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ERSA working paper 686

June 2017

Economic Research Southern Africa (ERSA) is a research programme funded by the National Treasury of South Africa.

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Information Contagion and Systemic Risk [☆]

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Abstract

We examine the effect of ex-post information contagion on the ex-ante optimal portfolio choices of banks and the 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. Systemic risk is defined as the ex-ante probability of joint bank default ex post. We find that information contagion increases systemic risk when banks are subject to common exposures since portfolio adjustments are small. In contrast, when banks are subject to counterparty risk, information contagion induces a large shift toward more prudential portfolios and therefore *reduces* systemic risk.

Keywords: information contagion, counterparty risk, common exposure, systemic risk

JEL Codes: G01, G21

[☆]The authors wish to thank Viral Acharya, Jose Berrospide, Falko Fecht, Douglas Gale, Prasanna Gai (discussant), Paul Glassermann (discussant), Itay Goldstein, Todd Keister, Anton Korinek, Yaron Leitner, Ralf Meisenzahl, Jean-Charles Rochet, Cecilia Parlatore Siritto, Javier Suarez, Ernst-Ludwig von Thadden, Dimitri Vayanos, and Tanju Yorulmazer, and seminar participants at the IMF, LSE, NYU, the Philadelphia Fed and conference participants at the RBNZ-UA "Stability and efficiency of financial systems" conference, the 2012 FDIC Bank Research Conference, and EEA 2011 meeting for fruitful discussions and comments.

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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 intermediaries and call them banks for short.

An investor of a bank finds information about another bank's profitability valuable for two reasons. First, both banks may have common exposure to an asset class, such as risky sovereign debt or mortgage-backed securities. Learning about another bank's profitability helps investors assess the profitability of its bank (Acharya and Yorulmazer (2008b); Allen et al., 2012). Second, a bank may have lent to another bank, for example to share liquidity risk (Allen and Gale, 2000). Learning about the debtor bank's profitability helps investors of the creditor bank assess its counterparty risk.

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

¹The 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.

²Lehman 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. For an overview, see Brunnermeier (2009).

Banks optimally choose the design of the demand-deposit contract (the withdrawal amount at the interim date), the amount of liquidity to hold, and the amount of interbank insurance against liquidity risk. In many economically interesting cases, a closed-form analytical solution of this problem cannot be obtained. We therefore compute the equilibrium of the withdrawal game explicitly by using numerical methods.

The algorithm we use is extremely simple and robust. We discretize the portfolio choice of the bank in one region. To solve for a Nash equilibrium, we compute the second bank's best response to the initial bank's portfolio choice. Since equilibrium requires the portfolio choice of each bank to be a best response to the other bank's choice, we arrive at an equilibrium if this best response equals the initial portfolio choice. We incur a small numerical error by discretizing the portfolio choice. However, this error becomes smaller as we refine the grid of portfolio choice variables. Our numerical results are confirmed in a number of benchmark cases for which we obtain closed form analytical solutions.

We obtain two results. We start by studying information contagion due to counterparty risk. When information spillover is *unanticipated*, such that it occurs with zero probability, the ex-ante optimal portfolio is unchanged and systemic risk unambiguously increases (Lemma 1). By contrast, anticipated information spillover makes the ex-ante portfolio choice more prudent to counteract ex-post information contagion. Banks choose to expose themselves less to counterparty risk by engaging in less liquidity co-insurance and hold more liquidity themselves. This *reduces* systemic risk (Result 1), which we label the *resilience effect*. The direct detrimental effect of information contagion on systemic risk is more than fully compensated by an indirect beneficial effect via the ex-ante portfolio choice. Overall, once information spillover is anticipated, systemic risk in the financial system is *reduced*.

Next, we study information contagion due to common exposures. When information spillover is unanticipated, systemic risk again increases (Lemma 2), similar to Lemma 1. When information spillover is anticipated systemic risk increases as well (Result 2), which we label 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. While financial fragility increases when banks are linked via common exposure, financial fragility decreases when banks are linked via 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. Counterparty risk as a source of information contagion and its consequences for the ex-ante portfolio choice have not been consistently studied before. Cooper and Ross (1998) and Ennis and Keister (2006) study the effect of ex-post individual bank 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.

Our counterparty risk mechanism builds on the literature of financial contagion due to balance sheet linkages. Building on Diamond and Dybvig (1983), Allen and Gale (2000) describe financial contagion as an equilibrium result.³ 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 spread 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 since contagion may occur with positive probability.⁴ 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 on the ex-ante portfolio choice of financial intermediaries, which is only partially ad-

³Freixas et al. (2000) consider spatial instead of intertemporal uncertainty about liquidity needs.

⁴Postlewaite 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. 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.

dressed in Dasgupta (2004). Furthermore, our focus is on the consequences for systemic risk and we also analyse the role of common exposures.

Our results also relate to the literature on information contagion due to common exposures. An early model of information-based individual fragility is Jacklin and Bhattacharya (1988). 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. In Acharya and Yorulmazer (2008b), information about the solvency of one bank is a signal about the health of other banks with similar exposure. The funding cost of one bank increases after adverse news about another bank because of correlated loan portfolio returns. 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. The anticipation of ex-post information contagion induces banks to correlate their ex-ante investment decisions, endogenously creating common exposures.⁵ By contrast, we consider counterparty risk as a principal source of information contagion. We also allow for a larger set of portfolio choice options. 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, and insurance of impatient investors against idiosyncratic liquidity shocks.

Leitner (2005) studies the ex-ante beneficial insurance effects of ex-post financial contagion in the absence of an explicit ex-ante risk sharing 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) study systemic risk stemming from the interaction of common exposures and funding maturity through an information channel. Banks swap risky

⁵Another consequence of having a common exposure is studied in Wagner (2011), where joint liquidation of an asset induces investors to choose heterogeneous portfolios and forego diversification benefits.

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, short-term debt is rolled over less often when assets are clustered, which increases systemic risk. In contrast, our focus is on the analysis of counterparty risk as a source of information contagion and its repercussions for systemic risk.

The remainder of this paper is as follows. Section 2 lays out the model. Section 3 analyses the equilibrium and discusses special limiting cases that provide further intuition to our model. We present our results in section 4, which also contains extensive robustness checks. Finally, section 5 concludes. Derivations, proofs, and tables are found in appendices Appendix A, Appendix B, and Appendix C, respectively.

2. Model

The economy extends over three dates labelled as initial ($t = 0$), interim ($t = 1$), and final ($t = 2$), and consists of two regions ($k = A, B$) interpreted as geographic regions or asset classes. Each region is inhabited by a bank and a unit continuum of investors. Our notion of financial intermediation is broad, capturing both the traditional case of retail investors at commercial banks and institutional investors at money market mutual funds. There is a single physical good used for consumption and investment. The focus of this paper is on systemic risk measured by the probability of the joint failure of banks at the initial date.

Inhabitants of each region have access to two investment opportunities at the initial date. First, storage produces one unit at the following date per unit invested. Second, a risky regional investment project matures at the final date and produces a stochastic output R_k that exceeds the output from storage in expectation ($\mathbb{E}[R_k] > 1$), where \mathbb{E} is the expectation operator. Liquidation of the project at the interim is costly, producing an inferior output $\beta \in (0, 1)$ per unit. Since the recovery rate is positive, liquidation is optimal if the realized output is known to be low. We adopt a bivariate specification of the project output:

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

where $R > 2$ and the regional fundamental is uniformly distributed ($\theta_k \sim U[0, 1]$) and interpreted as a regional solvency shock. Let $\text{corr}(\theta_A, \theta_B)$ denote the correlation between the regional fundamentals, where $\text{corr}(\theta_A, \theta_B) = 1$ refers to a common exposure. Despite common exposure, the realised regional project outputs can differ because of the individual randomness of each project. We abstract from portfolio diversification motivated by limits to monitoring, for instance.

As in Diamond and Dybvig (1983), investors learn their liquidity preference privately at the interim date. Early investors wish to consume at the interim date, while late investors wish to consume at the final date. The ex-ante probability of being an early investor $\lambda \in (0, 1)$ is identical across investors and equals the regional proportion of early investors by a law of large numbers. The investor's period utility function $u(c)$ is twice continuously differentiable, strictly increasing, strictly concave and satisfies the Inada conditions. Thus, the expected utility of an investor is:

$$\mathbb{E}_\lambda[U(c_1, c_2)] = \lambda u(c_1) + (1 - \lambda)u(c_2), \quad (2)$$

where c_t is the investor's consumption at date t . Investors in each region are endowed with one unit at the initial date to be invested or deposited at their regional bank.

The role for banks in our model is the traditional provider of liquidity insurance (Diamond and Dybvig (1983)), which arises from the smaller volatility of regional liquidity demand than individual liquidity demand. Banks offer demand deposit contracts that specify withdrawals (d_1, d_2) if funds are withdrawn at the interim or final date, where we set $d_2 \equiv \infty$ without loss of generality. Banks pay an equal amount to all withdrawing investors in case of default (pro-rata). There is free entry to the banking sector, ensuring that each

bank maximizes the expected utility of a representative investor. Investors deposit in full since their interest is fully aligned with their bank's.

A bank is illiquid if a sufficiently large proportion of late investors withdraws and investment has to be (partially) liquidated. A bank is insolvent if a yet larger proportion of late investors withdraws and the full liquidation of the project does not suffice to serve them. An important insight of Diamond and Dybvig (1983) is that the strategic complementarity in investors' withdrawal decisions generates multiple equilibria, of which the inefficient one features a bank run. We focus on essential bank runs as in Allen and Gale (1998), however, whereby a run takes place only if it is unavoidable. That is, the no-run equilibrium is selected if multiple equilibria exist. Let a_k be the default probability of an individual bank and $A \equiv a_A a_B$ be the probability of joint default, which is our measure of systemic risk.

Counterparty risk is introduced via interbank insurance as in Allen and Gale (2000) because of negatively correlated regional liquidity demand. A region has low liquidity demand ($\lambda_L \equiv \lambda - \eta$) or high liquidity demand ($\lambda_H \equiv \lambda + \eta$) with equal probability, where $\eta > 0$ is the size of the regional liquidity shock. To exclude bank runs merely driven by aggregate liquidity shortage, we study negatively correlated liquidity shocks of equal size:

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

At the initial date banks agree on mutual liquidity insurance interpreted as mutual lines of credit or cross-holding of deposits. Since banks are symmetric at the initial date, they wish to exchange the same amount of deposits. The bank with high liquidity demand receives an amount $b \geq 0$ from the bank with low liquidity demand at the beginning of the interim date. Repayment with interest ($\phi \geq 1$) takes place at the final date if the debtor bank is

solvent. A solvent debtor bank repays the creditor bank even if the latter is insolvent. We make the common assumption of seniority of interbank loans at the final date only (see also Dasgupta, 2004). Non-defaulted interbank claims can be liquidated at rate β .

There is strategic interaction between banks in their portfolio choices. At the initial date banks simultaneously choose the amount of investment in the project $1 - y_k$, the demand deposit contract, and agree on the volume of interbank insurance. A bank's portfolio choice affects its solvency threshold $\bar{\theta}_k$ below which an essential bank run occurs. Furthermore, it affects another bank's solvency threshold $\bar{\theta}_{-k}$ due to counterparty risk and information contagion at the interim date. The optimal portfolio choices of banks at the initial date are determined as a symmetric pure-strategy Nash equilibrium.

Turning to the information structure of the model, all prior distributions are common knowledge. Before making their withdrawal decision at the interim date, investors may receive independent signals about the success probabilities θ_k with probability q_k . Therefore, investors may receive no, one or two signals. If a signal is received, it perfectly reveals the regional success probability to the investor.

Information spillover occurs if investors of one bank learn about the solvency of another bank. Such information is valuable to investors for two reasons. In case of common exposure, investment returns are correlated and the knowledge about one bank's solvency helps to predict another bank's solvency. In case of counterparty risk, learning about the debtor bank's solvency helps investors predict the solvency of the creditor bank. Information contagion occurs if investors run on a bank upon learning about another bank's solvency but would not have done so without the information. Our interest is in analyzing the effect of such information contagion at the interim date on the optimal portfolio choice at the initial date and the implied systemic risk.

We close the description of the model by determining the investors' payoffs. Starting with the high liquidity demand or debtor region (H), the payoffs are independent of the

behavior in the low liquidity demand region. If the bank is insolvent, all funds are liquidated and the interbank loan is defaulted upon. The impatient investor's payoff is $d_H \equiv y + (1 - y)\beta + b$. There are never partial runs since all bank runs are essential. If the bank is liquid, no liquidation takes place and the interbank loan is repaid. The patient investor'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 or debtor 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 $y + (1 - y)\beta - b + \beta\phi\tilde{b}$. The repayment of the interbank claim \tilde{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 investors 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. Table (1) shows the timeline of events.

3. Equilibrium

In this section we compute the solvency thresholds below which investors withdraw from their bank, causing an efficient bank run. We obtain the expected utility of investors and the level of systemic risk for the cases of counterparty risk and common exposures. We also describe the numerical derivation of the equilibrium allocations and consider several limiting parameter values that yield a simple analytical solution to provide intuition.

Date 0	Date 1	Date 2
1. Endowed investors 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. Investors privately observe liquidity preference	3. Banks serve remaining withdrawals
	4. Investors observe regional solvency signals	
	5. Investors decide whether to withdraw	

Table 1: Timeline of the model.

3.1. Counterparty risk

Consider the case with counterparty risk ($\eta > 0$) and without common exposure ($corr = 0$). Suppose first that no information spillovers occurs (investors receive no signal about the solvency of the other bank), which we will relax below.

Start with the debtor bank (H) since the solvency threshold there is unaffected by events at the creditor bank (L). With probability q_H , investors at the debtor bank are informed and observe the realisation of the solvency shock θ_H . Because of essential bank runs, all investors withdraw if and only if the expected utility of final-date consumption, $\theta_H u(c_{2H}^G) + (1 - \theta_H)u(c_{2H}^B)$, falls short of the utility from their share of the liquidated bank portfolio $u(d_H)$. Therefore, the solvency threshold at the debtor bank $\bar{\theta}_H$ is:

$$\bar{\theta}_H \equiv \frac{u(d_H) - u(c_{2H}^B)}{u(c_{2H}^G) - u(c_{2H}^B)} \quad (3)$$

An essential bank run with full liquidation occurs if and only if $\theta_H < \bar{\theta}_H$. Given the distribution of fundamentals, the default probability of the debtor bank if informed is also $\bar{\theta}_H$.

With probability $1 - q_H$ investors are uninformed and base their efficient withdrawal behaviour on the prior distributions. We assume throughout that no bank runs occur without new information at the interim date. That is, the prior is sufficiently good as implied by a lower bound on the project output in the good state ($R \geq \underline{R}$). Thus, the overall default probability of the debtor bank is $a_{1H} \equiv q_H \bar{\theta}_H$. As shown in Appendix A, integrating the investors' respective payoffs over all possible signals yields the expected utility of investors at the debtor bank EU_H :

$$EU_H = (1 - q_H) \left\{ \lambda_H u(d_1) + (1 - \lambda_H) \frac{1}{2} (u(c_{2H}^G) + u(c_{2H}^B)) \right\} + q_H \left\{ \bar{\theta}_H u(d_H) + (1 - \bar{\theta}_H) \left(\lambda_H u(d_1) + (1 - \lambda_H) \frac{1}{2} [u(c_{2H}^G) + u(d_H)] \right) \right\}, \quad (4)$$

which completes the description of the debtor region.

The creditor bank is affected by a default of the debtor bank, both in terms of the repayment at the final date and the liquidation value of the interbank claim at the interim date. If investors are informed, the solvency threshold $\bar{\theta}_{1L}$ is:

$$\bar{\theta}_{1L} \equiv \frac{a_{1H}[u(d_L^D) - u(c_{2L}^{BD})] + (1 - a_{1H})[u(d_L^N) - u(c_{2L}^{BN})]}{a_{1H}[u(c_{2L}^{GD}) - u(c_{2L}^{BD})] + (1 - a_{1H})[u(c_{2L}^{GN}) - u(c_{2L}^{BN})]} = \bar{\theta}_{1L}(\bar{\theta}_H) \quad (5)$$

and the overall default probability of the creditor bank is $a_{1L} \equiv q_L \bar{\theta}_{1L}$.

Counterparty risk, the dependence of the creditor bank on the debtor bank, is reflected by the solvency threshold $\bar{\theta}_{1L}(\bar{\theta}_H)$. A higher solvency threshold at the debtor bank makes a default on the interbank claim more likely, thus raising the probability of default at the creditor bank ($\frac{\partial \bar{\theta}_{1L}}{\partial \bar{\theta}_H} > 0$). A failure of the debtor bank constitutes a negative externality on investors of the creditor bank. Early investors at the creditor bank receive their share of the liquidation value d_L instead of the higher promised payment d_1 . Late investors are paid out fewer resources. Consequently, the solvency threshold at the creditor bank strictly increases in the solvency threshold of the debtor bank.

As shown in Appendix A, the expected utility of investors in the creditor bank is:

$$\begin{aligned}
EU_{1L} = & (1 - q_L) \left\{ \lambda_L u(d_1) + (1 - \lambda_L) \frac{1}{2} \left((1 - a_H) (u(c_{2L}^{GN}) + u(c_{2L}^{BN})) \right. \right. \\
& \left. \left. + a_H (u(c_{2L}^{GD}) + u(c_{2L}^{GN})) \right) \right\} \\
& + q_L \left\{ \bar{\theta}_{1L} \left((1 - a_H) u(d_L^N) + a_H u(d_L^D) \right) + \lambda_L (1 - \bar{\theta}_{1L}) u(d_1) \right. \\
& + (1 - \lambda_L) \frac{1}{2} \left((1 - \bar{\theta}_{1L}^2) \left((1 - a_H) u(c_{2L}^{GN}) + a_H u(c_{2L}^{GD}) \right) \right. \\
& \left. \left. + (1 - \bar{\theta}_{1L})^2 \left((1 - a_H) u(c_{2L}^{BN}) + a_H u(c_{2L}^{BD}) \right) \right) \right\}
\end{aligned} \tag{6}$$

There is one main difference to the expected utility of investors at the debtor bank. Since no information spillover takes place, the expectation over whether the debtor bank defaults, which occurs with probability a_H , is taken.

Finally, the overall expected utility EU_{CR} and the level of systemic risk A_{CR} in the case of counterparty risk (CR) are:

$$A_{CR} \equiv a_{1L} a_{1H} = q_H q_L \bar{\theta}_H \bar{\theta}_{1L}, \tag{7}$$

$$EU_{CR} \equiv \frac{1}{2} (EU_H + EU_{1L}). \tag{8}$$

Since the regional solvency shocks are uncorrelated, the overall expected utility is the average of the expected utility of an investor at the debtor and creditor bank, respectively. This will be generalized once we allow for correlated solvency shocks.

We now allow for information spillover, that is news about the solvency of the bank in the other region. The efficient withdrawal behaviour of investors at the debtor bank is unchanged and so is their expected utility EU_H . By contrast, with probability q_H investors at the creditor bank are informed about the debtor bank's solvency and infer whether repayment at the final date occurs and whether the liquidation of the interbank claim yields revenue at the interim date. The creditor bank is not repaid if and only if investors at the debtor

bank are informed and the solvency of the debtor bank is low, which is a consequence of the seniority of interbank claims. Consequently, there are two solvency thresholds at the creditor bank: one if the debtor bank defaults ($\bar{\theta}_{2L}^D$) and one if the debtor bank repays ($\bar{\theta}_{2L}^N$):

$$\bar{\theta}_{2L}^N \equiv \frac{u(d_L^N) - u(c_{2L}^{BN})}{u(c_{2L}^{GN}) - u(c_{2L}^{BN})} \quad (9)$$

$$\bar{\theta}_{2L}^D \equiv \frac{q_H[u(d_L^D) - u(c_{2L}^{BD})] + (1 - q_H)[u(d_L^N) - u(c_{2L}^{BN})]}{q_H[u(c_{2L}^{GD}) - u(c_{2L}^{BD})] + (1 - q_H)[u(c_{2L}^{GN}) - u(c_{2L}^{BN})]} \quad (10)$$

If the information spillover is unanticipated, the spillover of information at the interim date has no effect on the optimal portfolio choice at the initial date. Then, the solvency thresholds can be ranked:

$$\bar{\theta}_{2L}^N < \bar{\theta}_{1L} < \bar{\theta}_{2L}^D \quad (11)$$

which captures both information contagion if the debtor bank defaults and stabilization if the debtor bank repays the creditor bank.

The expected utility of an investor at the creditor bank EU_{2L} changes to:

$$\begin{aligned} EU_{2L} = & (1 - q_L) \left\{ \lambda_L u(d_1) + (1 - \lambda_L) \frac{1}{2} \left[(1 - a_H) (u(c_{2L}^{GN}) + u(c_{2L}^{BN})) \right. \right. \\ & \left. \left. + a_H (u(c_{2L}^{GD}) + u(c_{2L}^{BD})) \right] \right\} \\ & + q_L \left\{ \left(\bar{\theta}_{2L}^N (1 - a_H) u(d_L^N) + \bar{\theta}_{2L}^D a_H u(d_L^D) \right) \right. \\ & + \lambda_L \left(a_H (1 - \bar{\theta}_{2L}^D) + (1 - a_H) (1 - \bar{\theta}_{2L}^N) \right) u(d_1) \\ & + (1 - \lambda_L) \frac{1}{2} \left((1 - a_H) [(1 - (\bar{\theta}_{2L}^N)^2) u(c_{2L}^{GN}) + (1 - (\bar{\theta}_{2L}^N)^2) u(c_{2L}^{BN})] \right. \\ & \left. \left. + a_H [(1 - (\bar{\theta}_{2L}^D)^2) u(c_{2L}^{GD}) + (1 - (\bar{\theta}_{2L}^D)^2) u(c_{2L}^{BD})] \right) \right\} \end{aligned} \quad (12)$$

where the solvency thresholds in the creditor region now depend on whether the debtor bank defaults. That is, the uninformed solvency threshold $\bar{\theta}_{1L}$ is replaced by the conditional thresholds $(\bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D)$.

The overall expected utility of an investor EU_{CR+IC} and the level of systemic risk A_{CR+IC} in case of counterparty risk and information contagion are:

$$EU_{CR+IC} \equiv \frac{1}{2}(EU_H + EU_{2L}) \quad (13)$$

$$A_{CR+IC} = q_H q_L \bar{\theta}_H \bar{\theta}_{2L}^D, \quad (14)$$

which yields the following result:

Lemma 1. *If information spillovers are unanticipated, then information contagion due to counterparty risk unambiguously increases systemic risk:*

$$A_{CR+IC} > A_{CR} \quad (15)$$

3.2. Common exposure

Consider the case with common exposures ($corr = 1$) and no counterparty risk ($\eta = 0$). Thus, the payoffs are symmetric across regions but investors are potentially asymmetrically informed about the common solvency shock. Final-date consumption simplifies to $c_2^G \equiv \frac{y - \lambda d_1 + (1-y)R}{1-\lambda}$ in the good state and $c_2^B \equiv \frac{y - \lambda d_1}{1-\lambda}$ in the bad state and the liquidation payoff to $d_\beta \equiv y + (1-y)\beta$. Again we start without information spillover. The solvency threshold in either region becomes:

$$\bar{\theta} = \frac{u(d_\beta) - u(c_2^B)}{u(c_2^G) - u(c_2^B)} \quad (16)$$

where an efficient bank run occurs if and only if the solvency level is below its threshold ($\theta < \bar{\theta}$). As derived in Appendix A, the expected utility in either region EU_{CE} and the level of systemic risk A_{CE} in case of pure common exposure are:

$$EU_{CE} = \frac{q_A + q_B}{2} \left[\bar{\theta} u(d_\beta) + (1 - \bar{\theta}) \left(\lambda u(d_1) + (1 - \lambda) \frac{1}{2} [u(c_2^G) + u(d_\beta)] \right) \right] \quad (17)$$

$$A_{CE} = q_A q_B \bar{\theta}, \quad (18)$$

We now allow for information spillover. While payoffs and the solvency threshold are unchanged, the probability of being informed changes to $q_A + (1 - q_A)q_B > q_A$. Naturally, information spillovers increases the probability of being informed. Therefore, the expected utility in case of common exposure and information contagion (CE+IC) places more weight on the two terms in which liquidation may take place (those involving $\bar{\theta}$) and a smaller weight on the term without information and liquidation:

$$EU_{CE+IC} \equiv (q_A + q_B - q_A q_B) \left[\bar{\theta} u(d_\beta) + (1 - \bar{\theta}) \left(\lambda u(d_1) + (1 - \lambda) \frac{1}{2} [u(c_2^G) + u(d_\beta)] \right) \right] \\ + (1 - q_A)(1 - q_B) \left[\lambda u(d_1) + (1 - \lambda) \frac{1}{2} (u(c_2^G) + u(c_2^B)) \right] \quad (19)$$

$$A_{CE+IC} = (q_A + (1 - q_A)q_B)\bar{\theta} \quad (20)$$

which leads to the following result that mirrors Lemma 1:

Lemma 2. *If information spillovers are unanticipated, then information contagion due to common exposure unambiguously increases systemic risk:*

$$A_{CE+IC} > A_{CE} \quad (21)$$

3.3. Optimal portfolio choice

We solve for the optimal portfolio choice and the optimal demand deposit payment of banks at the interim date. A bank faces the following constraints on its choice variables. The mutual insurance between banks trades off liquidity insurance with counterparty risk. It is never optimal to insure more than the maximum amount to compensate for the regional liquidity demand shock ($b^* \leq \eta d_1^*$), where stars denote equilibrium allocations. Furthermore, it is never optimal to face certain costly liquidation, which places a lower bound on the amount of storage: $y^* + b^* \geq \lambda_H d_1^*$ and $y^* - b^* \geq \lambda_L d_1^*$. Combined with the optimal amount of interbank insurance, we obtain a lower bound on storage:

$$y^* \geq \underline{y} \equiv \lambda_H d_1^* - b^* \geq \lambda \quad (22)$$

The interim payment d_1 is bounded from above by the available resources and achieves risk sharing between early and late investors only if it is positive:

$$0 < d_1^* \leq \min\left\{R, \frac{y^* + (1 - y^*)\beta + b^*}{\lambda_H}, \frac{y^* + (1 - y^*)\beta - b^*}{\lambda_L}\right\} \quad (23)$$

Our model does not admit a tractable analytical solution for two reasons. First, corner solutions of the form of no interbank insurance ($b^* = 0$) or no investment ($y^* = 1$) are optimal for some parameter values, invalidating interior solutions and calling for a global approach. Second, solvency thresholds are non-monotonic in several choice variables. For example, more liquidity is valued when the investment project fails, while less liquidity is valued when the investment project succeeds. Also, the change in the solvency thresholds with respect to interbank liquidity insurance is in general ambiguous.⁶ In sum, both corner solutions and the non-monotonicity of the solvency thresholds in the choice variables confound an analytical solution. However, we determine analytical solutions for several limiting parameter values in section 3.4 to provide intuition for the mechanics of our model.

We solve the optimization problem numerically. We find the global optimum of the expected utility by discretizing the choice variables (d_1, y, b) on a three-dimensional grid, where the expected utility is evaluated at each grid point. The grid point where the expected utility takes its global maximum value yields the best response for a given portfolio choice of the other bank. The intersection of the (symmetric) best response functions yields the (symmetric) equilibrium allocations. Even though we will incur a numerical error from discretizing, this error will be small for a sufficiently fine grid. We verify the validity of our numerical solution method in section 3.4. We compare the optimal choice variables obtained numerically with the optimal choices in the cases of limiting parameter values, which admit

⁶By contrast, more insurance against the idiosyncratic liquidity risk of a investor (higher d_1) raises payments at the interim date at the expense of payments at the final date, thus unambiguously increasing the solvency threshold. Goldstein and Pauzner (2005) study this trade-off between insurance on a higher interim payment and higher idiosyncratic financial fragility in a global games setup that allows for non-essential bank runs.

simple analytical solutions, and obtain negligible discrepancies.

We use the following baseline calibration. The period utility function is CRRA, where $\rho > 0$ parameterizes the coefficient of relative risk aversion. Baseline parameter values are $\beta = 0.7$, $R = 5.0$, $\phi = 1.0$, $\lambda = 0.5$, $\eta = 0.25$, $\rho = 1.0$, and $q_H = q_L = 0.7$. Alternative specifications are considered in Appendix B and in Section 4.3 that discusses the variation of each parameter within its feasible bounds. Our results hold across these various specifications.

3.4. Limiting parameter cases

Our model admits an analytical solution for several limiting parameter values that are discussed in this section. These cases help us build intuition for the model and serve as a benchmark for the accuracy of our numerical solution.

First, let the project output in the good state fall short of unity ($R \leq 1$). Then, the investment project is dominated by storage ($y^* = 1$). We verify this result across all benchmark calibrations listed in Appendix B.1 and obtain the numerical solution of $y_{num}^* = 0.98$. Second, let investors be risk-neutral ($\rho = 0$). Then, the project dominates storage as the former has a higher expected return and investors, who do not mind the uncertainty about the idiosyncratic liquidity shock, prefer to invest fully in the project ($d_1^* = 0 = y^*$). This result is confirmed numerically ($d_{1,num}^* = 0 = y_{num}^*$). Likewise, if investors are very risk averse ($\rho \rightarrow \infty$), they are not willing to bear any of the investment risk associated with the project or 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 investor ($\rho > 0$) 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 investor. 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 investor 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. Intuitively, the amount of liquidity insurance decreases in the degree of risk aversion. As investors become more risk averse, they hold more liquidity as part of the optimal portfolio composition of late investors. 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 investors ($\lambda = 0$), there is no need for insurance against idiosyncratic liquidity shocks. The amount of liquidity held fully reflects the optimal portfolio allocation of late investors ($0 < y^* < 1$) 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 investors ($\lambda = 1$) 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 insurance in this specification ($b^* = 0$) as there cannot be any liquidity shocks. Since all resources are used to serve early investors, the optimal interim payment must also be one ($d_1^* = 1$). This intuition is confirmed numerically ($d_{1,num}^* = 0.99$).

Finally, the prior distribution is assumed not to induce liquidation in case of being uninformed. Hence, no liquidation takes place ($\bar{\theta}_1 = \bar{\theta}_{2L}^N = \dots = 0$) if investors are never informed in either region ($q_A = q_B = 0$), which is again confirmed numerically.

4. Results

This section summarizes our two main findings. In subsection 4.1 we present a *resilience effect* that arises when information contagion occurs due to counterparty risk. In subsection 4.2 we show the existence of an *instability effect* that emerges when information contagion occurs due to common exposures. Subsection 4.3 provides a global parameter analysis, verifying the robustness of our two main results across feasible parameter values.

4.1. Resilience effect

How does information contagion affect systemic risk stemming from 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 of banks is unaffected and systemic risk strictly increases (Lemma 1). This result arises directly from the fact that a failure of the creditor bank becomes more likely after adverse news about the solvency of the debtor bank. Therefore, information contagion strengthens the effect of counterparty risk, which leads to a lower level of expected utility and higher systemic risk. This immediate result is also obtained numerically by comparing entries in the tables in Appendix B.2, notably entry (1,1) for the case of pure counterparty risk with entry (1,2) for the case of counterparty risk and information contagion, where both are evaluated at the optimal portfolio choice of the pure counterparty risk case.

The focus of our analysis is on anticipated information contagion. Taking information contagion at the interim date into account, banks alter their portfolio choice at the initial date. Specifically, a bank makes a more prudent portfolio choice to insure risk-averse investors against potential information contagion at the interim date. First, banks reduce the exposure to counterparty risk by engaging in less liquidity co-insurance (lower b). To cover the liquidity demand from early investors, a bank increases the amount of storage (larger y), which is akin to liquidity self-insurance. This reduces the investment in the risky project and funds a larger amount of insurance against idiosyncratic liquidity risk (larger d_1). The more

prudent portfolio choices reduces the range of solvency shocks ($(\bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D)$) for which counterparty risk after information contagion occurs. These results are obtained numerically 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.

The crucial insight is that the direct positive effect information contagion on systemic risk (Lemma 1) is more than fully compensated by an indirect negative effect via the change in the ex-ante portfolio choice. Therefore, the overall effect is a reduction in systemic risk if information contagion is anticipated. We label this the resilience effect and show in section 4.3 that it holds across all feasible parameter values.

Result 1. *Consider the setup with counterparty risk ($\eta > 0$). Anticipating ex-post information contagion induces a more prudent portfolio choice ex-ante. More specifically, liquidity co-insurance, which exposes banks to counterparty risk, is substituted by direct holdings of liquidity (self-insurance) that reduces the investment in the risky project. The overall effect is a reduction in both expected utility and systemic risk.*

4.2. Instability effect

We now analyze how information contagion affects systemic risk in a setup with common exposures ($corr = 1$). If information spillover is unanticipated, the optimal portfolio choice is unaffected, implying more systemic risk (Lemma 2). Since efficient withdrawals by investors become more likely after adverse news about the solvency of another bank, unanticipated information spillover always leads to greater systemic risk.

If information spillovers is anticipated, the bank adjusts its ex-ante optimal portfolio choice. Specifically, the optimal interim-date payment is unchanged, while the optimal liquidity level is slightly lower (within numerical accuracy) across all baseline cases and feasible parameter choices. However, the changes to the portfolio is small, implying a small indirect effect on systemic risk only. Therefore, the level of systemic risk increases overall, once information contagion is present. 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 2. *Consider the setup with common exposures ($\text{corr} = 1$). Anticipating information contagion has a small effect on the portfolio choice at the initial date. As a result, systemic risk and the expected utility increases.*

Additional information allows the late investors to decide on early withdrawals in more states of the world and has two consequences. First, liquidation is optimal for late investors after a bad solvency shock. Second, liquidation is detrimental to early investors who only receive their share of the liquidation value and not the (strictly larger) promised interim payment. Therefore, late investors impose a negative externality on early investors. Since 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.

4.3. Robustness checks

This section shows that the resilience effect and the instability effect are robust to exogenous parameter variations. In particular, we discuss a global variation of parameters by considering the entire range of feasible parameters and analyse the effect on systemic risk and expected utility. Details and further analyses, including the optimal portfolio choice and withdrawal thresholds, are contained in figures C.3 - C.9 in Appendix C.

Consider the resilience effect (Result 1) 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 return to

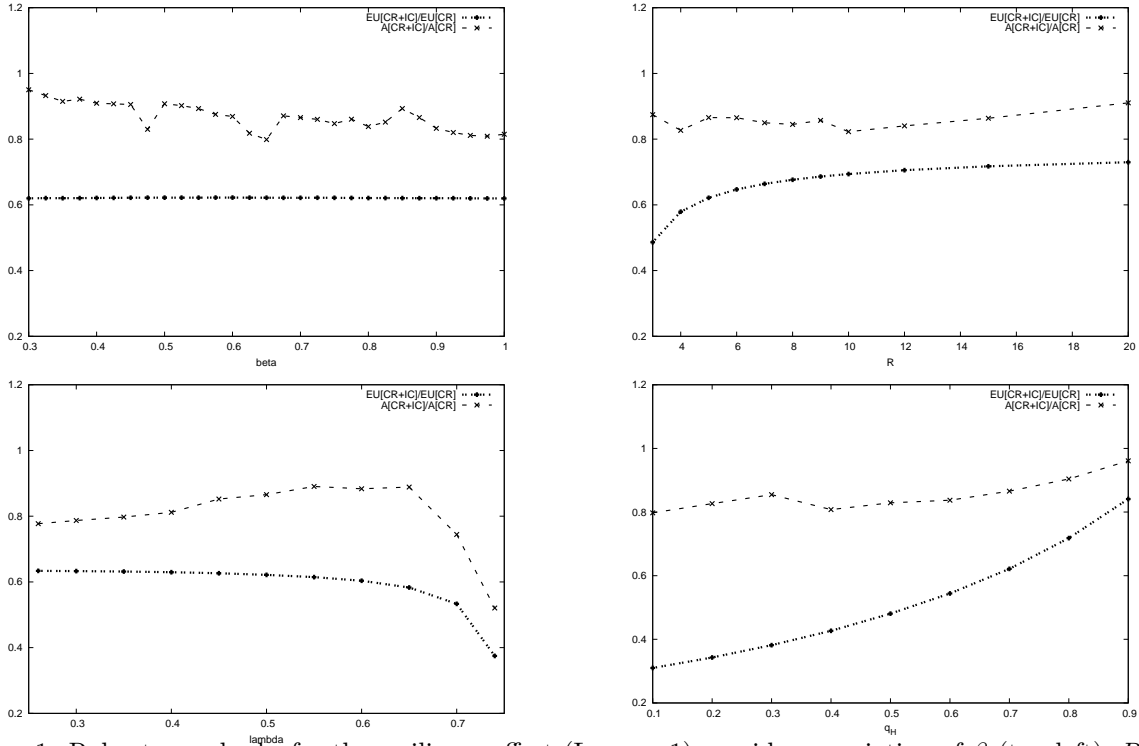


Figure 1: Robustness checks for the resilience effect (Lemma 1) consider a variation of β (top left), R (top right), λ (bottom left), and $q_H = q_L$ (bottom right). The figures display expected utility (dotted line) and the level of systemic risk (dashed line) in the case of counterparty risk and information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

the investment project in the good state (R), the proportion of early investors (λ), and the level of transparency (q). In all cases, the resilience effect prevails.

Turning to the instability effect (Result 2), 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. 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

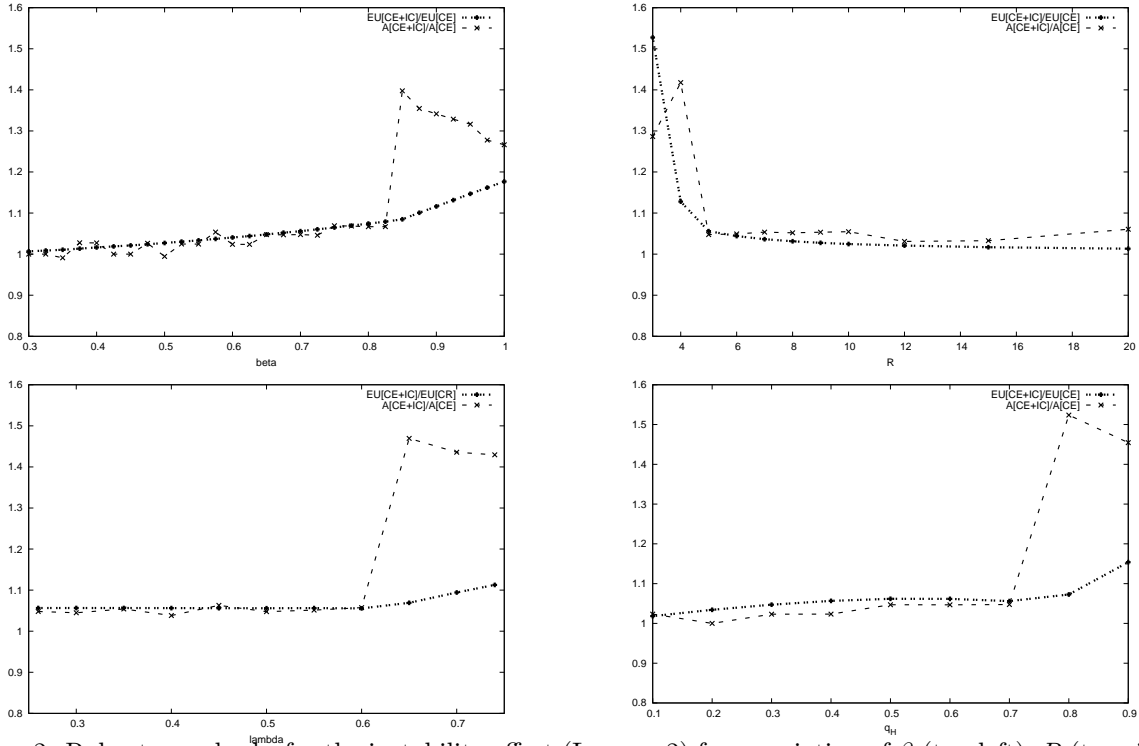


Figure 2: Robustness checks for the instability effect (Lemma 2) for a variation of β (top left), R (top right), λ (bottom left), and $q_H = q_L$ (bottom right). The figures display expected utility (dotted line) and the level of systemic risk (dashed line) in the case of common exposures and information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

bank default. One bank's investors find information about another bank's solvency valuable for two reasons. First, both banks might have invested into the same asset class like risky sovereign debt or mortgage backed securities. Learning about another bank's profitability helps the investor assess the profitability of its bank. Second, one bank might have lent to the other, for instance as part of a liquidity risk-sharing agreement. Learning about the debtor bank's profitability 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. Banks reduce their exposure to counterparty risk and rely more the self-insurance of liquidity instead of co-insurance. Overall, the level of systemic risk is reduced once information contagion is present. 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).

Appendix A. Derivations

Appendix A.1. Autarky

A depositor faces both idiosyncratic liquidity risk and the solvency risk of the investment project and decides about the level of investment $1 - y \in [0, 1]$. Early depositors withdraw and receive $c_{1A} \equiv y + (1 - y)\beta$ at the interim date. Late depositors do not withdraw and receive $c_{2A}^G \equiv y + (1 - y)R$ in the good state and $c_{2A}^B \equiv y$ in the bad state.

Optimal behaviour of a depositor in autarky has two steps: optimal liquidation at the interim date and optimal investment at the initial date. Comparing liquidation and continuation yields a threshold success probability below which the depositor liquidates the investment project ($\theta < \bar{\theta}^A$):

$$\bar{\theta}^A = \frac{u(c_{1A}) - u(c_{2A}^B)}{u(c_{2A}^G) - u(c_{2A}^B)} \quad (\text{A.1})$$

To determine the optimal investment decision, we find the expected utility of a depositor:

$$EU^A = \lambda u(c_{1A}) + (1 - \lambda) \left[\int_0^{\bar{\theta}^A} u(c_{1A}) d\theta + \int_{\bar{\theta}^A}^1 \theta u(c_{2A}^G) + (1 - \theta) u(c_{2A}^B) d\theta \right] \quad (\text{A.2})$$

$$= u(c_{1A})[\lambda + (1 - \lambda)\bar{\theta}^A] + (1 - \lambda)(1 - \bar{\theta}^A) \frac{u(c_{2A}^G) + u(c_{1A})}{2} \quad (\text{A.3})$$

The optimal choice of liquidity maximises the autarky expected utility $(y^A)^* \equiv \arg \max_{y^A} EU^A$.

Appendix A.2. Banking

$$EU^{CE} = \int_0^{\bar{\theta}^{CE}} u(d_\beta) d\theta + \int_{\bar{\theta}^{CE}}^1 \lambda u(d_1) + (1 - \lambda) [\theta u(c_2^G) + (1 - \theta) u(c_2^B)] d\theta \quad (\text{A.4})$$

$$= \bar{\theta}^{CE} u(d_\beta) + (1 - \bar{\theta}^{CE}) \left[\lambda u(d_1) + (1 - \lambda) \frac{u(c_2^G) + u(d_\beta)}{2} \right] \quad (\text{A.5})$$

Appendix A.3. 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 $\bar{\theta}_H$ is received, depositors receive a share of the liquidation proceeds and obtain d_H . If a signal above the threshold $\bar{\theta}_H$ is received, late households 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.⁷

Expected utility in the high liquidity demand region is given as:

$$EU_H = (1 - q_H) \left\{ \lambda_H u(d_1) + (1 - \lambda_H) \int_0^1 [\theta u(c_{2H}^G) + (1 - \theta) u(c_{2H}^B)] d\theta \right\} \quad (\text{A.6})$$

$$+ q_H \left\{ \int_0^{\bar{\theta}_H} u(d_H) d\theta + \int_{\bar{\theta}_H}^1 \lambda_H u(d_1) + (1 - \lambda_H) [\theta u(c_{2H}^G) + (1 - \theta) u(c_{2H}^B)] d\theta \right\}$$

which yields the expression in the text.

We proceed in the same way for the low liquidity demand region L . The behaviour in

⁷Note that in case of no bank run, the weights are equal because of the symmetry of the investment probabilities θ and $1 - \theta$ when integrated between zero and unity. This symmetry vanishes once the lower integration bound is above zero.

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_{1H} , the expected utility from liquidation is $a_{1H}u(d_L^D) + (1 - a_{1H})u(d_L^N)$. 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_{1H} 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 $(1 - a_{1H})$ 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 (5) and yields the expected utility of depositors in region L to be:

$$\begin{aligned}
EU_{1L} = & (1 - q_L) \left\{ \lambda_L u(d_1) + (1 - \lambda_L) \int_0^1 [\theta (a_H u(c_{2L}^{GD}) + (1 - a_H)u(c_{2L}^{GN})) \right. \\
& \left. + (1 - \theta) (a_H u(c_{2L}^{BD}) + (1 - a_H)u(c_{2L}^{BN}))] d\theta \right\} \\
& + q_L \left\{ \int_0^{\bar{\theta}_{1L}} (a_H u(d_L^D) + (1 - a_H)u(d_L^N)) d\theta \right. \\
& + \int_{\bar{\theta}_{1L}}^1 \lambda_L u(d_1) + (1 - \lambda_L) [\theta (a_H u(c_{2L}^{GD}) + (1 - a_H)u(c_{2L}^{GN})) \\
& \left. + (1 - \theta) (a_H u(c_{2L}^{BD}) + (1 - a_H)u(c_{2L}^{BN}))] d\theta \right\}
\end{aligned} \tag{A.7}$$

which yields the expression in the text.

Proof of Proposition 1. Similar to Dasgupta (2004) there is a region of fundamentals $[\bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D]$ for which the bank in region L defaults if and only if the the bank in region H defaults. A systemic crisis still occurs only if both regions receive an informative signal, which happens with probability $q_H q_L$ (Again, $\bar{\theta}_{2L}^D < \frac{1}{2}$). The information spillover from H to L induces failure in region L for a larger range of fundamentals ($\bar{\theta}_{2L}^D > \bar{\theta}_{1L}$). Again, there are no bank runs in the absence of information about the own region. With the definition of systemic risk in Equation (14) this proves (1).

Appendix A.4. 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:

$$EU_{CE} \equiv \frac{1 - q_A + 1 - q_B}{2} \int_0^1 \Gamma d\theta + \frac{q_A + q_B}{2} \int_0^{\bar{\theta}} u(d_\beta) d\theta + \frac{q_A + q_B}{2} \int_{\bar{\theta}}^1 \Gamma d\theta \quad (\text{A.8})$$

$$\begin{aligned} &\equiv \frac{q_A + q_B}{2} \left[\bar{\theta} u(d_\beta) + (1 - \bar{\theta}) \left(\lambda u(d_1) + (1 - \lambda) \frac{1}{2} [u(c_2^G) + u(d_\beta)] \right) \right] \\ &\quad + \frac{1 - q_A + 1 - q_B}{2} [\lambda u(d_1) + (1 - \lambda) \frac{1}{2} (u(c_2^G) + u(c_2^B))] \end{aligned} \quad (\text{A.9})$$

Appendix B. Tables

Section (Appendix 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 (Appendix B.2) contains the results of Section (4) of the main text.

Appendix B.1. Extreme parameter value benchmarks

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

Table B.2: Extreme 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: $\beta = 0.3$, $R = 5.0$, $\phi = 1.0$, $\lambda = 0.5$, $\eta = 0.25$, $\rho = 1.1$, $q_H = 0.7$.

Appendix B.2. Results

	cr	cr + ic	ce	ce + ic
	(EU, d_1^*, y^*, b^*) $(\bar{\theta}_H, \bar{\theta}_{1L}, A_{cr})$	(EU, d_1^*, y^*, b^*) $(\bar{\theta}_H, \bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D, A_{cr+ic})$	(EU, d_1^*, y^*, b^*) $(\bar{\theta}, A_{ce})$	(EU, d_1^*, y^*, b^*) $(\bar{\theta}, A_{ce+ic})$
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 B.3: Equilibrium allocation for different forms of financial fragility for calibration $\beta=0.7$, $R=5.0$, $\phi=1.0$, $\lambda=0.5$, $\eta=0.25$, $\rho=1.0$, $q_H=0.7$. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds $(\bar{\theta}_H, \bar{\theta}_{1,L}, \bar{\theta}_{2,L}^N, \bar{\theta}_{2,L}^D, \bar{\theta})$, and systemic financial fragility ($A_{cr}, A_{cr+ic}, A_{ce}, A_{ce+ic}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{1L}, A_{cr}$)	cr + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D, A_{cr+ic}$)	ce (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce}$)	ce + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce+ic}$)
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 B.4: Equilibrium allocation for different forms of financial fragility for calibration $\beta=0.9$, $R=5.0$, $\phi=1.0$, $\lambda=0.5$, $\eta=0.25$, $\rho=1.0$, $q_H=0.7$. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\bar{\theta}_H, \bar{\theta}_{1,L}, \bar{\theta}_{2,L}^N, \bar{\theta}_{2,L}^D, \bar{\theta}$), and systemic financial fragility ($A_{cr}, A_{cr+ic}, A_{ce}, A_{ce+ic}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{1L}, A_{cr}$)	cr + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D, A_{cr+ic}$)	ce (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce}$)	ce + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce+ic}$)
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 B.5: Equilibrium allocation for different forms of financial fragility for calibration $\beta=0.7$, $R=10.0$, $\phi=1.0$, $\lambda=0.5$, $\eta=0.25$, $\rho=1.0$, $q_H=0.7$. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\bar{\theta}_H, \bar{\theta}_{1,L}, \bar{\theta}_{2,L}^N, \bar{\theta}_{2,L}^D, \bar{\theta}$), and systemic financial fragility ($A_{cr}, A_{cr+ic}, A_{ce}, A_{ce+ic}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{1L}, A_{cr}$)	cr + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D, A_{cr+ic}$)	ce (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce}$)	ce + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce+ic}$)
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 B.6: Equilibrium allocation for different forms of financial fragility for calibration $\beta=0.7$, $R=5.0$, $\phi=1.0$, $\lambda=0.3$, $\eta=0.25$, $\rho=1.0$, $q_H=0.7$. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\bar{\theta}_H, \bar{\theta}_{1L}, \bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D, \bar{\theta}$), and systemic financial fragility ($A_{cr}, A_{cr+ic}, A_{ce}, A_{ce+ic}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

	cr (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{1L}, A_{cr}$)	cr + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}_H, \bar{\theta}_{2L}^N, \bar{\theta}_{2L}^D, A_{cr+ic}$)	ce (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce}$)	ce + ic (EU, d_1^*, y^*, b^*) ($\bar{\theta}, A_{ce+ic}$)
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 B.7: Equilibrium allocation for different forms of financial fragility for calibration $\beta=0.7$, $R=5.0$, $\phi=1.0$, $\lambda=0.5$, $\eta=0.25$, $\rho=1.0$, $q_H=0.4$. Expected utility (EU), portfolio choice variables (d_1, y, b), withdrawal thresholds ($\bar{\theta}_H, \bar{\theta}_{1,L}, \bar{\theta}_{2,L}^N, \bar{\theta}_{2,L}^D, \bar{\theta}$), and systemic financial fragility ($A_{cr}, A_{cr+ic}, A_{ce}, A_{ce+ic}$) in the different model variants (cr: counterparty risk, ic: information contagion, ce: common exposure).

Appendix C. Details for robustness checks (Online Appendix)

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.

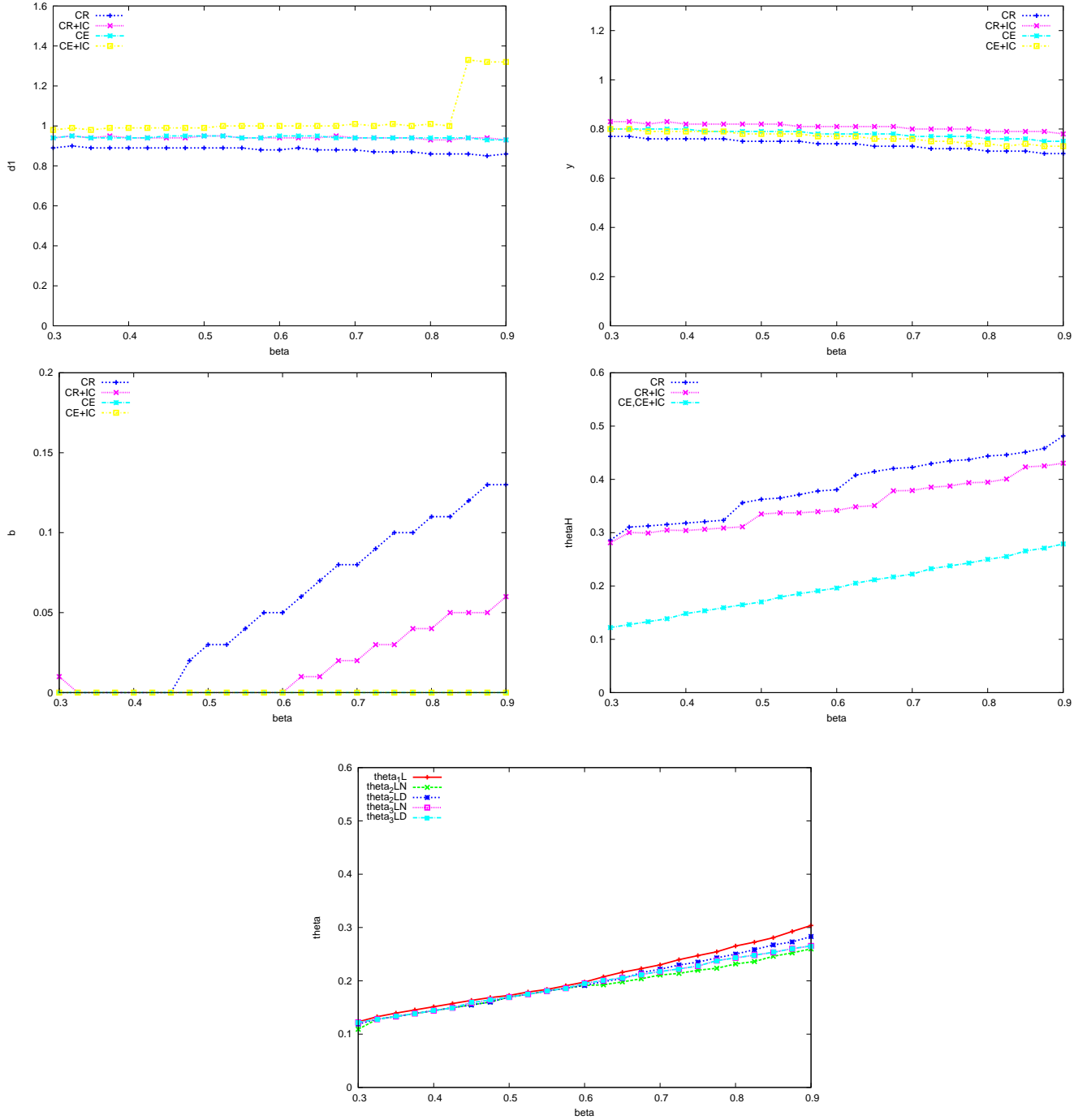


Figure C.3: Details of portfolio choice: d_1 , y (top), b and θ_H (middle), and various θ_L values for a variation of β . The baseline calibration is used for the non-varying parameters.

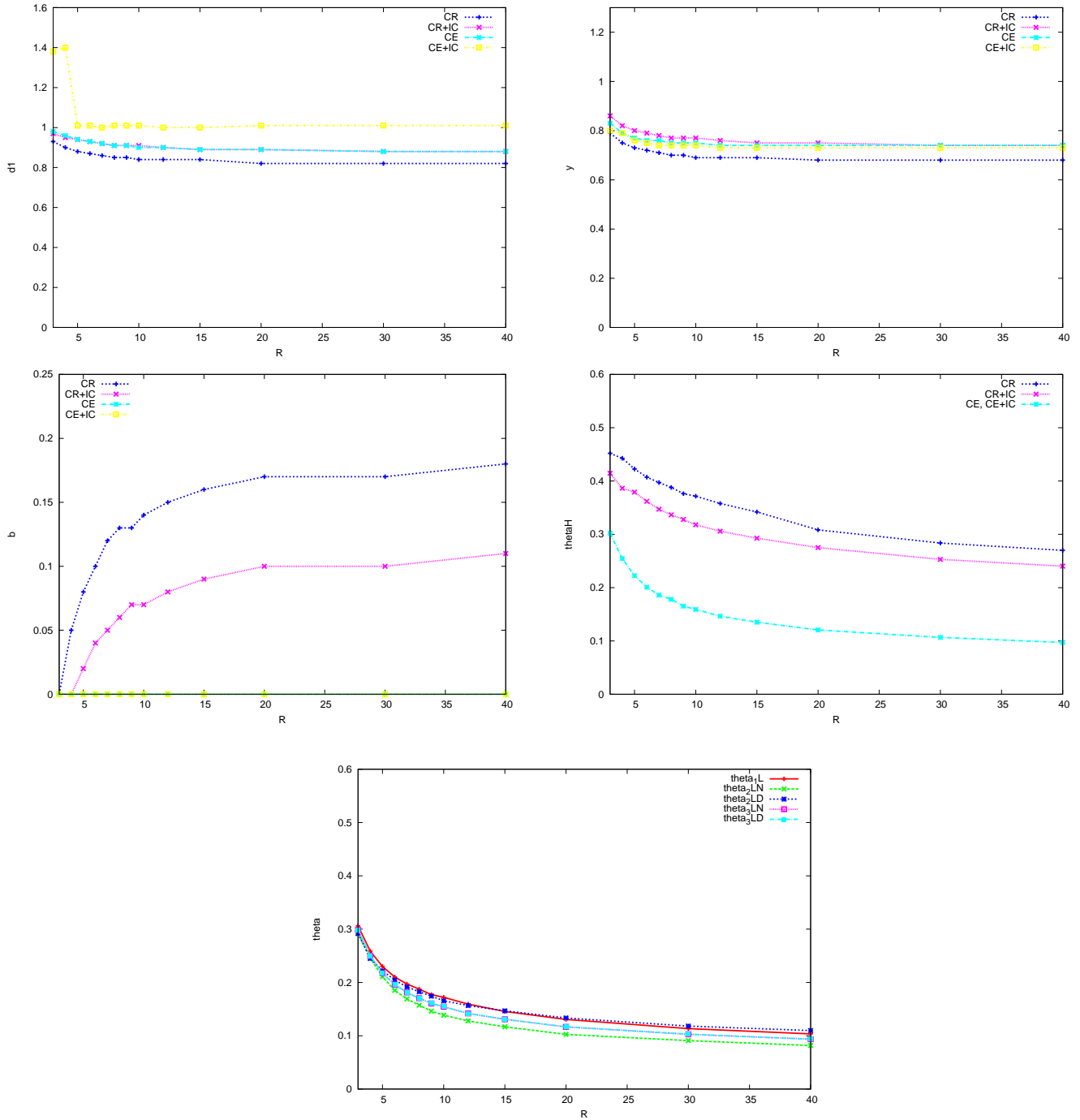


Figure C.4: Details of portfolio choice: d_1 , y (top), b and θ_H (middle), and various θ_L values for a variation of R . The baseline calibration is used for the non-varying parameters.

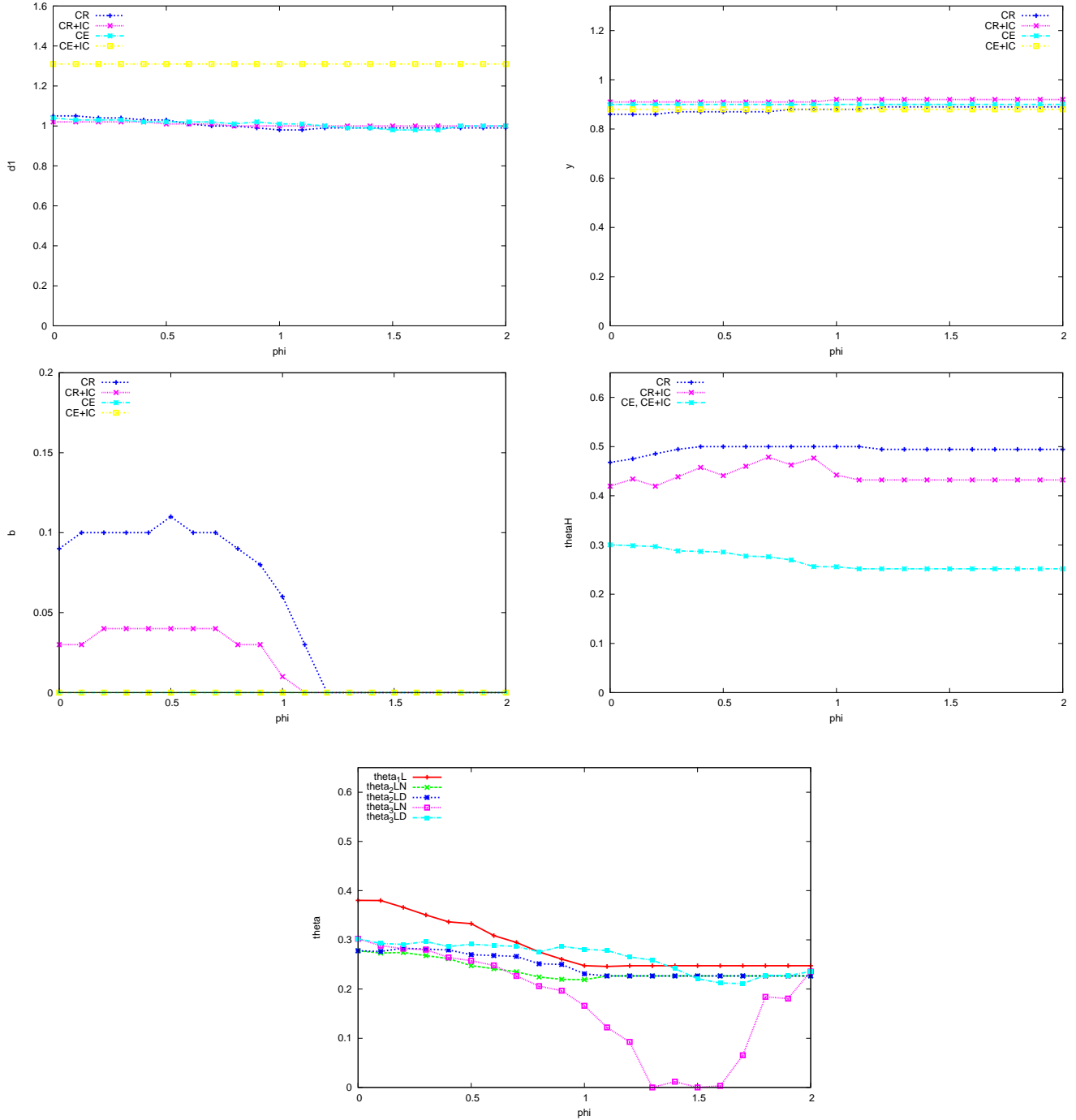


Figure C.5: Details of portfolio choice: d_1 , y (top), b and θ_H (middle), and various θ_L values for a variation of ϕ . The baseline calibration is used for the non-varying parameters.

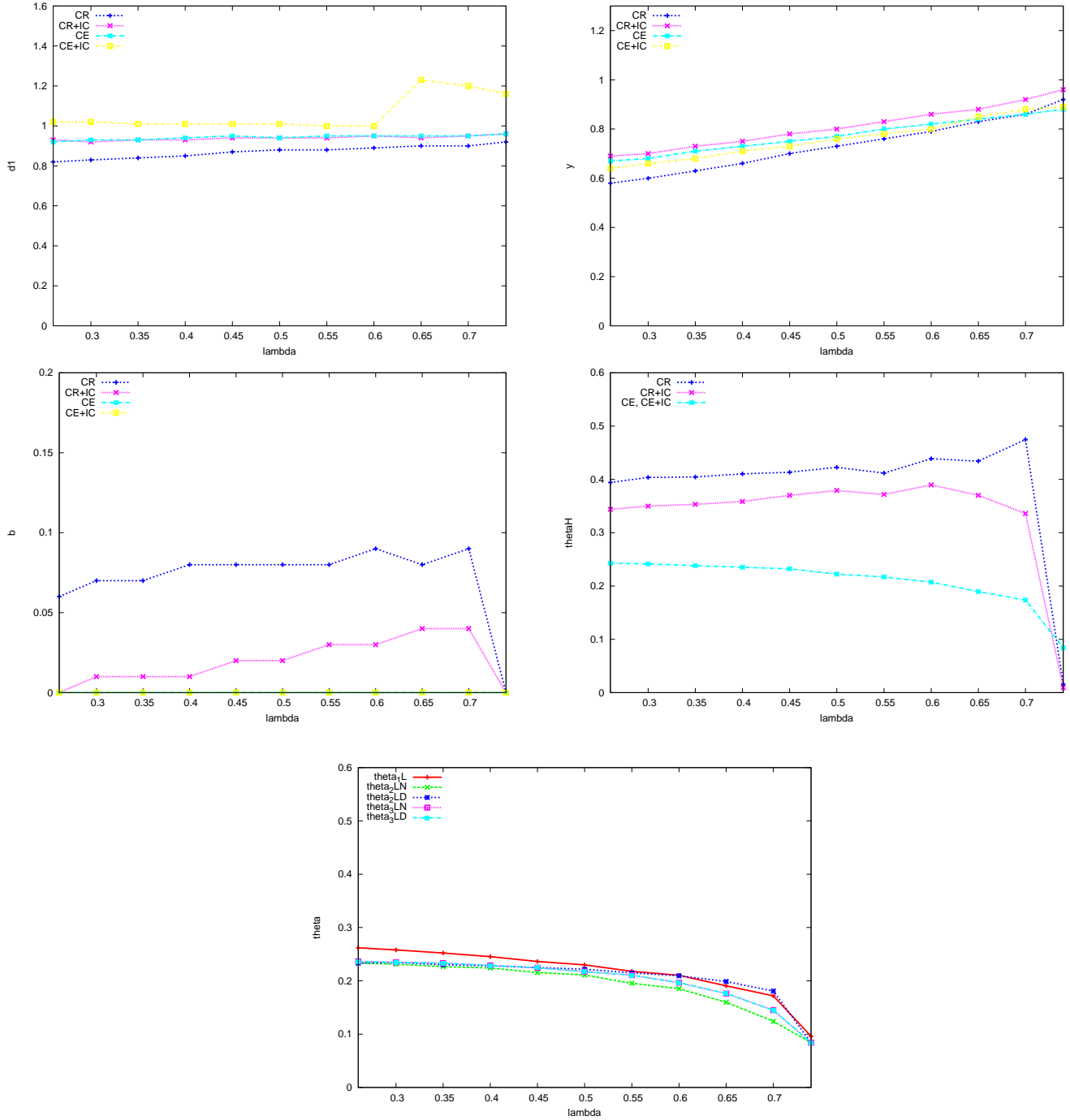


Figure C.6: Details of portfolio choice: d_1 , y (top), b and θ_H (middle), and various θ_L values for a variation of λ . The baseline calibration is used for the non-varying parameters.

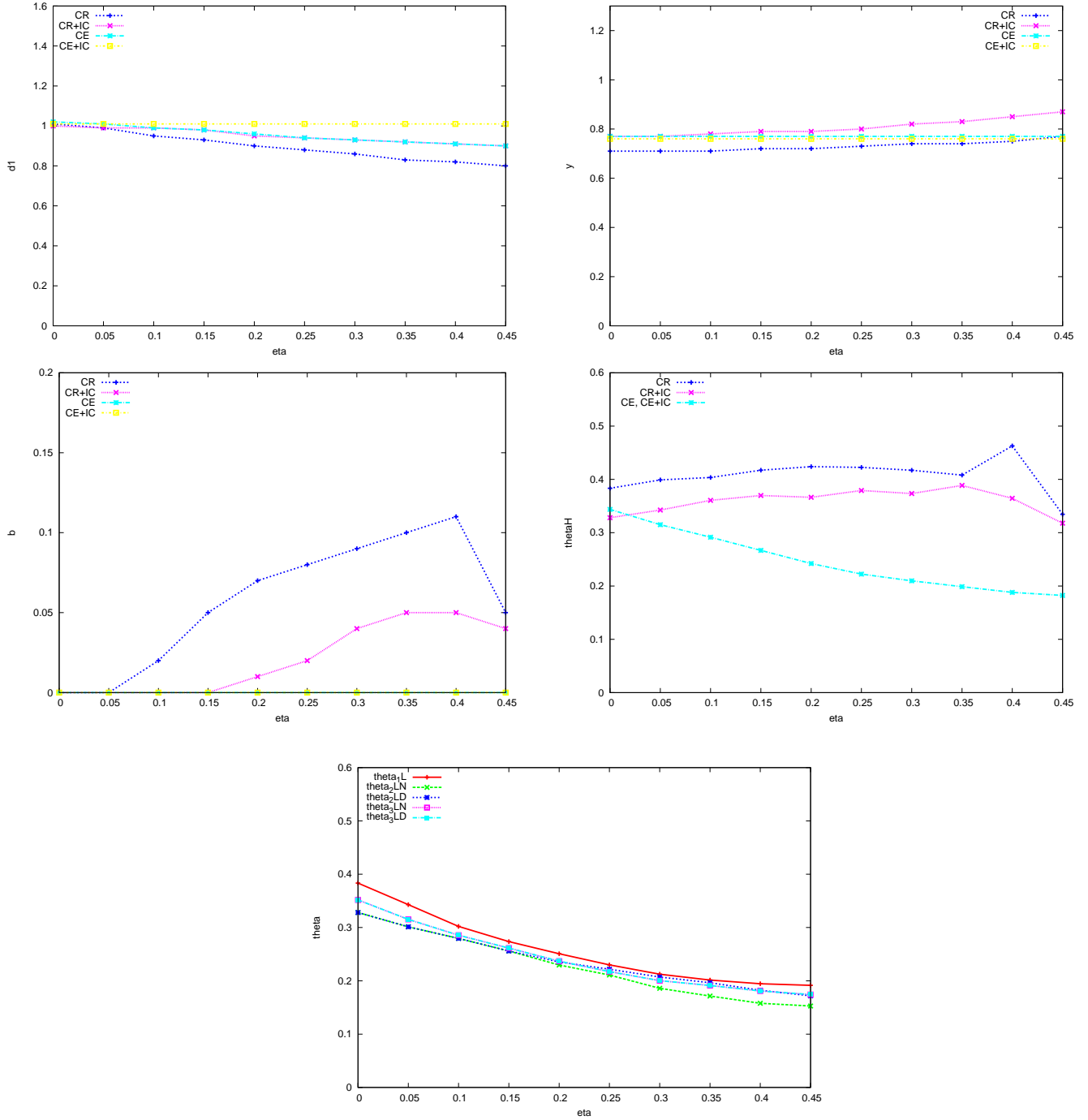


Figure C.7: Details of portfolio choice: d_1 , y (top), b and θ_H (middle), and various θ_L values for a variation of η . The baseline calibration is used for the non-varying parameters.

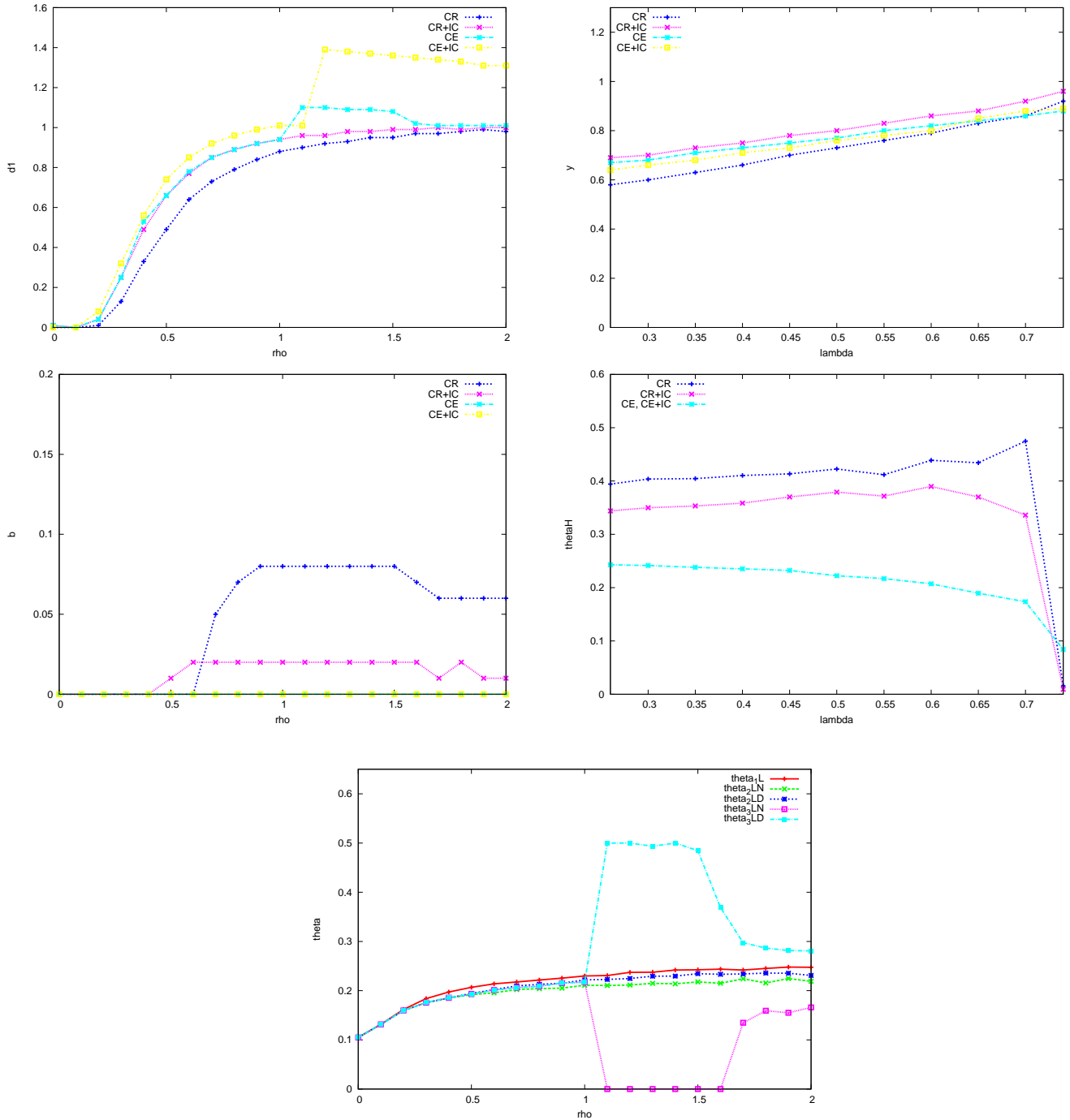


Figure C.8: Details of portfolio choice: d_1 , y (top), b and θ_H (middle), and various θ_L values for a variation of ρ . The baseline calibration is used for the non-varying parameters.

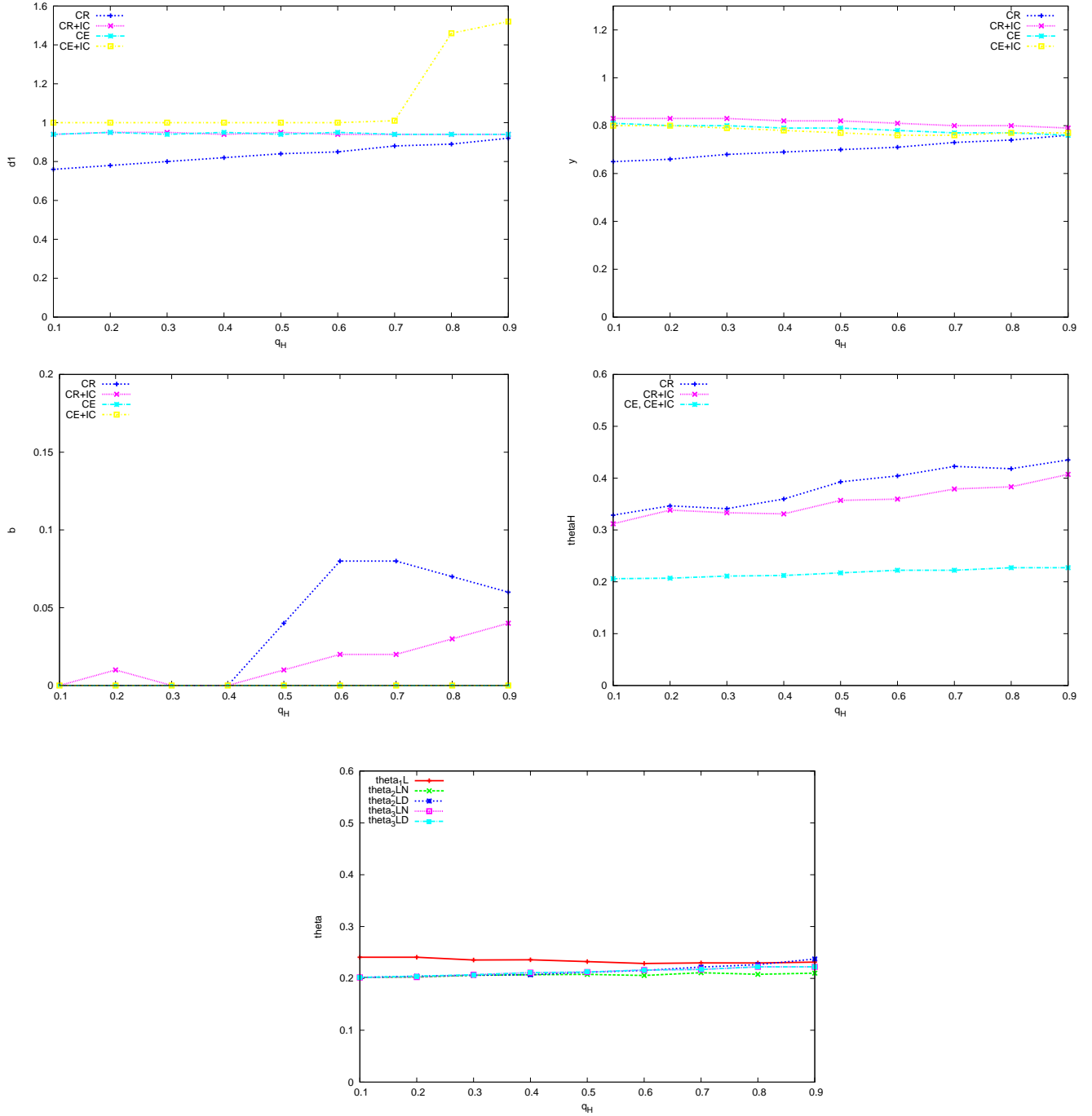


Figure C.9: Details of portfolio choice: d_1 , y (top), b and θ_H (middle), and various θ_L values for a variation of q_H . The baseline calibration is used for the non-varying parameters.

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