Information contagion and systemic risk*

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Abstract

Information contagion can reduce systemic risk defined as the joint default probability of banks. This paper examines the effects of ex-post information contagion on both the banks' ex-ante optimal portfolio choices and the implied welfare losses due to joint default. Because of counterparty risk and common exposures, bad news about one bank reveals valuable information about another bank, thereby triggering information contagion. We find that information contagion reduces (increases) the joint default probability when banks are subject to counterparty risk (common exposures). When applied to microfinance, our model also provides a novel explanation for higher repayment rates in group lending. [100 words.]

Keywords: information contagion, counterparty risk, common exposure, systemic risk, microfinance, group lending

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1 Introduction

Systemic risk is defined as the joint default of a substantial part of the financial system and is associated with large social costs.[1] One major source of systemic risk is information contagion: when investors are sensitive to news about the health of the financial system, bad news about one financial institution can adversely spill over to other financial institutions. For instance, the insolvency of one money market mutual fund with a large exposure to the investment bank Lehman Brothers spurred investor fears and led to a wide-spread run on all money market mutual funds in September 2008.[2] As information contagion affects various financial institutions including commercial banks, money market mutual funds, and shadow banks, we adopt a broad notion of financial institutions and call them banks for short.

There are at least two reasons for an investor of a bank to find information about another bank's profitability valuable. On the one hand, the first bank may have lent to the second bank in the past, for example to share liquidity risk as in Allen and Gale (2000). Learning about the debtor bank's profitability then helps the investor assess the counterparty risk of the creditor bank. On the other hand, both banks may have some common exposure to an asset class, such as risky sovereign debt or mortgage-backed securities. Learning about another bank's profitability then helps the investor assess the profitability of its bank. For example, the funding cost of one bank increases after adverse news about another bank because of correlated loan portfolio returns in Acharya and Yorulmazer (2008b).

We develop a model of systemic risk with information contagion. Our model features two banks, where systemic risk refers to the ex-ante probability of joint default. Due to both counterparty risk and common exposures, bad news about one bank can trigger the

[1] The Bank for International Settlements (1997) compares the cost of systemic bank crises in various developing and industrialized countries and document the range from about 3% of GDP for the savings and loan crisis in the United States to about 30% of GDP for the 1981-87 crisis in Chile.

[2] Lehman Brothers failed on September 15, 2008 and the share price of the Reserve Primary Fund dropped below the critical value of 1$ on September 16, 2008.

default of another bank. Information contagion in this setup is the amount of a bank's additional financial fragility caused by such bad news. We examine the effects of ex-post information contagion on the ex-ante optimal portfolio choice of a bank and the implied level of systemic risk.

Our main result refers to information contagion due to counterparty risk. When an information spillover is unanticipated, the ex-ante optimal portfolio is unchanged and systemic risk increases (Result 1).[3] By contrast, the ex-ante optimal portfolio choice is more prudent when the information spillover is anticipated, *reducing* systemic risk (Result 3) and the level of expected utility. In short, systemic risk is lower when anticipating information contagion, labelled as a *resilience effect*. The contrast between Result 1 and Result 3 demonstrates the importance of ex-post information contagion for the ex-ante optimal portfolio choice.

We also analyze information contagion due to common exposures. When information spillover is unanticipated, systemic risk increases (Result 2), as in Result 1. When information spillover is anticipated, however, systemic risk and expected utility increases (Result 4). This is labelled the *instability effect*. Taking these results together, the consequences of information contagion for the level of systemic risk (via changes of the ex-ante optimal portfolio choice) depend on the nature of the interbank linkage: financial fragility increases (decreases) when banks are linked via common exposure (counterparty risk).

Our main contribution is the analysis of information contagion due to counterparty risk and its effects on the ex-ante optimal portfolio choice and systemic risk. To the best of our knowledge, counterparty risk as a source of information contagion has not beeen previously addressed.[4] Our counterparty risk mechanism builds on the literature of finan-

[3]Similar to the aggregate liquidity shock in Allen and Gale (2000), the information spillover is a zero probability event when unanticipated ex-ante.

[4]Cooper and Ross (1998) and Ennis and Keister (2006) study the effect of ex-post individual bank

cial contagion due to balance sheet linkages. Building on Diamond and Dybvig (1983), Allen and Gale (2000) describe financial contagion as an equilibrium result.[5] Interbank lending insures banks against a non-aggregate liquidity shock and potentially achieves the first-best outcome. However, a zero-probability aggregate liquidity shock may travel through the entire financial system. While counterparty risk in our model also arises from the potential default on interbank obligations, we obtain the ex-ante optimal portfolio choice given that contagion may occur with positive probability.[6]

Our results also relate to the literature on information contagion due to common exposures. Information about the solvency of one bank is an informative signal about the health of other banks with similar exposure in Acharya and Yorulmazer (2008b).[7] The anticipation of ex-post information contagion induces banks to correlate their ex-ante investment decisions, endogenously creating common exposures. By contrast, we consider counterparty risk as a principal source of information contagion. We also allow for a larger set of portfolio choice options.[8] Leitner (2005) analyzes the ex-ante beneficial insurance effects of ex-post financial contagion in the absence of an explicit ex-ante risk sharing

runs on the ex-ante liquidity choice and the design of deposit contracts. By contrast, we analyze how information contagion due to counterparty risk affects the ex-ante portfolio choice and deposit contract design of banks and examine the consequences for the joint default probability of banks.

[5]Freixas et al. (2000) consider spatial instead of intertemporal uncertainty about liquidity needs.

[6]Postlewaite and Vives (1987) show the uniqueness of equilibrium with positive probability of bank runs in a Diamond and Dybvig (1983) setup with demand deposit contracts and four periods. By contrast, we analyse the impact of information contagion from counterparty risk and common exposures on the ex-ante optimal portfolio choice and the implied level of systemic risk. Dasgupta (2004) also demonstrates the presence of financial contagion with positive probability in the unique equilibrium of a global game version of the model described by Allen and Gale (2000), focusing on the coordination failure initiated by adverse information. By contrast, we analyse the impact of information contagion from counterparty risk and common exposures on the ex-ante optimal portfolio choice and the implied level of systemic financial fragility.

[7]Other models of common exposure include Acharya and Yorulmazer (2008a), who analyze the interplay between government bail-out policies and banks' incentives to correlate their investments. Chen (1999) shows that bank runs can be triggered by information about bank defaults when banks have a common exposure. Uninformed investors use the publicly available signal about the default of another bank to assess the default probability of their bank. An early model of information-based individual fragility is Jacklin and Bhattacharya (1988).

[8]While interconnectedness of banks only arises through the endogenous choice of correlated investments in Acharya and Yorulmazer (2008b), we maintain the exogenous correlation of the bank's investment returns as in Acharya and Yorulmazer (2008a) but endogenize liquidity holdings, interbank liquidity insurance (*co-insurance* as in Brusco and Castiglionesi (2007)), and insurance of impatient investors against idiosyncratic liquidity shocks.

mechanism due to limited commitment. By contrast, we focus on the ex-ante effects of ex-post *information* contagion in a model with commitment. Allen et al. (2012) analyze systemic risk stemming from the interaction of common exposures and funding maturity through an information channel.[9] However, our focus is on the novel analysis of counterparty risk as a source of information contagion and its repercussions for systemic risk.[10]

Our results on the interaction of information spillovers and counterparty risk are not limited to systemic risk in banking of advanced economies. Counterparty risk also arises from joint liability in group lending contracts commonly used by the Grameen bank and other microfinance institutions in developing economies (see e.g. Stiglitz (1990), Varian (1990), or Morduch (1999)). The idea behind group borrowing is to employ peer monitoring to overcome asymmetric information. Thus, borrowers in a group will know each other quite well (either neighbors from the same village, or even family members) and information spillover occurs frequently. In particular, our resilience effect predicts that (i) group loans have a higher repayment rate than individual loans and (ii) group borrowers hold more liquid assets. As discussed in Section (5), both predictions are verified in the empirical microfinance literature.

The remainder of this paper is as follows. The model is described in Section (2) and its equilibrium is analyzed in Section (3), including a discussion of special cases to provide further intuition to our model. We present our results in Section (4), which also contains extensive robustness checks. Our model is applied to microfinance in Section (5), providing a novel explanation for empirical findings in that literature. Finally, Section (6) concludes. Derivations, proofs, and tables are found in Appendices (A), (B), and (C).

[9]Banks swap risky investment projects to diversify, generating different types of portfolio overlaps. Investors receive a signal about the solvency of all banks at the final date. Upon the arrival of bad news about aggregate solvency, roll-over of short-term debt occurs less often when assets are clustered, leading to larger systemic risk.

[10]Furthermore, we consider an investment allocation between a safe and a risky asset instead of the choice between several risky assets and the information spillover about solvency is bank-specific in our model instead of system-wide.

2 Model

The economy extends over three dates labelled as initial ($t = 0$), interim ($t = 1$), and final ($t = 2$) and consists of two equally-sized regions $k = A, B$. There is a single physical good used for consumption and investment. Each region is inhabited by a bank and many depositors. Our setup is not limited to the traditional case of retail depositors and a commercial bank but incorporates, for instance, money market funds and investment banks.[11] This paper analyses systemic risk measured by the ex-ante probability of joint bank failure.

2.1 Investment opportunities

Two investment opportunities are publicly available in each region at the initial date. Storage matures after one period and produces one unit per unit invested. A risky long-term investment project matures after two periods and yields a regional return of R_k that exceeds unity in expectation ($\mathbb{E}[R_k] > 1$). Premature liquidation of a fraction $x \in [0, 1]$ at the interim date yields a return $\beta \in (0, 1)$.[12] As the liquidation value is below par (costly liquidation) but positive, liquidation is optimal for low realizations of the regional return. Specifically, regional investment returns R_k are bivariate:

$$R_k = \begin{cases} R & \text{w.p. } \theta_k \\ 0 & \text{w.p. } 1 - \theta_k \end{cases} \tag{1}$$

where the success probability (regional fundamental) is uniformly distributed ($\theta_k \sim U[0, 1]$) and interpreted as a solvency shock to region k. Positive equilibrium investment is ensured by $R > 2$. Let $corr(\theta_A, \theta_B)$ denote the correlation between the regional fundamentals. In particular, banks have a common exposure if $corr(\theta_A, \theta_B) = 1$. Because of the individual randomness of each investment project, the realised investment

[11] In the language of Uhlig (2010), our banks corresponds to core banks, while our depositors correspond to local banks.

[12] This captures, for example, an alternative use of resources by a low-value industry outsider as in Shleifer and Vishny (1992).

returns may differ even in the presence of common exposures. We abstract from portfolio diversification motivated by limits to monitoring, for instance.

2.2 Information structure

All prior distributions are common knowledge. Before making their withdrawal decision at the interim date, depositors may receive independent signals about the success probabilities (θ_A, θ_B) with probability (q_A, q_B). If a signal is received, it perfectly reveals the regional success probability to the depositor. If no signal is received, nothing is learnt. Depositors receive their signals independently.

Knowledge about the other bank's solvency is valuable to a given bank's depositors for two reasons. In case of common exposure investment returns are correlated and the knowledge about the other bank's investment return helps to predict a given bank's investment return. In case of counterparty risk, introduced via interbank lending as in Allen and Gale (2000), the value of knowledge about the other bank's investment return is indirect. It helps to predict whether the debtor bank will repay the creditor bank. In sum, information contagion occurs if the signal about the investment return in the other region is payoff-relevant to a given region.

2.3 Depositors and banks

Each region has a unit continuum ex-ante identical depositors with Diamond and Dybvig (1983) liquidity preferences. A depositor is either *early* or *late*, thus wishing to consume at the interim or final date, respectively. The ex-ante probability of being an early consumer is identical across consumers and given by $\lambda \in (0, 1)$, which is also the share of early consumers in that region by the law of large numbers. Depositors do not know their liquidity preference at the initial date but learn it privately at the beginning of the interim date. The depositor's period utility function $u(c)$ is twice continuously differentable,

strictly increasing, strictly concave and satisfies the Inada conditions, giving rise to the following depositor utility function:

$$U(c_1, c_2) = \begin{cases} u(c_1) & \lambda \\ & \text{w.p.} \\ u(c_2) & 1-\lambda \end{cases}, \tag{2}$$

$$\mathbb{E}[U(c_1, c_2)] = \lambda u(c_1) + (1-\lambda) u(c_2) \tag{3}$$

where c_t is the depositor's consumption at date t and $\mathbb{E}$ is the expectation operator. Risk-averse depositors prefer a strictly positive investment in the project as the expected return exceeds unity. Depositors in each region are endowed with one unit at the initial date to be invested or deposited at their bank.

There is a role for a bank as provider of liquidity insurance (Diamond and Dybvig (1983)). This arises from the smaller volatility of regional liquidity demand compared with individual liquidity demand. The bank offers demand deposit contracts that specify withdrawals (d_1, d_2) if funds are withdrawn at the interim or final date. The non-observability of the idiosyncratic liquidity shock prevents the deposit contract between the bank and the depositor from being contingent on the depositor's liquidity shock. Without loss of generality, we can set $d_2 \equiv \infty$. In case of default, the bank pays an equal amount to all demanding depositors (pro-rata). There is free entry to the banking sector following Diamond and Dybvig (1983). Thus, a bank chooses its portfolio and the interim withdrawal payment to maximize a depositor's expected utility. All depositors deposit in full given their interest is fully aligned with the bank.

There are negatively correlated regional liquidity shocks that motivate interbank insurance as in Allen and Gale (2000). A region can have excess liquidity: $\lambda_k = \lambda_L \equiv \lambda - \eta$ (low liquidity demand) or a liquidity shortage: $\lambda_H \equiv \lambda + \eta$ (high liquidity demand) with equal

probability, where $\eta > 0$ is the size of the regional liquidity shock.[13] We study negatively correlated liquidity shocks of equal size to exclude bank runs merely driven by aggregate liquidity surplus or shortage. However, we consider aggregate solvency shocks.

probability	region A	region B
$\frac{1}{2}$	$\lambda_A = \lambda + \eta$	$\lambda_B = \lambda - \eta$
$\frac{1}{2}$	$\lambda_A = \lambda - \eta$	$\lambda_B = \lambda + \eta$

Banks insure against regional liquidity shocks at the initial date. They agree on mutual liquidity insurance interpreted as mutual lines of credit or cross-holding of deposits. As in Dasgupta (2004), the bank with liquidity shortage receives an amount $b \geq 0$ from the bank with liquidity surplus at the beginning of the interim date. If the bank with liquidity shortage at the interim date is solvent, it repays the loan with interest ($\phi \geq 1$) at the final date.[14] Since banks are symmetric at the initial date, they wish to exchange the same amount of deposits. However, banks become asymmetric at the interim date once the bank in the liquidity shortage region (debtor bank) has withdrawn its funds from the bank in the excess liquidity region (creditor bank). Because of potential default on the interbank loan (counterparty risk), it is never optimal to hold more interbank insurance than compensation for the liquidity shock ($b^* \leq \eta d_1^*$), where stars denote equilibrium levels. We make the common assumption of seniority of interbank loans at the final date only. Non-defaulted interbank claims may be liquidated at rate β.

We focus on essential bank runs as in Allen and Gale (2007). Late depositors are labeled patient when holding their deposits until the final date and impatient otherwise. Sufficient withdrawals of impatient depositors lead to the illiquidity of the bank and partial liquidation, where insolvency arises for a sufficiently large proportion of impatient depositors. Already Diamond and Dybvig (1983) mention the issue of multiple equilibria arising

[13] Freixas et al. (2000) motivates interbank insurance by allowing for interregional travel of depositors who learn the location of their liquidity demand at the beginning of the first period.

[14] We assume the existence of a liquidator for the defaulting bank to which the surviving bank has to repay its debt at the final date. This assumption is natural as the liquidation of banks destroys value due to fire sales but not claims on viable institutions.

from the strategic complementarity in depositors' withdrawal decisions and the implied inefficient bank run equilibrium. We focus on unavoidable bank runs. All depositors withdraw if and only if the expected utility from the stochastic final-date consumption level falls short of the utility from their share of the liquidated bank portfolio. We denote the default probability of an individual bank as a_k and the joint default probability (systemic risk) as $A \equiv a_A a_B$.

2.4 Timeline

The timeline of the model is given in Table (1).

Date 0	**Date 1**	**Date 2**
1. Endowed depositors invest or deposit at regional bank	1. Regional liquidity shocks are publicly observed	1. Investment projects mature
2. Banks choose portfolio and initiate interbank deposits	2. Banks settle date-1 interbank claims	2. Banks settle date-2 interbank claims
	3. Depositors privately observe liquidity preference	3. Banks service remaining withdrawals
	4. Depositors observe regional solvency signals	
	5. Depositors decide whether to withdraw	

Table 1: Timeline of the model.

2.5 Payoffs

We close the description of the model by determining the depositors' payoffs. First, consider the high liquidity demand region (H), in which the payoffs are independent of the behavior in the low liquidity demand region. In the case of a bank run, all funds are liquidated (essential bank-runs) and the interbank loan is defaulted upon. The impatient depositor's payoff is $d_H \equiv y + (1-y)\beta + b$. In the absence of a bank run, no liqui-

dation takes place and the interbank loan is repaid. The patient depositor's payoffs is $c_{2H}^{G} \equiv \frac{(1-y)R+y-\lambda_H d_1-(\phi-1)b}{1-\lambda_H}$ in the good state and $c_{2H}^{B} \equiv \frac{y-\lambda_H d_1-(\phi-1)b}{1-\lambda_H}$ in the bad state. Superscripts (G, B) denote success (good state) and failure (bad state) of the investment project and occur with probability $1-\theta_H$ and θ_H, respectively.

The bank in the low liquidity demand region (L), pays b to the bank in the high liquidity demand region at the interim date. In the case of a bank run in L, all assets including the interbank claim are liquidated, yielding a payoff $y+(1-y)\beta-b+\beta\phi\widetilde{b}$. The repayment of the interbank claim $\widetilde{b}$ is uncertain: it yields b if H repays and zero otherwise. The resulting payoffs are $d_L^N \equiv y+(1-y)\beta+(\beta\phi-1)b$ and $d_L^D \equiv y+(1-y)\beta-b$. Superscripts (N, D) denote survival and default of the bank in H. The liquidation value of the interbank claim is positive in case of repayment only. Hence, patient depositors receive $c_{2L}^{GN} \equiv \left(\frac{(1-y)R+(y-\lambda_L d_1)+(\phi-1)b}{1-\lambda_L}\right)$ and $c_{2L}^{GD} \equiv \left(\frac{(1-y)R+(y-\lambda_L d_1)-b}{1-\lambda_L}\right)$ in the good state as well as $c_{2L}^{BN} \equiv \left(\frac{(y-\lambda_L d_1)+(\phi-1)b}{1-\lambda_L}\right)$ and $c_{2L}^{BD} \equiv \left(\frac{(y-\lambda_L d_1)-b}{1-\lambda_L}\right)$ in the bad state.

3 Equilibrium

This section computes the equilibrium allocations, considering the case of both counterparty risk and common exposures. We start by considering unanticipated information spillovers in each case and study their effect on systemic risk. Then, we obtain the ex-ante optimal portfolio choice when allowing for anticipated information spillovers. Information contagion occurs at the interim date with positive probability, causing a response of the ex-ante optimal portfolio choice and the implied level of systemic risk.

3.1 Counterparty risk

Negatively correlated liquidity shocks $(\eta > 0)$ induce interbank insurance $(b > 0)$, while common exposures are absent. We start by abstracting from information spillovers by assuming that the other region's signal is unobserved and consider information spillovers

afterwards.

Interbank loans are transferred from the low liquidity demand region L to the high liquidity demand region H. Since there is no strategic effect of region L on region H, we determine the optimal withdrawal behaviour of depositors in region H first. If depositors are informed about their region, which happens with probability q_H, they observe the realisation of the success probability θ_H. The withdrawal threshold $\overline{\theta}_{\mathrm{H}}$ in the high liquidity demand region is obtained from the indifference between being patient with expected utility $\theta_H u(c_{2H}^G) + (1-\theta_H)u(c_{2H}^B)$ and impatient with expected utility $u(d_H)$:

$$\overline{\theta}_{\mathrm{H}} \equiv \frac{u(d_H) - u(c_{2H}^B)}{u(c_{2H}^G) - u(c_{2H}^B)} \tag{4}$$

An essential bank run, and thus full liquidation, takes place if and only if $\theta_H < \overline{\theta}_{\mathrm{H}}$. Given the uniform distribution of the success probability, the probability of default in region H when informed is also $\overline{\theta}_{\mathrm{H}}$.

If depositors are uninformed about their region, which happens with probability $1 - q_H$, they use the prior distribution to compare liquidation with continuation. We assume throughout that there are no bank runs in the absence of new information at the interim date. In other words, the prior distribution is sufficiently good to ensure continuation, assured by a lower bound on the high investment payment in the good state, $R \geq \underline{R}$. Thus, the probability of the failure of bank H is:

$$a_{1,\mathrm{H}} \equiv q_H \overline{\theta}_{\mathrm{H}} \tag{5}$$

Regional expected utility in H is denoted by EU_H and obtained by integrating the de-

positors' respective payoffs over all possible signals (see Appendix A for details):

$$\begin{aligned} EU_H &= (1-q_H)\left\{\lambda_H u(d_1) + (1-\lambda_H)\frac{1}{2}(u(c_{2H}^G) + u(c_{2H}^B))\right\} \\ &\quad + q_H\left\{\overline{\theta}_{\mathrm{H}} u(d_H) + (1-\overline{\theta}_{\mathrm{H}})\left(\lambda_H u(d_1) + (1-\lambda_H)\frac{1}{2}\left[u(c_{2H}^G) + u(d_H)\right]\right)\right\} \end{aligned} \tag{6}$$

The behaviour in region H determines whether or not the bank in L is repaid at the final date. This affects both the expected utility from liquidation and the expected utility from continuation. The withdrawal threshold $\overline{\theta}_{1,\mathrm{L}}$ is again determined by the indifference of late depositors between withdrawal and continuation:

$$\overline{\theta}_{1,\mathrm{L}} \equiv \frac{a_{1,\mathrm{H}}[u(d_L^D) - u(c_{2L}^{BD})] + (1-a_{1,\mathrm{H}})[u(d_L^N) - u(c_{2L}^{BN})]}{a_{1,\mathrm{H}}[u(c_{2L}^{GD}) - u(c_{2L}^{BD})] + (1-a_{1,\mathrm{H}})[u(c_{2L}^{GN}) - u(c_{2L}^{BN})]} \tag{7}$$

The withdrawal decision of late depositors in region H affects the withdrawal decision of late depositors in region L, such that $\overline{\theta}_{1,\mathrm{L}} = \overline{\theta}_{1,\mathrm{L}}(\overline{\theta}_{\mathrm{H}})$. That is, the impatience of late depositors in region H constitutes a negative externality on the payoffs of depositors in region L (counterparty risk). Early depositors are affected as they receive their share of the liquidation value d_L instead of the higher promised payment d_1 for a larger range of fundamentals. Late depositors are affected as the available resources paid out to them is smaller. Consequently, the withdrawal threshold of informed depositors in the low liquidity demand region is strictly increasing in the withdrawal threshold in the high liquidity demand region. Formally, $\partial\overline{\theta}_{1,\mathrm{L}}/\partial\overline{\theta}_{\mathrm{H}} > 0$ arises from equation (7). There are again no withdrawals from late depositors in the uninformed case, as assured by the appropriate lower bound on the high investment payment in the good state. The probability of default of bank L is $a_{1,\mathrm{L}} \equiv q_L\overline{\theta}_{1,\mathrm{L}}$.

We are now ready to determine the level of systemic risk in the case of pure counterparty risk A_{CR} given as:

$$A_{\mathrm{CR}} \equiv a_{1,\mathrm{L}}a_{1,\mathrm{H}} = q_H q_L \overline{\theta}_{\mathrm{H}}\overline{\theta}_{1,\mathrm{L}} \tag{8}$$

The expected utility of depositors in region in L is:

$$\begin{aligned} EU_{1L} &= (1-q_L)\Big\{\lambda_L u(d_1) + (1-\lambda_L)\frac{1}{2}\Big((1-a_H)\left(u(c_{2L}^{GN}) + u(c_{2L}^{BN})\right) \\ &\quad + a_H\left(u(c_{2L}^{GD}) + u(c_{2L}^{GN})\right)\Big)\Big\} \\ &\quad + q_L\Big\{\overline{\theta}_{1,\mathrm{L}}\left((1-a_H)u(d_L^N) + a_H u(d_L^D)\right) + \lambda_L(1-\overline{\theta}_{1,\mathrm{L}})u(d_1) \\ &\quad + (1-\lambda_L)\frac{1}{2}\Big((1-\overline{\theta}_{1,\mathrm{L}}^2)\left((1-a_H)u(c_{2L}^{GN}) + a_H u(c_{2L}^{GD})\right) \\ &\quad + (1-\overline{\theta}_{1,\mathrm{L}})^2\left((1-a_H)u(c_{2L}^{BN}) + a_H u(c_{2L}^{BD})\right)\Big)\Big\} \end{aligned} \tag{9}$$

The payoffs are as in the liquidity shortage region (H) with one exception. As depositors in L do not observe the signal in the other region, they take expectation over whether or not H defaults on the bank in L, where a default takes place with probability a_H.

As both investment returns are independent, we can obtain the regional expected utilities separately. This will be invalid once we consider common exposures. A depositor is in a liquidity shortage region H with expected utility EU_H and in a liquidity surplus region with expected utility EU_L with equal probability. Thus, total expected utility in the case of pure counterparty risk is given by:

$$EU_{CR} \equiv \frac{1}{2}(EU_H + EU_{1L}) \tag{10}$$

Counterparty risk and information contagion Depositors now also receive a signal about the other region's success probability. The optimal behaviour of depositors in bank H is unchanged, and so is their expected utility EU_H. When the signal is informative, which occurs with probability q_H, depositors in L know whether or not they will be repaid at the final date if depositors in H are also informed. (Depositors in L then also know whether the liquidation of the interbank claim yields revenue.) Optimal behaviour in L is thus characterised by two thresholds: one if H defaults ($\overline{\theta}_{2,\mathrm{L}}^D$) and one if it does not

($\overline{\theta}^N_{2,\mathrm{L}}$). The comparison of liquidation value d^x_L with the continuation values c^{Gx}_{2L} and c^{Bx}_{2L} for $x \in \{D, N\}$ yields the thresholds:

$$\overline{\theta}^N_{2,\mathrm{L}} \equiv \frac{u(d^N_L) - u(c^{BN}_{2L})}{u(c^{GN}_{2L}) - u(c^{BN}_{2L})} \tag{11}$$

$$\overline{\theta}^D_{2,\mathrm{L}} \equiv \frac{q_H[u(d^D_L) - u(c^{BD}_{2L})] + (1-q_H)[u(d^N_L) - u(c^{BN}_{2L})]}{q_H[u(c^{GD}_{2L}) - u(c^{BD}_{2L})] + (1-q_H)[u(c^{GN}_{2L}) - u(c^{BN}_{2L})]} \tag{12}$$

The withdrawal thresholds are ranked:

$$\overline{\theta}^N_{2,\mathrm{L}} < \overline{\theta}^D_{2,\mathrm{L}} \tag{13}$$

Systemic risk in the case of counterparty risk and information contagion is:

$$A_{\mathrm{CR+IC}} = q_H q_L \overline{\theta}_{\mathrm{H}} \overline{\theta}^D_{2,\mathrm{L}} > A_{\mathrm{CR}} \tag{14}$$

This yields the following result:

Result 1 *If information spillovers are unanticipated, information contagion due to counterparty risk unambiguously systemic risk.*

As before we obtain the expected utility of a depositor in the liquidity surplus region (EU_{2L}):

$$EU_{CR+IC} \equiv \frac{1}{2}(EU_H + EU_{2L}) \tag{15}$$

where

$$
\begin{aligned}
EU_{2L} \;=\; & (1-q_L)\Bigg\{\lambda_L u(d_1) + (1-\lambda_L)\frac{1}{2}\Big[(1-a_H)\left(u(c_{2L}^{GN}) + u(c_{2L}^{BN})\right) \\
& +a_H\left(u(c_{2L}^{GD}) + u(c_{2L}^{BD})\right)\Big]\Bigg\} \\
& +q_L\Bigg\{\left(\overline{\theta}_{2,\mathrm{L}}^{N}(1-a_H)u(d_L^N) + \overline{\theta}_{2,\mathrm{L}}^{D}a_H u(d_L^D)\right) \\
& +\lambda_L\left(a_H(1-\overline{\theta}_{2,\mathrm{L}}^{D}) + (1-a_H)(1-\overline{\theta}_{2,\mathrm{L}}^{N})\right)u(d_1) \\
& +(1-\lambda_L)\frac{1}{2}\Big((1-a_H)[(1-(\overline{\theta}_{2,\mathrm{L}}^{N})^2)u(c_{2L}^{GN}) + (1-\overline{\theta}_{2,\mathrm{L}}^{N})^2 u(c_{2L}^{BN})] \\
& \quad +a_H[(1-(\overline{\theta}_{2,\mathrm{L}}^{D})^2)u(c_{2L}^{GD}) + (1-\overline{\theta}_{2,\mathrm{L}}^{D})^2 u(c_{2L}^{BD})]\Big)\Bigg\}
\end{aligned}
\tag{16}
$$

and where the interpretation for EU_{2L} is as for EU_{1L} with one change: the bank run probabilities in L now depend on whether or not there is a run in H as depositors in L observe the solvency status of the bank in H in case of information spillovers. If there is a bank run (no bank run), the relevant threshold is $\overline{\theta}_{2,\mathrm{L}}^{D}$ ($\overline{\theta}_{2,\mathrm{L}}^{N}$).

3.2 Pure common exposure

Regions are symmetric in terms of payoffs but depositors are potentially asymmetrically informed about the common fundamental. In the absence of regional liquidity shocks, final date consumption levels are $c_2^G \equiv \frac{y-\lambda d_1+(1-y)R}{1-\lambda}$ and $c_2^B \equiv \frac{y-\lambda d_1}{1-\lambda}$ and the liquidation level is $d_\beta \equiv y + (1-y)\beta$. Essential bank runs are initiated by late depositors if the solvency shock is sufficiently severe. That is, a depositor withdraws only if withdrawing is strictly better than continuation even if all depositors do not withdraw. The liquidation decision of late consumers is summarized by a threshold that is determined by the indifference between withdrawal and continuation:

$$
\overline{\theta} = \frac{u(d_\beta) - u(c_2^B)}{u(c_2^G) - u(c_2^B)} \tag{17}
$$

Informed depositors withdraw if and only if the solvency signal is below the threshold ($\theta < \overline{\theta}$). A sufficiently high final date repayment in the good state again ensures $\overline{\theta} \leq \frac{1}{2}$. The level of systemic risk and expected utility are (see Appendix A for details):

$$
\begin{aligned}
A_{\text{CE}} &= q_A q_B \overline{\theta} && (18)\\
EU_{CE} &= \frac{q_A + q_B}{2}\left[\overline{\theta} u(d_\beta) + (1-\overline{\theta})\left(\lambda u(d_1) + (1-\lambda)\frac{1}{2}[u(c_2^G) + u(d_\beta)]\right)\right] && (19)\\
&\quad + \frac{1 - q_A + 1 - q_B}{2}\left[\lambda u(d_1) + (1-\lambda)\frac{1}{2}(u(c_2^G) + u(c_2^B))\right]
\end{aligned}
$$

Common exposures and information contagion Regions are symmetric, both in terms of payoffs and information about the common fundamental. Payoffs and thresholds are unchanged, while the probabilities of being informed change and are given as $q_A + (1 - q_A)q_B > q_A$. Naturally, information spillovers increases the probability of being informed. Therefore, the expected utility EU_{CE+IC} places higher weight on the two terms in which liquidation may take place (those involving $\overline{\theta}$) and a smaller weight on the no-information term:

$$
\begin{aligned}
EU_{CE+IC} &\equiv (q_A + q_B - q_A q_B)\left[\overline{\theta} u(d_\beta) + (1-\overline{\theta})\left(\lambda u(d_1) + (1-\lambda)\frac{1}{2}[u(c_2^G) + u(d_\beta)]\right)\right]\\
&\quad + (1-q_A)(1-q_B)\left[\lambda u(d_1) + (1-\lambda)\frac{1}{2}(u(c_2^G) + u(c_2^B))\right] && (20)
\end{aligned}
$$

The level of systemic risk is given by:

$$
A_{\text{CE+IC}} = (q_A + (1-q_A)q_B)\overline{\theta} > A_{\text{CE}} \qquad (21)
$$

which leads to the following proposition:

Result 2 *If information spillovers are unanticipated, information contagion due to common exposures unambiguously increases systemic risk.*

3.3 Optimal portfolio choice and deposit contract design

We solve for the optimal portfolio and the optimal interim payment in this section. Because of free entry, banks choose their portfolio b, y and the promised interim payment d_1 to maximise the ex-ante expected utility of depositors. A bank faces the following constraints on its choice variables in case of interbank insurance. When mutually insuring themselves, banks face a trade-off between liquidity insurance and counterparty risk. As the marginal insurance benefits beyond $b = \eta d_1$ are zero, it is never optimal to hold more insurance: $0 \leq b^* \leq \eta d_1^*$. Likewise, it is never optimal to face certain liquidation such that $y^* + b^* \geq \lambda_H d_1^*$ and $y^* - b^* \geq \lambda_L d_1^*$. Combined with the optimal amount of interbank insurance, we obatin a lower bound on liquidity: $y^* \geq \underline{y} \equiv \lambda_H d_1^* - b^* \geq \lambda$. The non-negative interim payment is bounded from above by $\min\{R, \frac{y^*+(1-y^*)\beta+b^*}{\lambda_H}, \frac{y^*+(1-y^*)\beta-b^*}{\lambda_L}\}$, where it achieves risk sharing between early and late depositors if $d_1^* > 0$. Let the set of constraints be denoted by Δ. We use a CRRA utility function in which ρ parameterizes the coefficient of relative risk aversion. The optimal choice (d_1^*, y^*, b^*) solves:

$$\max_{(d_1,y,b)\in\Delta} EU(d_1, y, b) \tag{22}$$

Two issues confound an analytical solution of this problem. First, corner solutions of the form of no interbank insurance ($b^* = 0$) or no investment ($y^* = 1$) are optimal for some parameter constellations, invalidating interior solutions and calling for a global approach. We solve the model for a range of exogenous parameters and discuss the economic intuition of several limiting cases in the next section.

Second, the response of the thresholds with respect to liquidity is non-monotonic: more liquidity is valued when the investment project fails, while less liquidity is valued when the investment project succeeds. More liquidity also raises the liquidation proceeds at the interim date. The change in the withdrawal threshold with respect to interbank insurance is in general also ambiguous. In contrast to the previous cases, more insurance against

the idiosyncratic liquidity risk of a depositor (higher d_1) raises payments at the interim date at the expense of payments at the final date, thus unambiguously increasing the withdrawal threshold.

We determine the optimal choice variables numerically. That is, we find the global optimum of the expected utility in each variant of our model outlined above. Discretising the choice variables (d_1, y, b) on a three-dimensional grid, the expected utility is evaluated at each grid point. The grid point where the expected utility takes its global maximum value yields the optimal choice variables (d_1^*, y^*, b^*). Even though we will incur a numerical error from discretising, this error will be small for a sufficiently fine grid. We verify the validity of our numerical solution method by comparing the results for the optimal choice variables with analytical solutions for a number of extreme parameter values (see Section 3.4).

Our baseline calibration is as follows: $\beta = 0.7$, $R = 5.0$, $\phi = 1.0$, $\lambda = 0.5$, $\eta = 0.25$, $\rho = 1.0$, and $q_H = q_L = 0.7$. Alternative specifications are considered in Appendix B and we vary each parameter within its feasible bounds in Section (4.3) and Appendix (C). Our results hold across these various specifications.

3.4 Limiting parameter cases

While our general model admits a numerical solution only, we can obtain analytical results for several limiting parameter cases discussed in this section. These limiting cases serve two purposes. First, we build economic intuition for the model. Second, they serve as a benchmark for the accuracy of our numerical solution.

First, let the payoff of the investment project in the good state fall short of unity ($R \leq 1$). Then, the investment project is dominated by storage such that the optimal portfolio choice is $y^* = 1$. Across all benchmark calibrations listed in Appendix B.1, we obtain the numerical solution of $y^*_{num} = 0.98$.

Second, let depositors be risk-neutral; that is, the coefficient of relative risk aversion in the CRRA utility specification is zero ($\rho = 0$). The investment project dominates storage as the former has a higher expected return and depositors, who do not mind the uncertainty about the idiosyncratic liquidity shock, wish full investment in the project ($d_1^* = 0 = y^*$). This result is confirmed numerically ($d_{1,num}^* = 0 = y_{num}^*$). Likewise, if depositors are very risk averse (infinitely risk averse in the limit, $\rho \to \infty$), they are not willing to bear any of the investment risk associated with the project and any liquidity risk. Consequently, no investment takes place ($y^* = 1$) and there is full insurance ($d_1^* = 1$). In a numerically feasible and economically useful implementation we set $\rho = 200$ and obtain the affirmative results $y_{num}^* = 0.98$ and $d_{1,num}^* = 0.98$.

Third, no risk-averse depositor ($\rho > 0$) seeks liquidity insurance in the absence of regional liquidity shocks ($\eta = 0$) for any value of repayment ($\phi \geq 0$). From an ex-ante perspective, liquidity insurance in this case is a mean-preserving spread to both interim-date and final-date payoffs and is rejected by any risk averse depositor. We confirm this intuition numerically ($b_{num}^* = 0$).

We also consider the related situation of a positive liquidity shock ($\eta > 0$) but no repayment ($\phi = 0$). A risk averse depositor would then be partially insured against this risk $b^* > 0$, which is pure ex-ante liquidity insurance. Note that we require $\phi > 0$ in the baseline calibration and all other calibrations to maintain a counterparty risk mechanism as in Allen and Gale (2000). Intuitively, the amount of liquidity insurance decreases in the degree of risk aversion. As depositors become more risk averse, they hold more liquidity as part of the optimal portfolio composition of late depositors. The available liquidity serves as self-insurance against regional liquidity shocks at the interim date and is a substitute for interbank insurance. For example, a CRRA coefficient of risk aversion of $\rho = 1.0$ in the baseline calibration yields $b_{num}^* = 0.15$, while the same calibration with $\rho = 2.0$ yields

$b^*_{num} = 0.1$.

Fourth, if there are no early depositors ($\lambda = 0$), there is no need for insurance against idiosyncratic liquidity shocks. The amount of liquidity held fully reflects the optimal portfolio allocation of late depositors ($0 < y^* < 1$) and increases with the level of risk aversion (ρ). These predictions are confirmed numerically in the specification of $\lambda = 0.01$, where the amount of liquidity ranges from $y^*_{num} = 0.42$ in a baseline calibration with $\rho = 1.0$ to $y^*_{num} = 0.74$ in the baseline calibration with $\rho = 2.0$.

Likewise, if there are only early depositors ($\lambda = 1$) it is optimal not to invest into an asset that only matures at the final date and is costly to liquidate ($y^* = 1$). There is no role for liquidity co-insurance in this specification ($b^* = 0$) as there cannot be any liquidity shocks ($\eta = 0$). As all resources are used to service early depositors, the optimal interim payment must also be one ($d^*_1 = 1$). This intuition is confirmed numerically ($d^*_{1,num} = 0.99$).

Finally, in our model the prior distribution is (unconsequentially) assumed not to induce liquidation in case of being uninformed. Hence, we expect no liquidation to take place ($\overline{\theta}_1 = \overline{\theta}^N_{2,\mathrm{L}} = \ldots = 0$) whenever the probability of being informed is zero in both regions ($q_A = q_B = 0$), which is again confirmed numerically.

4 Results

This section summarises our findings. We demonstrate the existence of a *resilience effect* that arises when information contagion occurs due to counterparty risk. We also show the existence of an *instability effect* that emerges when information contagion occurs due to common exposures. Section (4.3) provides a global parameter analysis, verifying the robustness of our results across feasible parameter values.

4.1 Resilience effect

We study how information spillovers affect systemic risk in the presence of counterparty risk. We start by considering unanticipated information spillovers, similar to the aggregate liquidity shock in Allen and Gale (2000). In this case the ex-ante optimal portfolio choice is unaffected and systemic risk strictly increases (see Result 1). This result is also obtained by comparing the case of pure counterparty risk (entry (1,1)) with the case of counterparty risk and information contagion evaluated at the optimal portfolio choice of the pure counterparty risk case (entry (1,2)) in the tables in Appendix (B.2). The default on the interbank loan is observed with positive probability at the interim date, strengthening the counterparty risk channel. This leads to a lower level of expected utility and higher systemic risk.

Banks alter their ex-ante optimal portfolio choice when information spillovers are anticipated. A bank makes a more prudent portfolio choice at the initial date to insure risk-averse depositors against potential information contagion at the interim date. In particular, the bank provides more insurance against idiosyncratic liquidity risk (larger d_1) funded by a larger liquidity holding y. The exposure to counterparty risk is reduced by holding a smaller amount of interbank insurance (b is reduced). Therefore, the range of solvency shocks ($[\overline{\theta}^N_{2,\mathrm{L}}, \overline{\theta}^D_{2,\mathrm{L}}]$) for which counterparty risk materializes is reduced. These results are obtained by comparing the case of pure counterparty risk (entry (1,1)) with the case of counterparty risk and information contagion (entry (2,2)) in the tables in Appendix (B.2). In sum, introducing information contagion *lowers* the equilibrium level of systemic risk. As shown by the robustness checks in Section (4.3), the resilience effect holds across all feasible parameter values.

Result 3 *In the setup with counterparty risk, anticipating information contagion reduces systemic risk and expected utility.*

4.2 Instability effect

We now analyze how information spillovers affect systemic risk in a setup with common exposures. Again, we start by considering unanticipated information spillovers. As the portfolio choice is unaffected, the level of systemic risk increases (see Result 2). Taking Results 1 and 2 together, unanticipated information spillover always leads to larger systemic risk.

When information spillovers are anticipated, the bank adjusts its ex-ante optimal portfolio choice. Across all baseline cases and feasible parameter choices, the optimal interim-date payment is unchanged, while the optimal liquidity level is slightly lower (within numerical accuracy). Hence, the expected utility increases and the equilibrium level of systemic risk is much larger once an information spillover is introduced. These results are obtained by comparing the case of pure common exposure (entry (3,3)) with the case of common exposure and information contagion (entry (4,4)) in the tables in Appendix (B.2). This effect is again numerically robust, as demonstrated in Section (4.3).

Result 4 *In the setup with common exposures, anticipating information contagion increases systemic risk and expected utility.*

Additional information allows the late depositors to decide on early withdrawals in more states of the world and has two consequences. First, liquidation is optimal for late depositors as it only takes place after a bad solvency shock. Second, liquidation is detrimental to early depositors who only receive their share of the liquidation value and not the (strictly larger) promised interim payment. Therefore, late depositors impose an externality on early depositors. As the level of liquidity in case of common exposures is high to self-insure against investment risk, the second effect is quantitatively small such that additional liquidation increases overall expected utility.

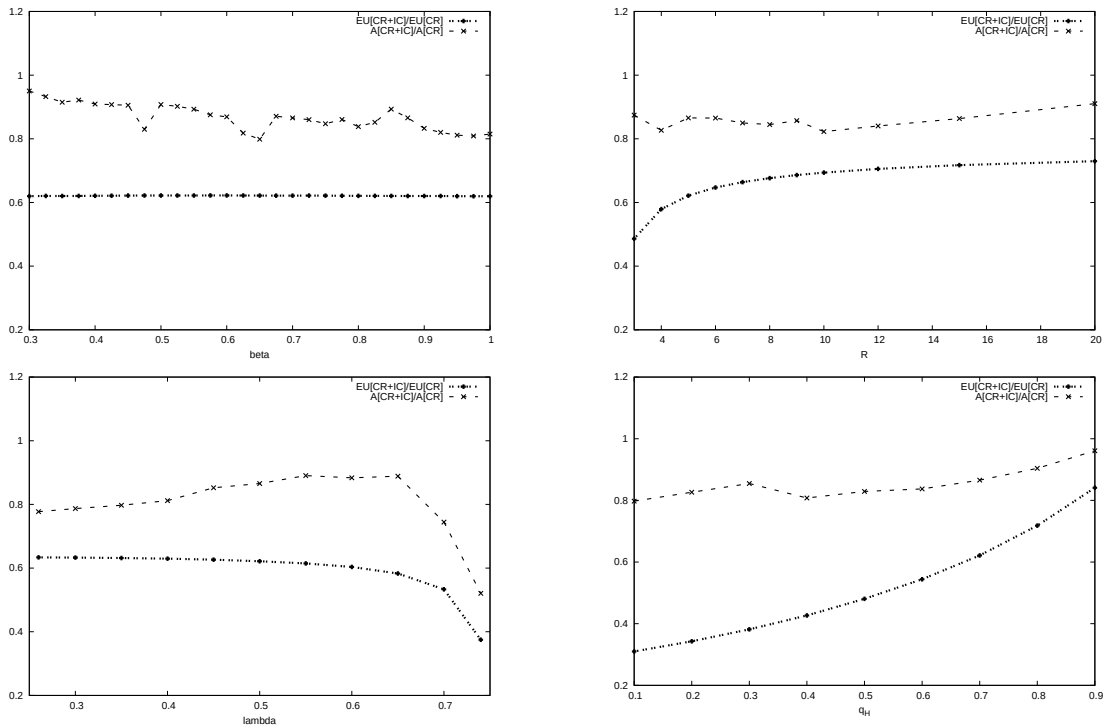

Figure 1: Robustness checks for the resilience effect (Result 3) consider a variation of β (top left), R (top right), λ (bottom left), and $q_H = q_L$ (bottom right). The figures display expected utility (dotted line) and systemic risk (dashed line) in the case of counterparty risk and information contagion as a fraction of their respective levels in case of pure counterparty risk.

4.3 Robustness checks

This section shows that the resilience effect and the instability effect are robust to exogenous parameter variations. In particular, this section discusses a global variation of parameters by considering the entire range of feasible parameters. We discuss the effect of various parameter values on systemic risk and expected utility. Further analysis, including the optimal portfolio choice and withdrawal thresholds, is contained in Figures (3) - (9) in Appendix (C).

Consider the resilience effect (Result 3) first. Figure (1) displays the expected utility (dotted line) and systemic risk (dashed line) in the case of counterparty risk and information contagion as a fraction of their respective levels in case of pure counterparty risk. Hence, the resilience effect is present if relative systemic risk is *below* unity. We consider parameter changes of the key variables of the model: the liquidation value (β), the final-date

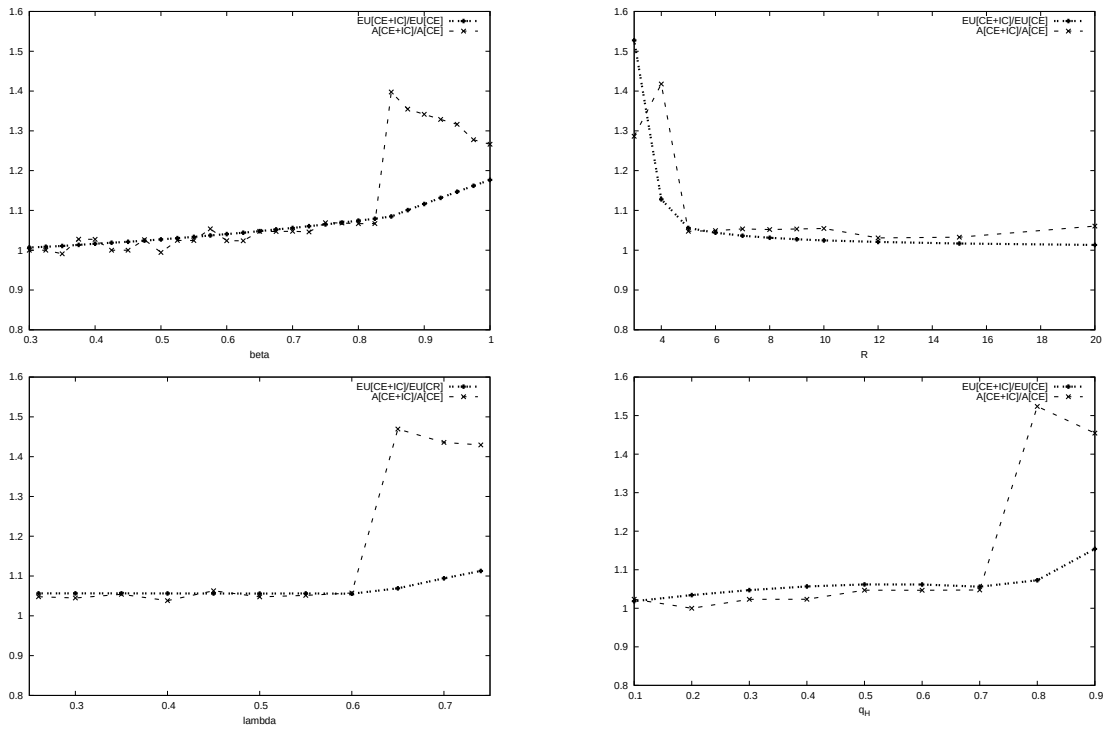

Figure 2: Robustness checks for the instability effect (Result 4) for a variation of β (top left), R (top right), λ (bottom left), and $q_H = q_L$ (bottom right). The figures display expected utility (dotted line) and systemic risk (dashed line) in the case of common exposures and information contagion as a fraction of their respective levels in case of pure common exposures.

return to the investment project when successful (R), the proportion of early depositors (λ), and the level of transparency (q). In all cases, the resilience effect prevails.

Now consider the instability effect (Result 4). Figure (2) displays the expected utility (dotted line) and systemic risk (dashed line) in the case of common exposure and information contagion as a fraction of their respective levels in case of pure common exposure. Hence, the instability effect is present if the relative systemic risk is *above*unity. We consider the same parameter changes again. In all cases, the instability effect prevails.

5 An application to microfinance

While our model focuses on systemic risk in the financial system of advanced economies, it is also applicable to the microfinance industry prevalent in many emerging countries.

Our model provides a novel theoretical explanation for several findings in the empirical microfinance literature. In particular, it predicts that (i) the repayment rates of group loans are higher than those of individual loans and (ii) group borrowers hold more liquid assets.

According to the Microcredit Summit Campaign (2012), microfinance institutions (MFIs) served over 205 million customers at the end of 2010, impacting the lives of an estimated 600 million household members. The growth of the microfinance industry is often attributed to group liability that is designed to overcome problems arising from asymmetric information (see e.g. Morduch (1999), or Armendáriz and Morduch (2010)) and beneficially transfers risks from the microlender to a group of borrowers (see e.g. Stiglitz (1990) and Varian (1990)). Group liability refers to an arrangement in which a lender grants a loan to a *group* of borrowers that monitor each other and jointly guarantee loan repayment. Borrowers are typically entrepreneurs from rural areas in developing countries that cannot pledge collateral.

The essential ingredients of microfinance are captured by our model. Due to joint liability, group lending is characterised by institutionalized counterparty risk. In particular, each group member guarantees the repayment of the entire loan even if another group member is unable (or unwilling) to repay such that an individual group member is exposed to (a large amount of) counterparty risk. Further, group members often know each other well and are in close contact. This implies that news about one group member easily spreads to other group members, constituting a spillover of information.[15] Finally, the close proximity of group members gives rise to common exposures such as natural disasters (e.g. a flood or an earthquake).

[15]Since it is more costly for banks to acquire this kind of information about the borrowers, monitoring is delegated to the group and rewarded with lowered interest rates on group loans. See Stiglitz (1990) and Varian (1990) for a rationalisation of peer monitoring.

The application to microfinance can be explicitly translated into our model setup. Consider two entrepreneurs $k = A, B$ that jointly wish to take out a group loan from a microfinance institution. Each entrepreneur has access to a safe storage technology (cash or durable goods) and is offered a risky investment opportunity R_k. This investment opportunity could be the start of a small local business (e.g. buying an ox to plow a field, or dwelling a well to sell the water) that has a probability to fail. In this interpretation, a region corresponds most naturally to a sector of the economy. The project pays R with a regional probability θ_k and zero with probability $(1-\theta_k)$. An alternative interpretation is that the investment project will always pay a safe return R but, with some probability $(1-\theta_k)$, the entrepreneur has to take this return to cover unexpected expenses such as an illness of a family member. Liquidation of investment projects is costly due to an alternative use argument similar to the banking case.[16] The timeline of our model applied to microfinance is given in Table (2).

Date 0	**Date 1**	**Date 2**
1. Microfinance institution (MFI) decides on group loan	1. Group loan institutionalizes counterparty risk	1. Investment projects mature
2. Entrepeneurs choose their portfolio	2. Entrepeneurs observe regional solvency signals	2. Group of entrepreneurs repays MFI
	3. Depositors decide whether to default	

Table 2: Timeline of the model application.

The information structure is equivalent to the banking case. At the interim date, before the success or failure of the local business projects is determined, entrepreneurs receive a signal about the regional return of the other entrepreneur in the group.[17] Such a signal can be informative about the business prospects of the group partners or, in the alter-

[16] In many cases, the MFI might be unable to seize the investment project at all due to its remoteness from the borrower or due to social pressure (seizing assets from somebody who is already poor).

[17] We take the probability of receiving an informative signal q as being fixed exogenously. An extension could consider the extent of group member monitoring, modelled by a change in this probability.

native interpretation with safe investment projects, information about the health of the family of a group partner. In either case, this signal contains valuable information since both entrepreneurs are linked via joint liability. In the banking application, we focus on the impact of ex-post information contagion on ex-ante systemic risk when banks are subject to counterparty risk. Translated into the microfinance setting, we focus on the impact of ex-post information contagion on the ex-ante default probability of a group loan.

Strategic default by group members in the microfinance application is the equivalent of withdrawals by late depositors in our banking model. Late depositors compare continuation and withdrawal in the banking model and make a privately optimal withdrawal decision. Likewise, entrepeneurs decide strategically whether to pay loan installments (interest and principal) to the MFI. The benefits of default (or diversion of funds) for an entrepreneur is not to repay his share of the group loan. Another benefit is not having to pay more upon default by other group members. In the alternative interpretation with safe investment projects, the benefits of default could be saving the life of a family member. The cost of default is exclusion from credit via group loans, foregoing future profits from investment projects. As default increases the burden on other group members, another cost of default is the possibility of facing hostile group loan cosigners.[18]

Similar to banks in our banking application, entrepreneurs decide about the portfolio shares of their funds ex-ante. When entrepeneurs decide between investment in their project and storage, they consider the possibility of a solvency shock, their business risk, and its effect on potential future exclusion from credit. The profits from future investment opportunities induce a precautionary motive for entrepeneurs. Hence, entrepreneurs try to avoid default by holding more of the safe asset (either cash or durable goods that have a high liquidation value). In our banking application, banks offer deposit contracts that

[18]There are news reports about large numbers of suicides that were caused by peer pressure after defaulting on a micro loan (see e.g. BBC News, "India's micro-finance suicide epidemic", 16 December 2010).

may be accepted by depositors. Likewise, in the microfinance application, entrepreneurs offer interest payments to a microfinance institution.

In the banking application, withdrawing late depositors at the debtor bank exert an externality on late depositors at the creditor bank. This correponds to the externality that one entrepreneur exerts on other members of the group loan when defaulting on its obligation. When making their ex-ante optimal portfolio choice, banks take this externality into account by holding more liquidity. This leads to reduced systemic risk. Translating this *resilience effect (Result 3)* into the microfinance application, our model predicts that (i) group loans have a higher repayment rate than individual loans and (ii) group borrowers hold more liquid assets.

The empirical microfinance literature supports these predictions. For example, Giné et al. (2009) constructs a series of *"microfinance games"* conducted in an urban market in Peru. They show that loan repayment rates are higher in joint-liability games (0.88) than in individual-liability games (0.68). Wydick (1999) analyzes group lending in Guatemala and shows that group repayment rates are determined by the ability to monitor one another in the presence of asymmetric information. In particular, group loan repayment rates are higher when group members live in close geographic proximity or have knowledge about weekly sales of their peers. The resilience effect also implies that entrepreneurs will hold more liquidity (either in the form of cash or durable goods). This has been analyzed empirically by Banerjee et al. (2010) who show in a randomized experiment in India that households with an existing business at the time of the program invest more in durable goods.

The usefulness of our results for microfinance is highlighted by the empirical confirmation of our predictions. This relates to both the ex-ante portfolio choices of entrepeneurs and the repayment rates for group loans.

6 Conclusion

The aftermath of the Lehmann bankruptcy in September 2008 demonstrated that information contagion can be a major source of systemic risk, defined as the probability of joint bank default. One bank's investors find information about another bank's solvency valuable for two reasons. First, and established in the literature, both banks might have invested into the same asset class like risky sovereign debt or mortgage backed securities. Learning about another bank's profitability then helps the investor assess the profitability of its bank. Second, and not previously analyzed as a source of information contagion, one bank might have lent to the other, for instance as part of a risk-sharing agreement. Learning about the debtor bank's profitability then helps investors assess the counterparty risk of the creditor bank.

This paper presents a model of systemic risk with information contagion. Information about the health of one bank is valuable for the investors of other banks because of common exposures and counterparty risk. In each case, bad news about one bank adversely spills over to other banks and causes information contagion. We examine the effects of ex-post information contagion on the bank's ex-ante optimal portfolio choice and the implied level of systemic risk.

We demonstrate that information contagion can *reduce* systemic risk. When banks are subject to counterparty risk, investors of one bank may receive a negative signal about the health of another bank. Given the exposure of the creditor bank to the debtor bank, adverse information about the debtor bank can cause a run on the creditor bank. Such information contagion ex-post induces the bank to hold a more prudent portfolio ex-ante. Overall, the level of systemic risk is reduced once information contagion is present.

Our model is also applicable to microfinance prevalent in many emerging countries. Group

loans with joint liability agreements induce counterparty risk among the group members. Since group loan borrowers typically have a common bond (e.g. living in the same village), peer monitoring helps to overcome problems of asymmetric information. The common bond implies that group members receive information about their peers, constituting information contagion. We show that counterparty risk and information contagion lead to reduced default rates of group loans and increased holdings of liquid assets by group borrowers. These predictions are verified in the empirical literature on microfinance, highlighting the applicability of our model to the microfinance setting.

We also show that the effects of information contagion on systemic risk depend on the source of the revealed information. In case of common exposures, ex-post information contagion increases systemic risk - similar to Acharya and Yorulmazer (2008a). This leads to the natural question about the overall effect of information contagion in a model that features both common exposures and counterparty risk. A *unified model of contagion* would be suited to identify the parameter regions characterized by higher (lower) levels of systemic risk and thus a less (more) stable financial system. Such a unified model of contagion would also contribute to our understanding of microfinance. While allowing for information spillover, the close geographic proximity between group lenders implies that they are subject to common exposures. Analysing joint liability agreements in the presence of informational spillovers and common exposure is an interesting research question. However, such a unified model of contagion is beyond the scope of the present paper and left for future research.

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A Derivations

A.1 Counterparty risk

If no signal is received, early depositors, of mass λ_H, receive the promised payment d_1 and late depositors, of mass $1-\lambda_H$, receive high and low consumption levels with equal probability. If a signal below the threshold $\overline{\theta}_{\mathrm{H}}$ is received, depositors receive a share of the liquidation proceeds and obtain d_H. If a signal above the threshold $\overline{\theta}_{\mathrm{H}}$ is received, late houesholds obtain a weighted average of the high payoff c_{2H}^G and the low payoff c_{2H}^B, where the weights depend on the threshold and early depositors again receive the promised payment.[19] Expected utility in the high liquidity demand region is given as:

$$\begin{aligned} EU_H &= (1-q_H)\left\{\lambda_H u(d_1) + (1-\lambda_H)\int_0^1 \left[\theta u(c_{2H}^G) + (1-\theta)u(c_{2H}^B)\right] \mathrm{d}\theta\right\} \\ &\quad + q_H\left\{\int_0^{\overline{\theta}_{\mathrm{H}}} u(d_H)\mathrm{d}\theta + \int_{\overline{\theta}_{\mathrm{H}}}^1 \lambda_H u(d_1) + (1-\lambda_H)\left[\theta u(c_{2H}^G) + (1-\theta)u(c_{2H}^B)\right] \mathrm{d}\theta\right\} \end{aligned} \tag{23}$$

which yields the expression in the text.

We proceed in the same way for the low liquidity demand region L. The behaviour in region H determines whether or not the bank in L is repaid at the final date. This affects both the expected utility from liquidation and the expected utility from continuation. As the interbank loan is repaid with probability $a_{1,\mathrm{H}}$, the expected utility from liquidation is $a_{1,\mathrm{H}}u(d_L^D) + (1-a_{1,\mathrm{H}})u(d_L^N)$. In the informed case, which happens with probability q_L, θ_L is known. Taking expectations over all possible fundamentals in region H, the expected utility from continuation is the sum of two terms: (i) with probability $a_{1,\mathrm{H}}$ the bank in region H defaults and patient depositors in region L receive $\theta_L u(c_{2L}^{GD}) + (1-\theta_L)u(c_{2L}^{BD})]$; (ii) with probability $(1-a_{1,\mathrm{H}})$ the bank in region H survives and patient depositors in region L receive $\theta_L u(c_{2L}^{GN}) + (1-\theta_L)u(c_{2L}^{BN})$. The withdrawal threshold is given in equation

[19] Note that in case of no bank run, the weights are equal because of the symmetry of the investent probabilities θ and $1-\theta$ when integrated between zero and unity. This symmetry vanishes once the lower integration bound is above zero.

(7) and yields the expected utility of depositors in region L to be:

$$
\begin{aligned}
EU_{1L} \;=\; & (1-q_L)\Bigg\{\lambda_L u(d_1) + (1-\lambda_L)\int_0^1 \Big[\theta\left(a_H u(c_{2L}^{GD}) + (1-a_H)u(c_{2L}^{GN})\right) \qquad (24)\\
& + (1-\theta)\left(a_H u(c_{2L}^{BD}) + (1-a_H)u(c_{2L}^{BN})\right)\Big]\,\mathrm{d}\theta\Bigg\}\\
& + q_L\Bigg\{\int_0^{\bar{\theta}_{1,\mathrm{L}}} \left(a_H u(d_L^D) + (1-a_H)u(d_L^N)\right)\mathrm{d}\theta\\
& + \int_{\bar{\theta}_{1,\mathrm{L}}}^1 \lambda_L u(d_1) + (1-\lambda_L)\Big[\theta\left(a_H u(c_{2L}^{GD}) + (1-a_H)u(c_{2L}^{GN})\right)\\
& + (1-\theta)\left(a_H u(c_{2L}^{BD}) + (1-a_H)u(c_{2L}^{BN})\right)\Big]\,\mathrm{d}\theta\Bigg\}
\end{aligned}
$$

which yields the expression in the text.

A.2 Common exposures

Turning to expected utility, using the short-hand notation for the continuation payoff: $\Gamma \equiv \lambda u(d_1) + (1-\lambda)[\theta u_2^G + (1-\theta)u_2^B]$, we find:

$$
\begin{aligned}
EU_C E \;\equiv\; & \frac{1-q_A+1-q_B}{2}\int_0^1 \Gamma \mathrm{d}\theta + \frac{q_A+q_B}{2}\int_0^{\bar{\theta}} u(d_\beta)\mathrm{d}\theta + \frac{q_A+q_B}{2}\int_{\bar{\theta}}^1 \Gamma \mathrm{d}\theta \qquad (25)\\
\equiv\; & \frac{q_A+q_B}{2}\left[\bar{\theta}u(d_\beta) + (1-\bar{\theta})\left(\lambda u(d_1) + (1-\lambda)\frac{1}{2}[u(c_2^G) + u(d_\beta)]\right)\right]\\
& + \frac{1-q_A+1-q_B}{2}[\lambda u(d_1) + (1-\lambda)\frac{1}{2}(u(c_2^G) + u(c_2^B))] \qquad (26)
\end{aligned}
$$

B Tables

Section (B.1) contains the extreme parameter value benchmarks discussed in Section (3.4) of the main text for additional baseline cases to show the robustness of our numerical implementation. Section (B.2) contains the results of Section (4) of the main text.

B.1 Extreme parameter value benchmarks

	Baseline 1	Baseline 2	Baseline 3	Baseline 4
$R = 1.0$	$y^* = 0.98$	$y^* = 0.98$	$y^* = 0.98$	$y^* = 0.98$
$\rho = 0.0$	$d_1^* = 0.0$	$d_1^* = 0.0$	$d_1^* = 0.0$	$d_1^* = 0.0$
	$y^* = 0.0$	$y^* = 0.0$	$y^* = 0.0$	$y^* = 0.0$
$\rho = 200.0$	$d_1^* = 0.98$	$d_1^* = 0.98$	$d_1^* = 0.98$	$d_1^* = 0.98$
	$y^* = 0.98$	$y^* = 0.98$	$y^* = 0.98$	$y^* = 0.98$
$\eta = 0.0$	$b^* = 0.0$	$b^* = 0.0$	$b^* = 0.0$	$b^* = 0.0$
$\phi = 0.0$	$b^* = 0.15$	$b^* = 0.15$	$b^* = 0.15$	$b^* = 0.1$
$\lambda = 0.01$	$d_1^* = 1.06$	$d_1^* = 1.0$	$d_1^* = 1.1$	$d_1^* = 1.16$
	$y^* = 0.42$	$y^* = 0.36$	$y^* = 0.48$	$y^* = 0.74$
$\lambda = 0.99$	$d_1^* = 0.98$	$d_1^* = 0.98$	$d_1^* = 0.98$	$d_1^* = 0.98$
	$y^* = 0.98$	$y^* = 0.98$	$y^* = 0.98$	$y^* = 0.98$
$q_H = 0.0$	$A_1, \ldots, A_6 = 0.0$	$A_1, \ldots, A_6 = 0.0$	$A_1, \ldots, A_6 = 0.0$	$A_1, \ldots, A_6 = 0.0$

Table 3: Exterme parameter values for four baseline cases. Baseline 1: $\beta = 0.7$, $R = 5.0$ $\phi = 1.0$, $\lambda = 0.5$, $\eta = 0.25$, $\rho = 1.0$, $q_H = 0.7$. Baseline 2: $\beta = 0.7$, $R = 5.0$ $\phi = 1.0$, $\lambda = 0.5$, $\eta = 0.25$, $\rho = 0.9$, $q_H = 0.7$. Baseline 3: $\beta = 0.7$, $R = 5.0$ $\phi = 1.0$, $\lambda = 0.5$, $\eta = 0.25$, $\rho = 1.1$, $q_H = 0.7$. Baseline 4: $\beta = 0.3$, $R = 5.0$ $\phi = 1.0$, $\lambda = 0.5$, $\eta = 0.25$, $\rho = 1.1$, $q_H = 0.7$.

B.2 Results

	cr (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{1,\mathrm{L}}$, A_{cr})	cr + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}^N_{2,\mathrm{L}}$, $\overline{\theta}^D_{2,\mathrm{L}}$, $A_{\mathrm{cr+ic}}$)	ce (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, A_{ce})	ce + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, $A_{\mathrm{ce+ic}}$)
cr	(0.172,0.88,0.73,0.08) (0.423,0.23,0.048)	(0.096,0.88,0.73,0.08) (0.423,0.212,0.252,0.052)		
cr + ic		(0.107,0.94,0.8,0.02) (0.379,0.211,0.222,0.041)		
ce			(0.13,1.0,0.77,0.0) (0.328,0.161)	(0.137,1.0,0.77,0.0) (0.328,0.161)
ce + ic				(0.137,1.01,0.76,0.0) (0.344,0.168)

Table 4: Equilibrium allocation for different forms of financial fragility for calibration β=0.7, R=5.0, ϕ=1.0, λ=0.5, η=0.25, ρ=1.0, q_H=0.7. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\overline{\theta}_H, \overline{\theta}_{1,L}, \overline{\theta}^N_{2,L}, \overline{\theta}^D_{2,L}, \overline{\theta}$), and systemic financial fragility ($A_{\mathrm{cr}}, A_{\mathrm{cr+ic}}, A_{\mathrm{ce}}, A_{\mathrm{ce+ic}}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{1,\mathrm{L}}$, A_{cr})	cr + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}^N_{2,\mathrm{L}}$, $\overline{\theta}^D_{2,\mathrm{L}}$, $A_{\mathrm{cr+ic}}$)	ce (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, A_{ce})	ce + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, $A_{\mathrm{ce+ic}}$)
cr	(0.188,0.86,0.7,0.13) (0.482,0.304,0.072)	(0.105,0.86,0.7,0.13) (0.482,0.278,0.329,0.078)		
cr + ic		(0.117,0.93,0.78,0.06) (0.43,0.26,0.283,0.06)		
ce			(0.142,1.0,0.75,0.0) (0.373,0.183)	(0.154,1.0,0.75,0.0) (0.373,0.183)
ce + ic				(0.158,1.32,0.73,0.0) (0.5,0.245)

Table 5: Equilibrium allocation for different forms of financial fragility for calibration β=0.9, R=5.0, ϕ=1.0, λ=0.5, η=0.25, ρ=1.0, q_H=0.7. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\overline{\theta}_H, \overline{\theta}_{1,L}, \overline{\theta}^N_{2,L}, \overline{\theta}^D_{2,L}, \overline{\theta}$), and systemic financial fragility ($A_{\mathrm{cr}}, A_{\mathrm{cr+ic}}, A_{\mathrm{ce}}, A_{\mathrm{ce+ic}}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{1,\mathrm{L}}$, A_{cr})	cr + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}^N_{2,\mathrm{L}}$, $\overline{\theta}^D_{2,\mathrm{L}}$, $A_{\mathrm{cr+ic}}$)	ce (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, A_{ce})	ce + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, $A_{\mathrm{ce+ic}}$)
cr	(0.343,0.84,0.69,0.14) (0.372,0.172,0.031)	(0.221,0.84,0.69,0.14) (0.372,0.15,0.206,0.038)		
cr + ic		(0.238,0.91,0.77,0.07) (0.318,0.139,0.166,0.026)		
ce			(0.274,1.0,0.75,0.0) (0.257,0.126)	(0.28,1.0,0.75,0.0) (0.257,0.126)
ce + ic				(0.28,1.01,0.74,0.0) (0.271,0.133)

Table 6: Equilibrium allocation for different forms of financial fragility for calibration β=0.7, R=10.0, ϕ=1.0, λ=0.5, η=0.25, ρ=1.0, q_H=0.7. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\overline{\theta}_H, \overline{\theta}_{1,L}, \overline{\theta}^N_{2,L}, \overline{\theta}^D_{2,L}, \overline{\theta}$), and systemic financial fragility ($A_{\mathrm{cr}}, A_{\mathrm{cr+ic}}, A_{\mathrm{ce}}, A_{\mathrm{ce+ic}}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{1,\mathrm{L}}$, A_{cr})	cr + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}^N_{2,\mathrm{L}}$, $\overline{\theta}^D_{2,\mathrm{L}}$, $A_{\mathrm{cr+ic}}$)	ce (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, A_{ce})	ce + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, $A_{\mathrm{ce+ic}}$)
cr	(0.262,0.83,0.6,0.07) (0.404,0.258,0.051)	(0.151,0.83,0.6,0.07) (0.404,0.249,0.271,0.054)		
cr + ic		(0.166,0.92,0.7,0.01) (0.35,0.231,0.234,0.04)		
ce			(0.182,1.01,0.68,0.0) (0.313,0.153)	(0.192,1.01,0.68,0.0) (0.313,0.153)
ce + ic				(0.192,1.02,0.66,0.0) (0.327,0.16)

Table 7: Equilibrium allocation for different forms of financial fragility for calibration β=0.7, R=5.0, ϕ=1.0, λ=0.3, η=0.25, ρ=1.0, q_H=0.7. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\overline{\theta}_H, \overline{\theta}_{1,L}, \overline{\theta}^N_{2,L}, \overline{\theta}^D_{2,L}, \overline{\theta}$), and systemic financial fragility ($A_{\mathrm{cr}}, A_{\mathrm{cr+ic}}, A_{\mathrm{ce}}, A_{\mathrm{ce+ic}}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{1,\mathrm{L}}$, A_{cr})	cr + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}^N_{2,\mathrm{L}}$, $\overline{\theta}^D_{2,\mathrm{L}}$, $A_{\mathrm{cr+ic}}$)	ce (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, A_{ce})	ce + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}$, $A_{\mathrm{ce+ic}}$)
cr	(0.232,0.82,0.69,0.0) (0.36,0.236,0.014)	(0.071,0.82,0.69,0.0) (0.36,0.236,0.236,0.014)		
cr + ic		(0.099,0.94,0.82,0.0) (0.331,0.207,0.207,0.011)		
ce			(0.121,1.0,0.79,0.0) (0.313,0.05)	(0.128,1.0,0.79,0.0) (0.313,0.05)
ce + ic				(0.128,1.0,0.78,0.0) (0.321,0.051)

Table 8: Equilibrium allocation for different forms of financial fragility for calibration β=0.7, R=5.0, ϕ=1.0, λ=0.5, η=0.25, ρ=1.0, q_H=0.4. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\overline{\theta}_H, \overline{\theta}_{1,L}, \overline{\theta}^N_{2,L}, \overline{\theta}^D_{2,L}, \overline{\theta}$), and systemic financial fragility ($A_{\mathrm{cr}}, A_{\mathrm{cr+ic}}, A_{\mathrm{ce}}, A_{\mathrm{ce+ic}}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

C Details for robustness checks

This section provides further details about the robustness checks performed in Section (4.3). In particular, we show the evolution of the portfolio choice variables and withdrawal thresholds when varying the exogenous parameters of the model.

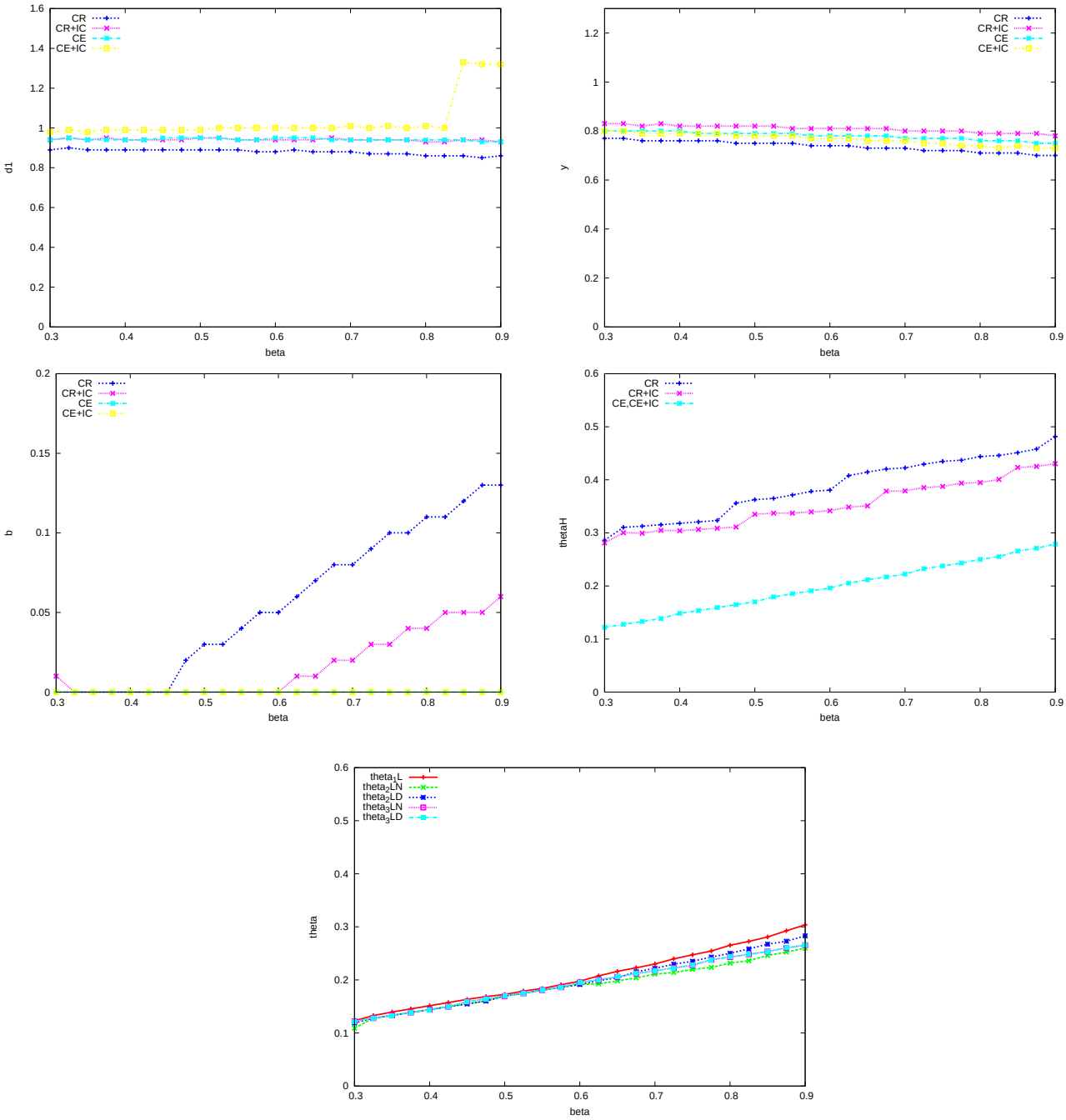

Figure 3: Details of portfolio choice: d_1, y (top), b and θ_H (middle), and various θ_L values for a variation of β. The baseline calibration is used for the non-varying parameters.

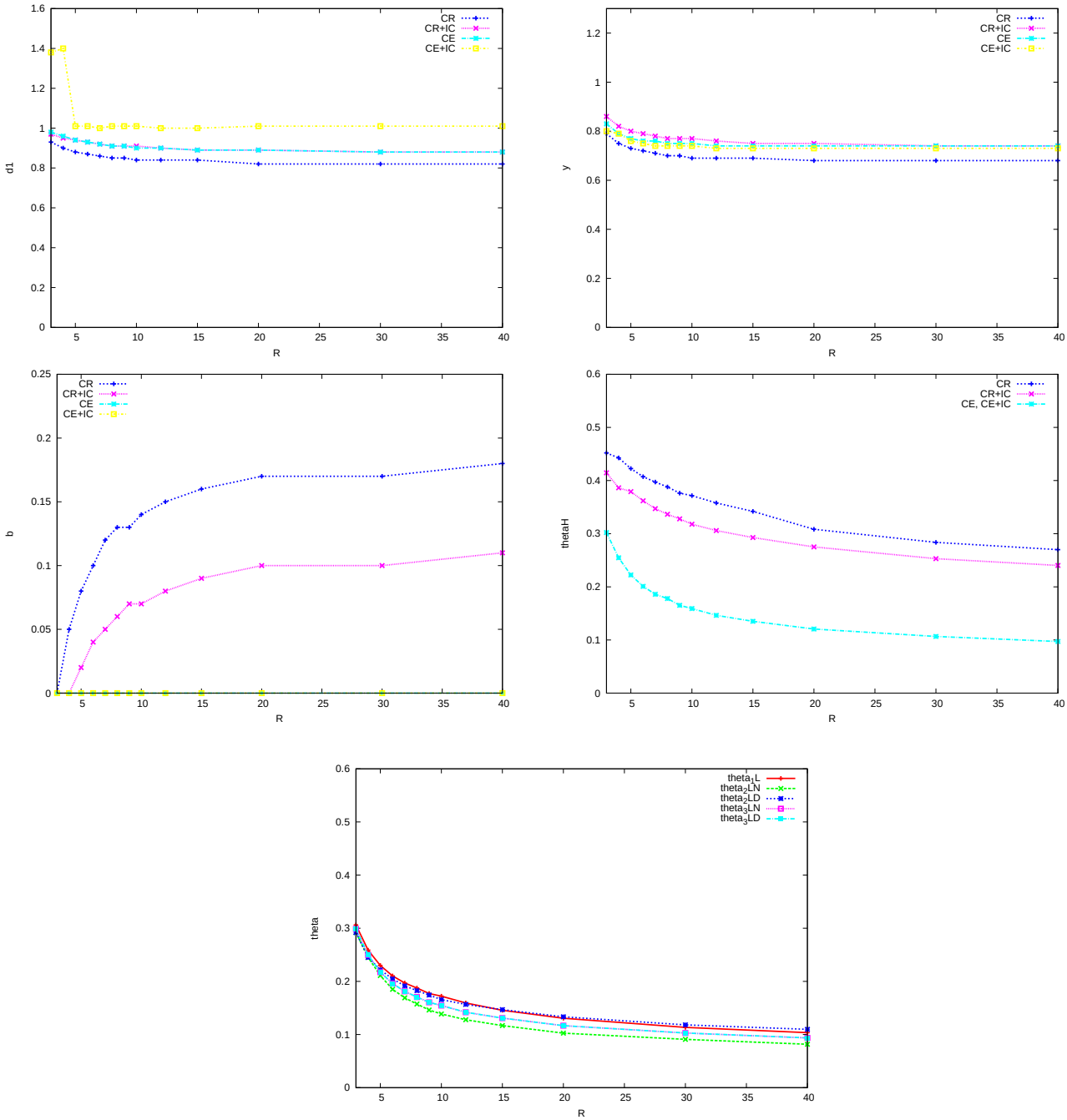

Figure 4: Details of portfolio choice: d_1, y (top), b and θ_H (middle), and various θ_L values for a variation of R. The baseline calibration is used for the non-varying parameters.

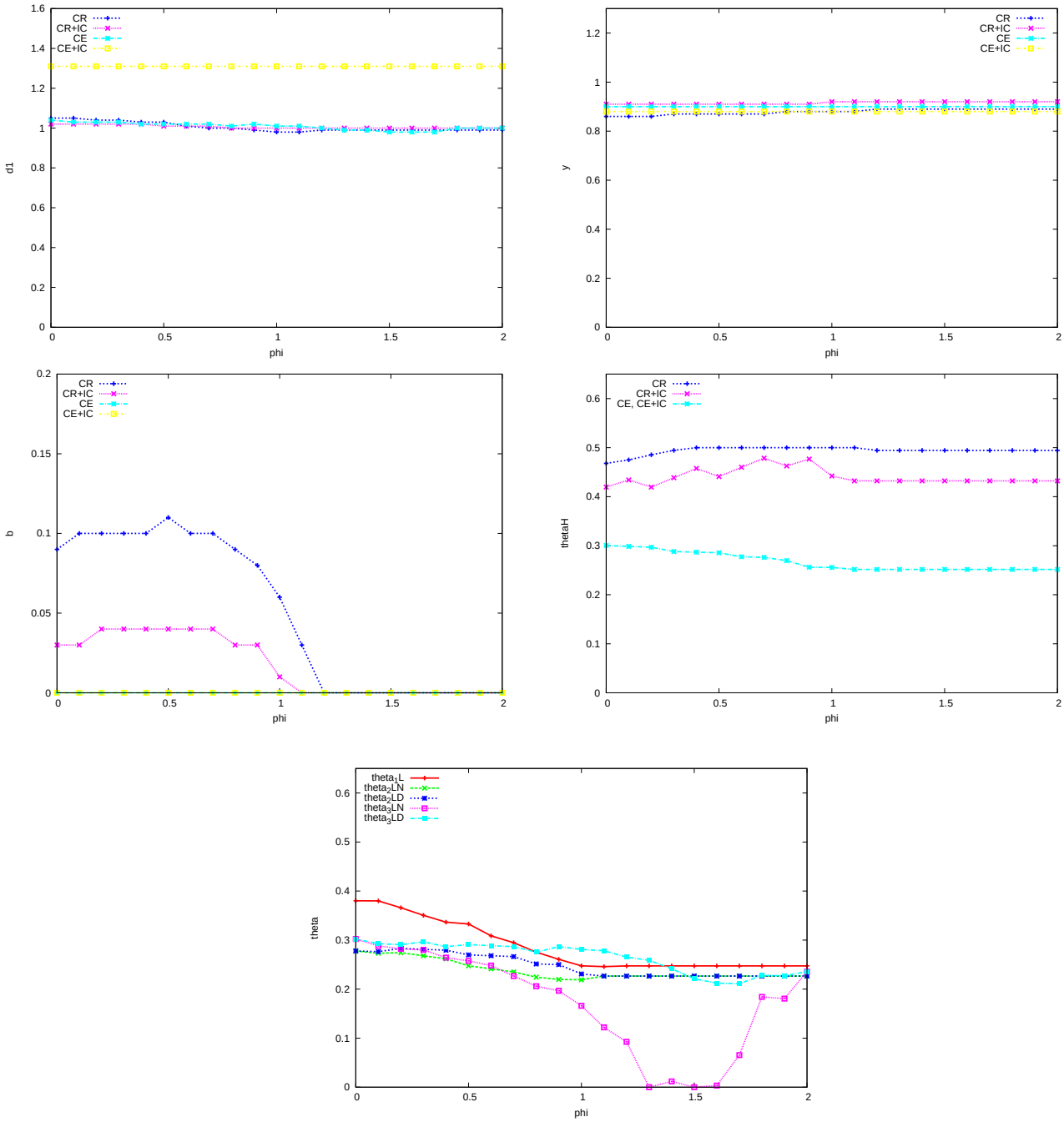

Figure 5: Details of portfolio choice: d_1, y (top), b and θ_H (middle), and various θ_L values for a variation of ϕ. The baseline calibration is used for the non-varying parameters.

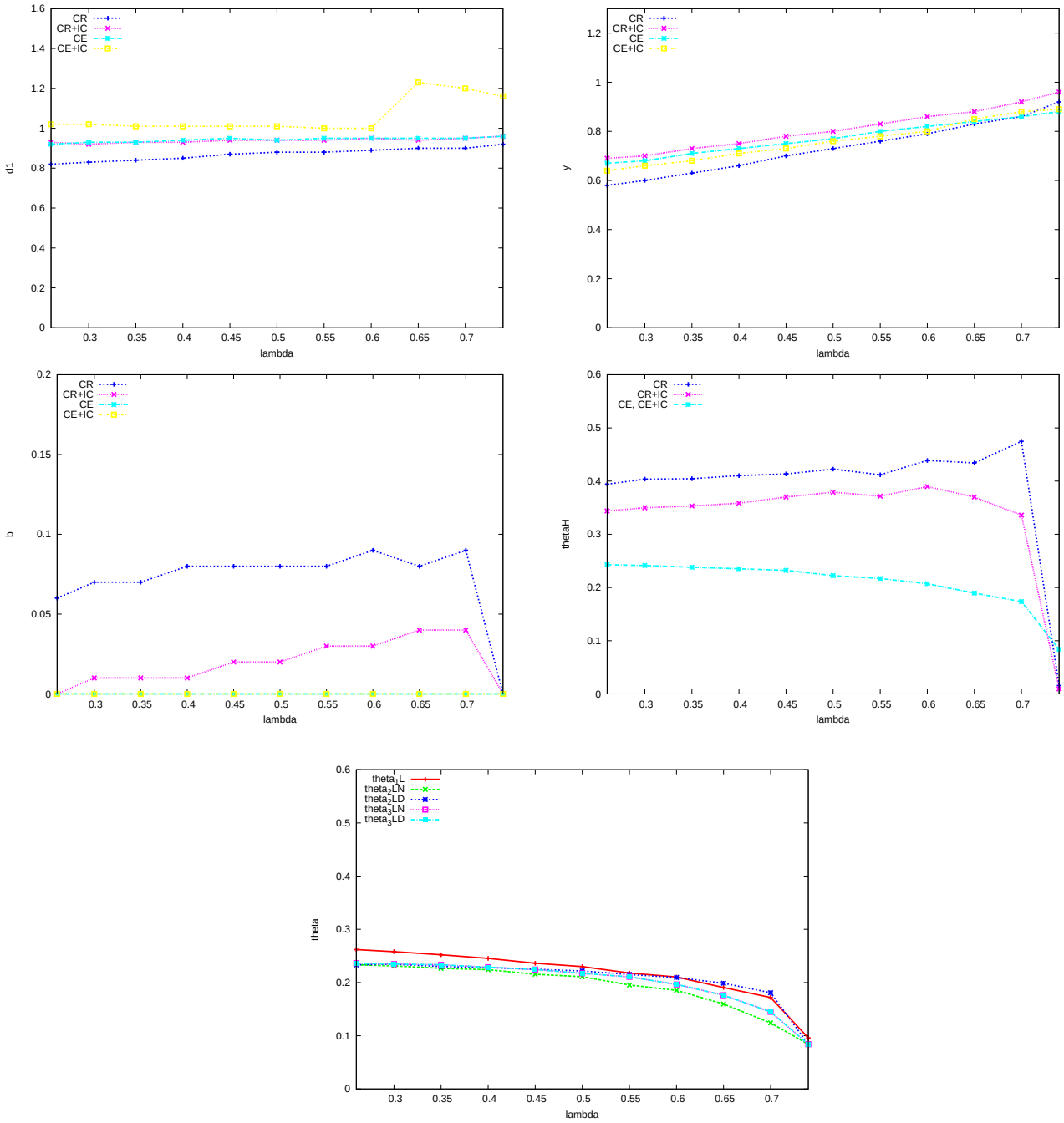

Figure 6: Details of portfolio choice: d_1, y (top), b and θ_H (middle), and various θ_L values for a variation of λ. The baseline calibration is used for the non-varying parameters.

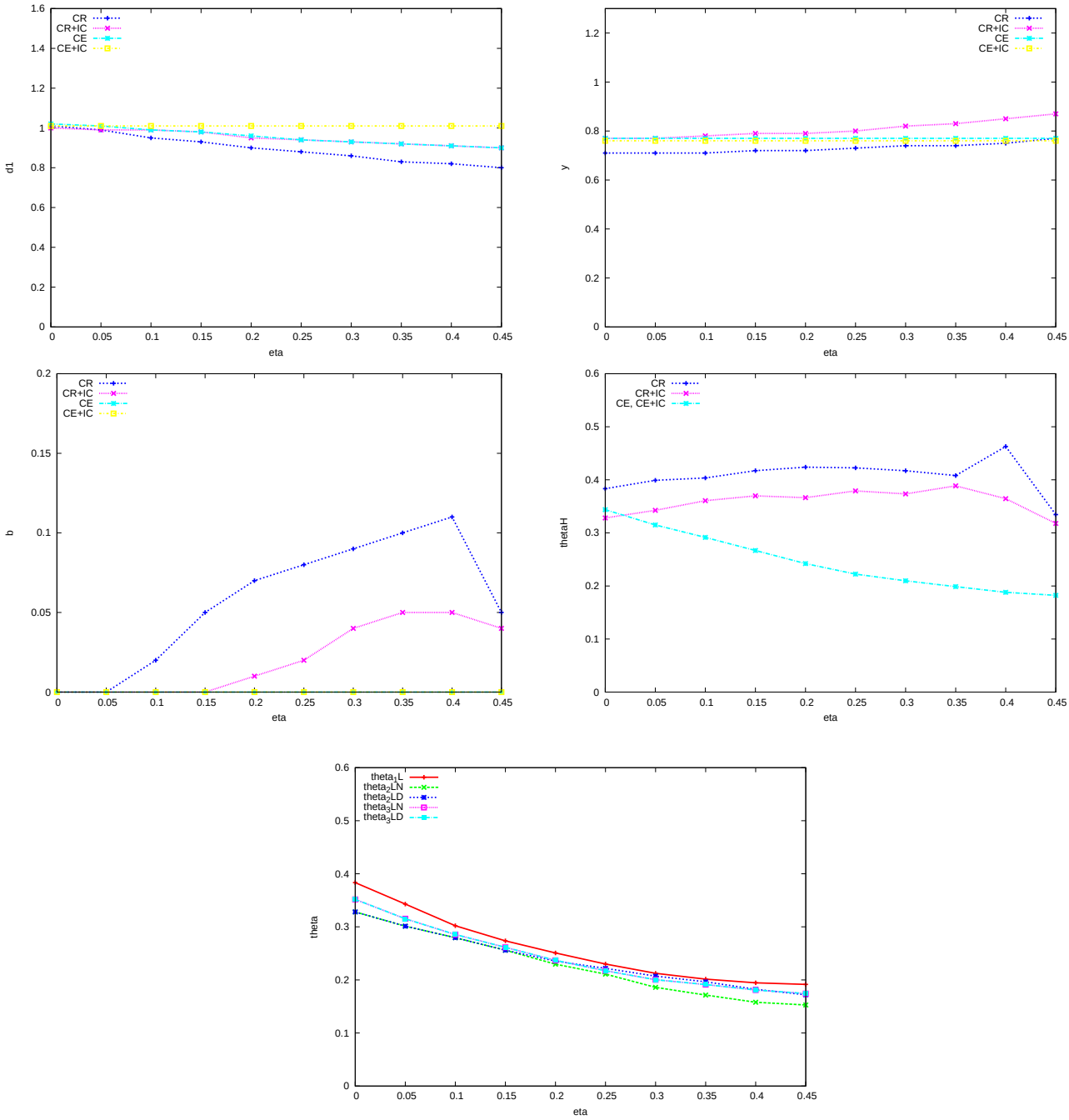

Figure 7: Details of portfolio choice: d_1, y (top), b and θ_H (middle), and various θ_L values for a variation of η. The baseline calibration is used for the non-varying parameters.

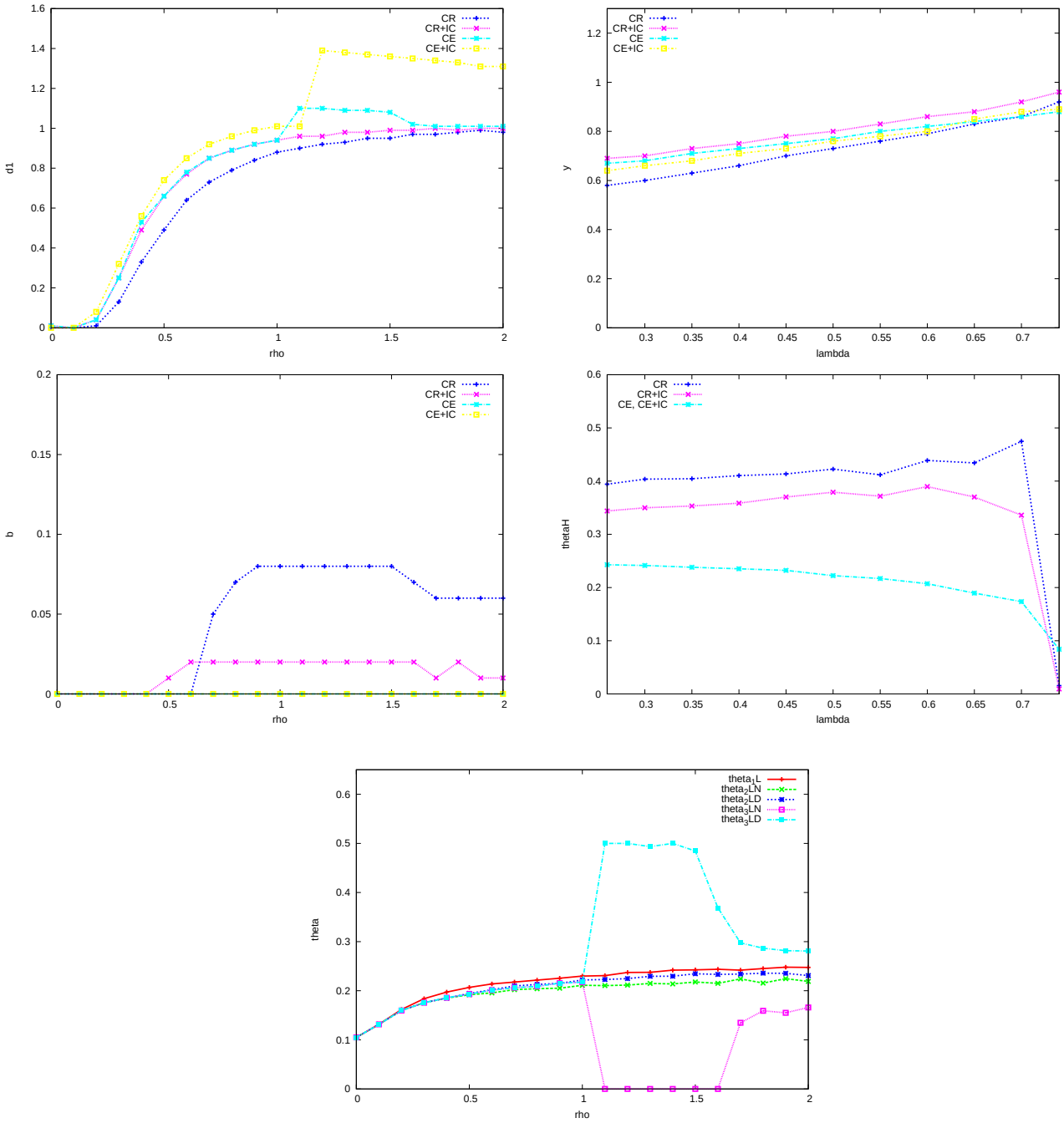

Figure 8: Details of portfolio choice: d_1, y (top), b and θ_H (middle), and various θ_L values for a variation of ρ. The baseline calibration is used for the non-varying parameters.

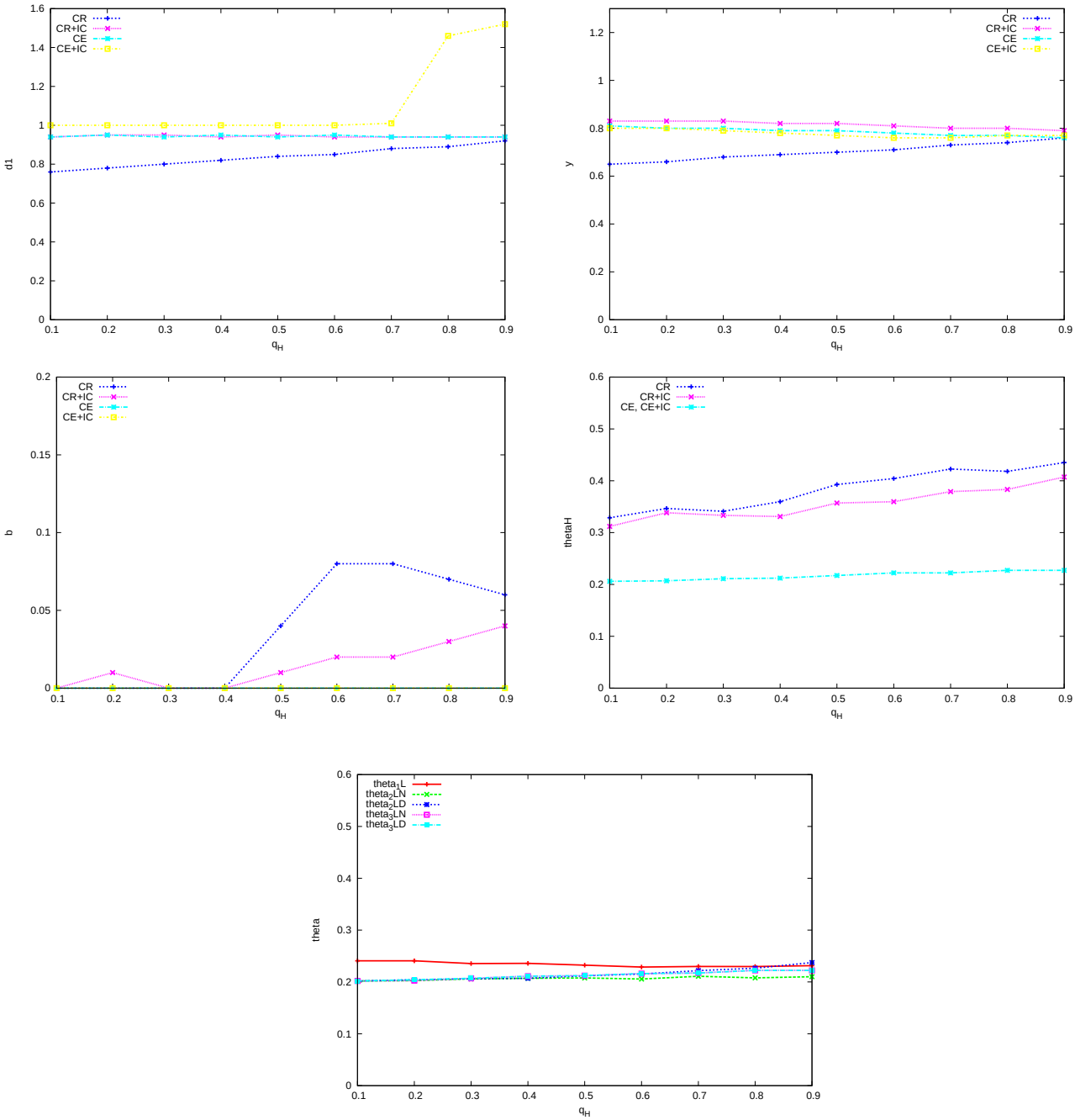

Figure 9: Details of portfolio choice: d_1, y (top), b and θ_H (middle), and various θ_L values for a variation of q_H. The baseline calibration is used for the non-varying parameters.