Strategic Complementarities, Banks' Stranded Asset Dynamics, and Financial Stability

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Abstract

Following the Paris Agreement, banks curtailed lending to fossil fuels. Local projections show that banks' lending adjustments respond to those of their peers. To rationalize these dynamics, this paper develops a global games model in which climate policy announcements act as public signals shaping beliefs about the fossil fuel sector's economic conditions. The model highlights two channels: fundamentals, reflecting policy-induced energy transition risk, and strategic complementarities, whereby banks' lending decisions reinforce one another. This interaction produces procyclical outcomes. Banks *en masse* may remain excessively exposed to fossil fuels when transition risks appear low, amplifying climate damages, or exit abruptly when risks rise, triggering disorderly adjustment and financial instability. Results show that a countercyclical macroprudential policy can curb these inefficiencies by discouraging excessive risk-taking when transition risks are low and limiting disorderly de-risking when risks intensify.

Keywords: Global games, banks, financial stability, capital requirement, transition risk.

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1 Introduction

A rapid transition to a low-carbon economy can threaten financial stability, potentially triggering what Carney (2018) termed a "climate Minsky moment." Transition risks stem from abrupt climate policy changes and technological breakthroughs in low-carbon innovation (Bolton et al., 2020). These risks can take the form of stranded assets—financial or real—by forcing unexpected or premature write-downs and devaluations under stringent climate policies (Van der Ploeg and Rezai, 2020). When investors revise their expectations collectively, asset prices may fall sharply, undermining the balance sheets of exposed financial institutions and amplifying systemic risk (Battiston et al., 2017; Pereira da Silva, 2019). This raises the central policy question of how prudential authorities should manage banks' exposures to stranded assets under transition risks.

Microprudential authorities, which focus on the soundness of individual banks, may promote rapid de-risking from stranded assets. Yet when banks withdraw simultaneously, financial stability itself may be at risk (Aikman and Barwell, 2022). Following the Bank of England, I define financial stability as the ability of the financial system to consistently deliver services to the real economy (Bank of England, 2023). A sudden stop in credit to fossil fuel producers constitutes a breakdown of banks' credit intermediation function, as they fail to meet firms' financing needs. The consequences extend beyond the fossil fuel sector itself: because the economy remains heavily dependent on fossil energy, disruptions can propagate through production networks and affect broader economic activity (Cahen-Fourot et al., 2021).

These risks highlight the limits of a purely microprudential perspective and motivate macroprudential intervention. Building on this motivation, I examine how banks respond to stranded assets under transition risk, whether their collective behaviour aligns with the social optimum, and how macroprudential policy can address potential inefficiencies.

Two empirical patterns motivate the theoretical analysis. First, global syndicated loan data shows that banks reduced fossil fuel lending relative to total credit supply after the Paris Agreement, consistent with studies showing that the Agreement led to reduced lending or higher pricing for carbon-intensive or fossil fuel borrowers (Mueller and Sfrappini, 2025;

Delis et al., 2024; Reghezza et al., 2022; Ehlers et al., 2022). Second, using a local projection approach, I show that banks' fossil fuel lending, referred to here as stranded asset dynamics, is influenced by their peers. While prior literature largely emphasises fundamentals, such as how transition risk affects these borrowers, as the primary driver of banks' lending decisions, the role of strategic complementarities, where banks' decisions reinforce one another, remains underexplored. This paper contributes by explicitly modeling strategic complementarities in banks' responses to transition risks and showing their macroprudential implications.

To rationalize the observed dynamics, I develop a two-period model in which a risky investment project, operated by the fossil fuel sector, is exposed to climate policy that may render it stranded. Policy announcements act as public signals of the fundamentals: all banks can observe these announcements, while the fundamentals themselves, which represent the true policy impact on profitability of fossil fuel production, are not directly observable. Banks lending to the project are subject to a capital requirement with a penalizing factor linked to their exposure to stranded assets. After observing the policy announcement, each bank decides whether to roll over its lending or withdraw.

Next, I introduce strategic complementarities into banks' decisions, where a bank's best response is to follow the strategy adopted by its peers (Bulow et al., 1985). Such complementarities can emerge through several channels. First, concerns about the solvency of fossil fuel companies may trigger a run on stranded assets when peers choose not to roll over, a mechanism akin to a bank run (see Goldstein and Pauzner, 2005). Second, withdrawals from stranded assets through open-market sales of project shares may generate fire sales (Pereira da Silva, 2019). Third, reputational pressures may induce banks to retreat from carbon-intensive assets when peers commit to "go green" (Aikman and Barwell, 2022).

Building on the global games model (Carlsson and Van Damme, 1993; Morris and Shin, 2001), the analysis shows that, under sufficiently precise private signals, a unique threshold equilibrium exists: a banker withdraws when the policy impact exceeds the threshold and otherwise rolls over. Although each individual bank behaves rationally, their collective behavior is highly procyclical: they take excessive risks when transition risks are perceived to be low and adopt defensive strategies—such as withdrawing or stopping lending—when risks are perceived to be high. This may lead to unintended macrofinancial outcomes. When

banks collectively roll over, fossil fuel production increases, which contribute to gross output, but at the cost of greater climate damages. Conversely, when banks withdraw, climate damages fall, but the abrupt contraction in credit supply leads to output losses.

This motivates a comparison with the social optimum. I introduce a planner who sets the threshold for bank lending to maximise aggregate output. Output is given by a three-factor Cobb–Douglas production function, with fossil fuels as an exhaustible natural resource input (Keen et al., 2019), and climate damages subtracted through a damage function (Nordhaus, 2014). The planner's threshold is set to achieve the level of fossil fuel production that maximizes net output through bank lending. Inefficiencies arise whenever the decentralised threshold implied by the global games equilibrium deviates from this benchmark.

To curb these inefficiencies, I propose a countercyclical capital requirement linked to banks' fossil fuel exposures. Transition risk can be viewed as an economic cycle: banks take excessive risks in good states and de-risk abruptly in bad states. This pattern mirrors traditional credit cycles, where similar procyclicality amplifies systemic risk (Aikman et al., 2015b; Eisenbach, 2017). When transition risk is high, policymakers should safeguard financial stability by lowering the capital requirement to incentivise banks to roll over the investments. Conversely, when risks are low, they should raise the requirement to encourage banks to withdraw and limit future climate damages.

The paper yields three main policy implications. First, it examines the role of macroprudential policy under transition risks and stresses the need to integrate these risks into prudential frameworks, thereby mitigating financial stability risks arising from coordination failures. In extensions, I also show how macroprudential policy can strengthen resilience by increasing the system's ability to absorb transition-related shocks. Second, in an extension of the framework, I consider an alternative fiscal–prudential instrument by examining how a countercyclical tax on fossil fuel exposures can replicate the incentives generated by capital requirements. Third, the analysis underscores the role of financial institutions in supporting an orderly transition to a low-carbon economy, complementing broader structural and climate policies that facilitate energy-sector reallocation and sustainable investment.

Related Literature. This paper contribute to the debate on the role of financial regulation in supporting an orderly transition to a low-carbon economy. For example, Oehmke and Opp (2022) show that capital requirements reduce the profitability of carbon-intensive lending but may also crowd out green credit. They further argue that while capital requirements are not effective at directly reducing emissions, they can strengthen the credibility of higher carbon taxes by ensuring that banks are sufficiently capitalised to absorb losses from stranded assets. In a model with the risk of runs on brown assets, Jondeau et al. (2021) highlight that firms may face refinancing shocks if lenders refuse to roll over loans once borrowers' carbon intensity exceeds a threshold. They propose a liquidity backstop—priced via a lump-sum fee contingent on emissions—as a mechanism to encourage transition while safeguarding financial stability. Gupta and Starmans (2023) introduce a novel government-mandated "greenwashing" policy, under which firms' greenness is temporarily obscured and later subject to stricter disclosure, helping overcome early transition bottlenecks.

Together, these studies underscore a fundamental trade-off in climate-related macrofinancial policies between facilitating the low-carbon transition and preserving financial stability. An optimal policy should support an orderly adjustment of the financial system—loosening when transition costs are high to mitigate financial stability risks, and tightening otherwise to incentivise transition.

This paper extends the literature on strategic complementarities and global games. Diamond and Dybvig (1983) analyse strategic complementarities in a model of bank runs, where all depositors can withdraw simultaneously, and coordination failures lead to multiple equilibria. This motivates the use of global games, which yield a unique equilibrium under mild assumptions on information. Carlsson and Van Damme (1993) develop the global games model, where each player observes a noisy signal of fundamentals; when noise is small, a unique equilibrium exists. Prior studies apply this approach to debt pricing (Morris and Shin, 2004) and currency crises (Morris and Shin, 1998). Building on this, Goldstein and Pauzner (2005) add noisy signals to the bank run model of Diamond and Dybvig (1983) and show that all depositors withdraw if fundamentals are sufficiently weak, with higher promised repayments raising the likelihood of runs. In this paper, I use the global games technique to study how strategic complementarities shape banks' stranded asset dynamics

under transition risk.

Angeletos et al. (2007) extend the framework to a dynamic setting, in which multi-period global games may again give rise to multiple equilibria. In contrast, the two-period model in this paper avoids such multiplicity, though I also discuss another possible multi-period extension, following the more recent approach of Morris and Yildiz (2019), which can maintain the uniqueness of equilibrium.

This research also connects to the literature on global games and prudential regulation. Leonello et al. (2025) show that the probability of bank runs depends on the level of deposits, with depositors failing to internalise the macroeconomic consequences of over-saving. They propose a tax on deposits to mitigate this externality. Ahnert et al. (2019) show that banks have incentives to excessively encumber assets for cheap long-term senior secured debt, reducing assets available for unsecured withdrawals and raising run risk; they suggest limits on encumbrance or a Pigouvian tax with lump-sum rebate.

Global games models have also been applied to examine and regulate banks' procyclicality. Eisenbach (2017) find that banks take excessive risk in good states when rollover risk is low and liquidate excessively in bad states when rollover risk is high; they propose a financial crisis bond to rebalance incentives across states. Aikman et al. (2015a,b) likewise underscore the role of countercyclical capital requirement to curb credit cycles. Building on these insights, I show how a countercyclical macroprudential policy can address the inefficiencies arising from banks' stranded asset dynamics, which likewise exhibit strong procyclicality.

More recently, global games techniques have been applied to contemporary financial stability issues such as stablecoins. Ahmed et al. (2024) apply this approach to analyse stablecoin runs, showing that information about reserve quality shapes coordination among holders and creates a trade-off between peg stability and issuer fragility.

The paper is structured as follows. Section 2 presents a set of stylized facts and empirical motivations. Section 3 introduces the global games model. Section 4 analyzes the policymaker's problem. Section 5 further discusses several extensions of the baseline model. Section 6 concludes.

2 Empirical Motivation

This section provides empirical motivation for theoretical analysis by examining how transition risk shapes banks' fossil fuel lending. Transition risks primarily arise from shifts in climate policy (Bolton et al., 2020), with the 2015 Paris Agreement being the most influential intervention to date. The analysis examines global data on newly issued syndicated loans from DealScan over the period 2008–2024. This period captures the post-crisis regulatory environment, when international banking reforms such as Basel III made lending and reporting standards more consistent across regions, and also includes the years following the Copenhagen Accord, which marked the start of sustained global climate negotiations and signaled that climate policy considerations might begin to influence financial institutions' lending to the fossil fuel sector.

Figure 1 illustrates the main patterns. It shows absolute lending volumes smoothed using a two-year moving average, with fossil fuel lending rescaled for comparability. Results remain similar when using a one-year rolling quarterly window or a two-year rolling monthly window.

Two regularities emerge. First, before 2015, fossil fuel lending closely tracked the aggregate credit supply, with its share stable at around 12%. This suggests that lending was primarily driven by the credit cycle rather than by transition risks. Second, after 2015, both the level and the share of fossil fuel lending declined sharply, coinciding with the Paris Agreement, which marked a turning point in the global climate policy regime and raised awareness of transition risks among financial institutions. While fluctuations in oil prices may also have influenced fossil fuel lending by raising banks' expectations or increasing credit demand from the oil sector, the evidence points to a more structural shift.[1]

These patterns are consistent with prior studies showing that the Paris Agreement reshaped banks' credit supply and pricing toward firms with high transition risk exposures. For example, European banks reallocated credit away from more polluting borrowers relative to greener ones (Reghezza et al., 2022), and firms more exposed to regulatory transition

[1]Table A1 reports regressions of fossil fuel lending—measured as a share of total new credit supply—on Paris Agreement indicators controlling oil price. The decline in fossil fuel lending remains strongly associated with the Paris Agreement even after controlling for oil prices.

risk received relatively less credit in countries with stringent climate policies (Mueller and Sfrappini, 2025). On the pricing side, prior studies document the emergence of a significant "carbon premium": carbon-intensive or fossil fuel firms faced higher loan spreads in the post-2015 period (Ehlers et al., 2022; Delis et al., 2024). These findings are reinforced by U.S. equity market evidence, where investors demanded higher stock returns from firms more exposed to transition risk following the Paris Agreement (Bolton and Kacperczyk, 2021).

The observed dynamics can be interpreted through two complementary channels. The first is a fundamentals channel: banks revised their expectations about the underlying conditions of the fossil fuel sector, guided by public signals such as international climate agreements, domestic policy initiatives, and growing investment in renewable and low-carbon technologies after the Paris Agreement. These signals implied higher expected financial costs and lower competitiveness for fossil fuel companies. For instance, the anticipated carbon pricing can raise perceived stranded asset risk of fossil fuel companies and lower the expected returns of fossil fuel-related investment projects.

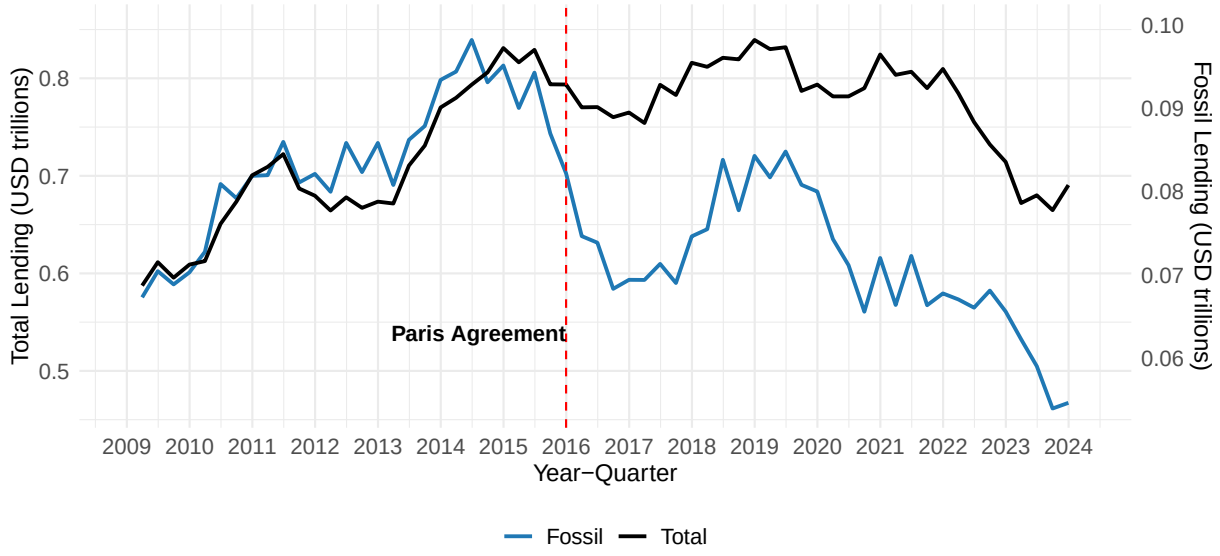
The second is a strategic channel: banks adjusted their lending decisions in anticipation of peer banks' behavior, consistent with the presence of strategic complementarities across financial institutions. Withdrawals by peer banks can increase the risk of rollover failure for fossil fuel companies, amplifies the likelihood of fire sales, and heightens reputational costs for banks that continue financing polluting borrowers when others exit. This highlights that collective behavior, alongside fundamentals, shaped banks' responses to transition risk.

2.1 Peer Effects in Fossil Fuel Lending

To assess the presence of strategic complementarities among financial institutions, the analysis examines whether banks adjust their fossil fuel exposures in response to peer behaviour. It draws on outstanding syndicated loan data from DealScan over the period 2008–2024. I first split loan tranches into lender-level portions to allocate loan amounts across banks, based on the lender share information reported in DealScan. When lender shares are missing, I impute them based on syndicate structure following Chodorow-Reich (2014). Consistent with Gropp et al. (2019), outstanding loans in each quarter are estimated using the maturity

Figure 1: Evolution of Fossil Fuel Lending and Total Credit Supply

This figure compares quarterly total syndicated loan lending to quarterly fossil fuel lending. To smooth the series, I apply the moving average of the quarterly new lending data. The plot shows absolute levels, with fossil fuel lending rescaled by its peak for comparability. The left axis corresponds to total lending, and the right axis to fossil fuel lending. Data source: DealScan.



variable in DealScan.[2]

The analysis restricts the sample to globally active banks whose outstanding loan exposures exceed USD 1 billion.[3] I focus on lenders operating in the US, the UK, the EU, Japan, and China. Banks from other regions are excluded because their samples are too small to allow meaningful peer group construction. Lenders are grouped by region and by outstanding loan size to form peer groups, reflecting that banks operating in the same area and of similar size are more likely to observe and respond to each other (e.g., Silva, 2016).

Identifying peer effects is often complicated by the reflection problem, as banks may react to each other simultaneously or to common shocks (Manski, 1993). To mitigate this concern, I classify banks with unusually large changes in fossil fuel exposures at a given quarter as system-wide "leaders," treating their extreme reallocations as plausibly exogenous signals observed by other banks. This setup makes it possible to capture directional peer responses among the remaining "follower" banks.

Let $E_{i,t}$ denote the fossil fuel exposure share of bank i in quarter t, expressed in percentage. Quarterly changes are defined as $\Delta E_{i,t} = E_{i,t} - E_{i,t-1}$, which provide a meaningful proxy for banks' adjustments in fossil fuel risk-taking. For each quarter t, I compute the 2.5th and 97.5th percentiles of $\Delta E_{i,t}$ across all banks. Banks with changes below or above these thresholds are classified as global outliers. These banks represent system-wide "leaders" exhibiting extreme increases or decreases in fossil fuel exposures. For each non-outlier ("clean follower") bank i, I define binary indicators that capture whether peers experienced extreme adjustments: $D^{+}_{i,t}$ ($D^{-}_{i,t}$) equals one if at least one peer sharply increased (decreased) its fossil fuel exposure in quarter t. Focusing on followers helps mitigate simultaneity concerns: leaders' extreme reallocations are assumed to influence, but not be contemporaneously influenced by, other peer banks. This directional leader–follower structure provides a tractable way to

[2]Originated loans may subsequently be traded in secondary markets. Nevertheless, I use them to measure banks' outstanding exposures to fossil fuel borrowers at a given quarter t, in line with Gropp et al. (2019) and Aldasoro and Barth (2017). Banks may also be exposed to transition risk from non-retained loans, for example through reputational or legal channels (Martini et al., 2025).

[3]Since DealScan includes both bank and non-bank lenders, I retain only those classified as banks following Aldasoro et al. (2025). A lender is classified as a bank if it falls under one of the following categories: African bank, Asia–Pacific bank, Eastern European/Russian bank, foreign bank, Middle Eastern bank, mortgage bank, thrift/S&L, U.S. bank and Western European bank. For lenders without classifications, I manually verify their status based on lender profiles.

identify peer effects in fossil fuel lending and partially mitigates the reflection problem.

In addition, within-group heterogeneity helps limit the influence of common shocks. A potential concern is that outlier shocks might merely capture common shocks affecting all banks within a peer group. However, this is unlikely to drive the results. The cross-sectional dispersion in exposure changes is typically large, and it is not uncommon that both positive and negative outliers appear within the same peer group. Such within-group heterogeneity is inconsistent with a common shock explanation, under which the distribution of exposure changes would concentrate or move in the same direction, and instead outlier shocks capture heterogeneity in banks' exposure adjustments following peers' reallocations.

Then, I estimate dynamic responses of clean followers to peer outlier shocks using a panel local projection:

$$\Delta E_{i,t+h} = \beta_h D_{i,t} + \sum_{p=1}^{P} \phi_{h,p} \, \Delta E_{i,t-p} + \alpha_i + \tau_t + \varepsilon_{i,t+h}, \tag{1}$$

where $h = 0, 1, 2, 3, 4$ captures the response horizons, with $h = 0$ denoting the contemporaneous effect and larger h values representing future quarters. The outlier shock $D_{i,t}$ captures either $D^{+}_{i,t}$ or $D^{-}_{i,t}$. The specification includes a one-quarter lag of $\Delta E_{i,t}$, allowing for short-term persistence in banks' exposure adjustments. It includes lender fixed effects α_i to control for unobserved, time-invariant lender heterogeneity and quarter fixed effects τ_t to absorb the common time-varying fundamentals, such as macrofinancial shocks and global oil prices. Standard errors are clustered at the lender level to account for serial correlation within banks over time. Summary statistics for key variables are reported in Table A2.

Figure 2 displays the local projections of banks' changes in fossil exposure in response to peer outlier shocks, and the results are consistent with the presence of peer effects through strategic channels.[4] Negative peer outlier shocks have adverse effects on non-outlier banks' exposure changes between $h = 0$ and $h = 2$. In contrast, positive peer shocks have immediate and significant effects at $h = 0$, followed by partial reversals and subsequent adjustments. These results suggest that peer effects are most pronounced in the short term: banks tend to

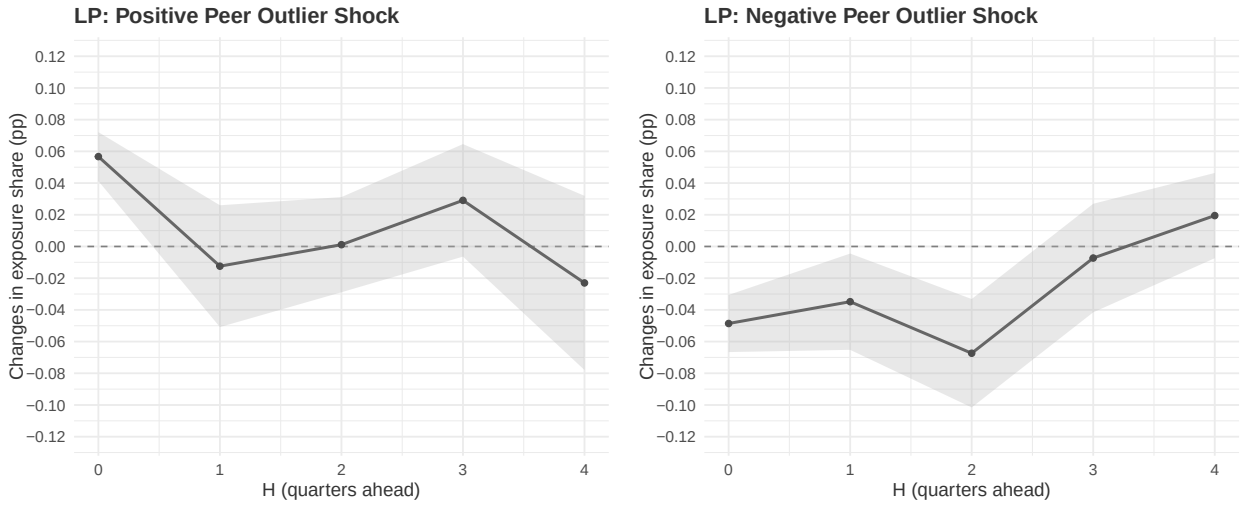
[4]Tables A3–A4 report the corresponding estimates. Results are robust to including both outlier shock dummies in the same specification.

adjust their fossil fuel exposures contemporaneously or within two quarters after observing extreme reallocations by their peers.

In terms of magnitude, a coefficient of 0.06 on $D^{+}_{i,t}$ implies that, following a positive peer shock, the quarterly change in fossil fuel exposure is higher by about 0.06 percentage points relative to the no-shock baseline in the same quarter. Conversely, a one-unit negative peer shock is associated with a decline in the quarterly change in fossil fuel exposure ($\Delta E_{i,t}$) of about 0.05 percentage points relative to the baseline, which deepens to around 0.07 percentage points at $h = 2$. Both effects are large in size relative to the average quarterly change in exposures, which is about 0.01 percentage points in absolute terms.

Figure 2: Local Projection: Peer Outlier Shocks (Positive vs. Negative)

This figure plots impulse responses from local projection regressions of changes in banks' fossil fuel exposure share ($\Delta E_{i,t+h}$) on peer outlier shocks. The left panel shows responses to the presence of a positive peer outlier, and the right panel to a negative peer outlier. Shaded areas denote 68% confidence intervals (see Känzig, 2023). All regressions include lender fixed effects, quarter fixed effects, and one lag of $\Delta E_{i,t}$. Standard errors are clustered at lender level.



2.2 From Empirical Puzzle to Theory

Prior studies extensively analyze how climate policy affects investor expectations and lending conditions, but they largely overlook how strategic complementarities among banks can amplify the resulting collective dynamics. When lending decisions are interdependent, shifts in beliefs can propagate across banks: as some banks reduce fossil fuel exposures, others

find it optimal to follow, resulting in a collective withdrawal from the fossil fuel sector with significant implications for financial stability.

The empirical findings are consistent with the presence of strategic considerations. Although the focus on outlier shocks helps mitigate potential reflection concerns, banks may in practice adjust their exposures in response to broader peer behavior. Several channels may give rise to such strategic responses. These include runs on stranded assets when peers choose not to roll over (see Goldstein and Pauzner, 2005), fire-sale dynamics generated by collective withdrawals through open-market sales (Pereira da Silva, 2019), and reputational pressures that lead banks to retreat from fossil fuels when peers commit to greener portfolios (Aikman and Barwell, 2022).

To rationalize these dynamics, I develop a global games model that incorporates both public signals about fundamentals and strategic complementarities across banks. To the best of the author's knowledge, this is among the first studies to analyze banks' fossil fuel lending through this lens.

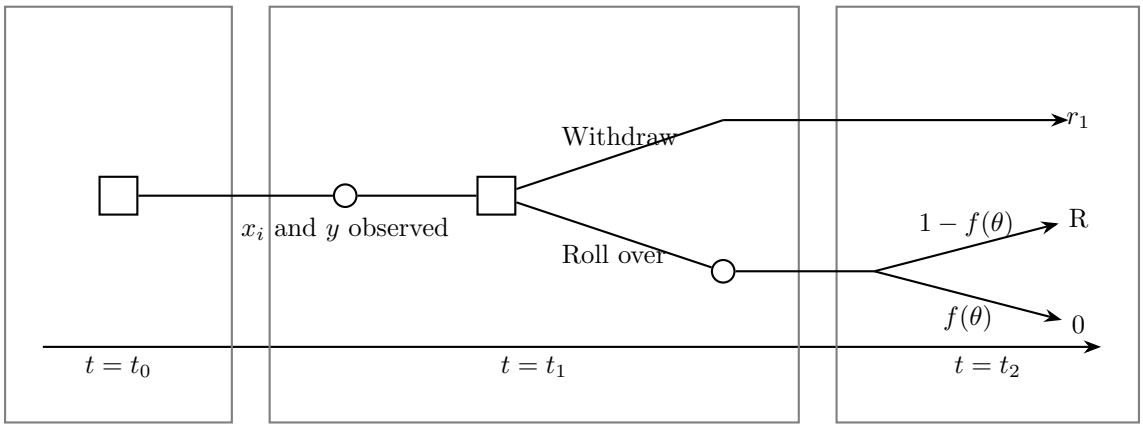
3 Model

3.1 General Set-up

This section develops a two-period model to study banks' stranded asset dynamics under transition risk. The model extends over three dates, t_0, t_1 and t_2, and there is a continuum of identical banks indexed by $i \in [0, 1]$. There is a risky investment project that matures at t_2. The timeline of project is illustrated in Figure 3, and the key elements are set out below.

Public Signal (Policy Announcement). At t_1, the government releases a public policy announcement y that reflects its commitment to climate mitigation. The public signal, observed by all banks, provides common information about transition risk and shapes expectations about the future policy impact. A higher y indicates stronger expected policy action against fossil fuel production and thus a higher perceived energy transition risk.

Figure 3: Project Timeline for Bank i



Fundamental (Policy Impact). The fundamental θ represents the true stringency of climate policy: a higher θ implies a stronger adverse impact on fossil fuel production. Banks i cannot directly observe θ at t_1. The variable θ is assumed to follow a normal distribution on the real line $(-\infty, \infty)$ with mean y and standard deviation τ, so that the public signal y provides a common reference point around which banks form their beliefs about the actual policy impact.

Private Signal. At t_1, each bank observes both the public signal y and a private signal $x_i = \theta + \varepsilon_i$, where ε_i is normally distributed with mean zero and standard deviation σ. The fundamental θ is not directly observable; hence, while y provides common information about transition risk, private signals x_i introduce heterogeneity across banks. This information structure follows the standard global games setup.

Project. The fossil fuel sector operates a risky investment project related to fossil fuel production P. At t_0, each bank invests one unit in the project. At t_1, banks choose whether to withdraw or roll over their investments (or lending). Withdrawal guarantees a fixed repayment, which banks reinvest in government bonds yielding r_1 at t_2. If rolled over, the project yields a high gross return R at t_2 with probability $1 - f(\theta)$, and zero with probability $f(\theta)$, with $f(\theta) \in (0, 1)$. The probability of asset stranding, $f(\theta)$, increases with the policy impact, i.e. $\partial f(\theta)/\partial\theta > 0$. I also set $R > r_1$ to make rollover potentially attractive. Project fossil fuel production at t_2 is proportional to the fraction of banks that roll over: $P = 0$ if

all banks withdraw, and $P = 1$ if all roll over.

Capital Requirement. With the conventional capital requirement normalized to zero, I introduce a capital requirement k that penalizes banks' exposures to the fossil fuel sector (e.g., Oehmke and Opp, 2022). The parameter k can be interpreted as a brown-penalizing factor and requires banks to fund a larger share of their fossil fuel lending with equity. Accordingly, for each unit of lending to the risky project, banks must finance at least a fraction k with equity.

Banks. At t_0, each bank invests one unit in the project, financed with k in equity and $1-k$ in deposits. Equity carries a per-period cost e, while deposits incur cost d, with $e > d$. The higher cost of equity reflects its higher required return relative debt, consistent with the credit risk interpretation formalized in Merton (1974). Following Aikman et al. (2015b), I normalize d to zero.

At t_1, banks sort into two types j: rollover banks (p) that continue their exposure, and withdrawal banks (g) that exit and reinvest the fixed repayment in a government bond that yields r_1 at t_2. For a bank of type j, the expected payoff is

$$V^j = \mathbb{E}[R^j] - \mathbb{E}[R_c^j], \tag{2}$$

where $\mathbb{E}[R^j]$ denotes the expected project return and $\mathbb{E}[R_c^j]$ the expected financing cost.

3.2 Games with Strategic Complementarities

The previous section identified patterns consistent with peer effects in banks' fossil fuel lending. Building on these findings, this section examines how banks decide whether to roll over or withdraw. To analyze this decision, I introduce strategic complementarities and develop four micro-foundations that illustrate how such complementarities may arise. Although these mechanisms differ in economic interpretation, each implies that a bank's payoff from withdrawing increases when more peers withdraw.

In Game 1 and Game 2, I model two conventional channels: rollover risk and fire sales.

Both affect banks' decisions by changing the gross return of the risky project. In Game 3 and Game 4, strategic complementarities stem from reputational concerns, as banks face increasing costs from continuing to finance the fossil fuel sector when a growing fraction of their peers chooses to "go green." These costs can be non-pecuniary (e.g., reputational penalties for bankers) or pecuniary (e.g., higher financing costs). I denote by $l \in [0, 1]$ the fraction of banks that withdraw from the risky investment project at t_1.

3.2.1 Game 1: Rollover Risk

In the first game, I model rollover risk faced by the project manager, whose probability of default rises with the share of banks that withdraw or cut their fossil fuel lending. Rollover risk arise from the difficulty of refinancing the debt. Prior studies show that for firms relying on bank financing, higher rollover risk translates into a higher probability of default, an effect that becomes more pronounced under tight credit conditions (Wang et al., 2017). In this framework, banks extend credit to project managers that represent fossil fuel firms. When more banks withdraw, these firms encounter tighter refinancing conditions, which weakens their ability to roll over maturing loans and increases their default risk.

The strategic structure of this environment is analogous to the classic bank-run mechanism, where depositors withdraw because they expect others to withdraw and anticipate that the bank may become insolvent (Carlsson and Van Damme, 1993; Goldstein and Pauzner, 2005; Leonello et al., 2025). The analogy operates with roles reversed. Fossil fuel firms occupy the position typically held by banks in run models, as they are vulnerable to creditors' (here, banks') decisions. Banks in this paper take the place of depositors, withdrawing credit when they believe that others will also withdraw.

Importantly, this paper has two distinctions from the standard bank run models. First, instead of being uniformly distributed, fundamentals which represent climate policy impact are assumed to follow a normal distribution centered around the policy announcement y, which is a natural assumption given that policy impacts are primarily shaped by government commitment. Second, withdrawals do not cause immediate default but weaken solvency. To capture how banks' collective actions affect this channel, I denote the project manager's default probability by $p(l)$, where $p(l)$ maps the share of banks that withdraw into the

likelihood of default. I then impose the following assumptions:

Assumption 1. *The probability of default $p(l)$ will increase if more banks choose to withdraw, with $\partial p(l)/\partial l > 0$ and $p(l) < 1$.*

With probability $p(l)$, the project manager decides to default on outstanding loans, in which case banks that choose to roll over receive zero return. With probability $1 - p(l)$, the project continues to maturity: a bank that chooses to roll over earns a high gross return R at t_2 with probability $1 - f(\theta)$, and zero otherwise. The condition $p(l) < 1$ reflects that, in this model, even if all banks withdraw, there remains a positive probability that the project manager avoids default—for example, if the project retains residual value through asset liquidation or collateral recovery after production ceases.

The expected payoff for a bank that withdraws and reinvests the repayment in government bonds is:

$$V_w = r_1 - ek. \tag{3}$$

Withdrawal banks face the cost of equity only between t_0 and t_1. After t_1, they exit from stranded assets and are no longer subject to the capital requirement k. The expected payoff for a bank that rolls over is:

$$V_r = (1 - p(l))(1 - f(\theta))R - 2ek. \tag{4}$$

Rollover banks must satisfy the capital requirement in both periods, which leads to a higher overall cost of equity. The expected payoff difference between withdrawing and rolling over is $v(\theta, l) \equiv V_w - V_r$, which yields:

$$v(\theta, l) = r_1 - (1 - p(l))(1 - f(\theta))R + ek. \tag{5}$$

This function satisfies the following monotonicity properties:

$$\frac{\partial v(\theta, l)}{\partial \theta} > 0, \quad \text{and} \quad \frac{\partial v(\theta, l)}{\partial l} > 0. \tag{6}$$

(See proof in Appendix B.1.).

3.2.2 Game 2: Fire Sales

In the second game, I consider a market-based liquidation mechanism. Unlike in the Game 1, now banks cannot redeem directly from the project manager but may sell their shares of project on the open market. As highlighted by Pereira da Silva (2019), under a disorderly transition in which abrupt changes in disclosure requirements or climate regulation reshape investors' perceptions of the viability of the fossil fuel sector, fire sales may occur and potentially destabilize the financial system. Fire sales can put downward pressure on asset prices (Greenwood et al., 2015; Fricke and Fricke, 2021).

As a result, early withdrawals generate a negative price externality: they depress the market value of the underlying stranded asset, thereby lowering the expected payoff for banks that roll over and remain exposed at t_2. To capture this price impact, I impose the following condition:

Assumption 2. *The ex-post price impact is* $\delta(l)$*, with* $\partial\delta(l)/\partial l > 0$ *and* $\delta(l) < 1$*.*

The restriction $\delta(l) < 1$ reflects that even under large-scale liquidations the asset retains some residual value. Then, the expected payoff for banks that withdraw is the same as in Game 1. For banks that roll over, the expected payoff is:

$$V_r = (1 - \delta(l))(1 - f(\theta))R - 2ek. \tag{7}$$

Accordingly, the expected payoff difference between withdrawing and rolling over is:

$$v(\theta, l) = r_1 - (1 - \delta(l))(1 - f(\theta))R + ek, \tag{8}$$

which satisfies the following monotonicity properties:

$$\frac{\partial v(\theta, l)}{\partial \theta} > 0, \quad \text{and} \quad \frac{\partial v(\theta, l)}{\partial l} > 0 \tag{9}$$

(See proof in Appendix B.1.).

3.2.3 Game 3: Pecuniary Reputation Costs

In the third game, reputation is modeled as a pecuniary cost borne by rollover banks at t_2. Investors observe banks' exposures to the fossil fuel sector and may penalize banks that are more polluting than their peers by imposing a higher cost of capital. This mechanism is motivated by existing research. Bolton and Kacperczyk (2021, 2023) show that investors demand a higher cost of equity from firms with greater carbon emissions. More specifically, using a sample of publicly listed banks from 35 countries, Pasiouras et al. (2025) document that financed (i.e., Scope 3) emissions are positively and significantly associated with banks' cost of equity, both statistically and economically.

Building on this evidence, the model formalizes the mechanism through a reputational channel, in which reputational costs are defined in relative terms and generate strategic complementarities: a bank's reputational penalty increases with its fossil fuel exposure relative to peers, or equivalently, with the share of other banks that have liquidated their exposure to the fossil fuel sector. As more banks exit, those that remain appear relatively more polluting and therefore face higher reputational costs.[5] Formally, I assume:

Assumption 3. *For rollover banks between t_1 and t_2, equity costs $e(l)$ per unit, with $\partial e(l)/\partial l > 0$ and $e(l) > e$.*

Under these assumptions, the expected payoff for greener banks that withdraw at t_1 and reinvest in government bonds is the same as in Game 1. For polluting banks that roll over their investments, the expected payoff is:

$$V_r = (1 - f(\theta))R - ek - e(l)k. \tag{10}$$

Accordingly, the expected payoff difference between withdrawing and rolling over is:

$$v(\theta, l) = r_1 - (1 - f(\theta))R + e(l)k, \tag{11}$$

[5] While depositors may also impose reputational costs on polluting banks, the analysis focuses on the cost of equity. In that case, depositors could demand higher compensation from polluting banks when a larger share of their peers have shifted toward greener portfolios. This mechanism is consistent with the literature on depositor switching behavior and competition in deposit markets (e.g., Almazan, 2002; Kim et al., 2003; Craig and Dinger, 2013; Shy et al., 2016).

which satisfies the following monotonicity properties:

$$\frac{\partial v(\theta, l)}{\partial \theta} > 0, \quad \text{and} \quad \frac{\partial v(\theta, l)}{\partial l} > 0 \tag{12}$$

(See proof in Appendix B.1.).

3.2.4 Game 4: Non-pecuniary Reputation Costs

In the fourth and final game, each banker derives a pecuniary benefit from the project payoff but also faces a non-pecuniary reputation cost from exposure to the fossil fuel sector. For instance, one can think of a banker subject to career concerns (e.g., Rajan, 1994). A banker who continues to roll over investments into fossil fuels incurs a higher reputation cost when more peers withdraw. I denote the reputation cost by $b(l)$. In contrast, a banker who withdraws and thus operates a green bank faces no reputational penalty:

Assumption 4. *The reputation cost $b(l)$ is increasing in the share of banks that withdraw, with $\partial b(l)/\partial l > 0$.*

For polluting banks that roll over their investments, the expected payoff is:

$$V_r = (1 - f(\theta))R - 2ek - b(l). \tag{13}$$

Accordingly,the expected payoff difference is:

$$v(\theta, l) = r_1 - (1 - f(\theta))R + ek + b(l), \tag{14}$$

which satisfies:

$$\frac{\partial v(\theta, l)}{\partial \theta} > 0, \text{ and } \frac{\partial v(\theta, l)}{\partial l} > 0 \tag{15}$$

(See proof in Appendix B.1.).

3.3 Information Structure and Equilibrium

This section describes the information structure of banks and presents how the equilibrium is determined given this structure. Following Morris and Shin (2001), an equilibrium is formed

when each bank chooses an action from the set of strategies that maximizes its expected payoff, given the information it observes and anticipating that other banks behave in the same way.

3.3.1 Information Structure

Recall that the policy impact θ is realized at t_2. It is normally distributed around the public signal y with variance τ^2 (i.e., precision $1/\tau^2$). The parameter τ captures the uncertainty surrounding the policy impact when it deviates from the announced commitment. At t_1, banker i observes a noisy private signal of policy impact

$$x_i = \theta + \varepsilon_i, \tag{16}$$

where $\varepsilon_i \sim N(0, \sigma^2)$ is independent across banks. The parameter σ captures the noise in each bank's private assessment. Hence, banks face both the inherent climate policy uncertainty (captured by τ) and the idiosyncratic noise in their private signals (captured by σ). Conditional on observing x_i, bank i's posterior belief about θ is normally distributed with

$$\text{Mean:} \quad \bar{\theta} = \frac{\sigma^2 y + \tau^2 x_i}{\sigma^2 + \tau^2}, \quad \text{Variance:} \quad \frac{\sigma^2 \tau^2}{\sigma^2 + \tau^2}. \tag{17}$$

This setup follows Morris and Shin (2001, 2002, 2007).

Then, this bank rationally anticipates that any other opponent's signal, x', is equal to θ plus a noise term normally distributed with mean 0 and standard deviation σ. Combining the posterior distribution of θ with the noise term, this banker infers that x' is normally distributed with mean $\bar{\theta}$ and variance $\frac{2\sigma^2\tau^2+\sigma^4}{\sigma^2+\tau^2}$.

Suppose this bank believes that all other banks will apply the same switching strategy with threshold κ—if their private signals x' satisfy

$$\frac{\sigma^2 y + \tau^2 x'}{\sigma^2 + \tau^2} \geq \kappa, \tag{18}$$

or equivalently

$$x' \geq \kappa + \frac{\sigma^2}{\tau^2}(\kappa - y), \tag{19}$$

then they will withdraw from the fossil fuel sector.

Accordingly, the bank computes the expected proportion of opponents that withdraw, denoted by $l(\bar{\theta}, \kappa)$, as the probability that any given opponent withdraws—that is, the probability that an opponent's posterior exceeds the cutoff κ. The expected fraction of banks that withdraw is therefore:

$$l(\bar{\theta}, \kappa) = \Pr[x' \geq \kappa + \frac{\sigma^2}{\tau^2}(\kappa - y)] = 1 - \Phi(\frac{\kappa - \bar{\theta} + \frac{\sigma^2}{\tau^2}(\kappa - y)}{\sqrt{\frac{2\sigma^2\tau^2+\sigma^4}{\sigma^2+\tau^2}}}), \tag{20}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

3.3.2 Equilibrium

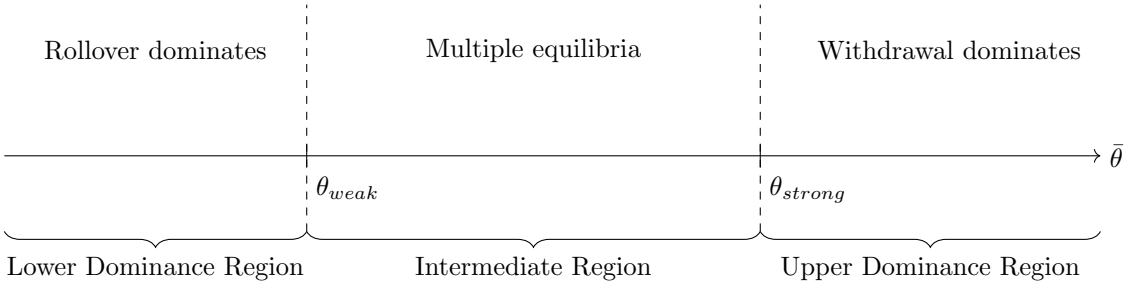
Suppose that banks follow switching strategies with a cutoff θ^*: they withdraw from fossil fuels if their posterior beliefs on θ exceed this threshold, and roll over otherwise:

$$s(\bar{\theta}) = \begin{cases} \text{Withdraw, if } \bar{\theta} \geq \theta^* \\ \text{Roll over, if } \bar{\theta} < \theta^*. \end{cases} \tag{21}$$

To characterize the equilibrium cutoff θ^*, consider how banks' payoffs vary across different values of the fundamental θ. The domain of fundamentals can be divided into three regions: an upper dominance region, a lower dominance region, and an intermediate region. In the two dominance regions, one action strictly dominates regardless of what other banks do. When the policy impact is sufficiently high, withdrawal dominates rollover even if no banks withdraw ($l = 0$), with the threshold defined by $v(\theta_{strong}, 0) = 0$. Conversely, when the policy impact is sufficiently low, rollover dominates withdrawal even if all banks withdraw ($l = 1$), with the threshold defined by $v(\theta_{weak}, 1) = 0$. In the intermediate region, $\theta_{weak} \leq \bar{\theta} \leq \theta_{strong}$, neither action strictly dominates, and multiple equilibria may arise, as shown in Figure 4.

With the information structure defined in the previous section, it can be shown that there exists a unique equilibrium $\bar{\theta} = \theta^*$ in the incomplete information game if the private signals are sufficiently precise. Given the posterior belief $\bar{\theta}$ and cutoff θ^*, the expected payoff

Figure 4: Dominance Regions



difference between withdrawing and rolling over is:

$$V(\bar{\theta}, \theta^*) = \int_{\theta=-\infty}^{\infty} \sqrt{\frac{\sigma^2\tau^2}{\sigma^2+\tau^2}} \phi\left(\frac{\theta - \bar{\theta}}{\sqrt{\frac{\sigma^2\tau^2}{\sigma^2+\tau^2}}}\right) v(\theta, l(\bar{\theta}, \theta^*)) d\theta, \tag{22}$$

where the conditional probability density function follows the notation in literature (see Morris and Shin, 2001; Aikman et al., 2015b), and $\phi(\cdot)$ denotes the standard normal density. The following lemma establishes the condition under which the equilibrium cutoff θ^* exists and is unique for all four games.

Lemma 1. *There exists a unique cutoff in equilibrium if private signal is sufficiently precise relative to the public signal (i.e., σ is sufficiently small). Expressing θ as $\theta = \theta' + \bar{\theta}$, the threshold $\bar{\theta} = \theta^*$ solves:*

$$\int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} v(\theta' + \theta^*, l(\theta^*, \theta^*)) d\theta' = 0 \tag{23}$$

and

$$l(\theta^*, \theta^*) = 1 - \Phi(\sqrt{\gamma}(\theta^* - y)), \tag{24}$$

where $\sqrt{\gamma} = \frac{\sigma}{\tau^2}\sqrt{\frac{\sigma^2+\tau^2}{\sigma^2+2\tau^2}}$, *and* $\sqrt{\rho} = \sqrt{\frac{\sigma^2+\tau^2}{\sigma^2\tau^2}}$.

Proof. See Appendix B.2. □

This lemma establishes the existence of a unique equilibrium, characterized by a switching strategy with a cutoff θ^*, where banks' actions depend on their posterior beliefs about the policy impact. Banks withdraw from the fossil fuel sector when their posterior exceeds this threshold.

The condition that private information is sufficiently precise relative to the public signal implies that the noise in a bank's private signal is smaller than the uncertainty surrounding the government's announced commitment and the eventual realization of policy impact. In practice, this reflects that public announcements of climate policy often leave considerable ambiguity regarding their timing and implementation—for instance, countries may differ in the speed and stringency with which commitments are translated into regulation—whereas banks' private assessments, informed by industry intelligence and market signals, can offer relatively more precise guidance on expected policy impacts.

3.3.3 Equilibrium Properties

Having established the existence of a unique equilibrium, the analysis now characterizes its properties:

Lemma 2. *The threshold θ^* is:*
a) decreasing in the public signal y;
b) decreasing in capital requirement k.

Proof. See Appendix B.3. □

The intuition is straightforward. Part (a) shows that a higher public signal y makes withdrawal more likely at t_1. Because policy impact is distributed around the public signal, a higher y signals a stronger θ in the future, reducing the probability that the project delivers a gross return R and increasing the risk of asset stranding. In this case, banks find withdrawal more attractive due to higher expected payoffs. As a result, the threshold falls and the posterior belief $\bar{\theta}$ is more likely to exceed it, implying a higher likelihood of withdrawal.

Part (b) shows that a higher capital requirement k similarly increases the likelihood of withdrawal. A larger k lowers the expected payoff from rolling over by increasing the cost of financing the risky investments, thereby reducing the threshold θ^* and making withdrawal the more attractive option.

3.3.4 Limiting Behaviour and Procyclicality

This section maintains the uniqueness condition that private signals are sufficiently precise relative to the public signal. I now consider the limiting case in which private signals become arbitrarily precise ($\sigma \to 0$). In this case, heterogeneity across banks disappears: they effectively observe the same realization of the fundamental θ and therefore behave in the same way (see Leonello et al., 2025). This does not mean $\sigma = 0$, which would imply complete information and multiple equilibria. Rather, the result concerns the limit in which private signals converge to the realized policy impact, so that all banks choose the same action.

Proposition 1. *As $\sigma \to 0$, all banks behave alike: banks collectively withdraw if $\theta > \theta^*(k, y)$ and roll over otherwise.*

Proof. See Appendix B.4. □

Two implications follow. First, collective bank behaviour becomes highly procyclical: when y is higher, the cutoff $\theta^*(k, y)$ decreases and banks collectively are more likely to withdraw; when y is lower, they are more likely to roll over. Second, this limiting case provides a natural benchmark for the social planner's problem discussed later in the paper, where the planner does not observe private signals but allocates bank lending based on the distribution of the policy impact θ. This point will be revisited in the section on the policymaker's problem.

3.4 Numerical Illustration

For illustrative purposes, this section focuses on the case with rollover risk. Recall that the expected payoff difference is

$$v(\theta, l) = r_1 - (1 - p(l))(1 - f(\theta))R + ek = r_1 + r(\theta, l) + ek, \tag{25}$$

where $p(l)$ denotes the project manager's default probability due to rollover failures. This function takes a linear form with $p(l) = r_l l$, where r_l measures the sensitivity of the project manager's default probability to the share of banks that withdraw, thereby capturing the

strength of strategic complementarities. I approximate $r(\theta, l) = -(1 - p(l))(1 - f(\theta))R$, which is monotonically increasing in both l and θ. The probability of this project being stranded is $f(\theta) = \Phi(\theta)$, where $\Phi(\cdot)$ denotes the cumulative distribution function of a normal distribution. The equilibrium threshold θ^* then solves

$$V(\theta^*, \theta^*) = r_1 - (1 - \Phi(\theta^*))[1 - r_l l(\theta^*, \theta^*)]R + ek = 0. \tag{26}$$

where $l(\theta^*, \theta^*) = 1 - \Phi(\sqrt{\gamma}(\theta^* - y))$ denotes the expected proportion of banks that withdraw.

The numerical example confirms the existence of a unique equilibrium and the properties (see Appendix B.5). Specifically, the results show that a unique equilibrium threshold exists when private signals are sufficiently precise, and that this threshold decreases with both the public signals and the capital requirement. Using parameter values reported in Appendix C, I illustrate these findings in two figures below.

Figure 5 describes how the uniqueness of the equilibrium threshold θ^* depends on the precision of private signals, represented by γ. Higher γ implies that private signals are less precise relative to the public signal. The figure shows that when γ is large, multiple equilibria can arise, or equivalently, $V(\theta^*, \theta^*) = 0$ has multiple solutions.

Figure 6 shows how public signal y and capital requirement k affect the equilibrium threshold θ^*. Both curves slope downward, indicating that θ^* decreases with the capital requirement k. In addition, comparing the solid blue line with the dashed blue line confirms that θ^* is also decreasing in the public signal y, consistent with Lemma 2.

4 Policymaker's Problem

This section examines the challenge faced by a policymaker who sets the capital requirement k to balance the social costs and benefits of banks' decisions under transition risk. To begin with, I introduce a social planner who selects a threshold to optimally allocate bank lending in order to maximize net output. The social planner's objective function combines a three-factor Cobb–Douglas production function with a climate damage function. Inefficiency arises when the equilibrium threshold derived in the global games model deviates from this

Figure 5: Precision of Private Signal and Uniqueness of Solution

This figure presents how precision of private signal determines the uniqueness of solution. The x-axis represents the equilibrium threshold θ^* determined in global games framework, while the y-axis represents the value of expected payoff difference $V(\theta^*, \theta^*)$. The blue line represents the expected payoff difference $V(\theta^*, \theta^*)$ when $\gamma = 10$, while the red line represents the expected payoff difference $V(\theta^*, \theta^*)$ when $\gamma = 1000$. The black line represents the benchmark where $V(\theta^*, \theta^*) = 0$. All other parameters take normal values as in Appendix C, and in this case $k = 0.6$.

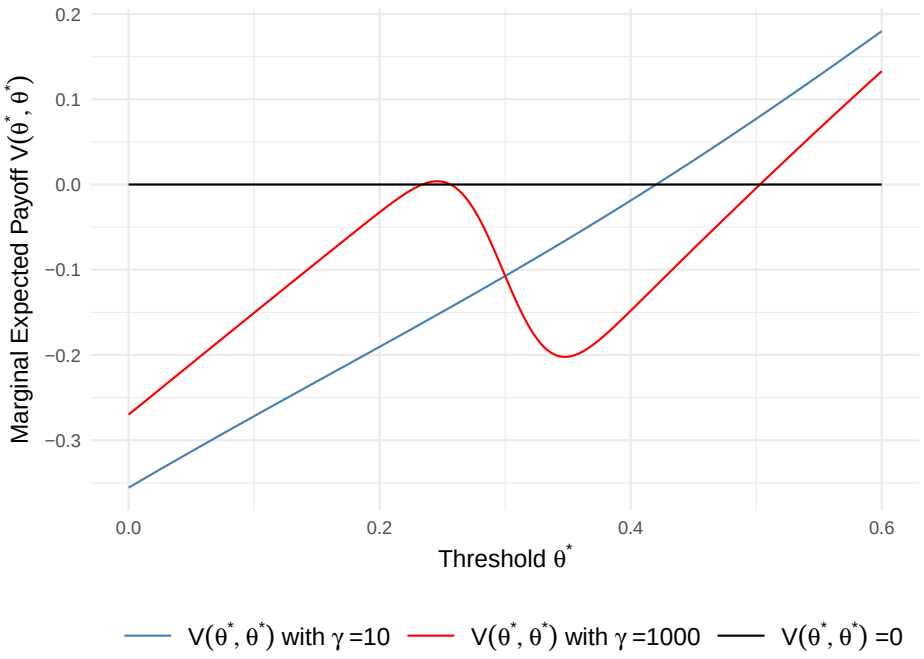
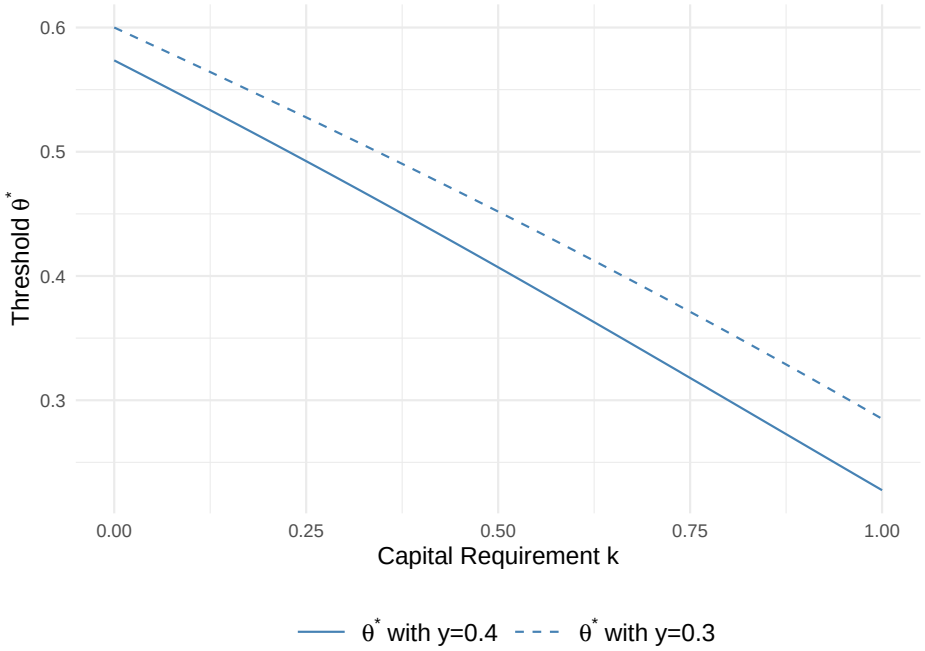


Figure 6: Equilibrium Properties

This figure presents properties of global games equilibrium. The x-axis represents the capital requirement, while the y-axis represents the equilibrium threshold θ^* determined in global games framework. The dashed blue line represents the threshold θ^* when mean fundamental $y = 0.3$. The solid blue line represents the threshold θ^* when mean fundamental $y = 0.4$. All other parameters take normal values as in Appendix C.



benchmark. Then, I analyze how the capital requirement can be deployed as a policy tool to narrow this gap. Finally, I characterize the properties of the optimal capital requirement.

4.1 Social Planner Benchmark

4.1.1 Model Set-up

To benchmark the efficiency of the decentralized global games equilibrium, I introduce a social planner who internalizes the externalities associated with banks' fossil fuel lending. The planner receives no private signals and directly determines the optimal threshold θ^*. Formally, the planner solves:

$$\max_{\theta^*} \quad Q(P(\theta^*)) = Y(P(\theta^*))[1 - \Omega(P(\theta^*))]. \tag{27}$$

Following the Dynamic Integrated Climate–Economy (DICE) model (Nordhaus, 2014), I denote $Q(P(\theta^*))$ as the gross economic output net of climate damages.[6] Net output $Q(P(\theta^*))$ depends on fossil fuel production $P(\theta^*)$, gross output $Y(P(\theta^*))$ and the associated climate damages $\Omega(P(\theta^*))$.

Recall that at t_2 the investment project yields fossil fuel production $P = 0$ if all banks withdraw and $P = 1$ if all banks roll over. Given the distribution of fundamentals θ, all banks roll over if $\theta < \theta^*$ and withdraw otherwise. The expected fossil fuel production is thus given by the probability of fundamentals below the threshold,

$$P = \Pr[\theta < \theta^*] = \Phi(\frac{\theta^* - y}{\tau}), \tag{28}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal, y is the public signal, and τ captures the standard deviation.

Gross output $Y(P(\theta^*))$ is specified as a three-factor Cobb–Douglas production function:

$$Y(P(\theta^*)) = AK^{1-\gamma-\alpha}L^{\gamma}H^{\alpha}(P(\theta^*)). \tag{29}$$

[6] In this paper, I abstract from the role of mitigation costs, which in Nordhaus (2014) are tied to the emission reduction rate (higher reduction implies higher costs). However, neither mitigation costs nor emission controls are determined by banks, and are therefore excluded from the model.

where Y denotes total production. A is a constant term representing total factor productivity (TFP), which captures technological efficiency in transforming inputs into output. K is the capital input, L is the labor input, and $H(P(\theta^*))$ represents the use of exhaustible natural resources, which is the fossil fuel input in this research (see Stiglitz, 1974; Kümmel et al., 2010; Keen et al., 2019).[7]

The total fossil fuel input is given by:

$$H(P(\theta^*)) = \bar{H}[w_0 + w_1 P(\theta^*)], \tag{30}$$

where $\bar{H}$ denotes the baseline business-as-usual amount of fossil fuels contributing to gross output.[8] The parameters w_0 and w_1 capture the reliance of the fossil fuel sector on riskless funding sources and on risky bank lending, respectively, with $w_0 + w_1 = 1$. Hence, $\bar{H}w_0$ represents the portion of fossil fuel input financed by riskless sources, while $\bar{H}w_1 P(\theta^*)$ corresponds to the part financed by banks. The parameter w_1 thus maps the amount of fossil fuel production financed by banks into the corresponding fossil fuel input to aggregate output, reaching its maximum $\bar{H}w_1$ when $P = 1$, which ensures that total input equals the business-as-usual level $\bar{H}$.

The parameters α and γ denote the output elasticities of fossil fuel and labor, respectively, while the elasticity of capital is $1 - \alpha - \gamma$ to ensure the sum equal to one. These elasticities measure the percentage change in output resulting from a one-percent change in the corresponding input, holding other inputs fixed, and thus capture the relative contribution of each factor to production. In practice, values for α and γ can be calibrated using the "cost-share theorem," which sets output elasticities equal to factor expenditure divided by GDP, that is, the share of each input's cost in total output (Kümmel et al., 2010).

Gross output is then given by:

$$Y(P(\theta^*)) = AK^{1-\gamma-\alpha} L^{\gamma} \bar{H}^{\alpha} [w_0 + w_1 P(\theta^*)]^{\alpha}, \tag{31}$$

[7] Keen et al. (2019) highlights that the role of energy in production is more appropriately captured as an input that enables labor and capital. In this paper, the production function is written in reduced form for tractability and does not aim to provide a thermodynamically complete description of the energy–production relationship.

[8] $\bar{Y}$ (defined below) represents the business-as-usual level of output under a scenario with no or limited climate policies, where all banks continue to finance fossil fuels.

and I denote the baseline output as:

$$\bar{Y} = AK^{1-\gamma-\alpha}L^{\gamma}\bar{H}^{\alpha}, \tag{32}$$

which represents the gross output under the business-as-usual scenario where fossil fuel input is fixed at its baseline level $\bar{H}$.

The climate damage function is:

$$\Omega(P(\theta^*)) = \Omega_0[w_0 + w_1 P(\theta^*)], \tag{33}$$

where Ω_0 denotes the maximum climate damage as a share of gross output, reached when all banks roll over their investments (i.e., $P(\theta^*) = 1$). The parameter w_0 represents the fraction of climate damages associated with riskless funding sources, whereas $w_1 P(\theta^*)$ reflects the portion linked to the bank-financed project, with $w_0 + w_1 = 1$.

Combining all components, net output as a function of $P(\theta^*)$ is:

$$Q(P(\theta^*)) = \bar{Y}(w_0 + w_1 P(\theta^*))^{\alpha}[1 - \Omega_0(w_0 + w_1 P(\theta^*))], \tag{34}$$

where the final expression is normalized by the baseline gross output $\bar{Y}$ under the business-as-usual scenario. The following lemma characterizes two properties.

Lemma 3. *Both gross output $Y(P(\theta^*))$ and climate damage $\Omega(P(\theta^*))$ are strictly increasing in fossil fuel production, with*

$$\frac{\partial Y(P(\theta^*))}{\partial P(\theta^*)} > 0, \quad \frac{\partial \Omega(P(\theta^*))}{\partial P(\theta^*)} > 0. \tag{35}$$

Proof. See Appendix B.6. □

This lemma highlights the fundamental trade-off between the social benefits and costs related to fossil fuel production $P(\theta^*)$. A higher $P(\theta^*)$ increases both gross output and climate damages: the output gain represents a social benefit, whereas the climate damages constitute a social cost. Conversely, a lower $P(\theta^*)$ reduces both output and damages. In this case, the decline in output, which captures economic disruptions and financial stability

risks, corresponds the cost of fossil fuel supply disruptions, while the mitigation of climate damages represents the corresponding benefit.

4.1.2 Optimal Allocation of Bank Lending

The optimal allocation of fossil fuel production, denoted $P(\theta^*_{sc})$, balances the trade-off between financial stability risks and climate damages. The social planner chooses the threshold $\theta^* = \theta^*_{sc}$ to maximize net output, which solves the first-order condition:

$$\frac{\partial Q(P(\theta^*))}{\partial P(\theta^*)} = 0. \tag{36}$$

Expanding this condition yields:

$$\frac{\partial Y(P(\theta^*))}{\partial P(\theta^*)}[1 - \Omega(P(\theta^*))] - Y(P(\theta^*))\frac{\partial \Omega(P(\theta^*))}{\partial P(\theta^*)} = 0, \tag{37}$$

where the first term represents the marginal contribution of fossil fuel production to gross output, and the second term captures the marginal increase in climate damages. For illustration, Figure 7 plots net output $Q(P(\theta^*))$ as a function of $P(\theta^*)$, with parameter values reported in Appendix C. Net output first increases with $P(\theta^*)$ and then decreases as $P(\theta^*)$ becomes large.

The analysis distinguishes three transition pathways aligned with NGFS (2022):

- **Orderly Transition:** climate policies are introduced early and tightened gradually, which yields a smooth adjustment with limited disruption. This corresponds to $P(\theta^*_{sc})$, the level of fossil fuel production that maximizes net output. Both financial instability and climate damages are minimized.

- **Disorderly Transition:** climate action is sudden or disorder, which leads to abrupt adjustments. This corresponds to $P(\theta^*) < P(\theta^*_{sc})$ with $\frac{\partial Q}{\partial P} > 0$, where fossil fuels are phased out too rapidly. In this case, output losses due to financial stability risks are high, while climate damages are relatively low.

- **Hot House World:** climate efforts remain weak, which leads to persistently high carbon emissions and eventually physical risks. This corresponds to $P(\theta^*) > P(\theta^*_{sc})$

with $\frac{\partial Q}{\partial P} < 0$. Fossil fuel production is excessive. This maintains short run financial stability but generating high climate damages in the long run.

Then, I examine the properties of the orderly transition scenario characterized by $P(\theta^*_{sc})$. Solving the first-order condition yields an interior solution for the optimal level of fossil fuel production, which depends on three parameters: the output elasticity of fossil fuels α, the maximum climate damages Ω_0, and the dependency on bank lending w_1. Specifically, the socially optimal level of fossil fuel production increases with the output elasticity of fossil fuels, decreases with the maximum climate damage, and increases with the dependency on bank lending. Comparative statics are provided in Appendix B.8.

The intuition is straightforward: when output depends more on fossil fuels (higher α), the social planner raises $P(\theta^*_{sc})$ to limit output losses; when climate damages are more severe (higher Ω_0), the planner lowers $P(\theta^*_{sc})$ to reduce damages; and when dependency on bank lending w_1 is higher, both output and damages become more sensitive to banks' decisions, but the output effect dominates because the production function is exponential while the damage function is linear. This makes the socially optimal $P(\theta^*_{sc})$ higher. Further illustrations are provided in Appendix D.

In this paper, these parameters are treated as exogenously given, so the value of $P(\theta^*_{sc})$ is taken as exogenous. I will analyze how parameter choices shape the policy intervention in a multi-period dynamic setting in the extension section.

4.1.3 Benchmark Properties

Because the orderly transition scenario maximizes net output, the social planner chooses the benchmark threshold that achieves the optimal allocation of fossil fuel production.

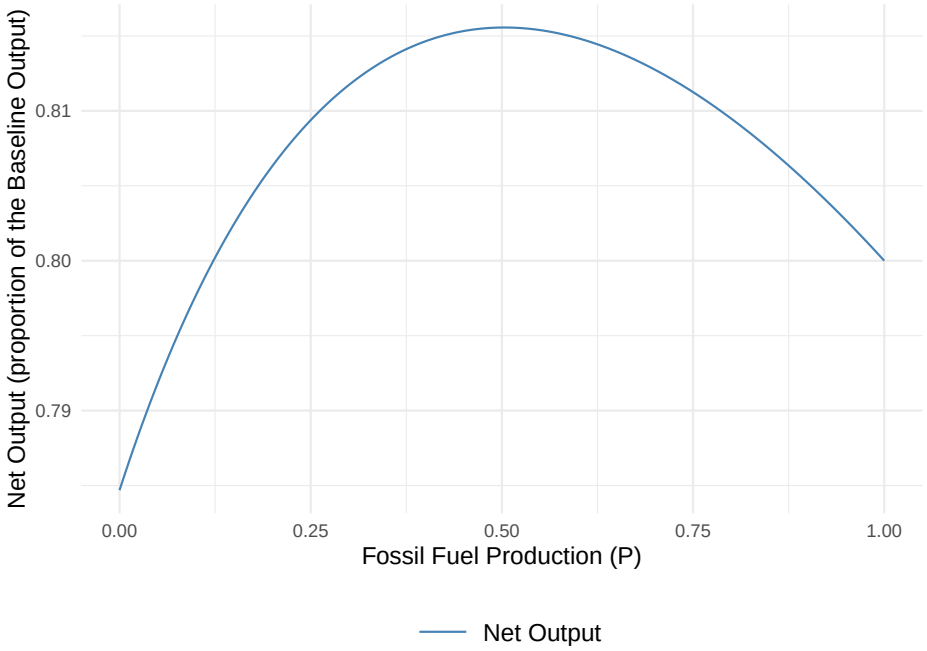
Lemma 4. *The social planner benchmark θ^*_{sc} is:*
a) increasing in the optimal fossil fuel production $P(\theta^*_{sc})$.
b) increasing in the public signal y.

Proof. See Appendix B.7. □

The intuition is immediate. Part (a) reflects that a higher optimal level of production requires a higher threshold to induce more banks to roll over. Part (b) reflects that when the

Figure 7: Net Output after Climate Damages

This figure presents the economic output net of climate damages. The x-axis represents the the expected value of fossil fuel production $P(\theta^*)$, while the y-axis represents the value of net output expressed as a percentage of the baseline gross output $\bar{Y}$. The blue line represents the net output $Q(P(\theta^*))$ as a function of $P(\theta^*)$. The maximum represents the socially optimal $P(\theta^*_{sc})$. All parameters take normal values.



public signal rises, the expected production level mechanically declines under the distribution of fundamentals θ. The planner must therefore raise the threshold to keep production fixed at the social optimum, reflecting that the social planner takes government commitment into account when making decisions.

4.2 Countercyclical Macroprudential Policy

This section examines how policy intervention can correct the inefficiency arising from the gap between the global games equilibrium $\theta^*(k, y)$ and the social planner benchmark θ^*_{sc}. When $\theta^*(k, y) > \theta^*_{sc}$, banks roll over fossil fuel lending more than the social planner would, leading to higher climate damages. Conversely, when $\theta^*(k, y) < \theta^*_{sc}$, banks withdraw excessively, triggering large output losses and financial instability. The gap between θ^*_{sc} and $\theta^*(k, y)$ provides the rationale for policy intervention.

Proposition 2. *Holding the public signal y fixed, if $\theta^*(k, y) > \theta^*_{sc}$, the policymaker should increase the capital requirement k. If $\theta^*(k, y) < \theta^*_{sc}$, the policymaker should decrease the capital requirement k. Otherwise, k should remain unchanged.*

Proof. See Appendix B.9. □

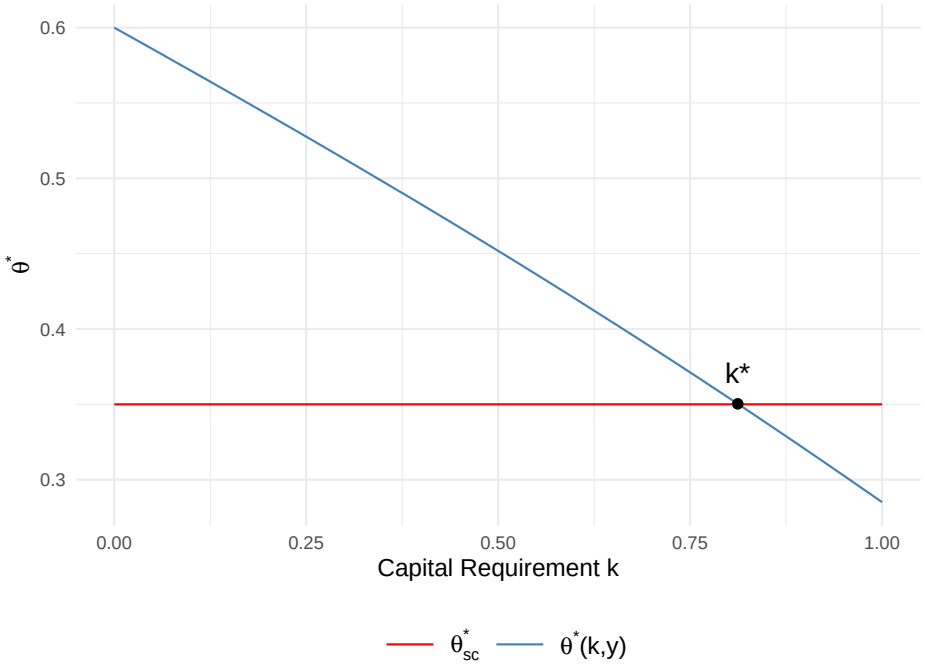
The policy implication is straightforward. If banks roll over too much ($\theta^*(k, y) > \theta^*_{sc}$), the capital requirement should be tightened to curb lending and mitigate climate damages. If banks withdraw too much ($\theta^*(k, y) < \theta^*_{sc}$), the requirement should be loosened to support rollover and prevent runs on stranded assets.

In a numerical example, I illustrate how the policymaker can use capital requirements to achieve the constrained efficient allocation. Strategic complementarities arise through rollover risk under the same assumptions as in the previous examples. Since the social planner benchmark is taken as exogenous, it is assigned directly for illustration. In Figure 8, the intersection of the global games threshold (blue line) and the benchmark (red line) identifies the optimal capital requirement k^*.

The analysis now turns to how the optimal capital requirement responds to changes in transition risk. Recall that k^* is defined by the condition $\theta^*_{sc} = \theta^*(k, y)$; the policymaker sets

Figure 8: The Optimal Capital Requirement

This figure describes the optimal capital requirement when $y = 0.3$. The x-axis represents the capital requirement k, while the y-axis represents the equilibrium threshold θ^*. The blue line represents the socially optimal threshold θ^*_{sc} selected by the social planner, which was set exogenously at $\theta^*_{sc} = 0.35$. The red line represents the threshold $\theta^*(k, y)$ determined in the global games framework. All parameters take the normal values as in Appendix C.



the capital requirement at $k = k^*$ so that banks' strategies align with the social optimum. Since $\theta^*(k, y)$ is decreasing in the public signal y, the optimal capital requirement k^* should also vary with y.

Proposition 3. *The optimal capital requirement k^* is decreasing in public signal y, with $\frac{\partial k^*}{\partial y} < 0$.*

Proof. See Appendix B.10. □

The intuition is straightforward. Banks behave in a highly pro-cyclical manner if transition risk is viewed as an economic cycle. In good states (low transition risk), banks take excessive risks; in bad states (high transition risk), they engage in excessive de-risking (Aikman et al., 2015a; Eisenbach, 2017). A countercyclical capital requirement curbs these externalities. When transition risk is high, the policymaker should lower the capital requirement to encourage rollover and safeguard financial stability. When transition risk is low, the policymaker should raise the capital requirement to induce withdrawal and mitigate climate damages. Figure 9 illustrates how changes in the public signal y affect the choice of k^*. The comparison between the equilibrium threshold (blue line) and the planner's benchmark (red line) confirms that k^* is decreasing in y.

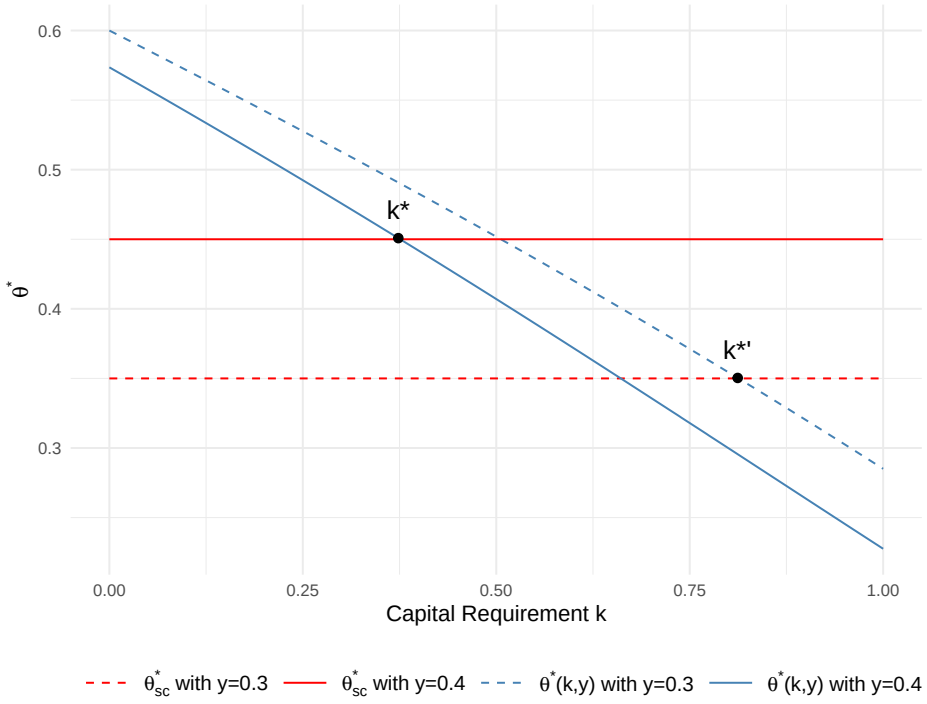
5 Discussion and Extensions

In this section, I discuss three directions that broaden or extend the baseline model: (i) a broader interpretation of capital requirements as buffers beyond mitigating coordination failures, (ii) a joint design of fiscal and macroprudential policy instruments, and (iii) a multi-period extension building on Morris and Yildiz (2019).

Climate-informed Capital Requirement. A key rationale for capital requirements in macroprudential policy is to ensure that banks can absorb unexpected losses and continue lending even in times of stress, thereby enhancing resilience of the financial system (e.g., see European Central Bank, 2025). In the model, the focus is on the countercyclical role of capital requirements in curbing the inefficiencies created by coordination failures in banks'

Figure 9: Climate Transition Risk and the Optimal Capital Requirement

This figure shows how optimal capital requirements adjust in response to climate transition risk. The x-axis represents the capital requirement k, while the y-axis represents the equilibrium threshold θ^*. The blue dashed line represents the socially optimal threshold θ^*_{sc} selected by the social planner when $y = 0.3$. The red dashed line represents the threshold $\theta^*(k, y)$ determined in the global games framework when $y = 0.3$, which was set exogenously at $\theta^*_{sc} = 0.35$. The blue solid line represents the socially optimal threshold θ^*_{sc} when $y = 0.4$. The red solid line represents the threshold $\theta^*(k, y)$ when $y = 0.4$, which was set exogenously at $\theta^*_{sc} = 0.45$. All other parameters take the normal values. The dot $k^{*'}$ is the initial optimal capital requirement when $y = 0.3$, while the dot k^* is the new optimal capital requirement when $y = 0.4$.



collective behavior (see Aikman et al., 2015a,b). This mechanism also highlights their broader function as climate-informed buffers. For instance, Oehmke and Opp (2022) show that capital requirements can enhance the credibility of future carbon taxation by ensuring that banks are well-capitalized against the stranded asset losses.

The concept of climate-informed buffers can be illustrated through two complementary dimensions of transition risk. First, although realized policy impacts are normally distributed around the policy announcement, there remains a non-negligible probability that actual impacts turn out to be much larger—that is, tail transition risks. For instance, even a modest commitment can have amplified effects if accompanied by rapid technological progress in renewables. A climate-informed capital buffer therefore acts as a precautionary tool that strengthens banks' resilience to tail transition risks without amplifying financial instability.

Second, while the analysis abstracts from physical risks—whose impact tends to increase when more banks roll over—such risks can affect banks' portfolios outside the fossil fuel sector, including both corporate and household lending. Climate damages may disrupt agricultural production, infrastructure projects, or household repayment capacity in vulnerable regions (Bolton et al., 2020), thereby increasing the credit risk of the firms and households to which banks lend. Although these physical risks are not explicitly modelled in this paper, they remain relevant for assessing banks' vulnerability. Recent evidence that lenders charge higher mortgage rates for properties exposed to sea-level rise illustrates banks' precautionary response to physical risks (Nguyen et al., 2022). Hence, although the model focuses on transition risks, a climate-informed capital requirement also strengthens banks' resilience to a wider range of climate-induced shocks, including physical risks.

Countercyclical Taxes or Subsidies for Banks. The literature has proposed several policy instruments beyond capital requirements to address the externalities arising from banks' procyclical behavior. For instance, Eisenbach (2017) introduce "financial crisis bonds," which increase banks' debt burden in good states to limit excessive risk-taking while being automatically written down in bad states to mitigate excessive de-taking. Relatedly, Jondeau et al. (2021) propose a liquidity backstop for carbon-intensive firms, priced through a lump-sum fee tied to effective emissions, as a tool to support the transition while

maintaining financial stability.

In a similar spirit, one can think of a fiscal–prudential policy instrument that imposes a direct tax on banks' fossil fuel exposures. Consider the same coordination game with strategic complementarities arising from rollover risk, but assume that there is no capital requirement so that banks are not subject to the cost of capital ek. In the expected payoff difference function, I replace the term ek with a policy variable c, which captures an effective tax (if $c > 0$) or subsidy (if $c < 0$) on banks fossil fuel exposures.

This modification does not affect the uniqueness of equilibrium, since the mathematical proof remains identical to that in Lemma 1. The main comparative statics in Lemma 2 also remain largely unchanged: ek is simply replaced by c in the relevant expressions. As in the case of capital requirement, the equilibrium threshold is decreasing in c, which implies that a higher tax makes banks more likely to withdraw, while a lower tax discourages withdrawals. The social planner benchmark remains independent of c.

Hence, countercyclical taxes or subsidies can serve as an alternative tool to influence banks' strategies. In practice, however, coordinating fiscal and prudential policies poses significant implementation challenges.

Multi-period Extensions. The two-period baseline model can be extended to a multi-period environment. This paper does not follow the dynamic global games framework of Angeletos et al. (2007), which generates multiple equilibria and complicates the analysis. Instead, the model builds on Morris and Yildiz (2019) and Ahmed et al. (2024).

At the beginning of each period t, a unit mass of banks receive a public signal $y_t = Y(\theta_{t-1})$, which depends on the previous period's policy impacts through a known process $Y : \mathbb{R} \to \mathbb{R}$. The evolution of fundamentals is given by

$$\theta_t = y_t(\theta_{t-1}) + \eta_t. \tag{38}$$

This specification allows policy announcements to evolve with the outcomes of past policy actions. As in the static benchmark, I assume $\eta_t \sim N(0, \tau^2)$.[9] Banks also receive private

[9]Prior studies assume fat-tailed distributions (for example, a Student-t with finite degrees of freedom) to capture the transparency of fundamentals (Morris and Yildiz, 2019; Ahmed et al., 2024). For tractability,

signals $x_{i,t} = \theta_t + \varepsilon_{i,t}$, based on which they choose whether to roll over or withdraw. At the end of period t, policy impacts and returns materialize (e.g., θ_t, R_t, and $r_{1,t}$).

Following the two-period model, the global games framework continues to yield a unique equilibrium threshold in each period, provided private signals are sufficiently precise (Lemma 1). This gives rise to a sequence of threshold strategies $\{\theta_t^*\}_{t=1}^T$, where each bank follows a strategy:

$$s(\bar{\theta}_t) = \begin{cases} \text{Withdraw, if } \bar{\theta}_t \geq \theta_t^*, \\ \text{Roll over, if } \bar{\theta}_t < \theta_t^*. \end{cases} \tag{39}$$

The key global games equilibrium properties extend to the multi-period environment. In each period t, the threshold θ_t^* remains decreasing in the public signal y_t and in the capital requirement k_t. Thus, while the multi-period extension introduces dynamics and path dependence, it does not change the uniqueness of equilibrium or the comparative statics identified in the two-period model.

The social planner updates the benchmark $\theta_{sc,t}^*$ each period, based on revised estimates of climate damages $\Omega_{0,t}$, dependencies on bank financing $w_{1,t}$, and the contribution of fossil fuel input to aggregate output α_t.[10] The policymaker then adjusts the capital requirement k_t^* to achieve the optimal allocation. Thus, climate-informed capital requirements can operate as state-contingent rules across periods, adjusting to updated exogenous parameters, while their stabilizing role—curbing excessive risk-taking and discouraging excessive de-risking—remains consistent with the two-period benchmark.

6 Concluding Remarks

This paper examines how banks collectively respond to transition risk and how macroprudential policy can mitigate the resulting inefficiencies. Using global syndicated loan data, I show that banks reduced fossil fuel lending relative to their total credit supply after the Paris Agreement, consistent with a rise in perceived transition risk. To interpret these dynamics, I develop a global games model in which climate policy announcements act as public signals

the analysis abstracts from this consideration and maintain a Gaussian assumption, because transparency is not the focus of this paper.

[10] In Appendix D, I provide details on how the exogenous parameters affect the choice of $\theta_{sc,t}^*$.

of transition risk, shaping beliefs about the profitability of fossil fuel production. The model introduces strategic complementarities among banks, whereby each bank's lending decision reinforces those of its peers. This interaction generates highly procyclical outcomes: when transition risks appear low, banks collectively may remain excessively exposed to fossil fuels, amplifying future climate damages; when risks rise, they may withdraw prematurely, triggering disorderly adjustment and potential financial instability.

Comparing the decentralized global games equilibrium with the social planner's benchmark reveals a coordination failure: individually rational decisions may not yield the socially optimal allocation of fossil fuel lending. To address this inefficiency, this paper proposes a countercyclical macroprudential policy that varies with the perceived level of transition risk. When transition risk is high, lowering the capital requirement can encourage banks to roll over and prevent runs on stranded assets. When transition risk is low, raising the requirement can curb excessive risk-taking and mitigate long-term climate damages. In this sense, climate-informed capital buffers serve not only as prudential safeguards but also as instruments that internalize the externalities arising from banks' coordination failures.

This paper provides a tractable foundation for integrating climate transition risk into macroprudential policy design. Future research could extend the analysis along several dimensions. First, the model implicitly assumes that the banking system remains sound and therefore focuses on how banks' strategic complementarities generate externalities. In practice, however, policymakers may need to balance not only output and climate damages but also the aggregate payoff of the banking sector from its investment projects. A macrofinancial extension of the planner's problem could explicitly incorporate this dimension, but I leave it to future research. Second, a more refined climate damage function could be developed. In particular, the current specification is linear and depends solely on banks' strategies, whereas in reality the relationships among fossil fuel investments, carbon emissions, and climate damages are highly nonlinear and complex.

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Appendix A Tables

Table A1: Impact of the Paris Agreement on *Fossil Share*

This table reports regressions where the dependent variable is the share of monthly fossil fuel lending relative to total new lending ($Fossil\ Share_t$, in percent). The sample covers 2008–2024 and includes two Paris Agreement indicators: $Post\ Paris\ Adoption_t$ (from December 2015) and $Post\ Paris\ Entry_t$ (from November 2016). The specification estimates OLS, AR(1), and AR(2) models to capture potential persistence in fossil fuel lending. Results are estimated at the monthly level, which remain robust when estimated at the quarterly level. All regressions control for the oil price (source: IMF). Standard errors are Newey–West (HAC) robust with a 12-month bandwidth. Coefficients on lagged dependent variables and the oil price are omitted for brevity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

	(1) OLS	(2) AR	(3) AR	(4) OLS	(5) AR	(6) AR
Post Paris Adoption$_t$	-2.5244***	-2.7287***	-2.6908***			
	(0.6181)	(0.7679)	(0.8298)			
Post Paris Entry$_t$				-2.3202***	-2.5082***	-2.4709***
				(0.5474)	(0.6857)	(0.7255)
Observations	204	203	202	204	203	202
R^2	0.1159	0.1212	0.1196	0.1146	0.1198	0.1183
AR order	0	1	2	0	1	2

Table A2: Summary Statistics

This table reports summary statistics. Panel A reports banks' outstanding loan exposures and fossil fuel exposures. All monetary amounts are expressed in USD millions. Panel B reports the main variables used in the local projection regressions. E_t denotes fossil fuel exposure, measured as the share of fossil fuel loans in total outstanding loans (in percent, %). ΔE_t represents the quarterly change in this exposure (in percentage points, pp). D_t^+ is a dummy equal to one if a bank experiences a positive peer outlier shock, and D_t^- equals one if a bank experiences a negative peer outlier shock. The sample consists of lender-quarter level observations.

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Median**
Panel A. Exposure Data				
Outstanding Loan Exposure ($millions)	13,132	36,299.96	68,326.10	9,909.35
Fossil Fuel Exposure ($millions)	13,132	3,669.05	7,583.85	660.92
Panel B. Local Projection Variables				
E_t (%)	13,132	8.03	7.68	6.27
ΔE_t (pp)	13,132	-0.014	0.633	0.000
D_t^+ (0/1)	13,132	0.178	0.382	0.000
D_t^- (0/1)	13,132	0.181	0.385	0.000

Table A3: Local Projection: Positive Peer Outlier D_t^+ and ΔE_{t+h}

This table reports local projection regressions of future changes in fossil fuel exposure, ΔE_{t+h}, on the positive peer outlier shock (D_t^+). All specifications include lender fixed effects and quarter fixed effects. Standard errors are clustered at the Lender level. Lagged changes in exposure (ΔE_{t-1}) are included but omitted here for brevity. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ΔE_t	(2) ΔE_{t+1}	(3) ΔE_{t+2}	(4) ΔE_{t+3}	(5) ΔE_{t+4}
D_t^+	0.0567***	-0.0124	0.0011	0.0291	-0.0230
	(0.0155)	(0.0385)	(0.0301)	(0.0356)	(0.0551)
Observations	12,936	12,740	12,544	12,348	12,152
R^2	0.0550	0.0227	0.0227	0.0316	0.0248
Lender FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Table A4: Local Projection: Negative Peer Outlier D_t^- and ΔE_{t+h}

This table reports local projection regressions of future changes in fossil fuel exposure, ΔE_{t+h}, on the negative peer outlier shock (D_t^-). All specifications include lender fixed effects and quarter fixed effects. Standard errors are clustered at the Lender level. Lagged changes in exposure (ΔE_{t-1}) are included but omitted here for brevity. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ΔE_t	(2) ΔE_{t+1}	(3) ΔE_{t+2}	(4) ΔE_{t+3}	(5) ΔE_{t+4}
D_t^-	-0.0486***	-0.0348	-0.0674*	-0.0073	0.0195
	(0.0181)	(0.0305)	(0.0343)	(0.0343)	(0.0270)
Observations	12,936	12,740	12,544	12,348	12,152
R^2	0.0548	0.0227	0.0230	0.0315	0.0248
Lender FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Appendix B Mathematical Proof

B.1 The Expected Payoff Difference

Proof. **Game 1: Rollover Risk**

In Game 1, the expected payoff difference between withdrawing and rolling over is $v(\theta, l) = r_1 - (1 - p(l))(1 - f(\theta))R + ek$. I first compute the partial derivative with respect to θ:

$$\frac{\partial v(\theta, l)}{\partial \theta} = (1 - p(l))R\frac{\partial f(\theta)}{\partial \theta}. \tag{40}$$

Since $\frac{\partial f(\theta)}{\partial \theta} > 0$ and $p(l) < 1$, it follows that $\frac{\partial v(\theta,l)}{\partial \theta} > 0$. Next, the partial derivative with respect to l is

$$\frac{\partial v(\theta, l)}{\partial l} = \frac{\partial p(l)}{\partial l}(1 - f(\theta))R. \tag{41}$$

Given that $\frac{\partial p(l)}{\partial l} > 0$ and $f(\theta) < 1$, it follows that $\frac{\partial v(\theta,l)}{\partial l} > 0$ in the Game 1.

Game 2: Fire Sales

In Game 2, the expected payoff difference between withdrawing and rolling over is $v(\theta, l) = r_1 - (1 - \delta(l))(1 - f(\theta))R + ek$. I first compute the partial derivative with respect to θ:

$$\frac{\partial v(\theta, l)}{\partial \theta} = (1 - \delta(l))R\frac{\partial f(\theta)}{\partial \theta}. \tag{42}$$

Since $\frac{\partial f(\theta)}{\partial \theta} > 0$ and $\delta(l) < 1$, it follows that $\frac{\partial v(\theta,l)}{\partial \theta} > 0$. Next, the partial derivative with respect to l is

$$\frac{\partial v(\theta, l)}{\partial l} = \frac{\partial \delta(l)}{\partial l}(1 - f(\theta))R. \tag{43}$$

Given that $\frac{\partial \delta(l)}{\partial l} > 0$ and $f(\theta) < 1$, it follows that $\frac{\partial v(\theta,l)}{\partial l} > 0$.

Game 3: Pecuniary Reputation Costs

In Game 3, the expected payoff difference between withdrawing and rolling over is $v(\theta, l) = r_1 - (1 - f(\theta))R + e(l)k$. I first compute the partial derivative with respect to θ:

$$\frac{\partial v(\theta, l)}{\partial \theta} = R\frac{\partial f(\theta)}{\partial \theta}. \tag{44}$$

Since $\frac{\partial f(\theta)}{\partial \theta} > 0$, it follows that $\frac{\partial v(\theta,l)}{\partial \theta} > 0$. Next, the partial derivative with respect to l is:

$$\frac{\partial v(\theta, l)}{\partial l} = \frac{\partial e(l)}{\partial l}k. \tag{45}$$

Given that $\frac{\partial e(l)}{\partial l} > 0$, it follows that $\frac{\partial v(\theta,l)}{\partial l} > 0$.

Game 4: Non-pecuniary Reputation Costs

In Game 4, the expected payoff difference between withdrawing and rolling over is $v(\theta, l) =$

$r_1 - (1 - f(\theta))R + ek + b(l)$. I first compute the partial derivative with respect to θ:

$$\frac{\partial v(\theta, l)}{\partial \theta} = R\frac{\partial f(\theta)}{\partial \theta}. \tag{46}$$

Since $\frac{\partial f(\theta)}{\partial \theta} > 0$, it follows that $\frac{\partial v(\theta,l)}{\partial \theta} > 0$. Next, the partial derivative with respect to l is:

$$\frac{\partial v(\theta, l)}{\partial l} = \frac{\partial b(l)}{\partial l}. \tag{47}$$

Given that $\frac{\partial b(l)}{\partial l} > 0$, it follows that $\frac{\partial v(\theta,l)}{\partial l} > 0$. □

B.2 Proof of Lemma 1

Proof. To establish uniqueness, I need to show that $V(\bar{\theta}, \theta^*)$ is increasing in $\bar{\theta}$ and that $V(\theta^*, \theta^*) = 0$ has a unique solution. The function $V(\bar{\theta}, \theta^*)$ represents the expected payoff difference of bank i given $\bar{\theta}$. I express $V(\bar{\theta}, \theta^*)$ using $\theta = \theta' + \bar{\theta}$, $\sqrt{\gamma} = \frac{\sigma}{\tau^2}\sqrt{\frac{\sigma^2+\tau^2}{\sigma^2+2\tau^2}}$, and $\sqrt{\rho} = \sqrt{\frac{\sigma^2+\tau^2}{\sigma^2\tau^2}}$:

$$V(\bar{\theta}, \theta^*) = \int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} v(\theta' + \bar{\theta}, l(\bar{\theta}, \theta^*))d\theta'. \tag{48}$$

First, I need to show that $V(\bar{\theta}, \theta^*)$ is increasing in $\bar{\theta}$. The proportion of banks that choose to withdraw $l(\bar{\theta}, \theta^*)$ increases with $\bar{\theta}$ because the underlying normal cumulative distribution function is monotonically increasing. Given that $\theta = \theta' + \bar{\theta}$, a higher $\bar{\theta}$ also raises the perceived fundamental. Since $v(\theta, l)$ is increasing in both θ and l, $v(\theta' + \bar{\theta}, l(\bar{\theta}, \theta^*))$ is increasing in $\bar{\theta}$. Therefore, $V(\bar{\theta}, \theta^*)$ is increasing in $\bar{\theta}$.

Second, I need to show that $V(\theta^*, \theta^*) = 0$ has a unique solution. At $\bar{\theta} = \theta^*$,

$$V(\theta^*, \theta^*) = \int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} v(\theta' + \theta^*, l(\theta^*, \theta^*))d\theta'. \tag{49}$$

Taking the partial differential of $V(\theta^*, \theta^*)$ with respect to θ^* yields:

$$\begin{aligned} \frac{\partial V(\theta^*, \theta^*)}{\partial \theta^*} &= \int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} [\frac{\partial v(.)}{\partial \theta} + \frac{\partial v(.)}{\partial l(.)}\frac{\partial l(.)}{\partial \theta^*}]d\theta' \\ &= \int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} \frac{\partial v(.)}{\partial \theta}[1 + \frac{\frac{\partial v(.)}{\partial l(.)}\frac{\partial l(.)}{\partial \theta^*}}{\frac{\partial v(.)}{\partial \theta}}]d\theta'. \end{aligned} \tag{50}$$

Note that $\frac{\partial\theta}{\partial\theta^*}=1$, as $\theta=\theta^{'}+\bar{\theta}$ and $\bar{\theta}=\theta^*$. At $\bar{\theta}=\theta^*$,

$$l(\theta^*,\theta^*)=1-\Phi(\frac{\frac{\sigma^2}{\tau^2}(\theta^*-y)}{\sqrt{\frac{2\sigma^2\tau^2+\sigma^4}{\sigma^2+\tau^2}}})=1-\Phi(\sqrt{\gamma}(\theta^*-y)). \tag{51}$$

Take the differential of $l(\theta^*,\theta^*)$ respective to θ^*:

$$\frac{\partial l(\theta^*,\theta^*)}{\partial\theta^*}=-\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))<0, \tag{52}$$

which shows that a higher cutoff implies a lower proportion of bankers that choose to withdraw, for a given public signal y. I take the partial differential of $l(\theta^*,\theta^*)$ respective to y:

$$\frac{\partial l(\theta^*,\theta^*)}{\partial y}=\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))>0, \tag{53}$$

which implies that higher public signal y implies a larger proportion of bankers that withdraw. Substituting these derivatives gives:

$$\frac{\partial V(\theta^*,\theta^*)}{\partial\theta^*}=\int_{\theta'=-\infty}^{\infty}\frac{\phi(\sqrt{\rho}\theta^{'})}{\sqrt{\rho}}\frac{\partial v(.)}{\partial\theta}[1-\frac{\frac{\partial v(.)}{\partial l(.)}}{\frac{\partial v(.)}{\partial\theta}}\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))]d\theta^{'}. \tag{54}$$

To ensure uniqueness of solution, I need to prove $V(\theta^*,\theta^*)$ is increasing in θ^*, which requires the expression in bracket to be positive:

$$\frac{\frac{\partial v(.)}{\partial l(.)}}{\frac{\partial v(.)}{\partial\theta}}\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))<1 \tag{55}$$

which is equivalent to

$$\gamma<(\frac{1}{\phi(.)}\frac{\frac{\partial v(.)}{\partial\theta}}{\frac{\partial v(.)}{\partial l(.)}})^2. \tag{56}$$

Given that $\phi(.)<\frac{1}{\sqrt{2\pi}}$,

$$\gamma<2\pi(\frac{\frac{\partial v(.)}{\partial\theta}}{\frac{\partial v(.)}{\partial l(.)}})^2. \tag{57}$$

This is sufficient for the uniqueness of solution, which shows that the private signals must be sufficiently precise relative to public signals. This parallels the standard global games

results in Morris and Shin (2001) and holds for all four games. □

B.3 Proof of Lemma 2

Proof. **Part (a): public signal y.**

At the equilibrium threshold θ^*, the share of withdrawals is:

$$l(\theta^*, \theta^*) = 1 - \Phi(\sqrt{\gamma}(\theta^* - y)). \tag{58}$$

In equilibrium, the expected payoff difference satisfies:

$$\int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} v(\theta' + \theta^*, l(\theta^*, \theta^*)) d\theta' = 0. \tag{59}$$

I take the differential of both side respective to y:

$$\int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} [\frac{\partial v}{\partial \theta}\frac{\partial \theta}{\partial \theta^*}\frac{\partial \theta^*}{\partial y} + \frac{\partial v}{\partial l}(\frac{\partial l}{\partial \theta^*}\frac{\partial \theta^*}{\partial y} + \frac{\partial l}{\partial y})] d\theta' = 0. \tag{60}$$

Next,

$$\frac{\partial v}{\partial \theta}\frac{\partial \theta}{\partial \theta^*}\frac{\partial \theta^*}{\partial y} + \frac{\partial v}{\partial l}(\frac{\partial l}{\partial \theta^*}\frac{\partial \theta^*}{\partial y} + \frac{\partial l}{\partial y}) = 0. \tag{61}$$

Therefore,

$$\frac{\partial \theta^*}{\partial y} = \frac{-\frac{\partial v}{\partial l}\frac{\partial l}{\partial y}}{\frac{\partial v}{\partial \theta} + \frac{\partial v}{\partial l}\frac{\partial l}{\partial \theta^*}}. \tag{62}$$

Since both $\frac{\partial v}{\partial l}$ and $\frac{\partial l}{\partial y}$ are positive, while the denominator is positive by the sufficient condition of uniqueness, it follows that $\frac{\partial \theta^*}{\partial y} < 0$.

Part (b): capital requirement k.

Taking the derivative with respect to k:

$$\int_{\theta'=-\infty}^{\infty} \frac{\phi(\sqrt{\rho}\theta')}{\sqrt{\rho}} (\frac{\partial v}{\partial k} + \frac{\partial v}{\partial \theta}\frac{\partial \theta}{\partial \theta^*}\frac{\partial \theta^*}{\partial k} + \frac{\partial v}{\partial l}\frac{\partial l}{\partial \theta^*}\frac{\partial \theta^*}{\partial k}) d\theta' = 0. \tag{63}$$

To guarantee above equality, it follows that:

$$\frac{\partial v}{\partial k} + \frac{\partial v}{\partial \theta}\frac{\partial \theta}{\partial \theta^*}\frac{\partial \theta^*}{\partial k} + \frac{\partial v}{\partial l}\frac{\partial l}{\partial \theta^*}\frac{\partial \theta^*}{\partial k} = 0. \tag{64}$$

This simplifies to:

$$\frac{\partial v}{\partial \theta}\frac{\partial \theta}{\partial \theta^*}\frac{\partial \theta^*}{\partial k} + \frac{\partial v}{\partial l}\frac{\partial l}{\partial \theta^*}\frac{\partial \theta^*}{\partial k} = (\frac{\partial v}{\partial \theta}\frac{\partial \theta}{\partial \theta^*} + \frac{\partial v}{\partial l}\frac{\partial l}{\partial \theta^*})\frac{\partial \theta^*}{\partial k} = -\frac{\partial v}{\partial k}. \tag{65}$$

The term in parentheses is positive by the uniqueness condition. In Games 1, 2 and 4, $\frac{\partial v}{\partial k} = e > 0$, while in Game 3, $\frac{\partial v}{\partial k} = e(l)$. Hence, for all four games, $\frac{\partial v}{\partial k} > 0$, which implies that $\frac{\partial \theta^*}{\partial k} < 0$. □

B.4 Proof of Proposition 1

Proof. When $\sigma \to 0$, each bank' private signal becomes perfectly precise, i.e., $x_i \to \theta$. The posterior mean then satisfies:

$$\bar{\theta} = \frac{\sigma^2 y + \tau^2 x_i}{\sigma^2 + \tau^2} \to x_i \to \theta, \tag{66}$$

and the posterior standard deviation converges to zero:

$$\text{Variance} = \frac{\sigma^2 \tau^2}{\sigma^2 + \tau^2} \to 0. \tag{67}$$

In this case, the private signal of any other bank, denoted x', also has mean $\bar{\theta}$ and zero variance. Their posterior expected value becomes $\bar{\theta}' \to x' \to \theta$.

Therefore, all banks share the same posterior expectation on the fundamentals, which equals θ. Given that they follow an identical switching strategy, they take the same action in equilibrium. □

B.5 The Numerical Example

Proof. **Equilibrium**

Recall that $\frac{\partial r(\theta,l)}{\partial l} > 0$ and $\frac{\partial r(\theta,l)}{\partial \theta} > 0$. At θ^*, it follows that

$$l(\theta^*, \theta^*) = 1 - \Phi(\sqrt{\gamma}(\theta^* - y)), \tag{68}$$

and the expected payoff difference between withdrawing and rolling over is given by:

$$\begin{aligned} V(\theta^*) &= r_1 - (1 - \Phi(\theta^*))[1 - r_l(1 - \Phi(\sqrt{\gamma}(\theta^* - y)))]R + ek \\ &= r_1 + r(\theta^*, l(\theta^*, \theta^*)) + ek = 0, \end{aligned} \tag{69}$$

where $r(\theta^*, l(\theta^*, \theta^*)) = -(1 - \Phi(\theta^*))[1 - r_l(1 - \Phi(\sqrt{\gamma}(\theta^* - y)))]R$.

To prove the uniqueness of θ^*, I take the derivative respect to θ^* and to guarantee the uniqueness, the following condition must hold:

$$\frac{\partial V(\theta^*, \theta^*)}{\partial \theta^*} = \frac{\partial r(.)}{\partial \theta^*} - \frac{\partial r(.)}{\partial l}\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^* - y)) > 0. \tag{70}$$

Rearranging yields:

$$\frac{\partial r(.)}{\partial \theta^*} > \frac{\partial r(.)}{\partial l}\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^* - y)). \tag{71}$$

Since $\phi(.)$ reaches its maximum value at $1/\sqrt{2\pi}$, there is a unique solution if γ is sufficiently small. In other words, uniqueness is guaranteed when private signals are sufficiently precise.

Property (a): public signal y.

At θ^*, $l = 1 - \Phi(\sqrt{\gamma}(\theta^* - y))$. Hence, it follows that

$$r(\theta^*, l(\theta^*, \theta^*)) = -(1 - \Phi(\theta^*))[1 - r_l(1 - \Phi(\sqrt{\gamma}(\theta^* - y)))]R. \tag{72}$$

At θ^*, the marginal payoff difference equals zero:

$$r_1 - (1 - \Phi(\theta^*))[1 - r_l(1 - \Phi(\sqrt{\gamma}(\theta^* - y)))]R + ek = 0. \tag{73}$$

I take the derivative of both sides with respect to y:

$$\phi(\theta^*)\frac{d\theta^*}{dy}[1-r_l(1-\Phi(\sqrt{\gamma}(\theta^*-y)))]R-(1-\Phi(\theta^*))r_l[\phi(\sqrt{\gamma}(\theta^*-y))(\sqrt{\gamma}(\frac{d\theta^*}{dy}-1))]R=0. \quad (74)$$

Then, I have:

$$\frac{d\theta^*}{dy}=\frac{-(1-\Phi(\theta^*))r_l\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))R}{\phi(\theta^*)[1-r_l(1-\Phi(\sqrt{\gamma}(\theta^*-y)))]R-(1-\Phi(\theta^*))r_l\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))R}. \quad (75)$$

Using derivatives of $r(\theta^*, l)$,

$$\frac{\partial r(\theta^*,l)}{\partial \theta^*}=\phi(\theta^*)[1-r_l l]R, \quad (76)$$

and

$$\frac{\partial r(\theta^*,l)}{\partial l}=(1-\Phi(\theta^*))r_l R. \quad (77)$$

Rewriting the expression:

$$\frac{d\theta^*}{dy}=\frac{-(1-\Phi(\theta^*))r_l\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))R}{\frac{\partial r(.)}{\partial \theta^*}-\frac{\partial r(.)}{\partial l}\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))}<0, \quad (78)$$

where the denominator is positive under the uniqueness condition, and the numerator is negative.

Property (b): capital requirement k.

Recall that:

$$r_1-(1-\Phi(\theta^*))[1-r_l(1-\Phi(\sqrt{\gamma}(\theta^*-y)))]R+ek=0. \quad (79)$$

Taking the derivative with respect to k,

$$\phi(\theta^*)\frac{d\theta^*}{dk}[1-r_l(1-\Phi(\sqrt{\gamma}(\theta^*-y)))]R-(1-\Phi(\theta^*))r_l[\phi(\sqrt{\gamma}(\theta^*-y))\sqrt{\gamma}\frac{d\theta^*}{dk}]R=-e. \quad (80)$$

Rearranging and applying the sufficient condition for uniqueness, I obtain:

$$\begin{aligned}\frac{d\theta^*}{dk} &= \frac{-e}{\phi(\theta^*)[1-r_l(1-\Phi(\sqrt{\gamma}(\theta^*-y)))]R-(1-\Phi(\theta^*))r_l\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))R} \\ &= \frac{-e}{\frac{\partial r(.)}{\partial \theta^*}-\frac{\partial r(.)}{\partial l}\sqrt{\gamma}\phi(\sqrt{\gamma}(\theta^*-y))} < 0.\end{aligned} \tag{81}$$

□

B.6 Proof of Lemma 3

Proof. To begin with, I consider gross output:

$$\frac{\partial Y(P(\theta^*))}{\partial P(\theta^*)} = \bar{Y}\alpha(w_0+w_1P(\theta^*))^{\alpha-1}w_1 > 0, \tag{82}$$

since $\bar{Y} > 0$, $\alpha > 0$, $(w_0 + w_1P(\theta^*))^{\alpha-1} > 0$, and $w_1 > 0$. For climate damages, I obtain:

$$\frac{\partial \Omega(P(\theta^*))}{\partial P(\theta^*)} = \Omega_0 w_1 > 0, \tag{83}$$

because $\Omega_0 > 0$ and $w_1 > 0$. Hence, both $Y(P(\theta^*))$ and $\Omega(P(\theta^*))$ are strictly increasing in $P(\theta^*)$. □

B.7 Proof of Lemma 4

Proof. The proof proceeds in two parts.

Part (a): fossil fuel production $P(\theta^*_{sc})$.

It follows that:

$$P(\theta^*_{sc}) = \Pr[\theta < \theta^*_{sc}] = \Phi(\frac{\theta^*_{sc}-y}{\tau}). \tag{84}$$

Taking the derivative with respect to $P(\theta^*_{sc})$, I obtain:

$$\frac{1}{\tau}\phi(\frac{\theta^*_{sc}-y}{\tau})\frac{\partial \theta^*_{sc}}{\partial P(\theta^*_{sc})} = 1. \tag{85}$$

Therefore,

$$\frac{\partial \theta_{sc}^*}{\partial P(\theta_{sc}^*)} = \frac{1}{\frac{1}{\tau}\phi(\frac{\theta_{sc}^* - y}{\tau})} > 0. \tag{86}$$

Part (b): public signal y.

Along the social planner benchmark, the optimal production level $P(\theta_{sc}^*)$ is fixed and therefore does not vary with y. Taking the derivative with respect to y, I have:

$$\frac{1}{\tau}\phi(\frac{\theta_{sc}^* - y}{\tau})[\frac{\partial \theta_{sc}^*}{\partial y} - 1] = 0. \tag{87}$$

Hence,

$$\frac{\partial \theta_{sc}^*}{\partial y} = 1 > 0. \tag{88}$$

□

B.8 Comparative Statistics for the Benchmark

Proof. **Part (a): output elasticity of energy α.**

Starting from the first-order condition, I have:

$$\alpha - \alpha\Omega_0 + \alpha\Omega_0 w_1 - \alpha\Omega_0 w_1 P(\theta_{sc}^*) - \Omega_0 + w_1\Omega_0 - w_1\Omega_0 P(\theta_{sc}^*) = 0. \tag{89}$$

Taking the derivative with respect to α yields:

$$1 - \Omega_0 + \Omega_0 w_1 - \Omega_0 w_1[P(\theta_{sc}^*) + \alpha\frac{dP(\theta_{sc}^*)}{d\alpha}] - w_1\Omega_0\frac{dP(\theta_{sc}^*)}{d\alpha} = 0. \tag{90}$$

Equivalently,

$$\frac{dP(\theta_{sc}^*)}{d\alpha} = \frac{1 - \Omega_0 + \Omega_0 w_1 - \Omega_0 w_1 P(\theta_{sc}^*)}{\Omega_0 w_1(1+\alpha)} > 0. \tag{91}$$

Part (b): the maximum climate damages Ω_0.

Starting again from the first-order condition, I have:

$$\alpha - \alpha\Omega_0 + \alpha\Omega_0 w_1 - \alpha\Omega_0 w_1 P(\theta^*_{sc}) - \Omega_0 + w_1\Omega_0 - w_1\Omega_0 P(\theta^*_{sc}) = 0. \tag{92}$$

Taking the derivative with respect to Ω_0, I obtain:

$$-\alpha + \alpha w_1 - \alpha w_1[P(\theta^*_{sc}) + \Omega_0 \frac{dP(\theta^*_{sc})}{d\Omega_0}] - 1 + w_1 - w_1[P(\theta^*_{sc}) + \Omega_0 \frac{dP(\theta^*_{sc})}{d\Omega_0}] = 0. \tag{93}$$

Equivalently,

$$\frac{dP(\theta^*_{sc})}{d\Omega_0} = \frac{-\alpha + \alpha w_1 - \alpha w_1 P(\theta^*_{sc}) - 1 + w_1 - w_1 P(\theta^*_{sc})}{\alpha w_1 \Omega_0 + w_1 \Omega_0} < 0. \tag{94}$$

Part (c): dependency on bank lending w_1.

Starting again from the first-order condition:

$$\alpha - \alpha\Omega_0 + \alpha\Omega_0 w_1 - \alpha\Omega_0 w_1 P(\theta^*_{sc}) - \Omega_0 + w_1\Omega_0 - w_1\Omega_0 P(\theta^*_{sc}) = 0. \tag{95}$$

Taking the derivative with respect to w_1, I obtain:

$$\alpha\Omega_0 - \alpha\Omega_0[P(\theta^*_{sc}) + w_1 \frac{dP(\theta^*_{sc})}{dw_1}] + \Omega_0 - \Omega_0[P(\theta^*_{sc}) + w_1 \frac{dP(\theta^*_{sc})}{dw_1}] = 0. \tag{96}$$

Equivalently,

$$\frac{dP(\theta^*_{sc})}{dw_1} = \frac{\alpha\Omega_0 - \alpha\Omega_0 P(\theta^*_{sc}) + \Omega_0 - \Omega_0 P(\theta^*_{sc})}{\alpha\Omega_0 w_1 + \Omega_0 w_1} > 0. \tag{97}$$

□

B.9 Proof of Proposition 2

Proof. In the global games model, the equilibrium threshold $\theta^*(k, y)$ is decreasing in k, i.e. $\frac{\partial\theta^*(k,y)}{\partial k} < 0$. If $\theta^*_{sc} > \theta^*(k, y)$, the policymaker can raise $\theta^*(k, y)$ by lowering k so that $\theta^*_{sc} = \theta^*(k, y)$. If $\theta^*_{sc} < \theta^*(k, y)$, the policymaker can lower $\theta^*(k, y)$ by raising k so that $\theta^*_{sc} = \theta^*(k, y)$. Otherwise, if $\theta^*_{sc} = \theta^*(k, y)$ already holds, no policy intervention is required. □

B.10 Proof of Proposition 3

Proof. At $k = k^*$, $\theta^*_{sc} = \theta^*(k^*, y)$. Taking derivatives of both sides with respect to y gives:

$$\frac{\partial \theta^*_{sc}}{\partial y} = \frac{\partial \theta^*(k^*, y)}{\partial k^*} \frac{\partial k^*}{\partial y} + \frac{\partial \theta^*(k^*, y)}{\partial y}. \tag{98}$$

In the social planner benchmark $\frac{\partial \theta^*_{sc}}{\partial y} > 0$, while in the global games model $\frac{\partial \theta^*(k^*,y)}{\partial y} < 0$ and $\frac{\partial \theta^*(k^*,y)}{\partial k^*} < 0$. For the equation to hold, it must be that $\frac{\partial k^*}{\partial y} < 0$.

Therefore, the optimal capital requirement k^* is decreasing in y. Intuitively, a stronger public signal y, which indicates higher transition risk, lowers the capital requirement, so that banks are incentivized to roll over and avoid destabilizing runs. □

Appendix C Parameters

Table A5: Parameters (for Section 3.3)

This table presents the parameters used to calibrate the models in Section 3.3. Columns (1) and (2) report variable definitions and corresponding symbols. Column (3) lists the baseline values, while Column (4) reports alternative (high) values used for illustrative or sensitivity analysis.

Variable Definition	Symbol	Normal	High
Precision of private signal relative to public signal	γ	10	1000
Public signal (e.g., policy announcement at t_1)	y	0.3	0.4
Return to withdrawal banks at t_2	r_1	1.05	-
Degree of strategic complementarity	r_l	0.25	-
Gross project return at t_2	R	4	-
Capital requirement with brown-penalizing factor	k_0	0.6	-
Cost of equity per period	e	0.3	-

Table A6: Parameters (for Section 4.1)

This table reports the exogenous parameters (as of t_1) used to calibrate the social planner benchmark in Section 4.1. Columns (1) and (2) report variable definitions and corresponding symbols. Column (3) lists the baseline values, while Column (4) reports alternative (high) values used for illustrative or sensitivity analysis.

Variable Definition	Symbol	Normal	High
Output elasticity of fossil fuels	α	0.15	0.2
Maximum climate damages (e.g., no bank withdrawals)	Ω_0	0.2	0.25
Dependency of fossil fuel sector on risky bank lending	w_1	0.7	0.9

Table A7: Parameters (for Section 4.2)

This table presents the parameters used to calibrate the two figures in Section 4.2. Columns (1) and (2) report variable definitions and corresponding symbols. Column (3) lists the baseline values, while Column (4) reports alternative (high) values used for illustrative or sensitivity analysis.

Variable Definition	Symbol	Normal	High
Public signal (e.g., policy announcement at t_1)	y	0.3	0.4
Social planner benchmark (set exogenously)	θ^*_{sc}	0.35	0.45
Precision of private signal relative to public signal	γ	10	-
Return to withdrawal banks at t_2	r_1	1.05	-
Degree of strategic complementarity	r_l	0.25	-
Gross project return at t_2	R	4	-
Cost of equity per period	e	0.3	-

Appendix D Comparative Statistics for the Benchmark

For illustrative purposes, I present auxiliary benchmark properties in the three figures below, which help clarify how the social planner benchmark is determined exogenously. The model

parameters are in Appendix C. The first figure compares the blue and red lines to show that $P(\theta^*_{\text{sc}})$ increases with the output elasticity of fossil fuels, α. The second figure illustrates how changes in the maximum climate damage, Ω_0, affect the socially optimal threshold. The comparison confirms that $P(\theta^*_{\text{sc}})$ decreases with Ω_0. Finally, the third figure shows how changes in dependency on bank funding, w_1, influence $P(\theta^*_{\text{sc}})$, with the comparison indicating that $P(\theta^*_{\text{sc}})$ increases in w_1.

Figure 10: Net Output with Normal Parameters vs. Net Output with High Output Elasticity of Energy

The x-axis represents the fossil fuel production $P(\theta^*)$, while the y-axis represents the net output $Q(P(\theta^*))$ expressed as a percentage of the baseline output. The blue line represents the net output when the output elasticity of fossil fuels $\alpha = 0.15$. The red line represents the net output when the output elasticity of fossil fuels $\alpha = 0.2$. Dots represent the local maxima—the orderly transition scenario $P(\theta^*_{sc})$. All other parameters take normal values.

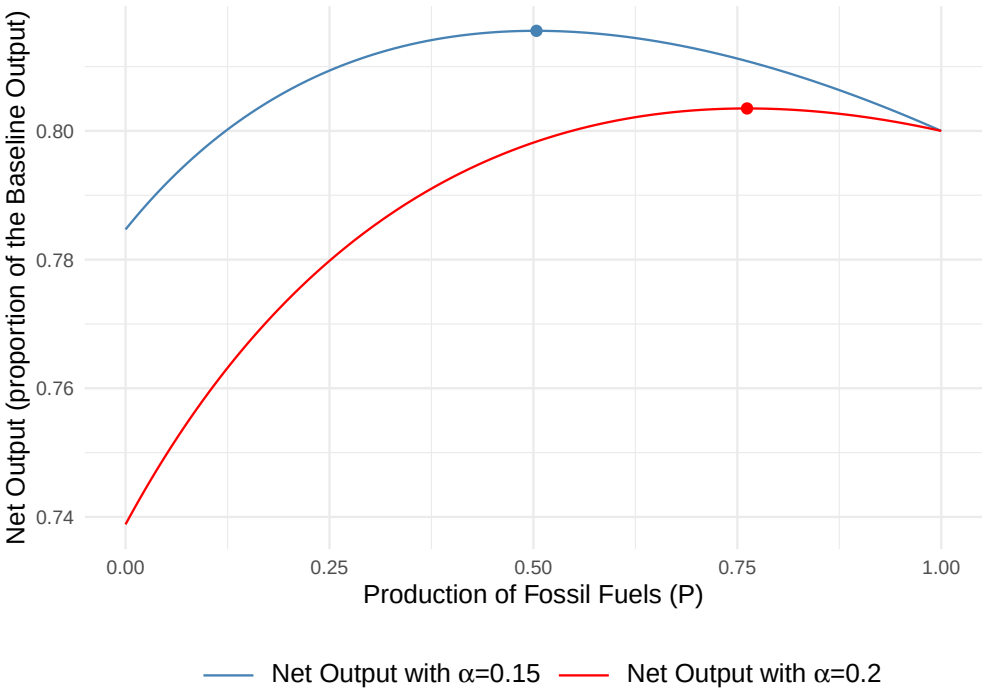


Figure 11: Net Output with Normal Parameters vs. Net Output with High Maximum Climate Damages

The x-axis represents the fossil fuel production $P(\theta^*)$, while the y-axis represents the net output $Q(P(\theta^*))$ expressed as a percentage of the baseline output. The blue line represents the net output when the maximum climate damage $\Omega_0 = 0.2$. The red line represents the net output when the maximum climate damage $\Omega_0 = 0.25$. Dots represent the local maxima—the orderly transition scenario $P(\theta^*_{sc})$. All other parameters take normal values.

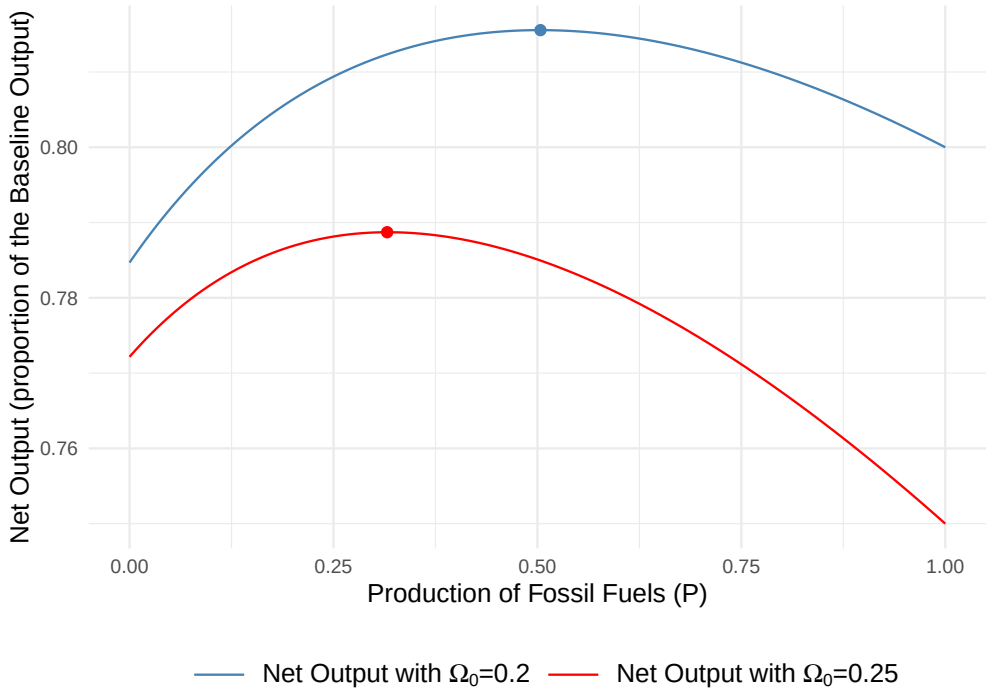


Figure 12: Net Output with Normal Parameters vs. Net Output with High Dependency on Bank Funding

The x-axis represents the fossil fuel production $P(\theta^*)$, while the y-axis represents the net output $Q(P(\theta^*))$ expressed as a percentage of the baseline output. The blue line represents the dependency on bank funding $w_1 = 0.7$. The red line represents the dependency on bank funding $w_1 = 0.9$. Dots represent the local maxima—the orderly transition scenario $P(\theta^*_{sc})$. All other parameters take normal values.

