. We then manually label each of these dates to a particular event by reading all the retrieved articles. This procedure ensures that the retrieved events received a relatively large media coverage. We then select events which we deem sufficiently important and related to an increase in transition risk. We identify 19 such events, which relate to both domestic and international developments. The resulting events are displayed in Table D1. As we can see and consistent with the secular increase in our CPR index since 2019, most of the transition risk events take place after this date. However, a number of events also take place before, such as the acceptance by Swiss voters of the revised Federal Energy Act in 2017M5, or the ratification of the Paris Agreement by Switzerland in 2017M10. Roughly half of the events relate to domestic development, while the other half is more internationally inclined.

5 The Macroeconomic Effects of Climate Policy Risk

In this section, we test empirically the theoretical prediction of Fried et al. (2022) on the macroeconomic effect of climate transition risk. In their model, climate transition risk –defined as the probability that a carbon tax will be implemented in the next period—distorts the composition of capital and results in lower output today, even before the actual implementation of the carbon tax. The mechanism is that higher transition risk reduces the expected return of fossil capital relative to clean capital and shifts the economy towards cleaner production. This compositional shift reduces output because it is different from the optimal allocation without risk. Transition

Table D1 TRANSITION RISK EVENTS

Date	Label	Type
2022-09-16	Switzerland sets out revised CO2 law plan	Domestic
2022-04-04	New IPCC report	International
2021-10-30	G20 meets in Rome	International
2021-09-26	Bern voters approve constitutional amendment codifying climate neutrality by 2050	Domestic
2021-08-09	IPCC report warns of the rapid degradation of the planet	International
2021-07-14	European Comissions unveils its plan for CO2 reductions (fit-for-55 package)	International
2021-06-04	127 Nobel Prize winners call for climate actions	International
2021-05-31	FINMA specifies transparency obligations for climate risks	Domestic
2021-03-16	Federal Environment Office warns of climate change risks in Switzerland	Domestic
2020-12-11	EU agrees on tougher climate goals for 2030	International
2020-11-07	Election of Joe Biden	International
2020-01-04	A right-wing-Green coalition takes office in Austria	International
2019-10-20	"Green wave" at the Swiss Federal Election	Domestic
2019-10-10	Report finds that climate change could have large costs for Swiss infrastructures	Domestic
2019-09-25	New alarming IPCC report	International
2019-08-16	A plane ticket tax is proposed by a state comission	Domestic
2019-06-22	FDP officially supports the Paris Climate Agreement	Domestic
2017-10-06	Switzerland ratifies the Paris Agreement	Both
2017-05-21	Swiss electorate accepts the revised Federal Energy Act	Domestic

NOTE. This table displays the transition risk events identified using our daily CPR index. The procedure to find these events is as follows. First, we isolate 100 days which feature the largest share of climate policy risk related articles. This step ensures that the underlying event received important media coverage. Second, we read manually all retrieved articles and link each dates to a particular event. The table displays the resulting events which can arguably be interpreted as an increase in the probability of adopting tighter climate policies.

risk leads to a reduction in emissions, both because the economy produces less, and because the remaining production is cleaner.

5.1 Econometric approach

To test the effect of climate policy risk on output, we rely on a monthly VAR with four standard macroeconomic variables (real GDP ($\boldsymbol{RGDP}_t$), an equity price index ($\boldsymbol{EQUITY}_t$), CPI ($\boldsymbol{CPI}_t$) and the policy rate ($\boldsymbol{IR}_t$)) to which we add our CPR index ($\boldsymbol{CPR}_t$) as well as the Economic Policy Uncertainty index from Baker et al. (2016) ($\boldsymbol{EPU}_t$) to ensure that our results are not driven by overall *economic* policy uncertainty. Following Sims et al. (1990), the VAR is estimated in levels. With the exception of $\boldsymbol{CPR}_t, \boldsymbol{EPU}_t$, and $\boldsymbol{IR}_t$, all the other variables enter in log-levels. The VAR is estimated with a constant term. The sample start is 2000M1 and is restricted by the availability of our CPR index. Following the recommendation of Lenza and Primiceri (2020), we do not include the COVID observations and end our sample in 2020M2. Based on the AIC criterion, we consider a baseline with $p = 3$ lags. Defining $\boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{CPR}_t & \boldsymbol{EPU}_t & \boldsymbol{RGDP}_t & \boldsymbol{EQUITY}_t & \boldsymbol{CPI}_t & \boldsymbol{IR}_t \end{bmatrix}'$, the VAR can be written as:

$$\boldsymbol{Y}_t = \boldsymbol{C} + \boldsymbol{\Phi}(L)\boldsymbol{Y}_{t-1} + \boldsymbol{u}_t \tag{5.1}$$

Where $\boldsymbol{C}$ is a constant term and $\boldsymbol{\Phi}(L)$ is the lag matrix in companion form and $\boldsymbol{u}_t$ are the reduced form residuals. We further assume a linear mapping between structural shocks ε_t and the reduced form residuals, as defined by the impact matrix $\boldsymbol{B}$: $\boldsymbol{u}_t = \boldsymbol{B}\varepsilon_t$

Identification of the impact matrix is achieved using a shock-based scheme à la Ludvigson et al. (2021) and narrative restrictions around the transition risk events identified in Table D1 which take place before the end of our sample in 2020M2. For these events, we require that the identified CPR shocks have contributed more than 20 percent to the unexpected increase in the CPR index. In Appendix D, we make sure that the results are not driven by the exact choice of the threshold by considering alternative values, namely 0 and 10 percent. As in Berthold (2023), inference is conducted using an extension of the wild bootstrap procedure from Gonçalves and Kilian (2004). In the bootstrap procedure, we work with K=1 million rotational orthonormal matrices. Confidence intervals are obtained by targeting different percentiles over all selected models. In Appendix E, we provide additional details about the identification strategy and the bootstrapping approach.

Given the lack of existing exogenous proxies for climate policy risk, as well as the lack of clear theoretical restrictions regarding the timing of the shock, we view the flexibility offered by the shock-based identification scheme as being particularly valuable in our setting. This flexibility, however, generally comes at the cost of wider confidence intervals, as for example compared to the more traditional Cholesky identification scheme which we also consider.

5.2 Results

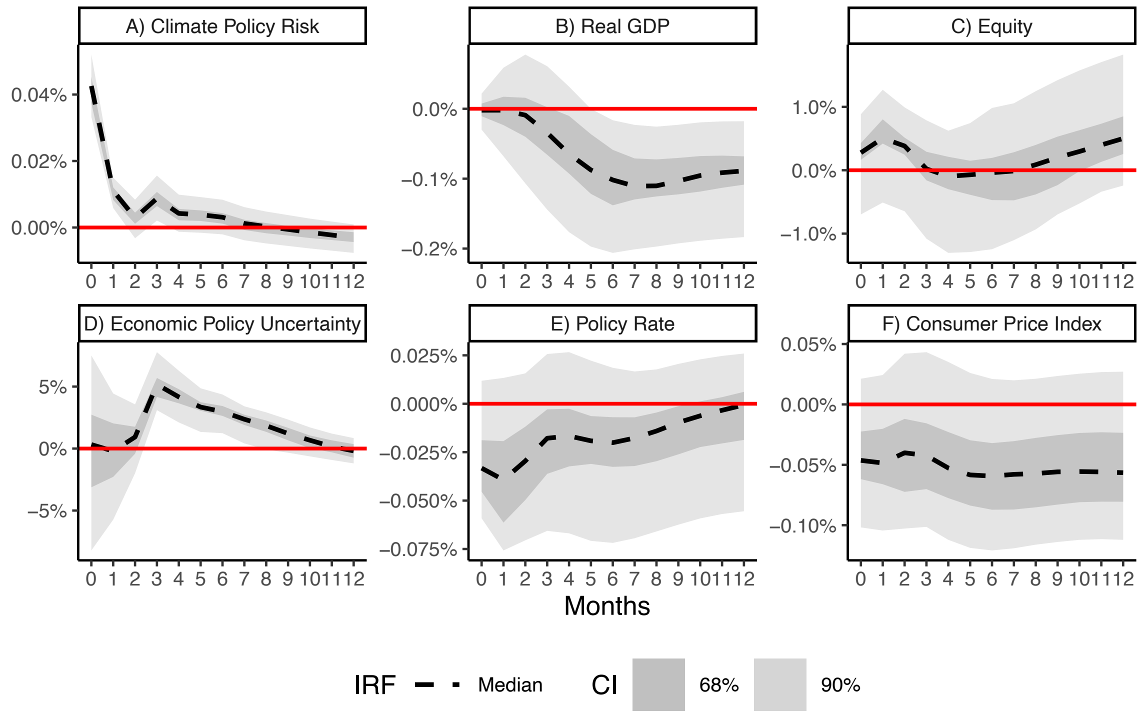
Figure E1 displays the dynamic response of the endogenous variables in the VAR to a narratively identified one standard deviation CPR shock. We find that CPR shocks are associated with a significant negative effect on real GDP, in line with the predictions from Fried et al. (2022). While significant, these responses tend to be quantitatively limited: a one standard deviation shock leads to a decline of around 0.1 percent in real GDP after 6 months. Interestingly, CPR shocks can lead to a significant increase in the EPU around 3 to 4 months after the initial shock, suggesting that climate policy risk can give rise to aggregate economic policy uncertainty. Although the response is insignificant, we find that consumer prices and the policy rate goes down, suggesting that CPR shocks may behave as negative aggregate demand shocks.

In contrast with the theoretical predictions from Fried et al. (2022), we find no significant effect of CPR shocks on equity prices. In Appendix C, we consider "green" and "brown" equity price index but do not find evidence in favor of heterogeneous responses depending on the type of firms (See Figure C5). In our view and as we will argue in Section 6, a potential explanation for this lack of result is that climate-related policy risks have only recently become a major source of concerns for investors (either because policies are becoming more stringent or receive more news coverage), and as such may not have been systematically included in asset prices until recently.

Robustness

We run a number of robustness checks in Appendix C. Figure C1 shows that the negative response of output is not driven by the Great Financial Crisis period, as restricting the sample from 2010M1 to 2020M2 leads to a similar negative response of real GDP. We also consider alternative thresholds for the narrative restrictions (namely 0 and 10 percent) in Figure C2 and find that it has virtually no effect on the median response, but generally lead to wider confidence intervals. Figure C3 re-estimates equation (5.1) using a Cholesky identification scheme ordering the CPR index first. Figure C4 also considers a Cholesky identification scheme but orders the CPR second and the EPU first. In both cases, the effect of CPR on real GDP is negative and even stronger than in our baseline regression at around -0.15 percent. Furthermore, the confidence bands are smaller, which is potentially a byproduct of the stricter identification restrictions imposed in that scheme. Overall, we conclude that the negative response of output to CPR shocks is robust and not driven by the exact sample choice, specification or the identification scheme.

Figure E1 Dynamic Effects of a CPR Shock



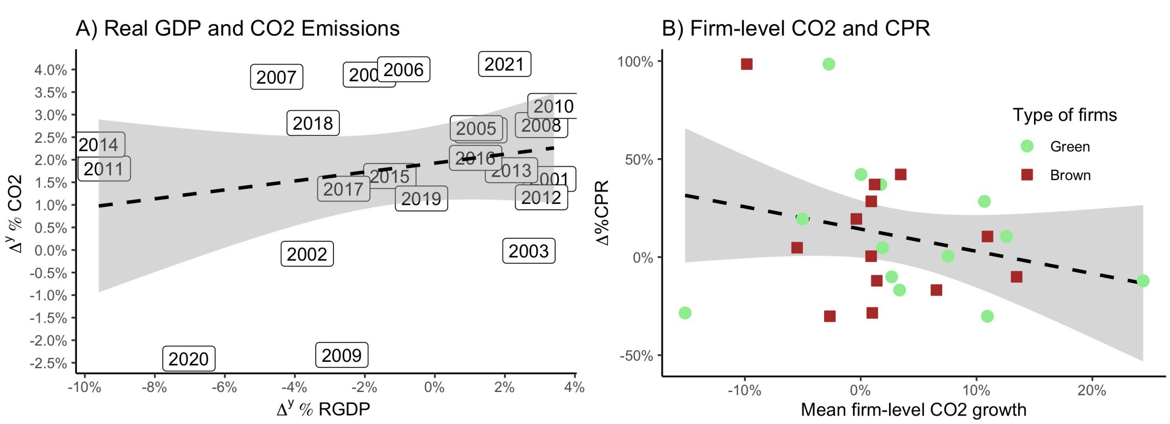
Note. Impulse Response Functions correspond to a one standard-deviation shock to the reduced form residual of the CPR index variable. Shocks are set-identified using narrative restrictions around the transition risk events from Table D1 which take place before the end of our sample in 2020M2. Confidence intervals and median response are obtained using the extension of the wild bootstrap procedure (Appendix E.3). We consider 1,000 bootstrap replications. The policy rate is expressed in percent and the EPU is normalized to have a mean equal to 100. All the other variables are in log-levels.

5.3 Climate Policy Risk and CO2 emissions

Another theoretical prediction from Fried et al. (2022) is that an increase in climate transition risk also reduces emissions today, even before the actual policy is implemented. This result is important because it runs counter to the prediction from the "green paradox" literature (e.g. Sinn (2008)) which argues that higher risk of future climate regulation would drive up current emissions by increasing the incentives to extract fossil fuel. In the VAR specification, we are not able to directly test this prediction because measures of CO2 emissions in Switzerland are only available at the yearly frequency.

However, we propose two types of indirect evidence to better understand the relationship between climate policy risk and CO2 emissions. Panel A) of Figure E2 plots the correlation between yearly growth in GDP and CO2 emissions. As we can see, the relationship is positive. This suggests that the negative response of output following CPR shocks that we find generally coincides with lower CO2 emissions, as predicted in Fried et al. (2022). Panel B) plots the correlation between yearly growth in our climate policy risk index and the subsequent average yearly growth of CO2 emissions at the firm-level. Similarly, we find that a higher CPR is generally associated with lower subsequent CO2 growth. Overall, we interpret this as suggestive evidence that CPR shocks lead to lower CO2 emissions.

Figure E2 FIRM-LEVEL CO2 EMISSIONS AND CPR GROWTH



NOTE. Panel A) of this Figure compares yearly growth in CO2 and RGDP. CO2 data is from OurWorldInData. Panel B) plots the relationship between yearly changes in the CPR index and subsequent (one-year ahead) firm-level average growth in CO2 emissions. Average-firm level growth in CO2 emissions is obtained by averaging across all firms which disclose their CO2 emissions in a given year.

6 The Financial Effects of Climate Policy Risk

In this section, we investigate the asset pricing implications of our CPR index for publicly-listed firms in Switzerland,[4] and investigate whether they are in line with theoretical literature such as Fried et al. (2022) and Pástor et al. (2021). Fried et al. (2022) find than an increase in climate transition risk disproportionately reduces the expected returns of brown capital. In Pástor et al. (2021), green assets can outperform brown ones when concerns about climate change rise unexpectedly. This results from a change in customers' and regulators' preferences for sustainability that leads to a downward revision of expected cash flows of brown firms. We postulate that variations in our CPR index can be interpreted as changes in sustainability preferences. The underlying argument is that, as the CPR index rises, policymakers are more likely to implement regulation that would disproportionately harm brown firms.

6.1 Multivariate Factor Analysis

As in Ardia et al. (2022), we first consider a multivariate panel linear regression to test whether an unexpected increase in our CPR index (denoted as ΔCPR_t) affects heterogeneously green and brown firms. The underlying argument is that, if climate policy risk is priced, the GMB portfolio should rise in value when climate policy risk increases, as green firms are expected to fare better than browner ones. To look at this, we regress the monthly returns of a green minus brown (GMB) portfolio (denoted by r_t^{GMB}) on ΔCPR_t and a set of standard risk factors F_t using OLS:

$$r_t^{GMB} = \alpha + \beta_{CPR} \Delta CPR_t + \Gamma F_t + e_t \tag{6.1}$$

[4]Given that our CPR index also covers domestic developments, we postulate that firms that are headquartered in Switzerland are likely to be the most affected by variations in our index.

Where α is a constant, β_{CPR} and Γ are regression coefficients and e_t is an error term. We define ΔCPR_t as the residual from an autoregressive process on the CPR index. For F_t, we follow standard factor models and consider four main factors, namely size, value, momentum, and the market following Ammann and Steiner (2008) who showed their relevance in the Swiss market. Appendix F provides details about their construction. Our sample covers the period 2000M4 to 2022M11. In light of the results from Fried et al. (2022) and Pástor et al. (2021), we expect β_{CPR} to be positive, that is green stocks outperform brown ones when CPR increases unexpectedly. Intuitively, a positive β_{CPR} means that the GMB portfolio yields higher returns when climate policy risk rises unexpectedly, which implies that it behaves as a hedge. An insignificant β_{CPR} implies that climate policy risk is not priced.

The GMB Portfolio

To build the GMB portfolio, we need to define what is considered as a green firm. In contrast to Engle et al. (2020) who rely on proprietary ESG scores, we decide to rely on CO2 emissions only. This is motivated in part because CO2 data are more easily available, and also because CO2 maps more directly to the definition of green and brown capital considered in Fried et al. (2022). Furthermore, Bolton and Kacperczyk (2021a) and Ardia et al. (2022) also consider firms' CO2 emissions in their analyses. On the other hand, ESG scores have advantages but are also subject to a number of limitations (see e.g. Pagano et al. (2018) for a discussion).

To measure CO2 emissions, we rely on the sum of scope 1 and scope 2 emissions. We consider two definitions of the brown dummy variable. In the first—which we refer to as the *relative* brown dummy–, a firm is defined as brown if its CO2 emissions are above the median within a given sector, and green otherwise. This definition ensures that the distribution of sectors for brown and green firms remains comparable. We refer to the resulting portfolio as the *sector-diversified* GMB portfolio. The second specification, referred to as the *absolute* brown dummy, labels a firm as brown if its CO2 emissions are above the median across all firms. As a result, brown firms are likely to be tilted towards sectors with relatively high emissions. We refer to this portfolio as the *non sector-diversified* GMB portfolio. For each dummy specification, we construct the green (brown) portfolio only considering firms with the brown dummy equal to zero (one). We then rank firms from the highest to the lowest polluting and use this ranking to define the weights of each firm in the green and brown portfolio.[5] As a robustness check, we ensure that the results presented in this paper are robust to an equal weighting scheme. The GMB portfolio is obtained by going long in the green portfolio and shorting the brown one. Letting Z^i_{t-1} be a weight vector and r^i_t the vector of monthly returns for firms of type $i \in \{Green, Brown\}$, we obtain the GMB portfolio according to:

$$r_t^{GMB} = Z^G_{t-1} r^G_t - Z^B_{t-1} r^B_t \tag{6.2}$$

Where $Z^G_{t-1} r^G_t$ and $Z^B_{t-1} r^B_t$ can be interpreted as the (weighted) returns of the green and brown portfolios, respectively.

Results

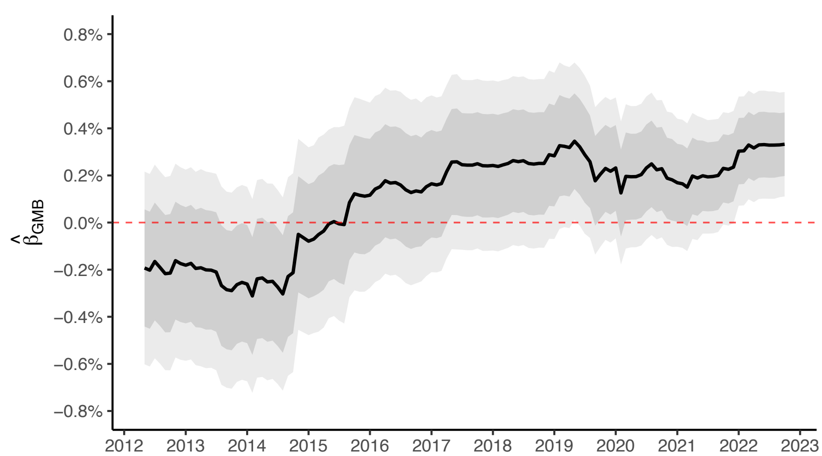
According to our SVAR exercise in Section 5, climate policy risk shocks do not appear to have an heterogenous effect on brown versus green firms over the whole sample, which runs counter to the predictions from Fried et al. (2022) and Pástor et al. (2021). However, a potential explanation is that widely-shared concern about climate change is a relatively recent phenomenon, and that investors may have only recently

[5]In more details: green (brown) firms with the lowest (highest) CO2 emissions get the largest weights in the green (brown) portfolio.

started to systematically incorporate these concerns into asset prices. As a result, our sample spanning the period 2000M1 to 2020M2 may blur some of the more recent developments.

To shed light on the potential time-series property of the relationship between CPR and asset prices, we estimate equation (6.1) using a rolling 10-year window and report the resulting estimated coefficient $\hat{\beta}_{CPR}$ over time, along with its 90th percentile. We report the resulting coefficients and their confidence intervals at the end of each estimation sample, such that a coefficient at a given date is actually estimated with data spanning the previous ten years. Figure F1 reports these coefficients using the sector-diversified specification of the GMB portfolio.

Figure F1 Evidence from Rolling Panel Linear Regressions



Note. This Figure plots the estimated coefficient $\hat{\beta}_{CPR}$ from running a rolling regression of equation (6.1) using the sector diversified specification of the GMB portfolio over a sample covering the 10 previous years. The coefficient in t is thus estimated using a sample covering the period $\{t \text{ minus } 10 \text{ years}, t\}$. The confidence intervals are obtained by adding 1, respectively 1.645 standard error.

As we can see, the estimated coefficient $\hat{\beta}_{CPR}$ is not statistically significant for most of the sample. In other words, the performance of the GMB portfolio is largely independent of the CPR factor. Since 2022, however, the coefficient turns significantly positive. This implies that, when considering data from 2012 (i.e. 10 years before 2022) onwards, we find that a sector-diversified GMB portfolio indeed tends to provide significantly higher returns when climate policy risk rises unexpectedly, in line with predictions from Pástor et al. (2021). This suggests that climate policy risk has only recently started to be systematically incorporated in asset prices in Switzerland.

According to our results, climate policy risk has negative macroeconomics effects and is increasingly reflected in asset prices. In this context, it may be particularly relevant for investors to develop strategies to hedge this type of risk. In Appendix H, we investigate the hedging properties of our two GMB portfolios in real-time (and out-of-sample) following the portfolio mimicking approach from Engle et al. (2020) We find that the sector-diversified GMB portfolio is a good real-time hedge to unexpected increases in our CPR index, while the non sector-diversified GMB portfolio does not offer hedging properties.

Robustness

Figure D1 of Appendix D displays a number of robustness checks of Figure F1. In Panel A), we re-estimate the rolling regressions by defining the brown dummy variable using scope 1 emissions only (instead of the sum of scope 1 and 2 as in the baseline). Similarly, Panel B) defines the brown dummy variable considering scope 2 emissions only. In Panel C), we consider an equal weighting scheme (rather than CO2-based weights as in the baseline). Results turn out to be remarkably robust to these three choices. In Panel D), we re-run equation (6.1) but considering the non-sector diversified GMB portfolio returns as the dependent variable. According to the results, the coefficient in the more recent period is not statistically different than zero. This suggests that the sector-diversified GMB portfolio provides stronger hedging properties to CPR shocks than the non sector-diversified portfolio. We confirm this in Appendix H. Taken at face value, this could suggest that investors care in priority about within-sector CO2 emissions, rather than absolute CO2 emissions (irrespective of the sector). We leave a more careful investigation of this question for future research.

6.2 Event-study approach

To complement our previous results, we adopt an event-study approach combined with local projections to investigate the dynamics of brown versus green firms around the transition risk events displayed in Table D1. These events appear particularly suited because they can arguably be interpreted as an increase in the probability of adopting stricter climate policies, which maps directly with the definition of climate policy transition risk considered in Fried et al. (2022).

Econometric approach:

We follow an approach similar to Ottonello and Winberry (2020) and use Jordà (2005)-type local projection methods. Let $p_{i,t}$ be the log equity price of firm i in t and $\Delta p_{i,t+h} = p_{i,t+h} - p_{i,t-1}$ be the percentage price change at horizon $t + h$ (in days or months depending on the specification) relative to the price in $t - 1$. We further define $I\{Event\}_t$ as a dummy taking the value 1 when a transition risk event from Table D1 takes place. Consistent with the sector-diversified specification of the GMB portfolio, we define $Brown_{i,t}$ as a within-sector brown dummy that takes the value 1 if a firm's CO2 emissions are above the median within a given sector. Finally, let $X_{i,t}$ be a vector of firm-level controls (sales growth, total assets, price-to-book value, and debt-to-assets). We estimate the following local projection regression for $h = 1, ..., 12$:

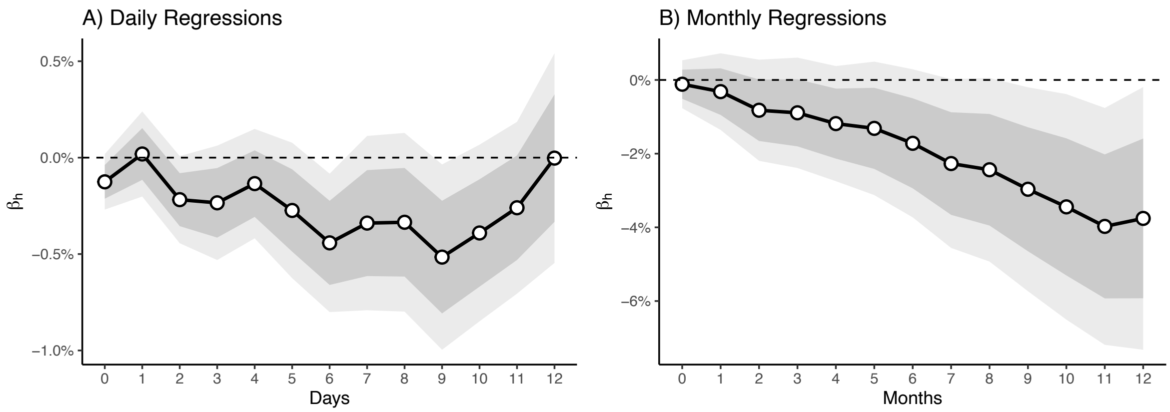
$$\Delta p_{i,t+h} = \alpha_i + \alpha_{h,s} + \beta_h(I\{\text{Event}\}_t \times Brown_{i,t}) + \Gamma X_{i,t} + u_{i,t+h} \tag{6.3}$$

On top of firm-level controls $X_{i,t}$, we control for firm fixed-effect (α_i) to capture permanent differences across firms. We further add a double interacted fixed-effect ($\alpha_{h,s}$ with horizon (h) and sector (s)) to control for any sectoral characteristics that may affect the firm price response over time. The coefficient of interest β_h captures the differing response in the variation of stock price at horizon h between a brown and a green firm in a given sector. A negative β_h indicates that brown firms see their stock prices react more negatively (either increase less or decrease more) than their greener counterparts, following a transition risk event.

Results

Figure F2 plots the results. 68 and 90% confidence bands are obtained by conservatively clustering standard errors two-ways (firm and event date level). Panel A) depicts the differing behaviour of brown versus green firms following a transition risk event at the daily frequency. As we can see, the coefficient is negative and statistically significant at the 90% confidence interval around 6 days after the event. Quantitatively, the drop in stock price is around 0.5% larger for brown firms 6 days after the event. Panel B) plots the same regression but at the monthly frequency. As we can see, the negative coefficient at the 12-month horizon suggests that the stock price of brown firms tend to react more negatively than greener firms, and that this effect is persistent. Quantitatively, a brown firm sees its stock price decrease by roughly 3-4% more 12 months after the event. Overall, the results confirm the relevance of transition risk for the dynamics of stock prices, both in the short and longer run and are in line with Fried et al. (2022) and Pástor et al. (2021).

Figure F2 EVENT STUDY : TRANSITION RISK EVENTS



NOTE. This Figure plots the coefficient β_h from equation (6.3) for $h = 1, ..., 12$. Panel A) estimates the equation using daily stock prices, while Panel B) uses monthly stock prices. Standard errors are clustered two-ways at the date and firm level. Confidence bands display the 68 and 90% intervals, respectively.

Robustness

Figure D2 in Appendix D displays a number of robustness checks. In particular, we re-run the regressions only considering *domestic* transition risk events. We also run robustness checks using only scope 1 or scope 2 to define the brown dummy variable (instead of the sum of scope 1 and 2 as in the baseline). In Figure D3, we also consider the absolute brown dummy specification (instead of the relative brown dummy specification as in the baseline). Results turn out to be robust to these different choices.

7 Conclusion

This paper develops a new index of climate policy risk and leverages on narratively-identified transition risk events to identify and quantify the macroeconomic and financial effects of climate policy risk. At the macroeconomic level, we find that CPR shocks lead to a significant drop in output and are associated with lower firm-level emissions. Using firm-level equity price data, we document that a sector-balanced portfolio that goes long (short) in firms with low (high) within-sector CO2 emissions is an increasingly good hedge to unexpected increases in climate policy risks. We further show the relevance of transition risk events for the dynamics of asset prices using an event-study approach combined with Jordà (2005)-type local projections.

Overall, our results highlight the (increasing) macro-financial importance of climate policy risk, and are in line with theoretical contributions such as Fried et al. (2022) and Pástor et al. (2021). We see work on empirically documenting the macroeconomic channels of adjustment to transition risk as being fruitful venues for future research.

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Appendix to Chapter 3

A Keywords CPR index

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

- **Climate:** *climat**, CO2, greenhouse gas, renewable energy, global warming*

- **Policy:** *Bern, government, parliament, law, regulation, federal, politic**

- **Risk:** *risk, uncertain*, doubt, unforeseen, unpredictable, unstable, unclear, unsafe, unknown*

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

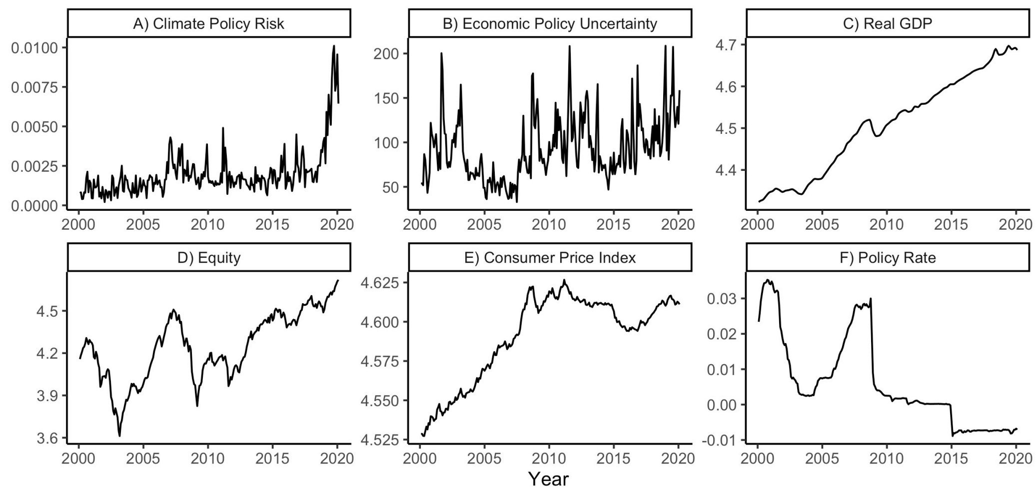
B Data Appendix

Table B1 NUMBER OF ARTICLES BY MEDIA OUTLETS

Media	Language	N. Articles
Blick	DE	427,359
NZZ	DE	940,309
Tages Anzeiger	DE	830,819
20 Minuten	DE	420,133
Tribune de Genève	FR	482,228
Le Matin	FR	285,097
Le Temps	FR	364,064
20 Minutes	FR	8,692
Total		3,758,701

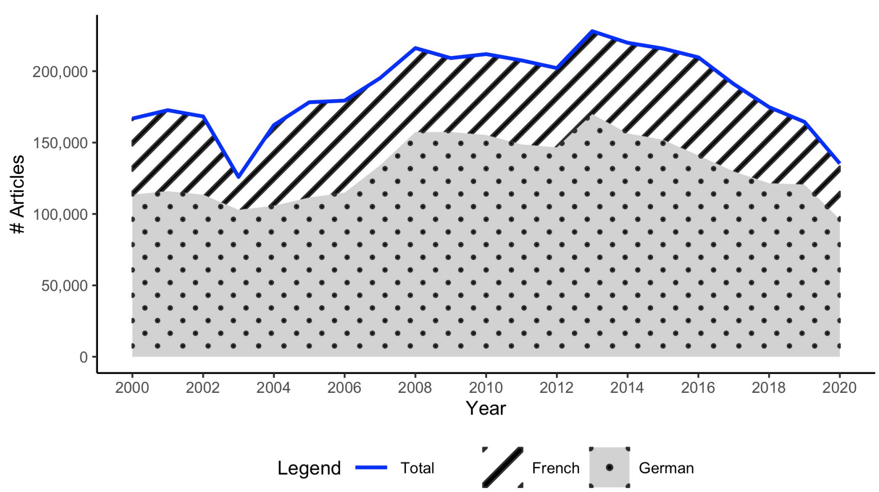
NOTE: This table displays the total number of articles per media outlet. The share of articles in German is 69.7% (30.3% in French).

Figure B1 MACROECONOMIC DATA



NOTE. This Figure plots the macroeconomic data from the VAR. The EPU index is obtained from https://www.policyuncertainty.com. Section 4 details the construction of the Climate Policy Risk index. The source for the other variables is Datastream.

Figure B2 NUMBER OF ARTICLES OVER TIME (BY LANGUAGE)



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

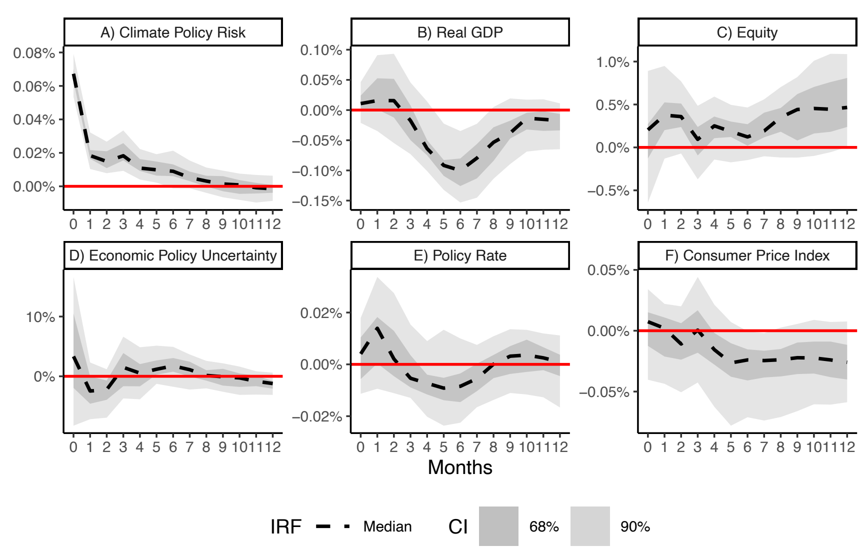
Table B2 SUMMARY STATISTICS FOR CH PUBLIC FIRM DATA

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

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

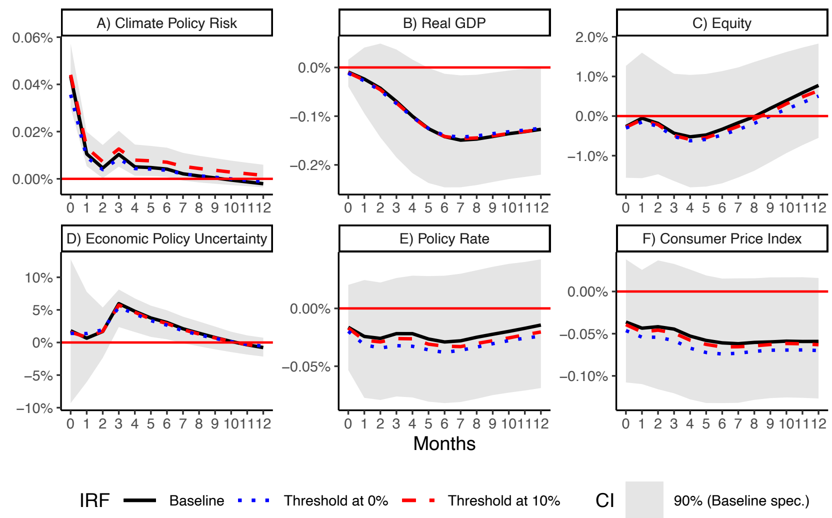
C Macroeconomic Evidence : Robustness

Figure C1 ROBUSTNESS IRF : EXCLUDING GFC



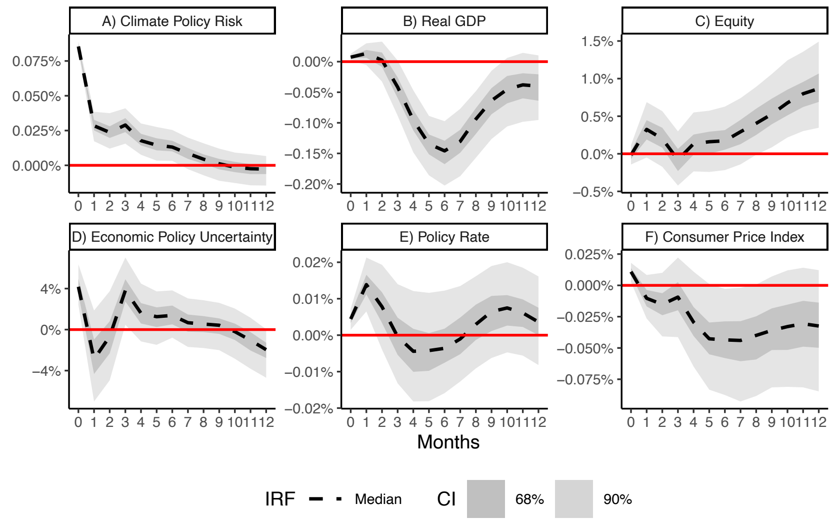
NOTE. This Figure re-estimates the IRFs to a one standard-deviation CPR shock excluding the Great Financial Crisis period and using 2010M1-2020M2 as the sample period. Shocks are set-identified using narrative restrictions around the transition risk events from Table D1 which take place before the end of our sample in 2020M2 and after 2010M1.

Figure C2 Robustness IRF : Alternative Thresholds Narrative Restrictions



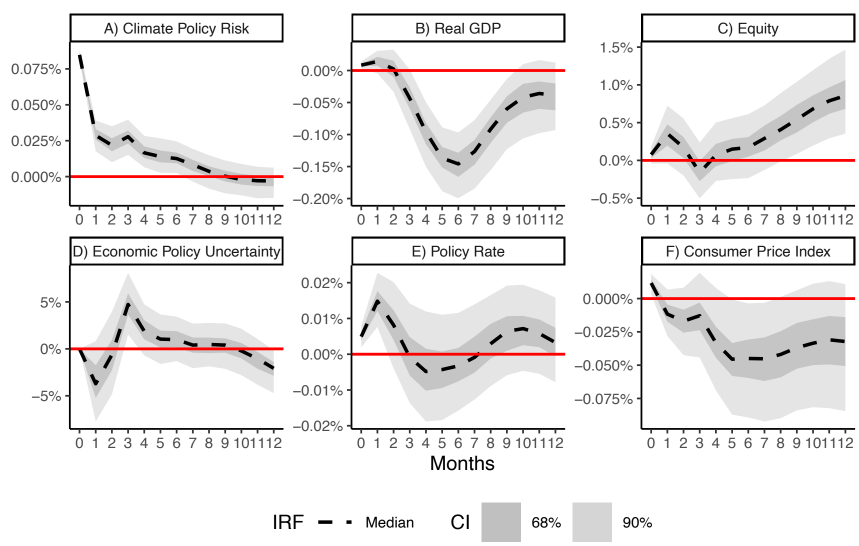
Note. This Figure re-estimates the IRFs to a one standard-deviation CPR shock by considering alternative threshold values for the historical contribution restrictions. In particular, we restrict the CPR shocks to have contributed more than 0%, respectively 10% to the unexpected variation in the CPR variable around the transition risk events from Table D1 (as compared to 20% in the baseline).

Figure C3 ROBUSTNESS IRF : CHOLESKY I



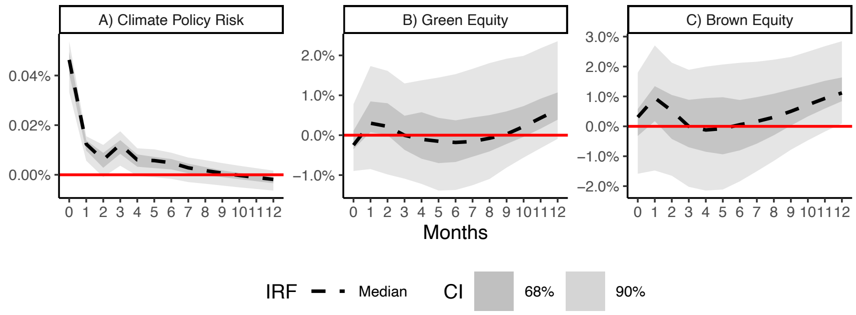
NOTE. This Figure re-estimates the IRFs to a one standard-deviation CPR shock using a Cholesky identification scheme instead of the shock-based approach. The CPR index is ordered first. The sample period is 2000M1 to 2020M2.

Figure C4 ROBUSTNESS IRF : CHOLESKY II



NOTE. This Figure re-estimates the IRFs to a one standard-deviation CPR shock using a Cholesky identification scheme instead of the shock-based approach. The CPR index is ordered second after the EPU index from Baker et al. (2016). The sample period is 2000M1 to 2020M2.

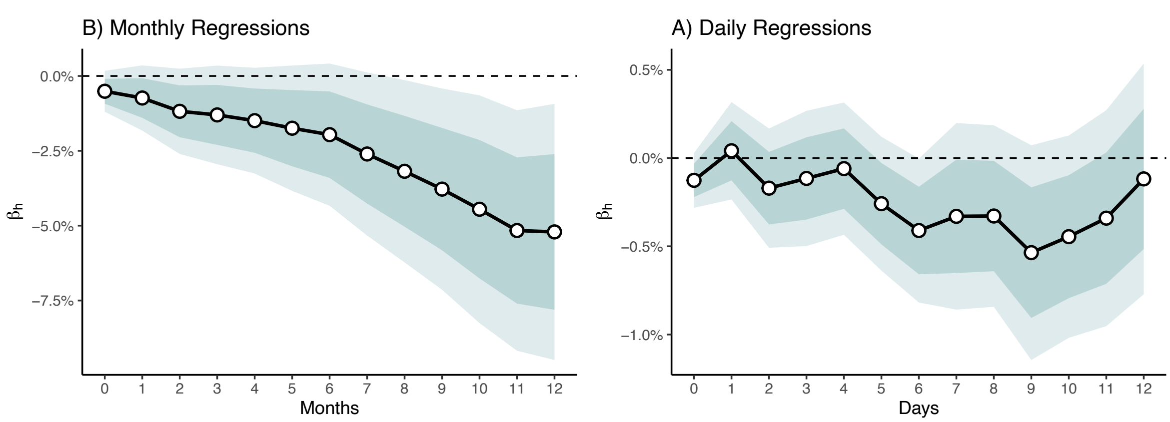
Figure C5 ROBUSTNESS IRF : GREEN VS BROWN EQUITY INDICES)



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

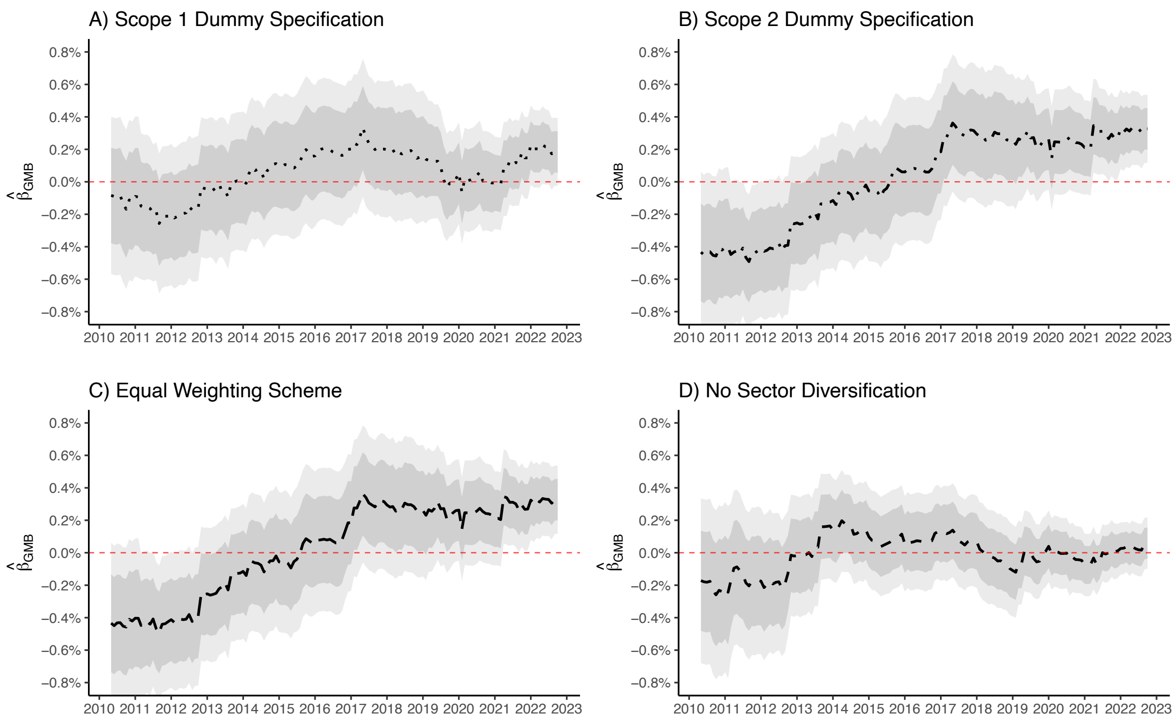
D Financial Evidence : Robustness

Figure D3 ROBUSTNESS EVENT-STUDY : DUMMY ACROSS ALL SECTORS



NOTE. This Figure re-estimates equation (6.3) $h = 1, ..., 12$ and plots the estimated coefficient β_h using the absolute specification of the brown dummy (instead of the relative specification as in the baseline). Panel A) estimates the equation using daily stock prices, while Panel B) uses monthly stock prices. Standard errors are clustered two-ways at the date and firm level. Confidence bands display the 68 and 90% intervals, respectively.

Figure D1 ROBUSTNESS CHECKS : TIME-SERIES PROPERTIES



NOTE. This Figure plots four different robustness check s regarding the time-series properties of the GMB portfolio. In Panel A), we estimate the regression (6.1) using a trailing 10-year sample window defining the brown dummy by relying on scope 1 (direct) CO2 emissions only (rather than the sum of scope 1 and 2 as in the baseline). Panel B) estimates the same regression but uses scope 2 (indirect) CO2 emissions to define the brown dummy. Panel C) uses an equal weighting scheme to build the GMB portfolio (rather than one based on CO2 emissions as in the baseline). Panel D) uses the absolute dummy specification (rather than the relative dummy specification as in the baseline).

E Identification strategy

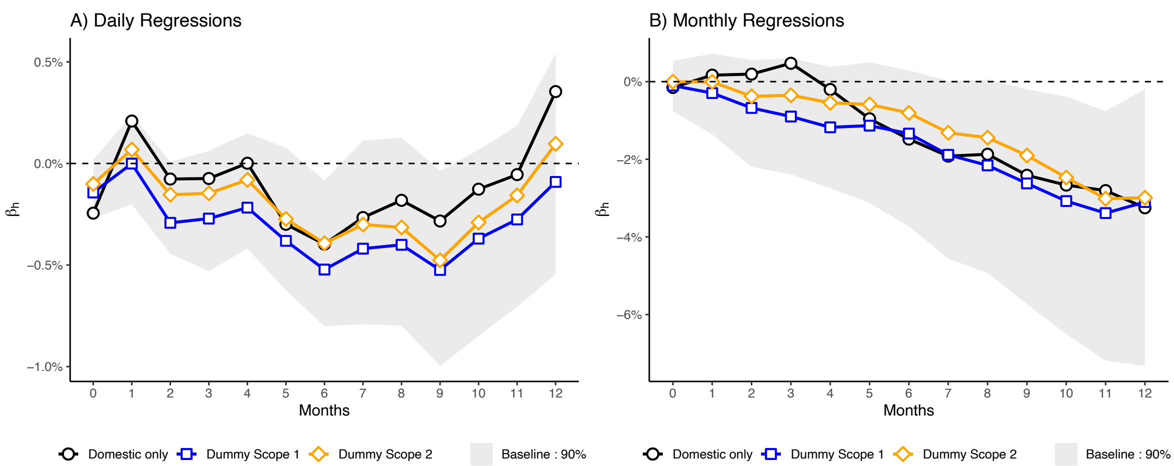
E.1 Shock-based identification scheme

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

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

Where $\boldsymbol{B}$ is the $n \times n$ impact matrix that governs the dynamic effect of structural shocks $\boldsymbol{\varepsilon}_t$ on the endogenous variables. $\boldsymbol{\Phi}(L)$ is the lag matrix in companion form. Note that we dropped the constant/trend term for notational convenience. We fur-

Figure D2 Robustness Event-Study : Daily Monthly Regressions



Note. This Figure re-estimates equation (6.3) $h = 1, ..., 12$ and plots the estimated coefficient β_h using different specifications of the brown dummy ($Brown_{i,t}$)) and the transition risk events. In particular, we consider a dummy using only scope 1, only scope 2. We also consider a case where we only rely on domestic transition risk events (rather than both domestic and international events as in the baseline). Panel A) estimates the equation using daily stock prices, while Panel B) uses monthly stock prices.

ther assume a linear mapping between the structural shocks and the reduced form residuals $\boldsymbol{u_t}$ $(n \times 1)$:

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

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

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

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

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

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

In this paper, we consider a "shock-based" identification scheme à la Ludvigson et al. (2021). Rather than imposing restrictions on the impact matrix as is common, the idea is to restrict *structural shocks* to behave in a certain way during some carefully selected economic events. In practice, we draw K (a large number) of $\boldsymbol{Q}$ matrices and recover structural shocks according to (E.3), and check that they fulfil our set of restrictions.[6] In our bootstrap replications, we work with $K = 1$ million. We collect each of these matrices in a set that we denote by $\mathcal{B} = \{\boldsymbol{B} = \boldsymbol{CQ}, \boldsymbol{Q} \in \mathcal{O}_n, diag(\boldsymbol{B}) \geq 0, \boldsymbol{BB}' = \boldsymbol{\Sigma_{uu}}\}$ where $\mathcal{O}_n$ is the set of $n \times n$ random orthonormal matrices. The restriction $diag(\boldsymbol{B})$ is for convenience and ensures that a positive structural shock implies an increase in the variable of interest. We refer to $\mathcal{B}$ as the "unconstrained set". For each K elements of the set $\mathcal{B}$, we can retrieve the related structural shocks $\boldsymbol{\varepsilon}_t$ using $\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t$. We denote the set of unconstrained structural shocks $\mathcal{E} = \{\boldsymbol{\varepsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t, \boldsymbol{B} \in \mathcal{B}\}$. Note that, for notational convenience, the dependence of $\boldsymbol{B}$ and $\boldsymbol{\varepsilon}_t$ on the draw k is dropped, but we keep in mind that they correspond to a particular draw $k \in \{1, ..., K\}$. Identification is then achieved by only keeping models (defined by a particular draw of the $\boldsymbol{B}$ matrix) which satisfy our narrative restrictions. Obviously, if the restrictions are too strict or incompatible with the data, the constrained set (denoted by $\tilde{\mathcal{B}}$) is empty. On the other hand, if restrictions are too lax, the unconstrained set is very similar to the constrained one and thus does not provide any identification gains.

E.2 Empirical restrictions

In this paper, we consider "historical contribution" restrictions around the transition risk events from Table D1 that take place before the end of our sample in 2020M2. Historical contribution restrictions are defined as restrictions on the share of the unexplained variation in a given variable that can be explained by a certain variable. Formally, we define the absolute contribution of the structural shocks at time t from a given draw (k) as follows:

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

Where $\odot$ is the Hadamard (or element-wise) product. The i, j-th element of $\boldsymbol{C}_t$ is the (absolute) effect at time t of the i-th structural shock on the j-th variable contained in $\boldsymbol{Y}_t$. It should be noted that the sum of each column j is equal to the reduced form

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

residual $u_{j,t}$. To get a sense of the relative importance of each structural shock i in the overal unexplained variation of variable j, we can normalise $\boldsymbol{C}_t$ by the respective reduced form residuals. We define the resulting matrix as:

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

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

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

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

E.3 Inference : extending the wild bootstrap procedure

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

F Risk-Factors for Switzerland

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

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

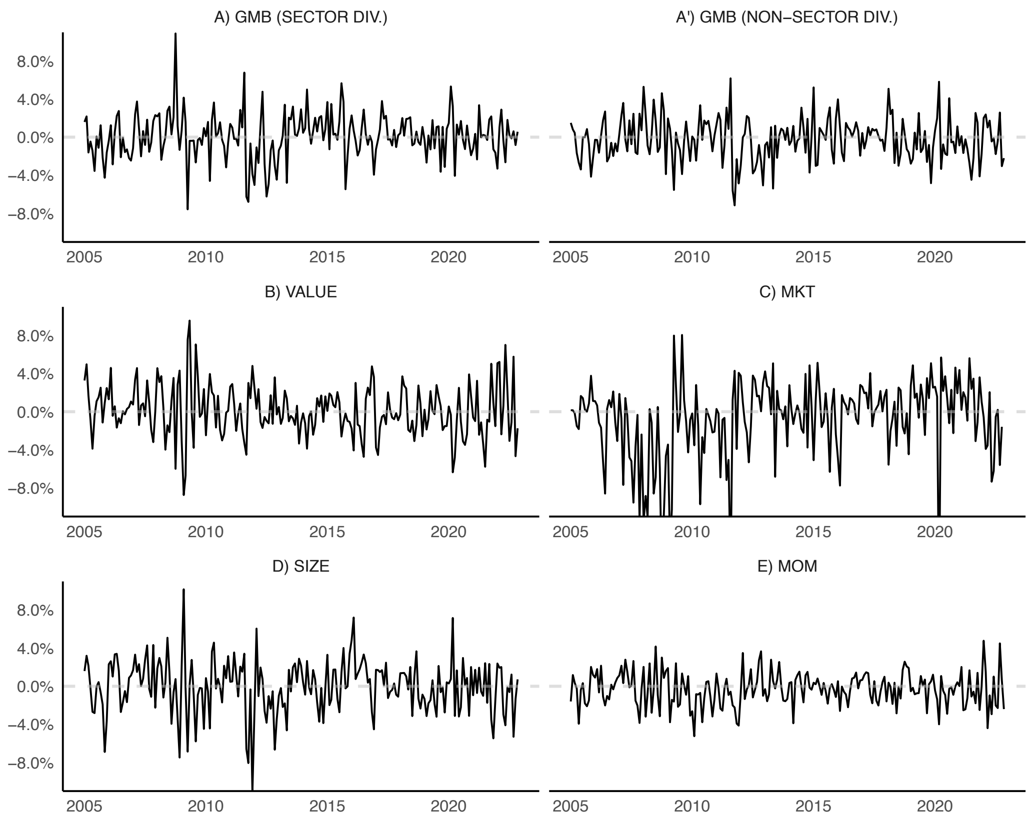
Where $R_{i,t}$ is the monthly (end-of-period) return of stock i and $R_{f,t}$ is the risk-free rate, and $RMRF_t$, SMB_t, HML_t and UMD_t are the excess returns from, respectively, the market portfolio, the small-minus-big portfolio (size factor), the high-minus-low portfolio (value factor), and the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

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

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

Intuitively, the SMB portfolio can be interpreted as a portfolio going long, while controlling for market, value, and momentum effects. The HML and UMD portfolios can be interpreted similarly. The resulting four risk factors as well as the returns from the two specification of the GMB portfolios (sector diversified and non sector diversified) are displayed in Figure F1.

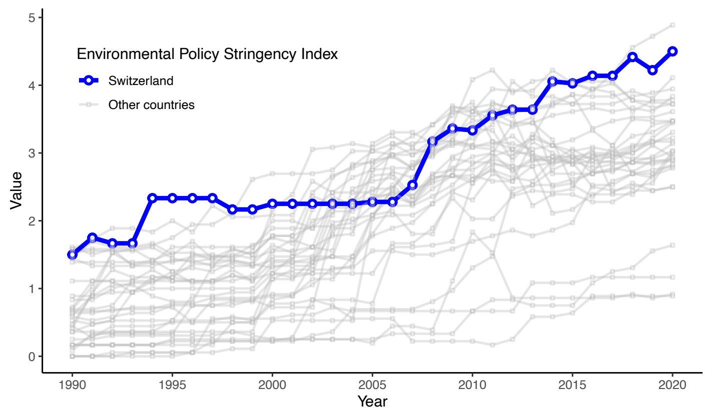
Figure F1 RISK FACTORS



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

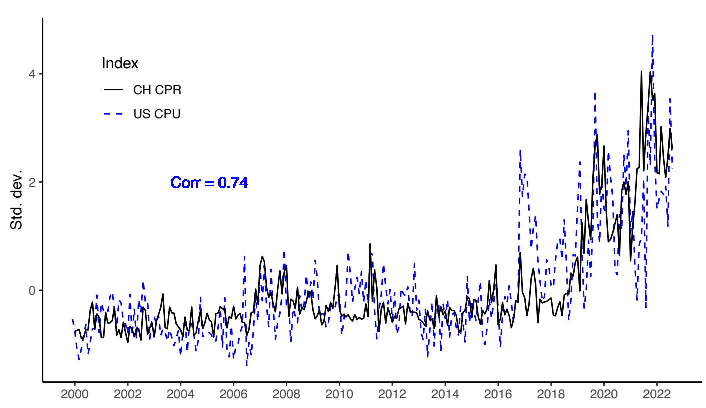
G Additional results

Figure G1 Environmental Policy Stringency Index



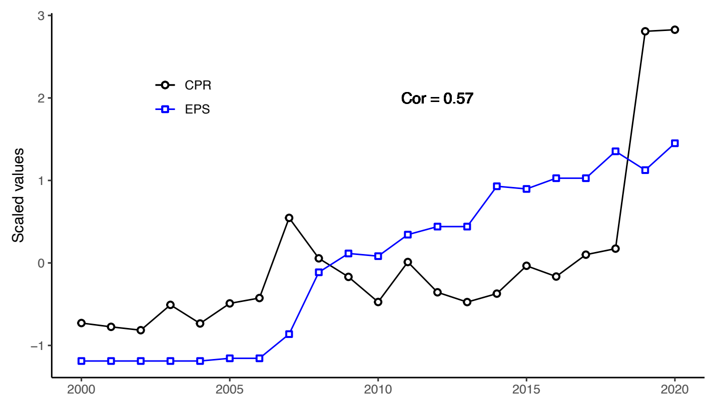
Note. This Figure displays the Environmental Policy Stringency Index from the OECD for all countries for which the index is available. The blue line depicts this index for Switzerland. According to this measure, Switzerland is the second best performing country in 2021.

Figure G2 CH Climate Policy Risk vs US Climate Policy Uncertainty



Note. This Figure compares the CH Climate Policy Risk from this paper to the US Climate Policy Uncertainty Index from Gavriilidis (2021).

Figure G3 COMPARISON EPS VS CPR



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

H Hedging Climate Policy Risk in Real Time

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

H.1 Portfolio-Mimicking Approach : Theory

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

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

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

The vector β_{CPR} $(n \times 1)$ is the risk exposure to the CPR factor, and β_F $(n \times p)$ denotes the risk exposures to the other p risk factors. γ_{CPR} and γ_F denote the risk-premium associated with the CPR factor and the other p risk factors, respectively. The objective is to construct a hedge portfolio, that is a portfolio with unit exposure to the CPR factor ($\beta_{CPR} = 1$) but no exposure to the other p risk factors. This ensures that investors can change their exposure to climate risk by trading in this portfolio, without modifying their exposure to the other risk factors. We refer interchangeably to the CPR factor as the "hedge target". Empirically, ΔCPR_t is estimated by taking the residual of an auto-regressive process on the Climate Policy Risk index displayed in Figure D1.

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

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

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

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

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

such that equation (H.2) becomes:

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

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

H.2 Constructing the Hedge Portfolios

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

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

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

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

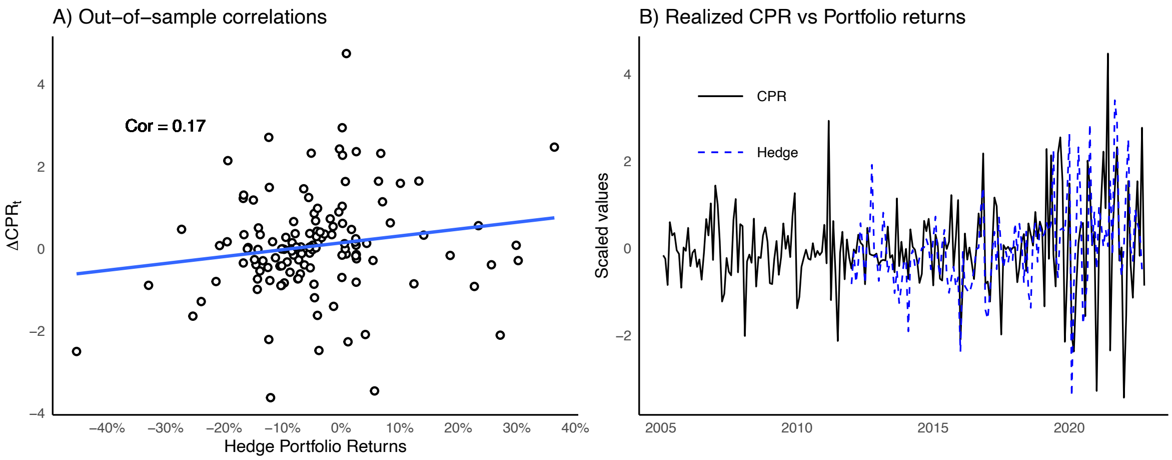
where $w_{GMB}, w_{SIZE}, w_{HML}, w_{MOM}, w_{MKT}$ are scalars that capture the weight of the corresponding portfolios in the mimicking (hedge) portfolio for ΔCPR_t.

H.3 Hedging CPR Risk in Real Time

To test the real-time hedging properties of the mimicking hedge portfolio, we follow Engle et al. (2020): at time t, we use data from t_{min} up to $t-1$ to estimate equation (H.5) and retrieve the optimal weights of each portfolio. We then compute the return of this portfolio in t and compare it with the actual realization of the Climate Policy Risk factor. In practice, we consider t_{min} =2005M1 to have sufficient data to estimate the model and report out-of-sample results starting from 2012M1. First, we consider using the sector diversified GMB portfolio. Panel A) of Figure H1 plots the correlations between realized ΔCPR_t values and the return of the GMB portfolio. The correlation is significant at around 17%, which is comparable to the performance of the hedge portfolio considered in Engle et al. (2020). Panel B) proposes a graphical representation of the real-time hedging exercise by comparing the realized ΔCPR_t with the actual portfolio returns. In summary, the sector-diversified GMB portfolio performs remarkably well in hedging Climate Policy Risk out-of-sample.

As mentioned, the GMB portfolio is defined in order to ensure sector diversification (i.e. 50% of firms within each sector are labelled as green while the rest is brown). How important is that type of diversification? To answer this question, we consider the non sector-diversified portfolio and re-runs our real time hedging exercise. Figure H2 plots the out-of-sample results from this approach. Clearly, this non-diversified GMB portfolio does not provide any hedging, as can be seen from the negative out-of-sample correlation of 4%. This highlights the importance of diversification when constructing hedge portfolios, and suggest that a within-sector approach may be more effective when trying to hedge climate-related risks. While we do not see our sector-diversified GMB portfolio as the ultimate hedge and acknowledge the limitations of

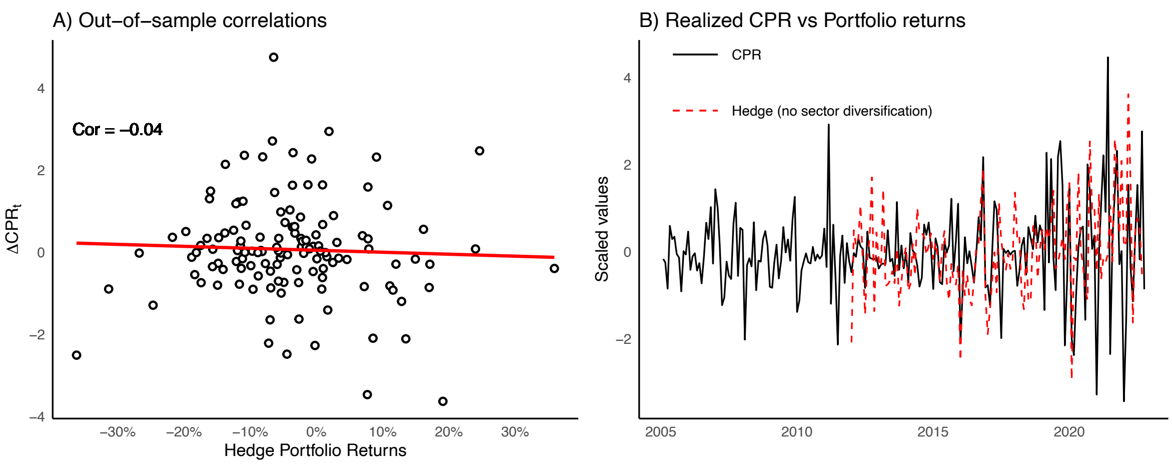
Figure H1 Out-of-sample : Sector-Diversified Portfolio portfolio



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

our measure of Climate Policy Risk, we interpret our results as suggesting that a CO2-based portfolio is a sensible starting point to hedge such risks.

Figure H2 OUT-OF-SAMPLE : NO DIVERSIFICATION OF SECTORS



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

CHAPTER 4

FOREIGN EXCHANGE INTERVENTIONS WITH UIP AND CIP DEVIATIONS IN SAFE HAVEN ECONOMIES

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Abstract

We examine the opportunity cost of foreign exchange (FX) intervention when both CIP and UIP deviations are present. We consider a small open economy that receives international capital flows through constrained international financial intermediaries. Deviations from CIP come from limited arbitrage or through a convenience yield, while UIP deviations are also affected by risk. We show that the sign of CIP and UIP deviations may differ for safe haven countries. We find that there may be a benefit, rather than a cost, of FX reserves if international intermediaries value more the safe haven properties of a currency that domestic households. We show that this has been the case for the Swiss franc and the Japanese Yen. We examine the optimal policy of a constrained central bank planner in this context.

Keywords: Foreign Exchange Interventions, UIP, CIP, Safe-Haven, Financial Intermediaries, Foreign Reserves

JEL: F31, F41, E58

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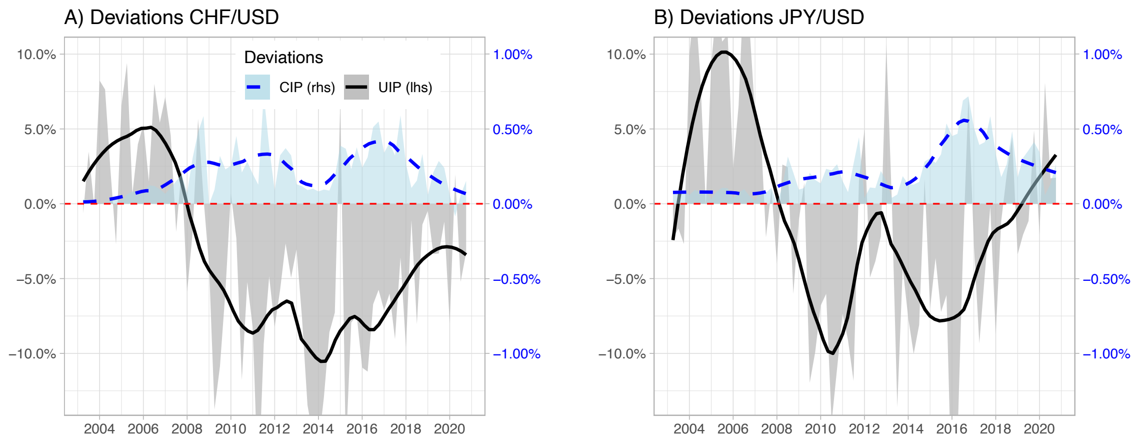
1 Introduction

A vast literature examines the optimal level of central bank international reserves in emerging markets (see Bianchi and Lorenzoni (2022) for a recent survey). A recurrent feature is that the accumulation of reserves bears an opportunity cost from an interest rate differential implied by an upward supply of international funding. In the recent literature on optimal Foreign Exchange (FX) interventions, some authors focus on Uncovered Interest Rate Parity (UIP) wedges (see Basu et al., 2020; Maggiori, 2021; Itskhoki and Mukhin, 2022). In contrast, other researcher argue that what matters are deviations from Covered Interest Rate Parity (CIP) (e.g., Amador et al., 2020; Fanelli and Straub, 2021). This distinction between CIP and UIP appears particularly relevant for safe haven countries, since CIP and UIP deviations may be of different signs. Figure 1.1 shows CIP and UIP deviations for Switzerland and Japan.[1] They are computed from the perspective of international investors and UIP deviations are estimated using survey expectation data. They show that since 2008, both countries have experienced positive CIP deviations and negative UIP deviations. The latter implies a negative excess return, which is typical of safe haven currencies.

To clarify these issues, we develop a model where both CIP and UIP deviations are present. We consider a small open economy that receives international capital flows through international financial intermediaries as in Gabaix and Maggiori (2015). The structure of the model is similar to those in recent papers examining the role of international reserves (see Cavallino, 2019; Amador et al., 2020; Fanelli and Straub, 2021; Basu et al., 2020; Maggiori, 2021), but financial intermediaries are risk averse. **?** propose a related framework in a two-country model, but do not analyze FX inter-

[1] See Appendix A for data description. Interestingly, Rime et al. (2022) show that CIP deviations for the CHF and the JPY with respect to the USD have been the most profitable for financial institutions.

Figure 1.1 UIP and CIP Deviations



Notes: This figure shows the UIP and CIP deviations in percentage points as defined in (2.4) and (2.3), taking the USD as the foreign currency and considering a 3-month horizon. Panel A) and B) consider the CHF and the JPY as the domestic currencies. UIP deviations are computed using monthly data from Datastream for the 3-month Libor rates and from Consensus Economics for the exchange rate forecasts and the spot exchange rates. The CIP deviations are monthly averages of daily observations and are computed using 3-month Libor rates, spot exchange rates and forward rates with a 3-month maturity from Datastream. All returns are annualised.

ventions. The international financial intermediaries are the marginal investors and determine both UIP and CIP deviations through their unhedged and hedged portfolio choices. These deviations typically do not coincide and may even be of different sign.

In this environment, we examine the opportunity costs of FX intervention in terms of welfare. We identify the conditions under which CIP or UIP deviations matter for this cost. We find that there may be no opportunity cost, or even a benefit, of FX intervention in a safe haven country, even if it faces a negative CIP deviation. We examine the implications for optimal FX intervention in these cases.

The presence of systematic deviations from CIP in the wake of the Global Financial Crisis is a major development in international finance (see Du and Schreger (2022) or **?** for recent surveys). The theoretical literature has provided explanations for CIP deviations, but has devoted limited attention to the link between CIP and UIP deviation. Several papers analyzing interest rate differentials assume complete markets so that either there is no UIP deviations or CIP deviations are equal to UIP deviations. This is not consistent with the data.

The recent literature has followed two main approaches to explain interest rate differentials. First, there may be financial frictions that limit arbitrage, e.g., by assuming constrained financial intermediaries. The other approach is to assume differences in convenience yields. The two approaches are present in our model and determine deviations from CIP. But we do not assume complete markets, so that UIP deviations differ from CIP deviations. A basic result from this analysis is the following relationship between UIP and CIP deviations:

$$devUIP_t = devCIP_t - \frac{cov_t(m^*_{t+1}, X^*_{t+1})}{E_t m^*_{t+1}} \tag{1.1}$$

where m^*_{t+1} is the stochastic discount factor (SDF) of financial intermediaries and X^*_{t+1} is the foreign currency excess return from the international intermediary perspective. If the small open economy is a safe haven country, we have $cov_t(m^*_{t+1}, X^*_{t+1}) > 0$, i.e., the safe haven currency yields a higher return in bad times. Therefore, it is possible to have a positive CIP deviation with a negative UIP deviation.

We derive equation (1.1) in a simple two-period small economy model with two assumptions that differ from most of the literature. First, international financial intermediaries face exchange rate risk. This risk could be hedged on the forward market, but it is not optimal to fully hedge a safe haven currency. The other assumption is that the financial constraint applies to the whole foreign exchange investment of financial intermediaries, whether it is hedged or not.[2]

We analyze the welfare cost of accumulating international reserves in this framework.

[2] In contrast, in Itskhoki and Mukhin (2021), intermediation frictions generate UIP deviation without CIP deviations. This is because the intermediation frictions originate in the intermediaries' risk aversion.

We show that if domestic households attribute less value to the safe haven properties of their currency than international financial intermediaries (i.e., the domestic SDF is less correlated to the excess return than for financial intermediaries), then FX reserves may have a benefit, not a cost. We examine this issue empirically by estimating the SDF of financial intermediaries following He et al. (2017). When considering the CHF and JPY with respect to the USD, we find that it is indeed the case that the SDF of financial intermediaries is more correlated with excess returns than the SDF of domestic households.

We examine the implications of this analysis for optimal FX intervention, by modeling the central bank as a constrained planner. We determine the various factors influencing optimal policy decisions, focusing on various types of FX interventions. We show that the central bank incentives are similar for sterilized interventions and unsterilized interventions at the Zero Lower Bound (ZLB).

For a more specific analysis, we consider a linearized version of the model where the distribution of shocks is such that the domestic currency is perceived as a safe haven by international investors. This allows us to derive precise expressions for the cost of FX intervention and CIP and UIP deviations and examine the impact of various parameters on these variables and on optimal FX inetrventions. For example, an increase in global risk leads to more beneficial FX interventions, larger positive CIP deviations and larger negative UIP deviations.

This paper complements the literature on the opportunity cost of FX reserves. There is a long tradition of estimating the cost and benefits of accumulating FX reserves (e.g., Jeanne and Rancière, 2011). Adler and Mano (2021) estimate the quasi-fiscal cost of interventions for 73 countries using UIP deviations. Using survey expectations or assuming a random walk for the nominal exchange rate, they find that the ex ante cost of intervention is negative for Japan and Switzerland in the period 2002-2013, while it is positive for most other countries.[3] In this paper, we examine the welfare cost of intervention. We find that it is also negative for Japan and Switzerland.

By focusing on countries like Switzerland or Japan, this paper provides a different perspective on safe haven economies. A growing literature has been analyzing the special role of the US dollar as a reserve currency. In particular, several papers have focused on the role of convenience yields in generating currency movements and expected excess returns (e.g., Jiang et al., 2021b,a; Valchev, 2020; Kekre and Lenel, 2021; Bianchi et al., 2022). We show that convenience yields are not the sole determinant for exchange rate movements and UIP deviations in safe haven economies.

The rest of the paper is organized as follows. Section 2 describes the model and the decentralized equilibrium. Section 3 analyzes the opportunity cost of reserves in this context. Section 4 discusses optimal FX intervention and Section 5 proposes linearized model of a safe haven country. Section 6 concludes.

2 The Model

This section presents a two-period model of a small open economy facing international financial intermediaries in the spirit of Gabaix and Maggiori (2015). These intermediaries buy domestic bonds and are the marginal investors both in the spot and the forward market.[4] They are risk averse so that there is a difference between their covered and uncovered positions. After presenting the financial intermediaries,

[3]In the case of developing or emerging economies, the opportunity cost may based on the country's borrowing cost, which implies a credit risk (e.g., Edwards, 1985). However, Yeyati and Gómez (2022) argue that when reserves are used for leaning-against-the-wind interventions, it is more appropriate to use UIP deviations.

[4]Since the objective of the model is to highlight the consequences of the differences between CIP and UIP deviations, we abstract from various interesting factors affecting the dynamics of spot and forward rates that are considered in the recent literature.

we describe the households, the government and the central bank, as well as the equilibrium in the asset markets.

We call the foreign currency the dollar and assume that the foreign interest rate i_t^* is given. Purchasing power parity is assumed to hold and the price of goods in dollars is normalized to one. S_t is the spot price of dollars in terms of domestic currency and F_t is the forward rate.

2.1 International Financial Intermediaries

International financial intermediaries value their expected profits with their stochastic discount factor m_{t+1}^*, which will be further described below. They typically invest in domestic bonds, but at the ZLB they may also hold domestic money.[5] Denote b_t^{H*} and h_t^{H*} their net positions in domestic bonds and money, expressed in dollars, and a_t^{H*} their total position: $a_t^{H*} = b_t^{H*} + h_t^{H*}$. When $i_t > 0$, $a_t^{H*} = b_t^{H*}$ as money is dominated by bonds. Financial intermediaries have a zero net position and fund their investments in domestic assets in dollars. We also assume that they can use forward contracts in quantities f_t^* and that they are the only players in the forward market.[6]

Moreover, financial intermediaries may value the liquidity of dollar assets. We assume that investors have operating costs that are increasing in non-dollar assets holdings a_t^{H*} and that it is a linear function: $\chi \cdot a_t^{H*}$, with $\chi \geq 0$. Their objective function is in dollars (and equivalently, in goods terms since the dollar price is constant):

$$V_t^* = E_t \left\{ m_{t+1}^* \left[a_t^{H*} \left((1+i_t) \frac{S_t}{S_{t+1}} - (1+i_t^*) \right) - f_t^* \left(\frac{1}{S_{t+1}} - \frac{1}{F_t} \right) \right] \right\} - \chi a_t^{H*}$$

[5]For notational convenience, we assume that financial intermediaries only potentially hold money at time t so that $h_{t-1}^{H*} = h_{t+1}^{H*} = 0$.

[6]These assumptions are similar to **?**. They consider a two-country model with financial intermediaries in both countries, but only the Home country arbitrages CIP deviations.

a_t^{H*} represents the total funds invested in the country, covered or uncovered. $f_t^*/(1+i_t)S_t$ is the covered amount, and $a_t^{H*} - f_t^*/(1+i_t)S_t$ is the uncovered amount.

To capture the role of financial intermediaries, we assume, as Gabaix and Maggiori (2015), that intermediaries can divert a fraction Γa_t^{H*} of the total invested funds, after the investment decisions are taken, but before shocks are realized. This yields a participation constraint for investors:

$$V_t^* \geq \Gamma (a_t^{H*})^2$$

Consider first the FOC w/f_t^*:

$$E_t \left\{ m_{t+1}^* \left(\frac{1}{S_{t+1}} - \frac{1}{F_t} \right) \right\} = 0 \tag{2.1}$$

The forward market is effectively frictionless, since it does not involve a transfer of funds ex ante. This implies a relationship between CIP and UIP deviations:

$$E_t(m_{t+1}^* Z_{t+1}^*) = E_t(m_{t+1}^* X_{t+1}^*) \tag{2.2}$$

where Z_{t+1}^* is the excess return hedged by a forward contract or the CIP deviation:

$$Z_{t+1}^* \equiv (1+i_t)\frac{S_t}{F_t} - (1+i_t^*) \tag{2.3}$$

and X_{t+1}^* is the domestic currency excess return, expressed in foreign currency:

$$X_{t+1}^* \equiv (1+i_t)\frac{S_t}{S_{t+1}} - (1+i_t^*) \tag{2.4}$$

Equation (2.2) can be rewritten as an equivalent of Equation (1.1):

$$E_t X^*_{t+1} = Z^*_{t+1} - \frac{cov_t(m^*_{t+1}, X^*_{t+1})}{E_t m^*_{t+1}} \tag{2.5}$$

Covered and uncovered carry trades yield the same returns in expectation, up to a covariance term, because intermediaries are risk-averse.

Using Equation (2.1), the participation constraint can be simplified as follows:

$$E_t \left(m^*_{t+1} a^{H*}_t X^*_{t+1} \right) - \chi a^{H*}_t \geq \Gamma (a^{H*}_t)^2 \tag{2.6}$$

If the participation constraint is binding, we have:

$$E_t \left(m^*_{t+1} X^*_{t+1} \right) = \Gamma a^{H*}_t + \chi \tag{2.7}$$

This, along with Equations (2.2) and (2.5), implies

$$Z^*_{t+1} = \frac{\Gamma a^{H*}_t + \chi}{E_t m^*_{t+1}} \tag{2.8}$$

and

$$E_t X^*_{t+1} = \frac{\Gamma a^{H*}_t + \chi}{E_t m^*_{t+1}} - \frac{cov_t(m^*_{t+1}, X^*_{t+1})}{E_t m^*_{t+1}} \tag{2.9}$$

The term $\Gamma a^{H*}_t + \chi$ in Equations (2.8) and (2.9) shows the impact of limited arbitrage and of the convenience yield on CIP and UIP deviations. Indeed, the intermediation frictions, which bear on both covered and uncovered intermediated funds, affect both CIP and UIP deviations.[7]

[7] Fanelli and Straub (2021) discuss a similar setup with frictions in intermediation and frictionless forward markets in an extension of their model. They find that, in that case, intermediation frictions generate both UIP and CIP deviations.

2.2 Domestic Households

Households' real consumption is c_t and they receive a real endowment y_t. They can hold money, H_t^H, domestic bonds B_t^H (both expressed in domestic currency), and foreign bonds b_t^F (expressed in foreign currency). Domestic bonds and money are perfect substitutes at the ZLB. We assume that households do not use the forward exchange market.

Since PPP holds, their budget constraint can be written as:

$$c_t = y_t - h_t^H - b_t^H - b_t^F + t_t \tag{2.10}$$

$$c_{t+1} = y_{t+1} + \frac{1}{1+\pi_t}h_t^H - h_{t+1}^H + \frac{1+i_t}{1+\pi_t}b_t^H + (1+i_t^*)b_t^F + t_{t+1} \tag{2.11}$$

where $b_t^H = B_t^H/P_t$ and $h_t^H = H_t^H/P_t$ are the real levels of domestic bonds and money holdings and t_t and t_{t+1} are real transfers.

Potentially, households face a cash-in-advance constraint in t and $t+1$:

$$h_t^H \geq Y_t,\ h_{t+1}^H \geq y_{t+1} \tag{2.12}$$

They also face short-selling constraints :

$$b_t^H \geq 0, \qquad\qquad b_t^F \geq 0 \tag{2.13}$$

Their utility function is:

$$U(c_t) + \beta E_t U(c_{t+1}) \tag{2.14}$$

Domestic households choose bonds and money holdings to maximize (2.14) subject to constraints (2.10) to (2.13). Using the assumption of PPP ($P_t = S_t$), the first-order conditions associated with bond portfolio choices are:

$$U'(c_t) - E_t\left(\beta U'(c_{t+1})(1+i_t^*)\right) \qquad -\lambda^F = 0 \tag{2.15}$$

$$E_t\left(\beta U'(c_{t+1})\left[(1+i_t^*) - (1+i_t)\frac{S_t}{S_{t+1}}\right]\right) \qquad +\lambda^F - \lambda^H = 0 \tag{2.16}$$

where λ^H and λ^F are the multipliers associated with the short-selling constraints (2.13). Equation (2.15) shows that the borrowing constraints affect intertemporal allocations. Equation (2.16) shows that they prevent households from reaching their optimal portfolio allocation between domestic and foreign currency bonds.

2.3 The Government

At time t the nominal government issues debt B_t^G (expressed in domestic currency) and transfers the funds to households:

$$B_t^G = T_t^G \tag{2.17}$$

At $t+1$, the government receives the central bank profits, Π_{t+1}^{CB} and repays its debt :

$$T_{t+1}^G = -(1+i_t)B_t^G + \Pi_{t+1}^{CB} \tag{2.18}$$

We assume that the government is passive and that the level of real debt $b_t^G = B_t^G/P_t$ is exogenous. [8]

[8] Alternatively, we could assume that it is the nominal debt level B_t^G that is exogenous. However, there would be an incentive for the central bank to alter the real debt level by moving the exchange rate.

2.4 The Central Bank

In period t, the central bank issues money H_t, and buys domestic and foreign bonds B_t^{CB} and b_t^{CBF} (expressed respectively in domestic and foreign currency). In period $t+1$, the central bank issues new money $H_{t+1} - H_t$ and distributes its profits Π_{t+1}^{CB} to the government. The central bank's budget constraint write then as follows:

$$S_t b_t^{CBF} + B_t^{CB} = H_t \tag{2.19}$$

$$\Pi_{t+1}^{CB} = (1 + i_t^*) S_{t+1} b_t^{CBF} + (1 + i_t) B_t^{CB} + H_{t+1} - H_t \tag{2.20}$$

In period t, the central bank has as instruments the nominal interest rate i_t, the total money supply H_t and the choice of foreign reserves b_t^{CBF} and domestic bonds B_t^{CB}. However, the interest rate cannot be negative, so the central bank loses the interest rate instrument when it hits this zero lower bound (ZLB).

In period $t+1$, we assume that the supply of money H_{t+1} is exogenous: $H_{t+1} = \bar{H} e^h$ where h is an exogenous shock. It represents variations in the net money supply to households due for instance to liquidity trading, or money velocity shocks.

From the budget constraint (2.19), there are two ways to change the level of reserves b_t^{CBF}. First, through a *sterilized* intervention where an increase in b_t^{CBF} is compensated by a decline in B_t^{CB}. Second, through an *unsterilized* intervention where an increase in b_t^{CBF} is associated with an expansion in H_t. Another possibility would be to allow the central bank to transfer funds to households in both periods. In that case, an increase in b_t^{CBF} could be implemented by changing transfer. We examine this fiscal foreign exchange intervention in the Online Appendix.

2.5 Gross and Net Foreign Liabilities

For the rest of our analysis, it is convenient to focus on the Home country's net and gross foreign liabilities. Moreover, since PPP holds, we replace P_t with S_t. Gross foreign liabilities are domestic bonds and money not held domestically. They are given by

$$gfl_t = \left(b_t^G - \frac{B_t^{CB}}{S_t} - b_t^H\right) + \left(\frac{H_t}{S_t} - h_t^H\right) \tag{2.21}$$

The first term corresponds to the foreign holdings of domestic bonds. The second term corresponds to the foreign holdings of domestic money.

Net foreign liabilities are given by

$$nfl_t = gfl_t - (b_t^F + b_t^{CBF}) = b_t^G - b_t^H - b_t^F - h_t^H \tag{2.22}$$

where $b_t^F + b_t^{CBF}$ are the domestic holding of foreign assets. The second equality is obtained by replacing b_t^{CBF} with $(H_t - B_t^{CB})/S_t$, using the central bank budget constraint, and replacing gfl_t using (2.21).

It is useful to notice that FX intervention affects gfl_t, but not nfl_t: an increase in b_t^{CBF} will increase gfl one-for-one, through an increase in H_t (unsterilized intervention) or a decline in B^{CB} (sterilized intervention), while in nfl the changes in b_t^{CBF} are offset either by changes in B_t^{CB} or by changes in H.

2.6 Equilibrium in Asset Markets

The amount of domestic debt held by international intermediaries is equal to the net domestic supply: $b_t^{H*} = b_t^G - B_t^{CB}/S_t - b_t^H$. Similarly, foreign money holdings are equal to the net domestic supply: $h_t^{H*} = H_t/S_t - h_t^H$. In equilibrium, gross foreign liabilities are equal to the bonds and money held by foreigners: $gfl_t = a_t^{H*} = b_t^{H*} + h_t^{H*}$. From

(2.9), this implies

$$\Gamma gfl_t + \chi = E_t(X^*_{t+1}) + \frac{cov_t(m^*_t, X^*_{t+1})}{E_t m^*_{t+1}} \tag{2.23}$$

The net supply of domestic liabilities to foreigners, gfl_t, determines the equilibrium expected domestic currency excess return $E_t(X^*_{t+1})$, which is defined in (2.4). At $t+1$, equilibrium on the money market yields $H^H_{t+1} = S_{t+1}y_{t+1} = He^h$, which determines S_{t+1}. Therefore, we can treat S_{t+1} as exogenous. Since the foreign interest rate i^*_t is exogenous as well, gfl_t determines $(1 + i_t)S_t$.

Outside the ZLB, $h^{H*}_t = H_t/S_t - h^H_t = 0$, and households hold the minimum amount of money: $H_t/S_t = h^H_t = Y_t$. This implies that S_t is determined by the equality between the demand and supply of money in the domestic economy $S_tY_t = H_t$. Since $E_t \frac{1}{S_{t+1}}$ is exogenous, and S_t clears the money market for a given supply of money H_t, Equation (2.23) determines i_t for a given H_t. An increase in $cov_t(m^*_t, X^*_{t+1})$ leads to a decline in the domestic interest rate i_t. Intuitively, the increase in covariance makes the domestic bonds more attractive to foreigners and generates an excess demand for domestic bonds. The decline in the interest rate clears this excess demand.

If the interest rate hits the ZLB, it cannot clear the domestic bond market. At the same time, the exchange rate is not determined by the money market, as now money and bonds become substitutes. We can see this by noting that h^{H*}_t can now be strictly positive, so that the net supply of money to foreigners $H_t/S_t - h^H_t$ is strictly positive. Since the interest rate i_t cannot adjust in the ZLB, the exchange rate adjusts. Now an increase in $cov(m^*_t, X^*_{t+1})$ leads to a domestic currency appreciation (decrease in S_t), for a given H_t. This reduces the excess return, which dampens the increase in demand.

3 On the Cost of Foreign Reserves

In this section, we derive the utility cost of FX reserves and determine how it is related to UIP and CIP deviations. We show that the key determinant is how excess returns are related to the SDF of domestic households or of international financial intermediaries. In the context of safe have currencies, it depends on whether international financial intermediaries value more the safe haven properties than domestic investors. We examine this issue empirically and show that it is the case for Switzerland and Japan.

3.1 Utility Cost of Reserves with UIP and CIP Deviations

After consolidating the household's budget constraints using the equilibrium in the domestic asset markets, and substituting transfers in the household's budget constraint, we obtain the period resource constraints:

$$\begin{aligned} c_t &= Y_t + nfl_t \\ c_{t+1} &= y_{t+1} - (1+i_t^*)nfl_t - X_{t+1}^* gfl_t + i_t \tfrac{S_t}{S_{t+1}} \left(\tfrac{H_t}{S_t} - h_t^H \right) \end{aligned} \tag{3.1}$$

The last term, which represents the economy's seigniorage revenue from the foreign holding of domestic money, can be neglected since we will either have $\frac{H_t}{S_t} = h_t^H$ (if $i_t > 0$) or $i_t = 0$. The intertemporal resource constraint is:

$$(1+i_t^*)c_t + c_{t+1} = (1+i_t^*)y_t + y_{t+1} - X_{t+1}^* gfl_t. \tag{3.2}$$

Everything else equal, FX interventions affect the economy's intertemporal resources through changes in gfl_t.[9] By holding more foreign reserve b_t^{CBF}, the central bank

[9] If the central bank could make transfers in t, then it could also affect the consumption profile through

increases the economy's gross foreign position by issuing more domestic bonds (decreasing B_t^{CB}) or more money if the economy is at the ZLB (increasing $\frac{H_t}{S_t} - h_t^H$).

The last term in (3.2) gives the monetary cost of holding reserves, since reserves affect gfl_t. It depends on the sign of X^*_{t+1}, which is the marginal cost of holding reserves, evaluated in units of goods. In a safe haven case with $E_t X^*_{t+1} < 0$, there is an expected gain of holding reserves, i.e., the central bank can exploit the UIP deviation. However, the increase in reserves also increases exchange rate risk, so the question is whether this could increase households' utility. We define the marginal *utility* cost of reserves as follows: [The marginal utility cost of FX interventions] The marginal utility cost of FX interventions is the expected product of the UIP deviation X^*_{t+1} and the SDF of domestic households m_{t+1}, divided by the expected discount factor:

$$UCFX_t = \frac{E_t(m_{t+1} X^*_{t+1})}{E_t(m_{t+1})} \tag{3.3}$$

where $m_{t+1} = \beta U'(c_t)/U'(c_{t+1})$. The excess return on domestic bonds X^*_{t+1} is valued using the utility-based stochastic discount factor. It is normalized by the expected discount factor so that it coincides with the monetary cost X^*_{t+1} in the absence of risk.

The marginal utility cost of FX interventions can be rewritten as

$$UCFX_t = E_t X^*_{t+1} + \frac{cov(m_{t+1}, X^*_{t+1})}{E_t m_{t+1}} \tag{3.4}$$

The utility cost is composed of the excess return on foreign bonds, minus the risk premium associated with this excess return. Since $E_t X^*_{t+1} < 0$ for safe haven countries, there may be a utility gain.

the economy's net position nfl_t. If the household is constrained, then the central bank could increase the net borrowing of the economy and hence transfer consumption from $t+1$ to t.

Substituting $E_t X^*_{t+1}$ using Equation (2.9), we can rewrite the utility cost of foreign exchange interventions:

$$UCFX_t = \underbrace{\frac{\overbrace{\Gamma g f l_t + \chi}^{devCIP}}{E_t m^*_{t+1}} - \frac{cov(m^*_{t+1}, X^*_{t+1})}{E_t m^*_{t+1}}}_{devUIP} + \frac{cov(m_{t+1}, X^*_{t+1})}{E_t m_{t+1}} \tag{3.5}$$

Equation (3.5) shows how CIP and UIP deviations affect the utility cost. This can be summarized in the following proposition:

Consider the SDF of domestic households, m_{t+1}, and of international financial intermediaries m^*_{t+1} and the excess return in foreign currency, X^*_{t+1}. The utility cost (or benefit) of foreign exchange intervention depends on

(i) CIP deviations when $cov(m_{t+1}, X^*_{t+1}) = cov(m^*_{t+1}, X^*_{t+1})$.

(ii) UIP deviations when $cov(m_{t+1}, X^*_{t+1}) = 0$.

In fact, the intermediation friction generates two wedges that are relevant for welfare. First, the CIP deviation, which is a riskless excess return. Second, the difference between the foreign and domestic risk premia. If the foreign and domestic agents have the same risk premium, only CIP deviations matter. This is the case in the absence of risk, as in Amador et al. (2020), or when financial intermediaries have the same discount factor as households. In contrast, in the limit case where the domestic agents have negligible risk aversion as compared to financial intermediaries, then the sum of the two wedges is equal to the UIP deviation, and the cost of reserves would be equal to UIP deviations.[10]

[10]This is what Itskhoki and Mukhin (2021) implicitly assume. In their linear approximation, they take the level of risk to zero but ensure that the risk premium of the financial intermediaries remains a first order object by rescaling their risk aversion, but not that of the households. This implies that the intermediaries' risk aversion is an order of magnitude higher than that of the households. As a result, it is optimal to eliminate UIP deviations.

However, in general, the sum of the two wedges does not coincide with either the CIP or the UIP deviations. In particular, a safe haven currency may be more desirable for foreign investors as a diversification hedge than for the domestic investors so that $cov(m^*_{t+1}, X^*_{t+1}) > cov(m_{t+1}, X^*_{t+1})$. If the difference is large enough, there may be a utility gain from accumulating reserves instead of a cost.

3.2 Estimating the Utility Cost for Switzerland and Japan

The theoretical analysis has shown that the utility cost FX interventions depends crucially on the difference between $cov(m^*_{t+1}, X^*_{t+1})/E_t m^*_{t+1}$ and $cov(m_{t+1}, X^*_{t+1})/E m_{t+1}$ (Equation (3.5)). In this subsection, we provide estimates of these two terms for Switzerland and Japan. First, Appendix 5 confirms that both countries can be considered as safe haven, in the sense that the excess return on their currencies is positively related to global risk variables.

A key issue is the measurement of stochastic discount factors m_{t+1} and m^*_{t+1}. For domestic households, we simply assume that $m_{t+1} = \beta(c_{t+1}/c_t)^{-\gamma}$, where $1/\gamma$ is the rate of intertemporal substitution. For international financial intermediaries, we follow the literature on intermediary asset pricing (e.g., see He and Krishnamurthy (2011) or Brunnermeier and Sannikov (2014)), and assume that their SDF is proportional to their net worth NW_t: [11]

$$m^*_{t+1} = \beta \left(\frac{NW_{t+1}}{NW_t} \right)^{-\gamma} \tag{3.6}$$

As in He et al. (2017), we assume that the financial intermediaries' net worth is related to the aggregate wealth in the economy (denoted by W_t) and the intermedi-

[11] Basically, financial intermediaries face two constraints: the Gabaix-Maggiori constraint on their international arbitrage and borrowing constraint on their overall balance sheet, such their constraint depends on their net worth, e.g. as in **?**.

aries' capital ratio (denoted by η_t). This specification implies that the marginal utility of wealth of financial intermediaries rises when the aggregate wealth in the economy or the equity capital ratio is low (or a combination of the two). The first term captures the asset pricing effect of weaker fundamentals, while the second captures the idea that the intermediaries' risk bearing capacity is impaired when the capital ratio is low. As a result, risk aversion increases the marginal value of wealth. Using time-series and cross-sectional asset pricing tests, He et al. (2017) show that this specification captures well the marginal utility of wealth of financial intermediaries, and find supporting evidence that financial intermediaries are indeed marginal investors for a wide class of assets.

In our empirical exercise, we consider two measures of the capital ratio (η_t) and two measures of total wealth (W_t), giving rise to four different possible specifications. For the first capital ratio measure, we consider the equity capital ratio of financial intermediaries (*Primary Dealer* counterparties of the New York Federal Reserve) from He et al. (2017), which we denote by η_{t+1}^{HKM}. The second measure is from Adrian et al. (2014), and is defined as the (inverse of) book leverage of security *Brokers & Dealers*.[12] We denote it as η_{t+1}^{AEM}. For total wealth, we consider a real measure using US GDP (W_t^{GDP}) and a financial measure using the US MSCI Equity Index (W_t^{MSCI}).[13]

As in He et al. (2017), our measure of net worth is obtained by interacting the capital ratio measure with the total wealth measure: $NW_t = \eta_t \times W_t$. To convert net worth into a growth rate (as suggested by (3.6)), we adopt an approach similar to He et al. (2017). For the capital ratio, we define the intermediary capital risk factor by dividing the residual from a regression of the capital ratio on its lag by the lagged capital ratio.

[12] It is obtained using balance sheet data reported in the Flow of Funds from the Federal Reserve Board. It is computed as the ratio of total equity (total financial assets minus total financial liabilities) to total financial assets.

[13] As a robustness, we also consider a "world version" of these two variables.

For the financial measure of wealth (W_t^{MSCI}), we compute the excess returns on the equity index, using the 3M US Libor as the risk-free rate. For the real measure of wealth (W_t^{GDP}), we simply compute the growth rate. $\frac{NW_{t+1}}{NW_t}$ is then defined by the interaction of the intermediary capital risk factor and the growth rate measure of total wealth. Appendix B provides additional details about the sources of the data and the construction of the excess returns and the stochastic discount factors.

We consider excess returns using $i \in \{CHF, JPY\}$ as the domestic currency and the USD as the foreign one. Let us define the log excess returns of going long in the domestic currency from the international investors' perspective:

$$x_{t+1}^* = i_t - i_t^* + s_t - s_{t+1} \tag{3.7}$$

We use x_{t+1}^* as an approximation of X_{t+1}^*.

Table 3.1 displays an estimate of $cov(m_{t+1}^*, x_{t+1}^*)/E_t m_{t+1}^*$ and $cov(m_{t+1}, x_{t+1}^*)/Em_{t+1}$ using either the CHF or the JPY as the domestic currency, keeping the USD as the foreign one. We assume that $\beta = 0.99$ and $\gamma = 10$. For each currency, we consider two subsamples (2000M1-2009M12 and 2010M1-2020M2) to highlight potential time-variation in these measures, as suggested by Figure 1.1. Columns 2 to 5 display the covariance terms from the perspective of financial intermediaries using the capital ratio measure from He et al. (2017) and Adrian et al. (2014) and the two measures of total wealth to compute the SDF. The last column displays the covariance term for the Swiss and Japanese households, using real consumption growth to compute the SDF. Statistical significance is assessed by regressing the excess returns on the different measures of SDF and using Newey-West standard errors.

The results show that, since 2010, the covariance term for financial intermediaries is clearly positive and statistically significant for most of the specifications of the

Table 3.1 $\frac{Cov(x^*_{t+1}, m^*_{t+1})}{E_t(m^*_{t+1})}$ and $\frac{Cov(x^*_{t+1}, m_{t+1})}{E_t(m_{t+1})}$

A) CHF domestic currency, USD foreign currency					
	Fin. Intermediaries				HH
$NW_{t+1} =$	$\eta^{HKM}_{t+1} \times W^{MSCI}_{t+1}$	$\eta^{AEM}_{t+1} \times W^{MSCI}_{t+1}$	$\eta^{HKM}_{t+1} \times W^{GDP}_{t+1}$	$\eta^{AEM}_{t+1} \times W^{GDP}_{t+1}$	C^{CH}_{t+1}
1999-2010	1.61	1.74	0.2	-1.17	0.25***
2010-2020	2.82**	1.32	5.1*	2.13**	0.01
B) JPY domestic currency, USD foreign currency					
$NW_{t+1} =$	$\eta^{HKM}_{t+1} \times W^{MSCI}_{t+1}$	$\eta^{AEM}_{t+1} \times W^{MSCI}_{t+1}$	$\eta^{HKM}_{t+1} \times W^{GDP}_{t+1}$	$\eta^{AEM}_{t+1} \times W^{GDP}_{t+1}$	C^{JP}_{t+1}
1999-2010	1.85	-2.9	-3.57	-2.56**	0.7***
2010-2020	6.39***	3.31**	7.93***	2.63**	0.33

Note:
This table estimates $\frac{Cov(x^*_{t+1}, m^*_{t+1})}{E_t(m^*_{t+1})}$ and $\frac{Cov(x^*_{t+1}, m_{t+1})}{E_t(m_{t+1})}$ from equation (3.5) using different proxies of the SDF of (international) financial intermediaries and Swiss and Japanese households. Values are expressed in percentage points. Appendix B provides provides details on their construction and the source of the data. Statistical significance is assessed by regressing excess returns on the different measures of the SDF using Newey-West standard errors. $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$.

stochastic discount factor, and quantitatively in line with the UIP deviations depicted in Figure 1.1, reaching as high as 7.9% for Japan and 5.1% for Switzerland. Interestingly, the covariance term is generally an order of magnitude smaller (or negative) before 2010. In words, since 2010, being long in CHF or JPY tends to provide higher returns when the marginal utility of wealth of financial intermediaries is high, which supports that the CHF and the JPY behave as a hedge for international intermediaries. On the other hand, the covariance term between excess returns and SDF based on real consumption growth tend to be much smaller and statistically not significant since 2010. These observations observations can help rationalise the large UIP deviations (and the low expected excess returns) observed post 2010 in the data. In the case of Switzerland and Japan, Proposition 1 implies that it is not CIP but UIP deviations that should matter for FX interventions, since $cov(m_{t+1}, x^*_{t+1})/E_t m_{t+1}$ is not significant while $cov(m^*_{t+1}, x^*_{t+1})/E_t m^*_{t+1} > 0$.

4 The Central Bank as a Constrained Planner

To determine how the cost of reserves influences the policy trade-offs of the central bank, we consider a central bank who maximizes households' welfare. The households' domestic participation constraint provides an incentive for the central bank to distort the domestic real interest rate. The cost of reserves may either conflict with this domestic objective, or facilitate it. We first reframe the central bank's problem as that of a constrained central planner. We then show how the resulting optimal allocation can be decentralized using foreign exchange interventions.

Before that, we relate the country's consolidated financial liabilities to the household participation constraints (2.13). Using the central bank's budget constraint, we can see that the households' constraint on domestic bond issuance translates into a constraint on gross foreign liabilities:

$$gfl_t \leq b_t^G + b_t^{CBF} - h_t^H \tag{4.1}$$

However, (4.1) is not an effective constraint since the central bank can change its holding of foreign bonds b_t^{CBF}.

Similarly, the foreign currency no-borrowing constraint implies:

$$nfl_t \leq gfl_t - b_t^{CBF} \tag{4.2}$$

This constraint cannot be relaxed by non-fiscal FX intervention since changes in gfl_t are offset by changes in b_t^{CBF}.[14] This constraint is effective except if we allowed the central bank to perform fiscal interventions, where changes in gfl_t need not be offset

[14] When capital controls are in place, however, Bacchetta et al. (2013) show that sterilized interventions can affect the country's intertemporal allocation.

by changes in b_t^{CBF}. Equations (4.1) and (4.2) are equivalent to the no-borrowing constraints (2.13).

4.1 The Constrained Planner's Program

Based on the previous equations, we can examine the planner's optimal choices.

[Constrained planner equilibrium] A constrained planner equilibrium is an equilibrium where a planner maximizes objective (2.14) subject to the economy's resource constraints (3.1); the asset pricing equation (2.7); the cash-in-advance constraints $h_t^H \geq Y_t$ and $\bar{H}e^h = S_{t+1}y_{t+1}$; the non-negativity of foreign domestic money holdings $h_t^{H*} \geq 0$; the equilibrium on the market for money $H_t = S_t(h_t^H + h_t^{H*})$; the consolidated bond and money market equilibrium $a_t^{H*} = gfl_t$; the zero lower bound $i_t \geq 0$; and the foreign liability constraints (4.1) and (4.2). The planner's choice variables are $(i_t, S_t, S_{t+1}, gfl_t, nfl_t, b_t^{CBF}, H_t, h_t^H, h_t^*, a_t^*)$.

The central bank's program is:

$$\max E\Bigg\{U(c_t) + \beta U(c_{t+1})$$

$$+\eta_t\left(y_t - c_t + nfl_t\right)$$

$$+\eta_{t+1}\left[y_{t+1} - c_{t+1} - (1+i_t^*)nfl_t + \left[(1+i_t^*) - (1+i_t)\tfrac{S_t}{S_{t+1}}\right]gfl_t + i_t\tfrac{S_t}{S_{t+1}}\left(\tfrac{H_t}{S_t} - h_t^H\right)\right]$$

$$+\xi i_t$$

$$+\Delta_t^H\left(h_t^H - y_t\right)$$

$$+\Delta_t^F\left(\tfrac{H_t}{S_t} - h_t^H\right)$$

$$+\Lambda\left(gfl_t - b_t^{CBF} - nfl_t\right)$$

$$+\tilde{\Lambda}\left(b_t^G + b_t^{CBF} - h_t^H - gfl_t\right)$$

$$+\alpha_0\left(E_t\left(m_{t+1}^*\left[(1+i_t^*) - (1+i_t)\tfrac{S_t}{S_{t+1}}\right]\right) + \Gamma gfl_t + \chi\right)\Bigg\}$$

and we treat S_{t+1} as an exogenous variable since $S_{t+1} = He^h/y_{t+1}$. Here, we substituted the foreign demand for domestic assets a_t^{H*} with gfl_t and h_t^{H*} with $H_t/S_t - h_t^H$. Consider the first order conditions for assets:

$$
\begin{aligned}
&/nfl_t: && \eta_t - E_t\left(\eta_{t+1}(1+i_t^*)\right) && -\Lambda && = 0 && (4.3)\\
&/gfl_t: && E_t\left(\eta_{t+1}\left[(1+i_t^*) - (1+i_t)\frac{S_t}{S_{t+1}}\right]\right) && +\Lambda - \tilde{\Lambda} + \alpha_0\Gamma && = 0 && (4.4)\\
&/H_t: && E_t\left(\eta_{t+1}\left[i_t\frac{S_t}{S_{t+1}}\right]\right) && +\Delta_t^F && = 0 && (4.5)\\
&/b_t^{CBF}: && && -\Lambda + \tilde{\Lambda} && = 0 && (4.6)
\end{aligned}
$$

Equation (4.6) implies that $\tilde{\Lambda} - \Lambda = 0$. This means that the central bank equalizes the marginal benefit of relaxing the foreign-currency and domestic-currency debt constraints by adjusting its assets and liabilities and going shorter in the asset whose shadow cost is higher and longer in the asset whose shadow cost is lower. Also note that $\eta_t = U'(c_t)$, $\eta_{t+1} = U'(c_{t+1})$, and that $m_{t+1} = \eta_{t+1}/\eta_t$ is the central bank's discount factor, which coincides with the household's (see Appendix C.1).

4.2 Optimal foreign exchange interventions

We can examine the impact of sterilized and unsterilized FX interventions by examining Equation (4.4) with $\Lambda - \tilde{\Lambda} = 0$.

Sterilized interventions

Equation (4.4), with $\Lambda - \tilde{\Lambda} = 0$, can be rewritten as follows:

$$
\underbrace{\overbrace{-E_t X_{t+1}^* - \frac{cov(m_{t+1}, X_{t+1}^*)}{E_t m_{t+1}}}^{-UCFX_t} + \frac{\alpha_0}{\eta_t E_t m_{t+1}}\Gamma}_{MBFX_t} = 0 \tag{4.7}
$$

The left-hand side, $MBFX_t$, corresponds to the marginal benefit of sterilized foreign exchange interventions, that is, of expanding the central bank's balance sheet by going long in foreign bonds and short in domestic bonds. It is composed of the marginal utility benefit of FX interventions ($-UCFX_t$) and of the marginal benefit of the resulting price distortions. If, in the absence of interventions, $MBFX_t$ is positive, then it would be optimal for the central bank to accumulate FX reserves. These interventions can drive the marginal benefit to zero, achieving an optimal central bank balance-sheet, as we will see in more details later.

Finally, we examine the last term in equation $MBFX_t$, which arises from the price (interest rate and exchange rate) distortions implied by the central bank's interventions. The central bank has an incentive to not fully shut down its risk-adjusted foreign currency excess return in order to maximize its profit. Appendix C.2 shows that this term is equal to:

$$\frac{\alpha_0}{\eta_t E_t m_{t+1}}\Gamma = -\Gamma g f l_t \frac{E_t\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E_t m_{t+1} E_t\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)} \tag{4.8}$$

It is of the same sign as $-gfl_t$, home's gross external position in domestic currency. If the country is short in domestic currency ($gfl_t > 0$), then this term is negative. When accumulating foreign currency assets by issuing domestic currency liabilities, the planner reduces the foreign currency excess return (by increasing i_t or depreciating the domestic currency). The resulting opportunity cost is proportional to the economy's gross external position. This term also depends on Γ, which measures the impact of domestic currency issuance on the excess return (see Equation (2.23)). The higher Γ, the more difficult it is for foreign intermediaries to absorb additional foreign currency assets, the higher the impact of foreign currency issuance on the excess return. This term reflects the central bank's rent as a monopolistic issuer of domestic bonds.

To summarize, there could be a benefit of interventions for a safe haven currency if its hedging property is more valued by international investors. But the central bank has also to consider how these interventions affect its monopoly rent.

Unsterilized interventions

In our framework, unsterilized interventions are ineffective outside the ZLB and are equivalent to sterilized intervention at the ZLB. Equation (4.5) implies that $\Delta^F > 0$ if $i_t > 0$, meaning that $H_t/S_t = h_t^H$ outside the ZLB. Therefore, issuing more money outside the ZLB would be purely inflationary since domestic households need a fixed real quantity of money and $H_t/S_t = h_t^H$. This would not increase the capacity of the central bank to buy foreign bonds.

At the ZLB, money and bonds are perfect substitues, so that sterilized and unsterilized interventions become equivalent. Then, $MBFX_t$ is the marginal benefit of both sterilized and unsterilized interventions, so that the above analysis applies. Whether foreign bonds are acquired by increasing H_t (unsterilized intervention) or by decreasing B_t^{CB} (sterilized intervention) does not matter.

Since unsterilized interventions have no specific impact, in what follows we fix arbitrarily the quantity of money H_t, and assume $H_t = 1$. In this case, the equilibrium is uniquely pinned down.

[Equilibrium determinacy] Conditional on H_t, the equilibrium is unique.

To understand, suppose that H_t is not fixed. Then, outside the ZLB, S_t and i_t are undetermined. Indeed, according to the equilibrium in the domestic bond market (2.23), the excess return is affected by the central bank's optimal FX policy (through the supply of b^{CB} and hence through gfl_t). For a given expectation of S_{t+1}, this equilibrium excess return determines the equilibrium value for $S_t(1+i_t)$, which is compatible with different combinations of S_t and i_t. At the ZLB, S_t would be the determined by the value that clears the bond market. However, H_t and B_t^{CB} are not determined. Indeed, the optimal S_t can be obtained with an infinite number of combinations of sterilized and unsterilized interventions (H_t and B_t^{CB}), since domestic money and bonds become substitutes at the ZLB.

4.3 Implementation of the Optimum in a Decentralized Equilibrium

Here we discuss how the optimum is implemented in a decentralized equilibrium by analyzing households' optimal choices. Consider the central bank's foreign exchange interventions (sterilized or unsterilized). These interventions are relevant for the economy' gross foreign liabilities. Suppose that the optimal gross foreign liability position of the economy is $\widehat{gfl}_t$.

The households' optimal portfolio allocation, characterized by Equation (2.16), can be compared with Equation (4.4). For Equation (4.4) to be implemented in the decentralized equilibrium, we need that

$$\lambda^H - \lambda^F = -\alpha_0 \Gamma \tag{4.9}$$

where we used $\eta_t = U'(c_t)$, $\eta_{t+1} = U'(c_{t+1})$ and $\Lambda - \tilde{\Lambda} = 0$.

In safe haven countries, where typically $\widehat{gfl}_t > 0$, α_0 is more likely to be negative, so optimal foreign exchange interventions are only consistent with the households being financially constrained when issuing domestic-currency bonds ($\lambda^H > 0$), since $\lambda^F \geq 0$. The central bank, as we have seen, does not fully exhaust the –private– marginal benefit of going long in foreign currency and short in domestic currency. Households can be prevented from exploiting this residual marginal benefit only if their domestic-currency borrowing constraint is binding.

In this case, the central bank desires fewer domestic liabilities than households. The optimum is then easily implementable for the central bank by supplying just the right amount of domestic liabilities to complement the existing public domestic supply and reach $\widehat{gfl}_t$, through foreign exchange interventions. More precisely, the optimal foreign exchange intervention must satisfy

$$\widehat{b}_t^{CBF} = \widehat{gfl}_t - \left(b_t^G - h_t^H\right) \tag{4.10}$$

The domestic currency bonds issued by foreign exchange interventions $\widehat{b}_t^{CBF}$ must close the gap between the optimal gross foreign liabilities $\widehat{gfl}_t$ and the existing real supply of domestic bonds, which is equal to the amount of government bonds that are not held by the central bank to back households' asset holding $b_t^G - h_t^H$. For that level of domestic currency bonds, households would like to issue more domestic currency bonds ($b_t^H < 0$), but they are prevented from doing so by their no-borrowing constraints. That way, the optimum is implementable.[15]

The central bank desires more foreign savings than households. It can then implement its optimum by holding enough foreign bonds to crowd out households savings, up to the point where households hit their foreign bond short-selling constraint. More precisely, the optimal foreign exchange intervention must satisfy

$$\widehat{b}_t^{CBF} = \widehat{gfl}_t - nfl_t \tag{4.11}$$

[15] Note that if $\widehat{gfl}_t < 0$ $(\alpha_0 > 0)$, then Equation (4.9) would imply that $\lambda^F > 0$ (since $\lambda^H \geq 0$), meaning that the household should be constrained in issuing foreign-currency bonds for the optimum to be implementable. Indeed, in that case, the central bank would typically save in domestic currency and borrow in foreign currency, but there would remain a private benefit of going short in foreign currency and long in domestic currency, which can only be consistent with a binding constraint on foreign liabilities in a decentralized economy. The optimum can be implemented by the central bank (or government) by supplying just the right amount of foreign-currency liabilities to reach $-\widehat{gfl}_t$.

For that level of foreign currency holdings, households would like to issue foreign currency liabilities ($b_t^F < 0$), but they are prevented from doing so by their no-borrowing constraints.

4.4 Adding a Domestic Motive for FX Intervention

The focus of this paper is on the opportunity cost of FX intervention, so that we have abstracted from the benefits of interventions. The literature discusses numerous motives for intervention. To illustrate the cost-benefit analysis, we assume that the central bank has an additional incentive for intervention. We now assume that households face short-selling constraints so that the real repayment on domestic debt $-b_t^H$ does not exceed some limit. The constraint in (2.13) is replaced by:

$$E_t \frac{(1+i_t)S_t}{S_{t+1}} b_t^H \geq \bar{b}^H \tag{4.12}$$

A non-zero level of $\bar{b}^H$ gives an additional motive for monetary policy. We assume that $\bar{b}^H$ can be either positive and negative. A positive sign for $\bar{b}^H$ implies an amount of forced savings. This generates an incentive for a higher interest rate and therefore an accumulation of FX reserves.

This additional motive for intervention affects the last term in the first-order condition (4.7). Equation (4.8) becomes:

$$\frac{\alpha_0}{\eta_t E_t m_{t+1}} \Gamma = -\Gamma g f l_t \frac{E_t \left(m_{t+1} \frac{S_t}{S_{t+1}} \right)}{E_t m_{t+1} E_t \left(m^*_{t+1} \frac{S_t}{S_{t+1}} \right)} + \Gamma \frac{\lambda^F}{\eta_t} \frac{\bar{b}^H}{E_t m_{t+1} E_t \left(\frac{(1+i_t)S_t}{S_{t+1}} \right) E_t \left(m^*_{t+1} \frac{(1+i_t)S_t}{S_{t+1}} \right)} \tag{4.13}$$

The second term is active in the presence of binding participation constraints ($\tilde{\Lambda} > 0$), and is of the same sign as $\bar{b}^H$, so it is positive if households are forced to save in domestic currency, i.e., if $\bar{b}^H > 0$. [16]

5 A Linear-Quadratic Version of a Safe Haven Economy

In this section, we focus on the safe haven currency case. We consider an approximated version of the model and assume lognormal shocks. We do not model the reasons behind the safe haven status and simply assume that the domestic currency is expected to appreciate when global output slows down.[17] The objective is to derive $cov(m^*_{t+1}, X^*_{t+1})$ and $cov(m_{t+1}, X^*_{t+1})$ to evaluate the opportunity cost of FX interventions given in (3.5).

We denote from now on the variables in log with a tilde: $\tilde{Y} = \log(Y)$ and $\tilde{Y}^* = \log(Y^*)$. We also define $\tilde{i}^*_t = \log(1 + i^*_t)$ and $\tilde{i}_t = \log(1 + i_t)$. In what follow, we consider the following specific case: [Specific case] Our specific case is characterized by

1. The utility is logarithmic: $U(c_t) = \log(c_t)$;
2. The SDF of international financial intermediaries is driven by world output Y^*: $m^*_{t+1} = \beta \frac{y^*_t}{y^*_{t+1}}$;
3. Period-t output is normalized to 1: $y_t = y^*_t = 1$;
4. Period-$t+1$ world output is log-normally distributed: $\tilde{y}^*_{t+1} \sim N(\sigma_y^2/2, \sigma_y^2)$, with $\sigma_y > 0$;
5. Foreign and domestic outputs are correlated: $\log(y_{t+1}) = \alpha \log(y^*_{t+1}) + (1-\alpha)\sigma_y^2/2$ for some real α;

[16] Note that if $\bar{b}^H < 0$ (if households face a borrowing limit), then the central bank would have a motive to depress the real domestic interest rate and hence to reverse FX interventions.

[17] There is a small literature trying to provide explanations for safe haven effects, but the focus is on the US and the mechanisms do not apply to a small countries. See Maggiori (2017) or Hassan et al. (2021). Papers that model time-varying safe haven effects include Gourinchas and Rey (2022), Devereux et al. (2022), and Kekre and Lenel (2021).

6. The exchange rate is correlated to world output $S_{t+1} = He^{\rho \log(y^*_{t+1})}$ for some real ρ.

Assumption 5.4 normalizes the expected foreign stochastic discount factor to β under log-utility: $E_t m^*_{t+1} = E_t(\beta / Y^*_{t+1}) = \beta$. Assumption 5.5 ensures that $E(y_{t+1}) = E(y^*_{t+1})$.

We make the following assumption on the parameters: [Safe haven] $\rho > 0$ and $\alpha < 1$. A positive ρ captures the hedging capacity of safe haven currencies: the exchange rate appreciates when global output is low, so the domestic currency is a good hedge against global output fluctuations. A low α reflects the small exposure of the domestic output to global risk. Domestic output comoves with global output, so the domestic currency is also a hedge for domestic households. However, since domestic output is less volatile, in equilibrium domestic households are willing to be short in domestic bonds.

5.1 The Utility Cost of Reserves

We first solve for the equilibrium for given nfl_t and gfl_t in order to evaluate the planner's optimality conditions as a function of nfl_t and gfl_t. We will consider in turn the case where the ZLB is not binding and the case where it is. We use second-order approximations.

The household's budget constraints yield:

$$\begin{aligned} \tilde{c}_t &= nfl_t - \frac{1}{2} nfl_t^2 \\ \tilde{c}_{t+1} &= \tilde{y}_{t+1}\left(1 + nfl_t + gfl_t\right) - \left(nfl_t - \frac{1}{2} nfl_t^2\right)(1 + i^*_t) - gfl_t X^*_{t+1} \end{aligned} \tag{5.1}$$

See the details of the derivation in Appendix D.1. Besides, we have $\tilde{S}_{t+1} = \rho \tilde{y}^*_{t+1}$.

The foreign and domestic interest rates must satisfy

$$E_t(e^{\tilde{m}^*_{t+1}+\tilde{i}^*_t}) = 1 \tag{5.2}$$

$$E_t(e^{\tilde{m}^*_{t+1}+\tilde{S}_t-\tilde{S}_{t+1}+\tilde{i}_t}) = 1+\chi+\Gamma gfl_t \tag{5.3}$$

This yields:

$$\begin{aligned} 1+i^*_t &= \frac{1}{\beta} \\ (1+i_t)S_t &= \frac{1}{\beta}(1+\chi+\Gamma gfl_t)e^{-\frac{1}{2}(1+\rho)\rho\sigma_y^2} \end{aligned} \tag{5.4}$$

See Appendix D.2 for a full derivation. These equations define respectively the foreign interest rate i^*_t as a function of the subjective discount factor and $(1+i_t)S_t$ as a function of financial frictions (Γ and χ), of the hedging properties of the domestic exchange rate and of gross foreign liabilities. This determines i_t outside the ZLB (since $S_t = 1$) and S_t at the ZLB (since $i_t = 0$).

What are the implications for the cost of foreign exchange interventions? We can write the difference in risk premia, which is a component of the utility cost of reserves $UCFX_t$ (see Equation (3.5)), as follows

$$\frac{cov(m^*_{t+1}, X^*_{t+1})}{E_t m^*_{t+1}} - \frac{cov(m_{t+1}, X^*_{t+1})}{E_t m_{t+1}} = \frac{1}{\beta}(1+\chi+\Gamma gfl_t)\left(1-e^{-\Delta cov}\right) \tag{5.5}$$

where $\Delta cov = cov(\tilde{m}_{t+1}, \tilde{S}_{t+1}) - cov(\tilde{m}^*_{t+1}, \tilde{S}_{t+1})$ is the difference between the covariance of the log-linearized domestic currency excess return with the intermediaries SDF and the covariance with the domestic SDF. In Appendix D.3 we show that

$$\Delta cov = \rho\sigma_y^2\left[1-\alpha(1+nfl_t+gfl_t)-\rho gfl_t\right] \tag{5.6}$$

In a safe haven economy as defined in 5, if nfl_t and gfl_t are not too high, this covariance differential is positive. This implies that the difference in covariances introduces a gain from foreign exchange interventions. The domestic economy is less exposed to global risk, so the planner benefits from going short in domestic bonds and long in foreign bonds. Notice that this covariance differential is decreasing in gfl_t. By increasing its balance-sheet exposure to exchange rate risk, the planner would increase the risk exposure of the domestic household and the domestic covariance would catch up to the foreign one.

5.2 Optimal Allocations with no Domestic Motive for FX Interventions

The marginal utility cost of FX interventions $UCFX_t$, and especially the covariance differential, is only one component of the planner's optimality condition (4.7). The following lemma lays down explicit expressions for the optimal FX interventions. For the moment, we abstract from the domestic motives of monetary policy by assuming that $\bar{b}^H = 0$.

Suppose that the economy is a safe haven as in Definition 5. Denote by $\widehat{gfl}_t$ and $\widehat{nfl}_t$ the optimal gross and net foreign liabilities. We focus on solutions where $\widehat{nfl}_t < -\log(\beta) + \alpha^2$. Then:

(i) $\widehat{nfl}_t = min\{b_t^G - 1, \overline{nfl}(\widehat{gfl}_t)\}$, where $\overline{nfl}(gfl_t)$ is defined in Appendix D.4;

(i) $\widehat{gfl}_t$ is implicitly defined by:

$$1 - (1 + \chi + 2\Gamma gfl_t)e^{-\Delta cov} = 0$$

where Δcov is defined by Equation (5.6).

See the proof in Appendix D.4. Result (i) comes from the fact that the household may be financially constrained. In that case, $nfl_t = b_t^G - h_t^H$, where $h_t^H = 1$. Otherwise, the level of net foreign liabilities nfl equalizes the domestic and foreign discount factors in expectations. Note that in that case, the household can only issue foreign bonds, because, as we have seen, we must have $\lambda^H > 0$. Result (ii) derives from the optimality condition with respect to gfl_t, Equation (3.5). It reflects the fact that the planner does not fully shut down the domestic currency excess return rent (hence the extra term in Γ on the left-hand side). The planner intervenes enough to take advantage of the excess return, but takes into account the fact that interventions decrease the domestic excess return.

5.2.1 Comparative statics

Lemma 5.2 implies that, at the optimum,

$$\widehat{gfl}_t = \frac{\rho\sigma_y^2[1 - \alpha(1 + \widehat{nfl}_t)] - \chi}{2\Gamma + \rho(\alpha + \rho)\sigma_y^2} \tag{5.7}$$

This is shown formally in Appendix D.5. Since we analyze safe haven economies, we focus on the case where $\widehat{gfl}_t \geq 0$.

Note that $\widehat{gfl}_t$ depends negatively on $\widehat{nfl}_t$. Indeed, higher leverage makes the economy more vulnerable to global risk and hence reduces the incentives of the central bank to take more risk on its balance sheet. What parameters drive $\widehat{nfl}_t$? In the case where the households are unconstrained, we show in Appendix D.5 that, under some conditions, $\widehat{nfl}_t$ is positive if σ_y^2 is high and α is low, while χ and Γ are not too large, even though the path of domestic output is the same as the foreign one on average. This is due to the fact that domestic households are less exposed to global risk than the foreign investors, which lowers the domestic discount factor relative to the foreign one. This is akin to an "inverse precautionary saving motive". This low risk exposure generates a borrowing motive that can drive the domestic households to hit their no-borrowing constraint if the government debt is too low ($b_t^G - 1 < \overline{nfl_t}$). In what follows, we suppose that the households are constrained so that $\widehat{nfl}_t = b_t^G - 1$ is given. In that case, the optimal level of intervention is given by

$$\widehat{b}_t^{CBF} = \frac{\rho\sigma_y^2[1-\alpha b_t^G] - \chi}{2\Gamma + \rho(\alpha+\rho)\sigma_y^2} - (b_t^G - 1)$$

where we used equations (4.10) and (5.7).

The comparative statics for optimal FX intervention is given in the following proposition:

Consider a safe haven economy as defined in 5 and assume that $\bar{b}^H = 0$. Suppose that $\widehat{gfl}_t \geq 0$ and $\widehat{nfl}_t = b^G - 1$. Then optimal foreign exchange interventions, $\widehat{b}_t^{CBF}$:

(i) are increasing in risk measures σ_y and ρ;

(ii) are decreasing in intermediaries financial frictions Γ and χ;

(iii) are decreasing in the supply of government bonds b_t^G;

(iv) are decreasing in the domestic output exposure to global risk α, as long as $b_t^G > 0$.

Points (i) to (iv) can be shown by taking the derivatives of $\widehat{b}_t^{CBF}$ with respect to σ_y, ρ,Γ, χ, α, and b_t^G. Risk tends to increase the covariance differential Δcov, which generates an excess benefit of foreign exchange interventions, while the intermediation frictions and a larger supply of government bonds generate a cost. The exposure of domestic output to global risk decreases the covariance differential and generates a cost.

Interestingly, an increase in risk, which increases the optimal gfl_t, typically generates both a more negative UIP deviation and a more positive CIP deviation, as the financial intermediaries have to absorb the excess domestic currency bonds. This is established formally in the following proposition: Suppose that $\widehat{gfl}_t \geq 0$ and $\widehat{nfl}_t = b^G - 1$. Then:

(i) Z^*_{t+1} is increasing in σ_y (it becomes more positive);

(ii) $E_t X^*_{t+1}$ is decreasing in σ_y (it becomes more negative) if Γ is not too large.

See the proof in Appendix D.6. The CIP deviation becomes more positive when risk increases, as financial intermediaries need to absorb more capital inflows (more gfl_t). As risk increases, the UIP deviation becomes more negative, because it affects positively the foreigners' risk premium. However, if the intermediation friction Γ is large, the increase in the CIP deviation can offset the increase in the risk premium, and the total impact on the UIP deviation becomes ambiguous.

5.2.2 Numerical Illustration

These comparative statics hold both outside and inside the ZLB. The only difference is that at the ZLB, i_t is constant at zero, while S_t adjusts. To illustrate this, we show a numerical example varying the level of risk σ_y^2.

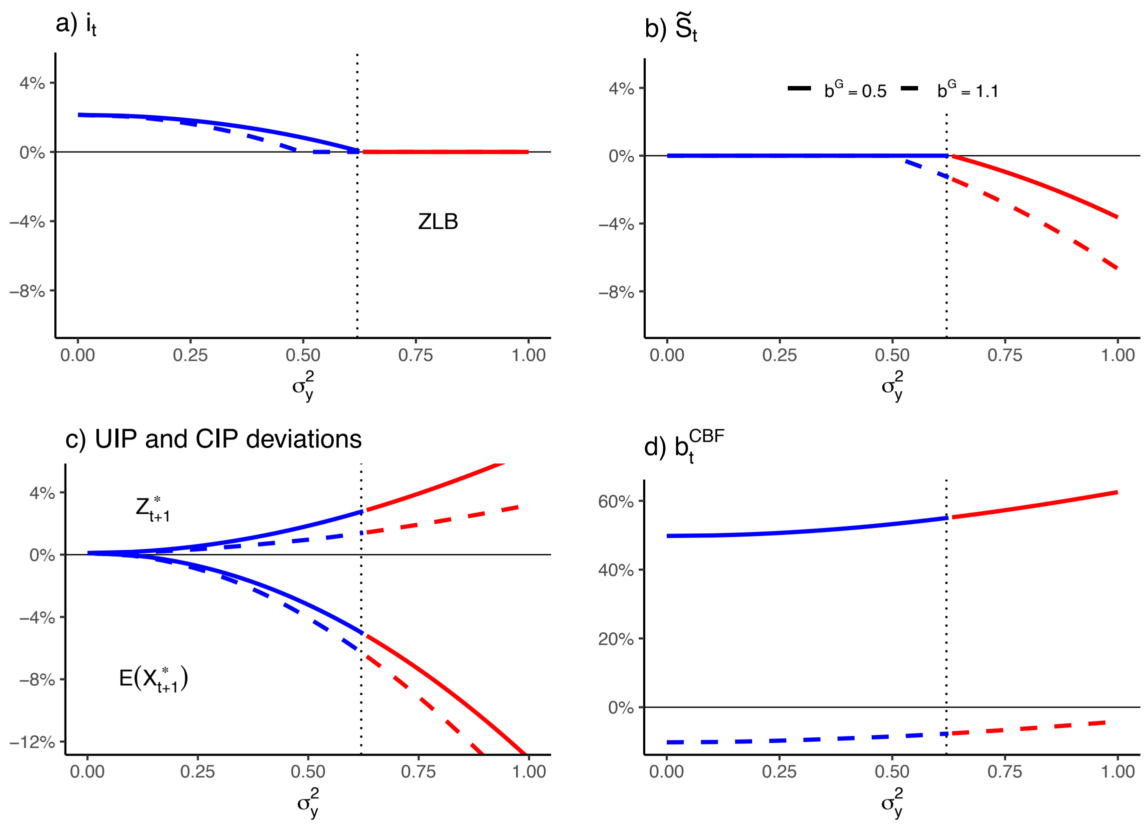
Figure 5.1 shows the comparative statics of σ_y^2 under a baseline specification of parameters, both for ZLB and non-ZLB. We also consider two levels of b_t^G: 0.5 and 1.1. Panel a) shows the negative relationship between the domestic interest rate and risk: the higher demand for domestic bonds is accommodated through a decline in the domestic nominal interest rate. The ZLB is attained at $\sigma_y^2 \geq 0.62$. At the ZLB, it is the exchange rate which adjusts to accommodate, through an appreciation, the higher demand for domestic bonds (see Panel b)). Panel c) displays the deviations from UIP ($E_t X^*_{t+1}$) and CIP (Z^*_{t+1}). As we can see, an increase in risk leads to a more negative UIP deviation, and a more positive CIP deviation, as explained in Proposition 5.2.1.

For Panels a) to c), a higher public debt b_t^G reduces the domestic interest rate and the domestic currency excess return (generating a less positive CIP deviation and a more negative UIP deviation). Indeed, with a higher level of net foreign liabilities nfl_t, the central bank targets lower domestic gross liabilities gfl_t, as explained above (and as illustrated in Panels a) and b) of Figure E1 in the Appendix). The lower equilibrium interest rate then results from the relative scarcity of domestic assets.

Panel d) shows that $\widehat{b}_t^{CBF}$ increases with risk because of the positive covariance differential (see equation (5.6)) resulting from the assumption of safe-haven ($\alpha < 1$ and $\rho > 0$). An increase in risk raises the benefit of FX interventions, which the central bank takes advantage of by buying FX reserves. However, the level of $\widehat{b}_t^{CBF}$ is only positive when $b_t^G = 0.5$. When b_t^G is large, the central bank is long in domestic bonds rather than foreign bonds, and short in foreign bonds rather than domestic bonds. In that case, an increase in risk pushes the central bank to sell domestic bonds and decrease its foreign currency leverage. However, this is possible only if the central bank is allowed to be short in foreign currency. Otherwise, the central bank cannot exploit its advantage. This perspective is consistent with the experience of Switzerland and Japan. Swiss public debt has been below 50% in the last 15 years, while it has been higher than 200% for Japan.

Note that households need not be constrained in their capacity to smooth consumption between periods for the central bank interventions to be effective. In Figure E1 in the Appendix, we can see that in the case with a large public debt (dashed lines), the foreign-currency no-borrowing constraint is not binding for most values of σ_y^2 (see Panel c)), as government debt helps households achieve their desired level of nfl_t without having to borrow themselves. In fact, as risk increases, the discount factor of the domestic households decreases relative to the foreign one, leading to an increase in nfl_t (see Panel b)). This net foreign position is achieved by decreasing foreign currency bonds holdings b_t^F (see Panel e)), as long as the foreign-currency no-borrowing constraint is not binding. Despite that, the central bank can achieve its target gfl_t, because it can crowd out private domestic savings b_t^H by holding just the right amount

Figure 5.1 Comparative statics of σ_y^2



Notes: Baseline parameters : $\beta = 0.98, \chi = 0.002, \Gamma = 0.5, \alpha = 0.6, \rho = 0.2$. We assume that $\bar{b}^H = \bar{b}^F = 0$.

of domestic bonds to achieve its desired gfl_t. As discussed above, households want to issue *more* gross foreign liabilities than the central bank, but they are prevented from doing so by the domestic bond short-selling constraint. We can see that, indeed, households are still constrained in their capacity to issue domestic bonds ($\lambda^H/\eta_t > 0$, although it is very small, as shown in Panel d), and $(1+)b_t^H$ remains constant at $\bar{b}^H$, as shown in Panel f)).

5.3 Optimal Allocations with a Domestic Motive for FX Interventions

So far, we have examined the case where $\bar{b}^H$, the households' minimum domestic bond holdings, is equal to zero. This assumption suppresses any "domestic" motive for FX interventions, as distorting the domestic interest rate cannot improve the households' consumption smoothing. In that case, the only motive for FX interventions stems from the utility gains of holding FX reserves.

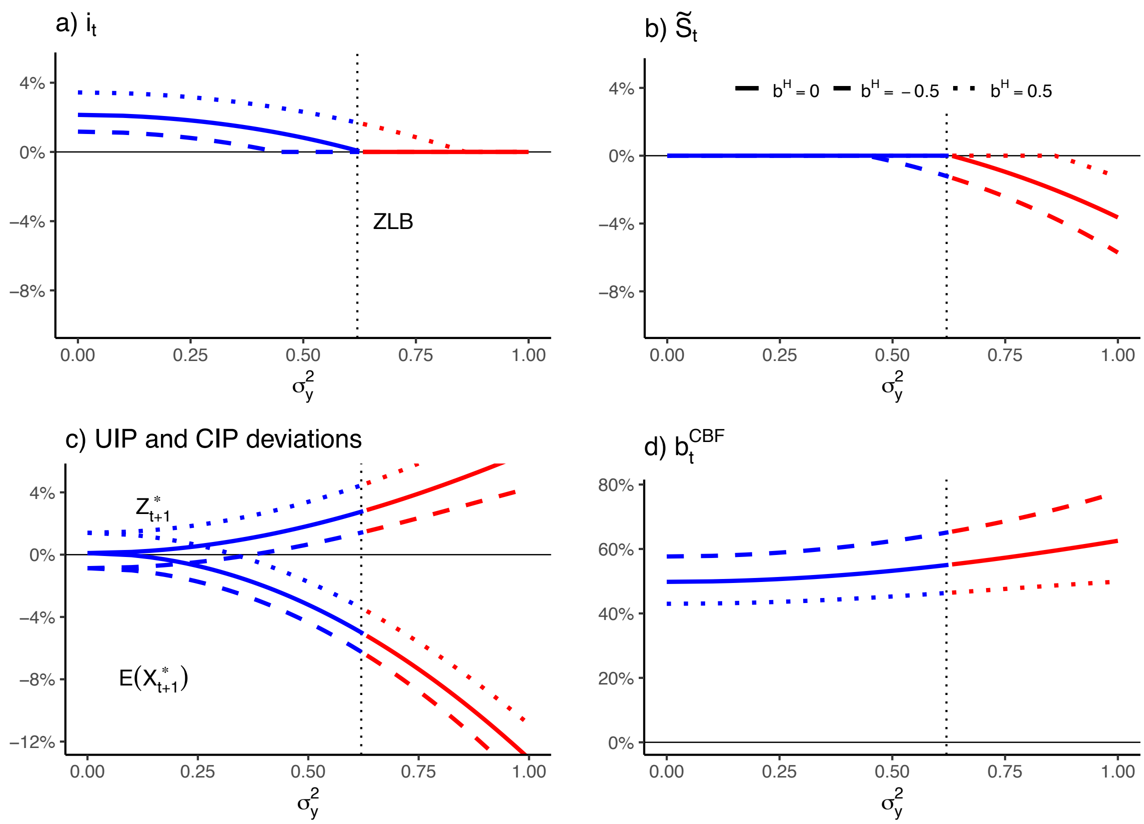
We now discuss the case where $\bar{b}^H \neq 0$. In that case, as we can infer from Equations (4.7) and (4.13), the central bank can have an additional motive of buying or selling FX reserves if $\Lambda > 0$. Note that, since $\lambda^F = \Lambda$, this means that this motive emerges when households are unable to achieve their desired nfl_t. If $\bar{b}^H$ is positive, households are forced to save. In that case, because the forced savings constraint bears on the total returns of savings, the central bank can reduce the amount of forced savings by maintaining a higher real interest rate. This is achieved through more FX interventions. If $\bar{b}^H$ is negative, households have a limited borrowing capacity. Here, on the opposite, the central bank would like to achieve a lower real interest rate to generate a higher borrowing capacity for the households, since the constraint bears on total debt repayments. This is achieved through less FX interventions.

Figure 5.2 illustrates this. Panel d) shows that a positive $\bar{b}^H$ shifts the central bank's FX reserve holdings upwards, while a negative $\bar{b}^H$ produces a downward shift. The price implications are shown in Panels a), b) and c). In the former case, the equilibrium nominal interest rate is higher (outside the ZLB) and the nominal exchange rate is more depreciated (in the ZLB), which generates a higher real interest rate, and hence a downward shift in both CIP and UIP deviations. In the latter case, the opposite happens.

6 Conclusion

The GFC was followed by significant changes in the international monetary system. We have been observing systematic deviations from CIP, an increased demand for safe assets, a strengthening role of the USD as a reserve currency and strong increase in

Figure 5.2 Comparative statics of σ_y^2 with and without a "domestic motive"



Notes: Baseline parameters : $\beta = 0.98, \chi = 0.002\, \Gamma = 0.5, \alpha = 0.6, \rho = 0.2, b^G = 0.5$.

central bank balance sheets. In this context, there has been a stronger demand for safe have currencies and a higher motivation of central banks in these countries for FX intervention. In the case of the Swiss National Bank, the spectacular increase in its balance sheet has occurred exclusively through the purchase of foreign assets.

The objective of this paper is to provide a simple framework to clarify some aspects of these developments. To explain UIP and CIP deviations in safe haven economies, we follow the recent literature that gives a key role to constrained international financial intermediaries. However, we assume that these intermediaries face exchange rate risk and value the hedging properties of safe haven currencies. The increased demand of these currencies may push the central bank to intervene and limit the extent of currency appreciation.

We examine the opportunity cost of FX intervention when CIP and UIP deviations are of different sign. We show that whether CIP or UIP matters depends on how domestic residents value the hedging property of their currency compared to international investors. If they give no value to its hedging property, UIP deviations should matter. This may imply an opportunity benefit, and thus a higher incentive, for FX accumulation. We show that the incentives to accumulate FX reserves in safe haven countries increase with the level of global risk or of effective risk aversion of international intermediaries. In contrast, the incentive decreases with the level of global debt.

We also attempt to estimate the opportunity cost of intervention for Switzerland and Japan. We find that in both countries, domestic households value less the hedging properties of their currency than international investors. Overall, the incentives for intervention are stronger for Switzerland as the difference with international investors is larger and its public debt is much smaller than in Japan. While our analysis focuses on small safe haven countries, it also sheds some light on the difference between the properties of safe haven currencies and those of a reserve currency such the USD.

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Appendix to Chapter 4

A CHF and JPY as Safe Haven Currencies

The safe haven properties of the Swiss franc and the Japanese yen have been documented by various authors, e.g., Stavrakeva and Tang (2021), Ranaldo and Söderlind (2010), Grisse and Nitschka (2015), or Fink et al. (2022). We confirm this by relating expected excess returns to various sources of risk.

We compute UIP deviations using short-term rates from Datastream and survey data from Consensus Economics.[18] Table A1 shows the correlation between expected excess returns in CHF and JPY (Ex^*_{t+1}) and different measures of risk. Since 2010, this correlation is systematically positive, suggesting that agents tend to expect the CHF and JPY to yield excess returns at times of heightened uncertainty. When considering the entire sample (from 1999 to 2021), the correlation is systematically weaker or negative, which suggests that the CHF and JPY have reinforced their perceived safe-haven properties since 2010.

Table A1 Correlation between UIP deviations and (global) risk variables

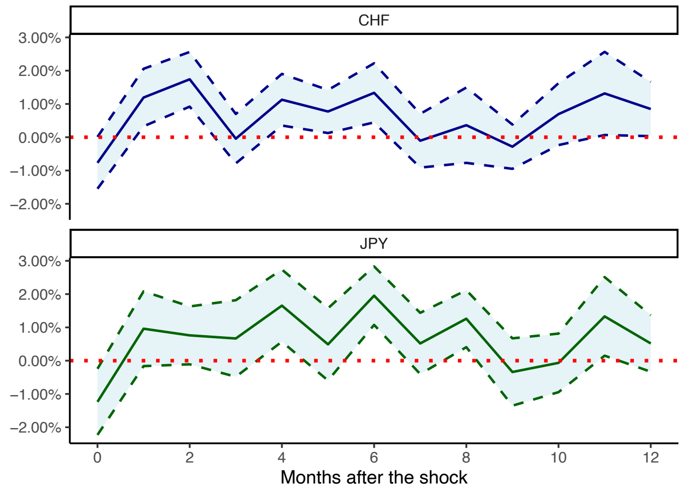
$Corr(RiskVariables, E(x^*_{t+1}))$						
	A) CHF/USD			B) JPY/USD		
Sample	USEPU	GEPU	WUI	USEPU	GEPU	WUI
1999-2021	-0.23	-0.29	-0.30	-0.11	-0.03	0.06
2010-2021	0.14	0.26	0.41	0.14	0.32	0.43

Notes: This table displays the correlation between Ex^*_{t+1} (at a 3-month horizon) and different risk variables for the whole sample and a subsample starting in 2010. Panel A) displays this correlation taking the CHF as the domestic currency and the USD as the foreign one. Similarly, Panel B) considers the JPY as the domestic currency. USEPU is the US Eonomic Policy Uncertainty index developed in Baker et al. (2016). GEPU is the Global EPU. WUI is the World Uncertainty Index developed in Ahir et al. (2022). Since WUI is only available at a quarterly frequency, we take the quarterly mean of UIP deviations when computing the correlation.

To examine the dynamic impact of uncertainty shocks, Figure A1 runs a local-projection regression (Jordà (2005)) of a Global Economic Policy Uncertainty (EPU) shock on $E(x^*_{t+1})$ for the period 2010-2021. The results show that, following an unanticipated shock to the Global EPU, $E(x^*_{t+1})$ tends to increase both for the CHF and the JPY. In other words, the CHF and the JPY are generally expected to appreciate following an uncertainty shock.

[18] See Kalemli-Özcan and Varela (2021) for a recent analysis of UIP deviations using Consensus Economics survey.

Figure A1 Local Projections to a Global EPU shock



Notes: This figure shows the results from the local projection of a Global EPU shock on the UIP deviations over the sample 2010-2021, using the CHF and the JPY as the domestic currency, respectively. Formally, we identify an uncertainty shock ($shock_t$) outside of the system by taking the residual of an AR(1) on our Global EPU variable in the spirit of Stock and Watson (2012) who uses the VIX. We then run $E(x^*_{t+h}) = \alpha^h + \beta_h shock_t + \phi^h x_t + u^h_{t+h}$ for $h = 0, ..., 12$ where x_t are control variables made of $p = 3$ lags of the dependent variable. We then report β^h at each horizon as well as the 90% confidence intervals using the Newey-West estimator.

B Computing excess returns and stochastic discount factors

In this section, we discuss the construction of $cov(x^*_{t+1}, m^*_{t+1})/E_t m^*_{t+1}$ and $cov(x^*_{t+1}, m_{t+1})/E_t m_{t+1}$ considering either the CHF and the JPY as the domestic currency, and keeping the USD as the foreign one.

B.1 Excess returns

First, we compute excess returns. For i_t, we rely on the domestic (CHF or JPY) 3-month risk-free rate, while i^*_t is the US 3-month risk-free rate. For s_t we rely on nominal spot exchange rate data expressed in amount of domestic currency per unit of USD. All data is from Datastream and retrieved at the daily frequency. The daily data is aggregated to the quarterly frequency by taking the mean within each quarter. To compute excess returns, we first compute quarterly excess returns according to (3.7). We assume that what matters for the financial intermediaries is the moving excess returns of this carry-trade over the past year by taking a moving sum of excess returns over that of the current and last three quarters. This allows to have a smoother version of excess returns.

B.2 Stochastic discount factors

International Financial Intermediaries

We now discuss the construction of the SDF of financial intermediaries, which is defined as $m^*_{t+1} = \beta \left(NW_{t+1}/NW_t\right)^{-\gamma}$. Similar to He et al. (2017), we define $NW_{t+1} = \eta_{t+1} \times W_{t+1}$, where η_{t+1} is a measure of the capital ratio of financial intermediaries and W_t is a measure of total wealth. The SDF is obtained by interacting a measure of the growth rate of the capital ratio and total wealth. Below, we discuss the construction of these growth rates.

We consider two measures of the capital ratio. The first specification (HKM) relies on the capital ratio measure from He et al. (2017) which is retrieved from Zhiguo He's website at the daily frequency and aggregated at the quarterly frequency by taking the mean. The second specification (AEM) is based on Adrian et al. (2014) and is computed using quarterly balance sheet data from the Federal Reserve Flow Of Funds (Table L.130). To obtain an annual growth rate, we divide the residual of a regression of the capital ratio in t on its one-year lagged value by the one-year lagged value of the capital ratio. This gives rise to the intermediary capital risk factor. The two resulting measures are defined as $\Delta\eta^{HKM}_{t+1}$ and $\Delta\eta^{AEM}_{t+1}$, respectively.

For total wealth growth, we rely on a financial measure (MSCI US Equity Index) and a real measure (US GDP). For the financial measure, we consider moving annual excess returns. Every quarter, they are obtained by summing up daily excess returns over the past 4 quarters and subtracting the 3-month US risk-free rate. The resulting series is defined as ΔW^{MSCI}_{t+1}. For the real measure, we compute moving annual growth every quarter. The resulting series is defined as ΔW^{GDP}_{t+1}.

The SDF of financial intermediaries is then computed as $m^*_{t+1} = \beta(\Delta\eta^i_{t+1} \times \Delta W^j_{t+1})^{-\gamma}$ for $i \in \{AEM, HKM\}$ and $j \in \{MSCI, GDP\}$, with $\beta = 0.99$ and $\gamma = 10$. This gives rise to 4 potential specifications of the SDF of financial intermediaries.

Domestic Households

For Households (HH), the SDF is defined as $m_{t+1} = \beta \left(C_{t+1}/C_t\right)^{-\gamma}$. Real consumption for Switzerland and Japan is retrieved from the FRED website at the quarterly frequency. As for the SDF of financial intermediaries, we compute a moving annual growth rate and assume $\gamma = 10$ and $\beta = 0.99$.

C Proofs - Constrained Planner Program

C.1 Other FOCs

We take the derivative with respect to h^H_t:

$$/h^H_t : -E_t\left(\eta_{t+1}\left[i_t\frac{S_t}{S_{t+1}}\right]\right) + \Delta^H_t - \Delta^F - \tilde{\Lambda} = 0 \tag{C.1}$$

Equations (C.1) and (4.5) then imply that $\Delta_t^H = \tilde{\Lambda} = \Lambda$. Therefore, when $\Lambda = \tilde{\Lambda} = 0$, $\Delta_t^H = 0$. This reflects the fact that, while households want to minimize their money holdings because they represent a cost (when $i_t > 0$), the amount of money held by the households is not relevant to the central bank when the economy is not constrained in its capacity to issue debt, since seigniorage is redistributed to households in period $t+1$. The cash-in advance constraint is relevant only to the extent that it also restrains the capacity of the economy to supply domestic assets to the rest of the world, just like the no-borrowing constraints.

We now take the derivatives with respect to prices:

$$\begin{aligned} /i_t: \quad & -E\left[\eta_{t+1}(1+i_t)\frac{S_t}{S_{t+1}}\left(gfl_t + \frac{H_t}{S_t} - h_t^H\right)\right] + (1+i_t)\xi \\ & -\alpha_0 E\left(m_{t+1}^*(1+i_t)\frac{S_t}{S_{t+1}}\right) + \tilde{\Lambda}\frac{\bar{b}^H}{E_t\frac{(1+i_t)S_t}{S_{t+1}}} = 0 \end{aligned} \tag{C.2}$$

$$\begin{aligned} /S_t: \quad & -E\left(\eta_{t+1}\left[(1+i_t)\frac{S_t}{S_{t+1}}gfl_t - i_t\frac{S_t}{S_{t+1}}h_t^H\right]\right) - \Delta^F\frac{H_t}{S_t} \\ & -\alpha_0\left[E\left(m_{t+1}^*(1+i_t)\frac{S_t}{S_{t+1}}\right)\right] + \tilde{\Lambda}\frac{\bar{b}^H}{E_t\frac{(1+i_t)S_t}{S_{t+1}}} = 0 \end{aligned} \tag{C.3}$$

Finally, we derive with respect to consumption:

$$/C_t: \quad U'(C_t) - \eta_t = 0 \tag{C.4}$$

$$/C_{t+1}: \quad E\left(\beta U'(C_{t+1}) - \eta_{t+1}\right) = 0 \tag{C.5}$$

These equations imply that $m_{t+1}^{CB} = \eta_{t+1}/\eta_t = \beta U'(C_{t+1})/U'(C_t) = m_{t+1}$.

C.2 Monopolistic term and interest and exchange rate determinacy

Here we have to distinguish two cases. Either $i_t > 0$, and in that case $\xi = 0$, $H_t/S_t = h_t^H$ and $\Delta^F > 0$. Or $i_t = 0$, and in that case $\xi > 0$ and $\bar{\Delta}^F = 0$.

In the former case (if $i_t > 0$), Equation (C.2) yields

$$\frac{\alpha_0}{\eta_t} = -gfl_t\frac{E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E\left(m_{t+1}^*\frac{S_t}{S_{t+1}}\right)} + \frac{\tilde{\Lambda}}{\eta_t}\frac{\bar{b}^H}{E_t\left(\frac{(1+i_t)S_t}{S_{t+1}}\right)E_t\left(m_{t+1}^*\frac{(1+i_t)S_t}{S_{t+1}}\right)} \tag{C.6}$$

where we have used $E(\eta_{t+1}/\eta_t) = m_{t+1}$. If $\bar{\Lambda} = 0$, α_0 is of the same sign as $-gfl$, home's gross external position in domestic currency. In that case, if the country is short in domestic currency, then α_0 is negative.

Using Equation (4.5), Equation (C.3) yields the same equation, so it is redundant. This means that there is some nominal indeterminacy. This nominal indeterminacy does not come from the future exchange rate, which is exogenously fixed, but from the amount of excess return adjustment that comes from i_t and S_t. In other terms, the optimal nominal money supply H_t is undetermined. For instance, if the supply of money H_t is higher, then the exchange rate S_t will be higher (more depreciated), so that the optimal interest rate i_t will be have to be lower to generate a given excess return.

In the latter case (if $i_t = 0$), Equation (C.6) remains true. Note that in that case, the exchange rate is not undetermined, because $i_t = 0$.

D Proofs - Linear-Quadratic Case

D.1 Equation (5.1)

We can rewrite the resource constraints (3.1) as

$$\begin{aligned} C_t &= Y_t \left(1 + \tfrac{nfl_t}{Y_t}\right) \\ C_{t+1} &= Y_{t+1} \left(1 - \tfrac{nfl_t}{Y_t} \tfrac{1+i_t^*}{1+g_{t+1}} - \tfrac{gfl_t}{Y_t} \tfrac{X_{t+1}^*}{1+g_{t+1}}\right) \end{aligned}$$

with $1+g_{t+1} = Y_{t+1}/Y_t$. We used the fact that, in equilibrium, $(H_t/S_t - h_t^H) i_t S_t/S_{t+1}$ is equal to zero (either $H_t/S_t - h_t^H = 0$ or $i_t = 0$). Taking logs and using a second-order approximation (assuming $\tilde{Y}_{t+1}$, nfl_t/Y_t, gfl_t/Y_t, X_{t+1}^* and g_{t+1} are small), we obtain

$$\begin{aligned} \tilde{C}_t &= \tilde{Y}_t + \tfrac{nfl_t}{Y_t} - \tfrac{1}{2}\left(\tfrac{nfl_t}{Y_t}\right)^2 \\ \tilde{C}_{t+1} &= \tilde{Y}_{t+1} - \tfrac{nfl_t}{Y_t}(1 + i_t^* - g_{t+1}) + \tfrac{1}{2}\left(\tfrac{nfl_t}{Y_t}\right)^2 (1 + i_t^*) - \tfrac{gfl_t}{Y_t}(X_{t+1}^* - g_{t+1}) \end{aligned}$$

Finally, we use the approximation $g_{t+1} = \tilde{Y}_{t+1} - \tilde{Y}_t$ along with the assumption that $Y_t = 1$ and hence $\tilde{Y}_t = 0$ to obtain Equation (5.1)

D.2 Equations (5.4)

Equation (5.2) yields

$$\begin{aligned} & & E_t(e^{\tilde{m}_{t+1}^* + \tilde{i}_t^*}) &= 1 \\ \Leftrightarrow & & e^{E(\tilde{m}_{t+1}^*) + \frac{1}{2} V(\tilde{m}_{t+1}^*) + \tilde{i}_t^*} &= 1 \\ \Leftrightarrow & & e^{\log(\beta) + E(\tilde{-} y_{t+1}^*) + \frac{1}{2} V(\tilde{y}_{t+1}^*) + \tilde{i}_t^*} &= 1 \\ \Leftrightarrow & & e^{\log(\beta) + \tilde{i}_t^*} &= 1 \end{aligned}$$

Similarly, Equation (5.2) yields

$$\begin{aligned} & E_t(e^{\tilde{m}^*_{t+1}-\tilde{S}_{t+1}+\tilde{i}_t+\tilde{S}_t}) = 1+\chi+\Gamma gfl_t \\ \Leftrightarrow \quad & e^{E(\tilde{m}^*_{t+1}-\tilde{S}_{t+1})+\frac{1}{2}V(\tilde{m}^*_{t+1}-\tilde{S}_{t+1})+\tilde{i}_t+\tilde{S}_t} = 1+\chi+\Gamma gfl_t \\ \Leftrightarrow \quad & e^{\log(\beta)-E((1+\rho)\tilde{y}^*_{t+1})+\frac{1}{2}V((1+\rho)\tilde{y}^*_{t+1})+\tilde{i}_t+\tilde{S}_t} = 1+\chi+\Gamma gfl_t \\ \Leftrightarrow \quad & e^{\log(\beta)+\frac{(1+\rho)\rho}{2}\sigma_y^2+\tilde{i}_t+\tilde{S}_t} = 1+\chi+\Gamma gfl_t \end{aligned}$$

This yields (5.4).

D.3 Optimal foreign exchange interventions

The difference in risk premia can be written as follows

$$\frac{cov(m^*_{t+1}, X^*_{t+1})}{E_t m^*_{t+1}} - \frac{cov(m_{t+1}, X^*_{t+1})}{E(m_{t+1})} = \frac{1}{\beta}(1+\chi+\Gamma gfl_t)\left(1-e^{cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})-cov(\tilde{S}_{t+1},\tilde{m}_{t+1})}\right)$$

We used

$$\begin{aligned} cov(m^*_{t+1}, X^*_{t+1}) &= cov\left(m^*_{t+1}, (1+i_t)\frac{S_t}{S_{t+1}}\right) - \underbrace{cov(m^*_{t+1}, (1+i^*_t))}_{=0} \\ &= E\left(m^*_{t+1}(1+i_t)\frac{S_t}{S_{t+1}}\right) - E\left(m^*_{t+1}\right)E\left((1+i_t)\frac{S_t}{S_{t+1}}\right) \\ &= E\left(e^{\tilde{m}^*_{t+1}+\tilde{i}_t+\tilde{S}_t-\tilde{S}_{t+1}}\right) - E\left(e^{\tilde{m}^*_{t+1}}\right)E\left(e^{\tilde{i}_t+\tilde{S}_t-\tilde{S}_{t+1}}\right) \\ &= \underbrace{E\left(e^{\tilde{m}^*_{t+1}+\tilde{i}_t+\tilde{S}_t-\tilde{S}_{t+1}}\right)}_{1+\chi+\Gamma gfl_t}\left[1-e^{cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})}\right] \end{aligned}$$

where we used (5.3), and

$$E(m^*_{t+1}) = \beta$$

which yields

$$\frac{cov(m^*_{t+1}, X^*_{t+1})}{E_t m^*_{t+1}} = \frac{1}{\beta}(1+\chi+\Gamma gfl_t)\left[1-e^{cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})}\right] \tag{D.1}$$

Similarly:

$$
\begin{aligned}
\frac{cov(m_{t+1},X^*_{t+1})}{E(m_{t+1})} &= \frac{cov\left(m_{t+1},(1+i_t)\frac{S_t}{S_{t+1}}\right)-\underbrace{cov(m_{t+1},(1+i^*_t))}_{=0}}{E(m_{t+1})}\\
&= \frac{E\left(m_{t+1}(1+i_t)\frac{S_t}{S_{t+1}}\right)}{E(m_{t+1})} - E\left((1+i_t)\frac{S_t}{S_{t+1}}\right)\\
&= \frac{E\left(e^{\tilde{m}_{t+1}+\tilde{i}_t+\tilde{S}_t-\tilde{S}_{t+1}}\right)}{E\left(e^{\tilde{m}_{t+1}}\right)} - E\left(e^{\tilde{i}_t+\tilde{S}_t-\tilde{S}_{t+1}}\right)\\
&= e^{-\log(\beta)+\tilde{i}_t+\tilde{S}_t-E(\tilde{S}_{t+1})+\frac{V(\tilde{S}_{t+1})}{2}-cov(\tilde{S}_{t+1},\tilde{m}_{t+1})}\left[1-e^{cov(\tilde{S}_{t+1},\tilde{m}_{t+1})}\right]\\
&= \frac{1}{\beta}e^{\tilde{i}_t+\tilde{S}_t-E(\tilde{S}_{t+1})+\frac{V(\tilde{S}_{t+1})}{2}+E(\tilde{m}^*_{t+1})+\frac{V(\tilde{m}^*_{t+1})}{2}-cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})}\left[e^{cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})-cov(\tilde{S}_{t+1},\tilde{m}_{t+1})}-e^{cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})}\right]\\
&= \frac{1}{\beta}\underbrace{E\left(e^{\tilde{m}^*_{t+1}+\tilde{i}_t+\tilde{S}_t-\tilde{S}_{t+1}}\right)}_{1+\chi+\Gamma gfl_t}\left[e^{cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})-cov(\tilde{S}_{t+1},\tilde{m}_{t+1})}-e^{cov(\tilde{S}_{t+1},\tilde{m}^*_{t+1})}\right]
\end{aligned}
$$

where we used $-\log(\beta)=E(\tilde{m}^*_{t+1})+\frac{V(\tilde{m}^*_{t+1})}{2}$. This yields Equation (5.5).

Now note that

$$
\tilde{m}^*_{t+1}=\log(\beta)-\tilde{Y}^*_{t+1}, \tag{D.2}
$$

and, from (5.1), we get

$$
\begin{aligned}
\tilde{m}_{t+1} &= \tilde{C}_t-\tilde{C}_{t+1}\\
&= \log(\beta)-\alpha\tilde{Y}^*_{t+1}(1+nfl_t+gfl_t)+(nfl_t-nfl_t^2/2)(2+\tilde{i}^*_t)+gfl_t(\tilde{i}_t-\tilde{i}^*_t+\tilde{S}_t-\rho\tilde{Y}^*_{t+1}),
\end{aligned} \tag{D.3}
$$

using $\tilde{Y}_{t+1}=\alpha\tilde{Y}^*_{t+1}$, $X^*_{t+1}=\tilde{i}_t-\tilde{i}^*_t+\tilde{S}_t-\tilde{S}_{t+1}$ and $\tilde{S}_{t+1}=\rho\tilde{Y}^*_{t+1}$. Therefore, we find Equation (5.6).

D.4 Proof of Lemma 5.2

Another way to write Equation (3.5) is:

$$
\begin{aligned}
E\left(m_{t+1}(1+i^*_t)\right)-E\left(m_{t+1}(1+i_t)\frac{S_t}{S_{t+1}}\right)+\frac{\alpha_0\Gamma}{\eta_t} &= 0\\
\underbrace{(1+i^*_t)}_{\frac{1}{E(m^*_{t+1})}}E\left(m_{t+1}\right)-\underbrace{(1+i_t)}_{\frac{1+\chi+\Gamma gfl_t}{E\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)}}E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)+\frac{\alpha_0\Gamma}{\eta_t} &= 0\\
\frac{1}{E(m^*_{t+1})}-\frac{1+\chi+\Gamma gfl_t}{E\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)}\frac{E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m_{t+1})}+\frac{\alpha_0\Gamma}{\eta_t E(m_{t+1})} &= 0\\
1-(1+\chi+\Gamma gfl_t)\frac{\frac{E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m_{t+1})}}{\frac{E\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m^*_{t+1})}}+\frac{\beta\alpha_0\Gamma E(m^*_{t+1})}{\eta_t E(m_{t+1})} &= 0
\end{aligned}
$$

Equation (4.8) yields

$$
\begin{aligned}
1-(1+\chi+\Gamma gfl_t)\frac{\frac{E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m_{t+1})}}{\frac{E\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m^*_{t+1})}}-\Gamma gfl_t\frac{\frac{E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m_{t+1})}}{\frac{E\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m^*_{t+1})}} &= 0\\
1-(1+\chi+2\Gamma gfl_t)\frac{\frac{E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m_{t+1})}}{\frac{E\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m^*_{t+1})}} &= 0
\end{aligned}
$$

Besides,

$$\frac{\frac{E\left(m_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m_{t+1})}}{\frac{E\left(m^*_{t+1}\frac{S_t}{S_{t+1}}\right)}{E(m^*_{t+1})}}=e^{cov(\tilde{m}^*_{t+1},\tilde{S}_{t+1})-cov(\tilde{m}_{t+1},\tilde{S}_{t+1})}=e^{-\Delta cov} \tag{D.4}$$

Hence result (ii) of Lemma 5.2.

Note that (4.3) implies that

$$\frac{\Lambda}{\eta_t} = 1-E[m_{t+1}(1+i^*_t)]$$

$\Lambda=0$ is equivalent to

$$
\begin{aligned}
E[m_{t+1}(1+i^*_t)] &= 1\\
E(m_{t+1}) &= \beta\\
e^{E(\tilde{m}_{t+1})+\frac{1}{2}V(\tilde{m}_{t+1})} &= \beta
\end{aligned}
$$

where we used (5.4) and where $\tilde{m}_{t+1}$ is given by (D.3).

We have

$$E(\tilde{m}_{t+1})=\log(\beta)-(1+nfl+gfl)\frac{\sigma_y^2}{2}+[1-\log(\beta)]\left(nfl_t-\frac{1}{2}nfl_t^2\right)+\left(-\frac{\rho^2\sigma_y^2}{2}-\rho\sigma_y^2+\chi+\Gamma gfl_t\right)gfl_t$$

where we used $\log(1+\chi+\Gamma gfl_t)\simeq\chi+\Gamma gfl_t$, and

$$\frac{1}{2}V(\tilde{m}_{t+1})=\alpha^2(1+nfl+gfl)\frac{\sigma_y^2}{2}+\frac{\rho^2\sigma_y^2}{2}gfl_t$$

Therefore, $\Lambda=0$ is equivalent to $\tilde{m}(nfl_t,gfl_t)=0$ with

$$\tilde{m}(nfl_t,gfl_t)=-(1-\alpha^2)(1+nfl+gfl)\frac{\sigma_y^2}{2}+[1-\log(\beta)]\left(nfl_t-\frac{1}{2}nfl_t^2\right)+\left(-\rho\sigma_y^2+\chi+\Gamma gfl_t\right)gfl_t \tag{D.5}$$

$\tilde{m}(nfl_t,gfl_t)$ is increasing in nfl_t if $nfl_t<-\log(\beta)+\alpha^2)$. We consider only solutions that satisfy this condition. In that case, the solution is unique. Denote by $\overline{nfl}(gfl_t)$ this solution. If $\overline{nfl}(gfl_t)>b^G-h_t^H=b^G-1$, then $nfl_t=b^G-1$ and $\Lambda>0$.

D.5 Solutions for $\widehat{gfl}_t$ and $\widehat{nfl}_t$

For a given nfl_t, gfl_t is implicitly defined by

$$1-(1+\chi+2\Gamma gfl_t)e^{-\rho\sigma_y^2[1-\alpha(1+nfl_t+gfl_t)-\rho gfl_t]}=0$$

Using $\log(1+\chi+2\Gamma gfl_t)\simeq\chi+2\Gamma gfl_t$, this yields

$$\chi+2\Gamma gfl_t-\rho\sigma_y^2\left[1-\alpha(1+nfl_t+gfl_t)-\rho gfl_t\right]=0$$

After rearranging, we obtain (5.7).

If $\lambda=0$, (5.7) and $\tilde{m}(nfl_t,gfl_t)=0$ jointly define nfl_t and gfl_t. If $\Lambda>0$, then gfl_t is defined by (5.7) with $nfl_t=b_t^G-1$.

Consider the case where $\Lambda=0$. As before, consider solutions where $nfl_t<-\log(\beta)+\alpha^2)$ and denote by $\overline{nfl}(gfl_t)$ the unique solution. Suppose additionally that $1+\overline{nfl}(gfl_t)+gfl_t>0$. If σ_y^2 is large, and α, χ and Γ are small, then $\tilde{m}(nfl_t,gfl_t)=0$ implies that $nfl_t-nfl_t^2/2>0$. As long as $nfl_t<2$, this implies that $nfl_t>0$.

Special case with $\alpha=0$

In the special case where $\alpha=0$, we can compute implicit solutions for nfl_t and gfl_t when $\Lambda=0$.

First, in that case, (5.7) implies

$$\widehat{gfl}_t=\frac{\rho\sigma_y^2-\chi}{2\Gamma+\rho^2\sigma_y^2}$$

and $\widehat{nfl}_t$ is the solution to the second-order polynomial equation $\tilde{m}(nfl_t,gfl_t)=0$ that is on the increasing segment of the polynomial $\tilde{m}(nfl_t,gfl_t)$:

$$\widehat{nfl}_t=\frac{1}{2}\left[1-\frac{\sigma_y^2}{2[1-\log(\beta)]}-\sqrt{\left[1-\frac{\sigma_y^2}{2[1-\log(\beta)]}\right]^2-4\frac{\frac{\sigma_y^2}{2}(1+\widehat{gfl}_t)-(-\rho\sigma_y^2+\chi+\Gamma\widehat{gfl}_t)\widehat{gfl}_t}{1-\log(\beta)}}\right]$$

D.6 Proof of Proposition 5.2.1

Note that the CIP deviation, as defined in (2.8), is increasing in gfl_t (hence (i)), since $E(m_{t+1}^*)=\beta$ is fixed, and $a_t^{H*}=gfl_t$.

Finally, note that the UIP deviation can be written as (we use (2.9), (D.1) and

$E(m^*_{t+1}) = \beta$ as well):

$$\begin{aligned} E_t X^*_{t+1} &= \frac{1}{\beta}\left[\chi + \Gamma gfl_t - (1+\chi+\Gamma gfl_t)(1-e^{-\rho\sigma_y^2})\right] \\ &= -\frac{1}{\beta}\left[1-(1+\chi+\Gamma gfl_t)e^{-\rho\sigma_y^2}\right] \end{aligned}$$

where we used the results in D.3. Replacing gfl_t with $\widehat{gfl}_t$ and nfl_t with $b^G_t - 1$, we obtain

$$\begin{aligned} E_t X^*_{t+1} &= -\frac{1}{\beta}\left[1-\left(1+\chi+\Gamma\frac{\rho\sigma_y^2[1-\alpha b^G_t]-\chi}{2\Gamma+\rho(\alpha+\rho)\sigma_y^2}\right)e^{-\rho\sigma_y^2}\right] \\ &\simeq -\frac{1}{\beta}\left[1-e^{\chi+\Gamma\frac{\rho\sigma_y^2[1-\alpha b^G_t]-\chi}{2\Gamma+\rho(\alpha+\rho)\sigma_y^2}-\rho\sigma_y^2}\right] \end{aligned}$$

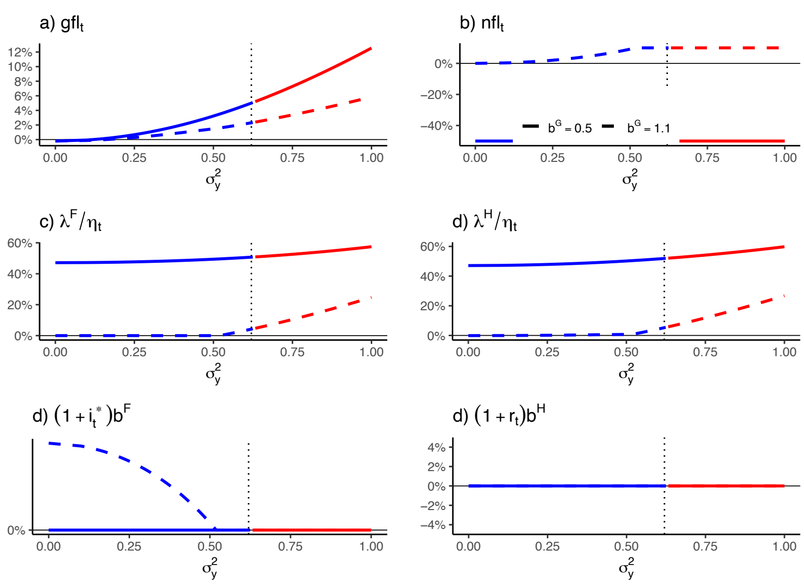
The derivative of $E_t X^*_{t+1}$ with respect to σ_y^2 is of the same sign as

$$-\rho + \Gamma\frac{2\Gamma\rho(1-\alpha b^G_t)+\chi\rho(\alpha+\rho)}{[2\Gamma+\rho(\alpha+\rho)\sigma_y^2]^2}$$

Therefore, $E_t X^*_{t+1}$ is decreasing in σ_y if Γ is not too large (hence (ii)).

E Additional Figures

Figure E1 Comparative statics of σ_y^2 - continued



Notes: Baseline parameters : $\beta = 0.98, \chi = 0.002\,\Gamma = 0.5, \alpha = 0.6, \rho = 0.2$. We assume that $\bar{b}^H = \bar{b}^F = 0$.