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Published in:
Journal of Empirical Finance

DOI:
[10.1016/j.jempfin.2017.09.012](https://doi.org/10.1016/j.jempfin.2017.09.012)

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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2017

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

IJtsma, P., & Spierdijk, L. (2017). Systemic risk with endogenous loss given default. *Journal of Empirical Finance*, 44, 145-157. <https://doi.org/10.1016/j.jempfin.2017.09.012>

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Systemic risk with endogenous loss given default

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ARTICLE INFO

JEL classification:

G01
G21
G33

Keywords:

Financial stability
Systemic risk
Firesales

ABSTRACT

When many financial institutions fail simultaneously, the remaining institutions in the system are unlikely to have sufficient liquidity to acquire all failed institutions. As a result, some assets will have to be liquidated and sold to outsiders at firesale prices, giving rise to a potentially high losses given default (LGDs) for creditors of failed institutions. This study analyzes the consequences of this firesale mechanism for systemic risk. Our findings suggest that systemic risk is likely to be heavily underestimated when the potential for firesales, and thereby the endogenous nature of LGDs, is not taken into account. The magnitude of the negative bias increases with asset return correlations, banks' return variability, the degree of asset specificity of bank loans and the degree of concentration in the banking sector. The analysis suggests that time-varying liquidity requirements are an effective way to reduce the potential for firesales and thereby lower systemic risk.

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1. Introduction

Since the outbreak of the global financial crisis that started with the fall of Lehmann Brothers in September 2008, macroprudential regulation of the financial system has become a major concern to regulators and policymakers. The main objective of macroprudential regulation is to safeguard the stability of the financial system as a whole, in order to prevent the occurrence of a systemic crisis in which many financial institutions fail simultaneously. Such systemic crises tend to be costly because they are associated with high fiscal costs and lead to large output losses due to disruptions in lending to the real economy (Hoggarth et al., 2002; Allen and Carletti, 2013). Consequently, a growing body of economic research analyzes and measures systemic risk.

This study adds to the literature by analyzing how the potential for a firesale during times of distress in the financial system affects systemic risk through the effect of firesales on losses given default (LGDs).¹ Although there are a number of studies in the literature that show how firesales can result from the joint failure of multiple financial institutions (Shleifer and Vishny, 1992; Acharya and Yorulmazer, 2008), their consequences for systemic risk have not yet been analyzed. We analyze these consequences and quantify them using the widely used concept of Expected Shortfall (ES).² Our analysis thereby bridges a gap in the literature that exists between those studies dealing with firesales during periods of systemic distress and those that deal with the measurement of systemic risk.

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¹ A firesale occurs when during a bankruptcy, assets are sold at extremely discounted prices. This is especially likely to happen when the failing firm's sector is in distress (Shleifer and Vishny, 1992; Acharya and Yorulmazer, 2008; James and Kizilaslan, 2014).

² The $\alpha\%$ Expected Shortfall is the average loss of the $\alpha\%$ worst losses. As such, Expected Shortfall is a measure of tail risk.

Following Acharya (2009), we define systemic risk as the risk that creditors of financial institutions incur large losses as a result of the joint failure of multiple institutions due to correlated returns on the asset side of their balance sheets.³ While most studies take LGDs as exogenously given, we show that when there is a potential for firesales, LGDs become endogenous. Our study illustrates that LGDs depend, among other things, on the degree of return correlation across banks' loan portfolios as well as the aggregate liquidity in the financial system, the latter of which is endogenous in our model. Monte Carlo simulations indicate that systemic risk is underestimated when LGDs are assumed to be exogenous. Furthermore, the magnitude of the negative bias increases with an increase in banks' asset return variability, the return correlations of their loan portfolios, the asset-specificity of loans and the degree of concentration in the banking system.

Our findings emphasize the importance of appropriately modeling LGDs associated with joint defaults of multiple financial institutions. Furthermore, they show that liquidity plays an important role in this respect, and suggest that regulations regarding minimum liquidity ratios for systemically important financial institutions (SIFIs) are an effective way to reduce the potential for firesales and thereby lower systemic risk. More specifically, during 'normal times' SIFIs should be required to hold a certain proportion of their assets in the form of a liquidity buffer, which could be used to purchase the assets of failed institutions during times of systemic distress.

The outline of the remainder of this paper is as follows. Section 2 embeds our study in the existing literature. Firesales and LGDs are modeled in Section 3. The effects of firesales on systemic risk are then analyzed in Section 4. Finally, some concluding thoughts follow in Section 5.

2. Overview of the literature

This section summarizes the literature on systemic risk and elaborates on the literature dealing with firesales and LGDs. Finally, we position our study in these two strands of the literature.

2.1. Systemic risk

The literature on systemic risk can largely be categorized into two strands. The first strand mainly deals with the possibility of contagious defaults, which occur when the failure of an individual financial institutions spreads as a contagion through the financial system, causing other institutions to fail as well. These studies generally focus on direct interlinkages between financial institutions (i.e. interbank loans), using network models and simulations to assess the vulnerability of a particular system to contagious defaults. Some studies that use this approach are Furfine (2003), Upper and Worms (2004), Müller (2006), Hałaj and Kok (2013) and Peralta and Zareei (2016). For an overview of this strand of the literature, see Upper (2011). The second strand of the literature – to which the current study contributes in particular – analyzes how systemic risk arises as a result of correlations in institutions' asset portfolios.⁴ The rationale for this approach is that simultaneous defaults might occur even in the absence of direct connections between financial institutions if their asset portfolios are very similar. When asset portfolios are similar, different institutions are likely to incur large losses at the same time. As a result, failures are likely to be correlated. Since bank-specific risk measures do not take such indirect linkages into account, a number of new measures related to systemic risk have been developed, which we discuss below.

Early contributions by Lehar (2005) and Kuritzkes et al. (2005) define systemic risk as the risk that a (hypothetical) deposit insurer, which has insured the liabilities of all financial institutions in the system, incurs significant losses. In this framework, the liability of the deposit insurer can be interpreted as a portfolio of short put options on correlated assets, so that the Merton (1974) model can be applied to obtain an estimate of systemic risk. Adrian and Brunnermeier (2016) propose a measure (called CoVaR) to capture the contribution of individual institutions to systemic risk. Their measure is calculated as the Value-at-Risk (VaR) of the financial system as a whole conditional on a particular financial institution being in distress. Acharya et al. (2017) introduce a measure that is conceptually quite similar to CoVaR. Their Systemic Expected Shortfall (SES) refers to the propensity of a financial institution to be undercapitalized when the system as a whole is undercapitalized. Again, by conditioning on a systemic event, SES measures the *contribution* of a particular bank to systemic risk rather than systemic risk itself. This also holds for the SRISK measure developed by Brownlees and Engle (2016). Huang et al. (2009, 2012) construct a so-called Risk Insurance Premium, which measures the insurance premium that protects against distressed losses of a hypothetical debt portfolio consisting of the total liabilities of all financial institutions in a system. They estimate this premium by combining information about CDS spreads of individual institutions and asset return correlations across banks. Jobst and Gray (2013) analyze systemic risk by looking at the multivariate distribution of losses associated with the default of different combinations of institutions in a financial system and subsequently derive the distribution of the aggregate loss.

³ Note that *systemic* risk is a concept that is fundamentally different from *systematic* risk, which is the risk of a particular firm that can be explained by the risk of the market as a whole.

⁴ We only summarize the most relevant studies below. For a complete overview of this strand of the literature, please refer to Bisias et al. (2012).

2.2. Firesales and LGDs

In addition to contributing to the systemic risk literature, our analysis is also related to the growing literature on firesales and LGDs in the context of systemic events. This literature took off with an important study by Shleifer and Vishny (1992), who argue that LGDs tend to be higher during episodes of industry-wide distress. Their argument is that industry peers of failed firms are unlikely to be able to purchase liquidated assets during such episodes. As a result, some assets will have to be sold to outsiders, who typically lack the expertise to manage them and are therefore not willing to pay a high price. The resulting fall in liquidation prices, typically referred to as a firesale, increases LGDs. Empirical evidence for this phenomenon is provided by Pulvino (1998), Brown et al. (2006), Acharya et al. (2007) and James and Kizilaslan (2014). Allen and Gale (1994) elaborate on the idea with the concept of *cash-in-the-market pricing*. They show that if participation in a market is limited, the liquidity of market participants plays an important role in determining equilibrium prices because their aggregate liquidity (the cash in the market) may put an upper limit on the equilibrium price. These ideas are combined by Acharya and Yorulmazer (2008), who formally derive the equilibrium price of liquidated assets following bank failures in a system with n equally sized banks and outsiders. They show that when the number of failures is above a certain threshold, the equilibrium price is determined by the available cash in the market (i.e. the aggregate liquidity of surviving banks and outsiders), so that LGDs increase with the number of bank failures.

2.3. Position of our study in the existing literature

Firesales and their consequences for systemic risk have been analyzed previously by a number of other studies, such as Cifuentes et al. (2005) and Brunnermeier and Pedersen (2009). However, the channel through which this effect takes place is entirely different from our analysis. While those studies analyze potential contagion effects of firesales in a situation in which banks' assets are marked-to-market, we focus on the effect of firesales on LGDs and rule out contagion effects. Hence, our study adds to this strand of the literature by highlighting a different channel through which firesales affect systemic risk. Our analysis is also related to Huang et al. (2009, 2012) and Jobst and Gray (2013). The difference between Huang et al. (2009, 2012) and our approach is that we explicitly model LGDs, whereas they make an assumption about LGDs and then derive default probabilities (PDs) from CDS spreads. We believe that their approach is somewhat problematic, because if the assumed LGDs are inaccurate, the implied PDs will be inaccurate as well. The main difference between our approach and that of Jobst and Gray (2013) is that we explicitly model LGDs, whereas they take LGDs as exogenously given. Finally, the way in which we model the optimal liquidity holdings of banks resembles the approach of Wagner (2011). However, whereas Wagner (2011) studies the portfolio choice decision of investors in a setting with two risky assets and a liquid asset, we take the composition of banks' portfolio of risky assets as given and analyze loss given default and systemic risk in a setting where banks choose their optimal holdings of liquidity.

3. Modeling firesales and LGDs

In this section, we model firesales and derive the LGDs associated with them. Our approach generalizes the model of Acharya and Yorulmazer (2008) by allowing for an arbitrary bank size distribution and endogenizing the aggregate liquidity in the system. Furthermore, while they model the liquidation procedure as a common-value share auction, we let the seller of the assets simply set a price and derive the demand for the assets for any given price. Modeling the liquidation procedure as an auction is problematic, as shown by Wilson (1979). The equilibrium price in such auctions is much lower than suggested by Acharya and Yorulmazer (2008), since the bidders have an incentive to understate their demand for the assets.

The model consists of one period with financial institutions (banks), outsiders (e.g. foreign banks, pension funds, governments, etc.) and a regulator, all of which are risk neutral. Banks are financed with insured deposits and equity and invest in a combination of risk-free liquid assets (liquidity) and risky illiquid assets (loans) at the beginning of the period.⁵ They fail if they are insolvent at the end of the period, which happens when the fundamental (book) value of their assets falls below the value of their liabilities.⁶ More specifically, bank i fails when:

$$d_i > \ell_i + a_i(1 + R_i) - \alpha_i d_i, \quad (1)$$

where d_i refers to the deposits of bank i , while ℓ_i and a_i are the bank's liquidity and loans, respectively. Furthermore, $R_i \sim N(\mu_i, \sigma_i)$ is the bank's return on loans, which is the source of uncertainty in the model, and α_i is the bank's deposit insurance premium. Rewriting Eq. (1) gives the critical return on loans (c_i) below which the bank fails:

$$c_i = \frac{d_i(1 + \alpha_i) - \ell_i}{a_i} - 1 = \frac{d_i^*}{a_i} - 1, \quad (2)$$

where $d_i^* = d_i(1 + \alpha_i) - \ell_i$ refers to the bank's liabilities net of its liquidity. When a bank fails, the regulator, who has insured the deposits, takes over the bank's loan portfolio and liquidates the loans by selling them to the surviving banks and/or outsiders. Surviving banks attach a relatively high value of $\bar{p}$ per unit to the loans ($0 < \bar{p} \leq 1$), but have limited liquidity. Outsiders have unlimited aggregate

⁵ The investment in liquidity can be interpreted as the purchase of Treasury securities with a risk-free rate that is normalized to zero. This investment can generate a positive return, however, in the case of a firesale at the end of the period, when it can be used to purchase liquidated loans at discounted prices.

⁶ The model could alternatively be interpreted as a two-period model, where banks choose their asset portfolio in period 0, and returns are realized in period 1

liquidity, but are inefficient at managing loans and therefore value liquidated them at a lower value of $\underline{p}$ per unit.⁷ This notion captures the idea that bank loans are asset-specific, in the sense that they cannot easily be managed by outsiders. The parameter $\underline{p}$ measures the degree of loans' asset-specificity, with a lower value corresponding to a higher degree of asset-specificity. Shleifer and Vishny (1992) provide a theoretical justification for this approach, while James (1991) shows that losses given default are significantly higher when failing banks are not acquired by surviving banks. The regulator knows the aggregate amount of liquidity held by surviving banks and its objective is to minimize its loss by maximizing the proceedings from the liquidation. The liquidation procedure is as follows: First, the regulator announces the liquidation price. Then, the surviving banks and outsiders indicate the quantity of loans they wish to purchase. Finally, the regulator distributes the loans over the surviving banks and outsiders. The problem for the regulator is thus to set the price in such a way as to maximize the proceedings from the liquidation. To find this optimal price, we first derive the demand schedule for the loans.

Demand.

The surviving banks maximize profits, taking the liquidation price and their holdings of liquidity (which is chosen at the beginning of the period) as given. Since they value the assets at $\bar{p}$ per unit, they want to purchase as many loans as possible when the liquidation price is below $\bar{p}$, and will not purchase any loans when it is above $\bar{p}$.⁸ It follows that their aggregate demand for liquidated loans can be expressed as:

$$q_b = \begin{cases} \frac{\ell_S}{\bar{p}} & \text{if } 0 < p \leq \bar{p} \\ 0 & \text{if } p > \bar{p}, \end{cases} \quad (3)$$

where q_b is the surviving banks' aggregate demand and ℓ_S is the aggregate liquidity of the surviving banks. A similar reasoning holds for outsiders. Hence, their demand can be expressed as:

$$q_o = \begin{cases} \frac{w}{\underline{p}} & \text{if } 0 < p \leq \underline{p} \\ 0 & \text{if } p > \underline{p}, \end{cases} \quad (4)$$

where q_o is the outsiders' aggregate demand and w is the aggregate liquidity held by outsiders. As mentioned above, we assume that outsiders have unlimited aggregate liquidity. Hence, their demand is unlimited whenever $p \leq \underline{p}$, and 0 otherwise.

The regulator.

The regulator determines the liquidation price, taking the amount of loans to be liquidated and the demand curve of surviving banks and outsiders as given. Its maximization problem can be formulated as:

$$\begin{aligned} \max_p \quad & \pi = p(q_b + q_o) \\ \text{s.t.} \quad & q_b \leq \frac{\ell_S}{\bar{p}} \\ & (p - \bar{p})q_b \leq 0 \\ & (p - \underline{p})q_o \leq 0 \\ & q_b + q_o \leq q, \end{aligned} \quad (5)$$

where π refers to the revenues of the liquidation procedure, q_b is the quantity of loans sold to surviving banks, q_o is the quantity of loans sold to outsiders and q is the quantity of loans to be liquidated. The optimal price is⁹:

$$p^* = \begin{cases} \bar{p} & \text{if } q \leq \frac{\ell_S}{\bar{p}} \\ \frac{\ell_S}{q} & \text{if } \frac{\ell_S}{\bar{p}} < q \leq \frac{\ell_S}{\underline{p}} \\ \underline{p} & \text{if } q > \frac{\ell_S}{\underline{p}}. \end{cases} \quad (6)$$

Hence, as long as the quantity of loans to be liquidated is below some threshold, they can be liquidated for the high price $\bar{p}$. Whenever it is larger than this threshold, however, a firesale occurs in the sense that the loans will have to be sold for a price below the value that surviving banks attach to them. The liquidation price will continue to fall with an increase in the amount of loans to be liquidated until

⁷ We assume that the aggregate liquidity of outsiders is unlimited in order to simplify the model. The results of our analysis do not hinge on this assumption.

⁸ We assume that banks can use all of their liquidity to purchase liquidity. In practice, banks are constrained in their use of liquidity through liquidity requirements. Hence, the liquidity that we refer to here could be interpreted as banks' *excess liquidity*, i.e. liquidity in excess of the requirement. Note also that it could be argued that, in practice, banks are able to borrow from the central bank to obtain additional liquidity with which to purchase assets. However, this requires an additional assumption that banks have excess capital, i.e. capital in excess of the capital requirement, since borrowing from the central bank will increase leverage. We abstract from this possibility in this study.

⁹ This is actually one of many solutions, but they all give the same revenue, which is what we are ultimately interested in. A proof is given in Section A.1.

it equals p , after which a further increase does not affect the price because liquidity-abundant outsiders participate in the liquidation procedure from then on. As such, the proceedings from the liquidation are:

$$\pi^* = \begin{cases} \bar{p}q & \text{if } q \leq \frac{\ell_S}{\bar{p}} \\ \ell_S & \text{if } \frac{\ell_S}{\bar{p}} < q < \frac{\ell_S}{\underline{p}} \\ \underline{p}q & \text{if } q > \frac{\ell_S}{\underline{p}}. \end{cases} \quad (7)$$

The loss given default, which is defined as the loss of the regulator, equals the difference between the liabilities of failed banks net of their liquidity and the proceedings from the liquidation. It can be expressed as:

$$S = \begin{cases} d_F^* - \bar{p}q & \text{if } q \leq \frac{\ell_S}{\bar{p}} \\ d_F^* - \ell_S & \text{if } \frac{\ell_S}{\bar{p}} < q \leq \frac{\ell_S}{\underline{p}} \\ d_F^* - \underline{p}q & \text{if } q > \frac{\ell_S}{\underline{p}}, \end{cases} \quad (8)$$

where S is the (systemic) loss given default and $d_F^* = \sum_{i \in F} [d_i(1 + \alpha_i) - \ell_i]$, where F is the set of failed banks. Note that if $\underline{p} = \bar{p}$ (i.e. bank loans are not asset-specific), the loss is always equal to $d_F^* - \bar{p}q$, which implies that there is no firesale mechanism, prices are deterministic, and loss given default is exogenous. Hence, exogenous LGDs follow from a special case of the model.¹⁰

Deposit insurance premium.

The deposit insurer charges a risk-based deposit insurance premium, according to the following pricing rule:

$$\alpha_i = \beta \omega_i, \quad (9)$$

where ω_i is the bank's loan-to-assets ratio. It follows that the bank's deposit insurance premium increases linearly in its loans-to-assets ratio and that the bank only pays a premium when it holds a strictly positive amount of loans. This is reasonable, since a bank which holds only liquidity has a zero failure probability and therefore a zero probability of generating losses for the deposit insurer. In the spirit of Acharya et al. (2010), we additionally assume that deposit insurance premia are actuarially fair in the aggregate, so that the deposit insurer's revenues are equal to the expected systemic loss. This gives the following equilibrium condition:

$$E(S) = \beta \sum_{i=1}^n \omega_i d_i \quad (10)$$

When Eq. (10) is satisfied, the regulator's income from insurance premia is exactly sufficient to cover its expected loss, so that it breaks even in expectation.¹¹

Optimal liquidity.

Given the auction procedure described above, banks determine their optimal holdings of liquidity at the beginning of the period. Since banks are risk neutral, they maximize their ex-ante expected return on overall assets. This return is a weighted average of the bank's expected return on loans and expected return on liquidity. We can thus write the bank's expected return on overall assets as¹²:

$$E(ROA_i) = \omega_i E(R_i) + (1 - \omega_i) E[\bar{p} - p^*(\omega_i) | R_i > c_i(\omega_i)] - \alpha_i(\omega_i)(1 - k_i), \quad (11)$$

where ROA_i is the bank's return on overall assets and k_i is its capital ratio. The equilibrium price depends on the aggregate liquidity in the banking sector and therefore on the bank's asset composition. Taking the derivative of Eq. (11) with respect to ω_i and substituting the pricing rule of the deposit insurer gives the bank's equilibrium condition for determining its optimal amount of liquidity¹³:

$$E(R_i) - \beta(1 - k_i) = \frac{\partial}{\partial \omega_i} \left((1 - \omega_i) E[\bar{p} - p^*(\omega_i) | R_i > c_i(\omega_i)] \right) \quad (12)$$

The left-hand side of Eq. (12) is the expected marginal net return on loans after taking into account the costs of deposit insurance. The right-hand side is the expected marginal return on liquidity, which depends on the expected equilibrium price of liquidated assets

¹⁰ We have also derived the equilibrium under the assumption that the regulator is able to price discriminate between surviving banks and outsiders. This affects the results in a quantitative sense, but not the mechanism illustrated here. Proofs are available upon request.

¹¹ As long as the loans of failed banks are liquidated by one agent, an alternative interpretation of our model is a situation in which banks borrow from (uninsured) creditors rather than insured depositors. In this case, the deposit insurance premium would be replaced by a premium paid to creditors, which is charged to cover their expected losses. This case might be relevant in the context of e.g. shadow banking. We thank an anonymous referee for pointing this out.

¹² See Section A.2 in the mathematical appendix for a derivation.

¹³ Note that there are also two corner solutions, where banks choose to invest only in loans or liquidity, respectively. See Section A.2 in the mathematical appendix for details.

Table 1
Overview of the most important variables of the model.

Endogenous variables	Exogenous variables
Liquidity ratio (ω)	Return on loans (R)
Liquidation price (p^*)	Debt-to-assets ratio ($\frac{d}{a+\ell}$)
Deposit insurance premium (α)	Insider price ($\bar{p}$)
Systemic loss (S)	Outsider price ($\underline{p}$)

conditional on the bank's survival. An increase in a bank's liquidity affects its return on liquidity in two ways. First, it ensures that the bank can sustain larger losses before it fails. If the returns on banks' loan portfolios are positively correlated, this implies that there is a higher probability that the bank survives when there is a firesale. As a result, the expected equilibrium price of liquidated loans conditional on the bank's survival will fall, thereby increasing the bank's return on liquidity. Second, an increase in a bank's liquidity increases the aggregate pool of liquidity in the system, thereby increasing the expected equilibrium price of liquidated loans and decreasing the expected return on liquidity. This effect is mostly relevant for large banks, of which the liquidity constitutes a large portion of aggregate liquidity, and gives large banks an incentive to choose a strategically low amount of liquidity in an attempt to lower the expected equilibrium price of liquidated loans.

To conclude this section, Table 1 gives an overview of the most important variables included in the model, distinguishing between variables of which the value is endogenously determined by the model and those that are taken as exogenously given.

4. Modeling systemic risk

This section assesses the consequences of the above-mentioned firesale mechanism for systemic risk. Our conceptualization of systemic risk is similar to Lehar (2005) and Kuritzkes et al. (2005), but we adopt a more realistic framework. While the latter studies assume that banks' assets can always be liquidated for their fundamental value, we explicitly model the equilibrium price for which bank loans are liquidated. Our approach is more realistic, since it is unlikely that the demand for the loans of failed institutions is sufficiently high to liquidate them for their fundamental value during episodes of system-wide distress.

We interpret systemic risk as the risk that the regulator incurs large losses and refer to the loss of the regulator as the *systemic loss* in the remainder of this section. We use simulations to get a sense of the quantitative effects of firesales. In our simulations, we explicitly calculate the banks' liquidity-to-assets ratios (liquidity ratios), thereby recognizing that it is an endogenous variable. We also demonstrate how systemic risk is affected by changes in (i) the degree of asset-specificity of bank loans, (ii) the return correlation across banks' loan portfolios, (iii) banks' failure probabilities, and (iv) the degree of market concentration in the banking sector.

4.1. Analytical illustration

For the sake of exposition, we first derive the probability distribution function of the systemic loss in a system with two banks and show analytically how the distribution is affected by the potential occurrence of firesales. Note that in this illustration, we take the aggregate liquidity in the system as given even though it is endogenous in the model. The reason for this is that we do not have a closed-form expression of equilibrium aggregate liquidity. We believe that an analytical approach in a two-bank setting is nevertheless useful because it highlights the mechanism through which firesales affect systemic risk.

When the banking system consists of two banks, the systemic loss can be expressed as a function of their (random) returns, which we denote $S(R_x, R_y)$. When both banks fail, the banks' loans are necessarily purchased by outsiders, so that the liquidation price equals $\underline{p}$. Furthermore, when neither bank fails, the loss is equal to 0. Finally, when one of the two banks fails, the liquidation price is given by Eq. (6). Combining these cases gives the expression stated below in Eq. (13).¹⁴ Here S is the systemic loss, d_i^* denotes the book value of liabilities (including the deposit insurance premium) of bank i net of its liquidity, while a_i refers to the book value of its loans. Furthermore, $c_i = \frac{d_i^*}{a_i} - 1$ denotes the critical return of bank i below which it fails, so that the systemic loss is zero when the return of both banks is above c_i , while it is equal to the expression in the first line when the return is below c_i for both banks. In addition, $\tau_x = \frac{\ell_y}{\bar{p}a_x} - 1$ is the critical return of bank x below which bank y , if y survives, has sufficient liquidity to purchase the loans of x for the high price (and vice versa for τ_y). If the return of the failed bank is below this critical value, the liquidation price is equal to $\bar{p}$, which implies a loss equal to the second or third line of Eq. (13). In the same spirit, $\eta_x = \frac{\ell_y}{\bar{p}a_x} - 1$ is the critical return of x above which the regulator maximizes its revenues by setting the price equal to $\underline{p}$ when x fails and y survives (and vice versa for η_y). If the return of the failed bank is above this critical value, the liquidation price will be $\underline{p}$, which implies a loss equal to line 6 or 7 of Eq. (13). Finally, when the return of the failed bank is between the critical values τ_i and η_i , the regulator charges the price in such a way that the surviving bank has exactly sufficient liquidity to purchase the assets of the failed bank, which implies a systemic loss equal

¹⁴ A formal proof is given in Section A.3.

Fig. 1. Systemic loss distribution of a system with two equally sized banks. Notes: This figure presents the probability distribution of the systemic loss of a system with two banks of equal size. The pdf is conditional on the systemic loss being strictly positive. The loss is measured relative to the size of the banking system in terms of assets. The banks' returns are assumed to be multivariate normally distributed with a mean of 0.01, a standard deviation of 0.0172, and a correlation of 0.75. Banks are assumed to have a debt-to-assets ratio of 0.97 and a liquidity ratio of 0.05, and to value each others' assets at their book value.

to the expression in line 4 or 5 of Eq. (13) below:

$$S(R_x, R_y) = \begin{cases} d_x^* + d_y^* & \text{if } R_x < c_x \text{ and } R_y < c_y \\ -\bar{p}[(1 + R_x)a_x + (1 + R_y)a_y] & \text{if } R_x < \min[\tau_x, c_x] \text{ and } R_y \geq c_y \\ d_x^* - \bar{p}(1 + R_x)a_x & \text{if } R_x \geq c_x \text{ and } R_y < \min[\tau_y, c_y] \\ d_y^* - \bar{p}(1 + R_y)a_y & \text{if } \tau_x \leq R_x < \min[\eta_x, c_x] \text{ and } R_y \geq c_y \\ d_x^* - \ell_x a_y & \text{if } R_x \geq c_x \text{ and } \tau_y \leq R_y < \min[\eta_y, c_y] \\ d_x^* - \bar{p}(1 + R_x)a_x & \text{if } \eta_x \leq R_x < c_x \text{ and } R_y \geq c_y \\ d_y^* - \bar{p}(1 + R_y)a_y & \text{if } R_x \geq c_x \text{ and } \eta_y \leq R_y < c_y \\ 0 & \text{if } R_x \geq c_x \text{ and } R_y \geq c_y \end{cases} \quad (13)$$

Note that when $\bar{p} = \bar{p}$, there is no firesale mechanism and the expression collapses to:

$$S(R_x, R_y) = \begin{cases} d_x^* + d_y^* - \bar{p}[(1 + R_x)a_x + (1 + R_y)a_y] & \text{if } R_x < c_x \text{ and } R_y < c_y \\ d_x^* - \bar{p}(1 + R_x)a_x & \text{if } R_x < c_x \text{ and } R_y \geq c_y \\ d_y^* - \bar{p}(1 + R_y)a_y & \text{if } R_x \geq c_x \text{ and } R_y < c_y \\ 0 & \text{if } R_x \geq c_x \text{ and } R_y \geq c_y \end{cases} \quad (14)$$

As an illustration, Fig. 1 gives, for different values of $\bar{p}$, the pdf of the systemic loss conditional on the loss being positive, i.e. $f_S(s|S > 0)$. This picture arises when the banks are of equal size and have multivariate normally distributed returns with means of 0.01, standard deviations of 0.0172, and a correlation of 0.75. Furthermore, they are assumed to have a debt-to-assets ratio of 0.97, a liquidity ratio of 0.05, and to value each others' assets at their book value (i.e. $\bar{p} = 1$).¹⁵ Note that the systemic loss is expressed as a fraction of the size of the banking system in terms of assets.

As illustrated by the solid line in Fig. 1, the loss distribution is described by a relatively steep downward-sloped curve when there is no firesale mechanism (i.e. when $\bar{p} = \bar{p} = 1$). Hence, the probability of observing large losses is negligible in this case. The reason for this is that when the assets can always be liquidated for their fundamental value, large losses only occur as a result of a bank failing by a large margin, which is very unlikely. When outsiders value bank loans lower than banks do, however, the probability of large losses becomes significant. In a system with two equally sized banks with a relatively low liquidity ratio, a failure by one bank will automatically trigger a firesale. This is because the surviving bank will never have sufficient liquidity to purchase the failed bank for the high price. As a result, a large loss will occur even when one of the banks fails by only a slight margin. Consequently, the pdf

¹⁵ These parameters imply a failure probability of approximately 1% for both banks. We choose an expected return on loans of 1%, which is the approximate mean return on assets of a sample of European banks in the period from 1998 to 2014. The debt-to-assets ratio of 0.97 corresponds with the 3% capital requirement of the Basel III framework. Note that we take liquidity as exogenous here even though it is endogenous in the model because we do not have a closed-form solution for aggregate liquidity. Moreover, determining the equilibrium conditions for the optimal amount of liquidity in a two-bank system is not straightforward. We present the pdf thus purely for illustrative purposes. The general expression of the pdf as well as its derivation are given in Section A.3.

Fig. 2. Systemic loss distribution of a system with 50 equally sized banks. Notes: This figure presents Kernel density estimates of the probability distribution of the systemic loss of a system with 50 banks of equal size. The pdf is conditional on the systemic loss being strictly positive. The loss is measured relative to the size of the banking system in terms of assets. Banks have debt-to-assets ratios of 0.97 and expected returns and return standard deviations of 0.01 and 0.0172, respectively, which corresponds with a failure probability of approximately 1%. All bivariate return correlations are 0.25 and banks are assumed to value each other's assets at their book value. The parameter p refers to the ratio between the value that outsiders attach to banking assets and their book value. The kernel density estimates are calculated in Matlab using the *kdensity* command with the bandwidth parameter set to $1/3$.

of the systemic loss consists of two peaks. The first peak is related to the probability that one bank fails, whereas the much smaller second peak is associated with the simultaneous failure of both banks. A decrease in the value of p shifts both peaks to the right, as illustrated by the dotted line in Fig. 1.

4.2. Simulations

How strongly does the above-mentioned firesale mechanism affect systemic risk? To get an idea of the quantitative effect, we use simulations to determine the equilibrium liquidity ratios and deposit insurance premia in a system with 50 banks of equal size, and analyze the associated distribution of the systemic loss. The simulation procedure consists of repeatedly taking a million draws from a 50-dimensional multivariate normal distribution with means of 0.01, standard deviations of 0.0172 and correlations of 0.25 to obtain the distribution of the banks' joint returns, and calculating the systemic loss for each draw. During the procedure, we continuously update the banks' deposit insurance premia and liquidity ratios until the conditions in Eqs. (10) and (12) of Section 3 are simultaneously satisfied. As before, we assume that banks have debt-to-assets ratios of 0.97 and value each other's assets at their book value. We apply numerical differentiation to calculate the right-hand side of Eq. (12).

Fig. 2 gives the kernel density estimates of the pdf of the loss distribution in the equilibrium for various values of p . As can be observed in the figure, the probability of observing large losses is negligible when outsiders value bank loans at their fundamental value. Indeed, the systemic loss is never above 1% of the size of the system in terms of assets in this case. When outsiders value bank loans less than banks do, however, the systemic loss could be substantial under the assumptions given above. More specifically, when outsiders value the loans at 50% or less of their book value, the systemic loss could exceed 10% of the size of the banking system in terms of assets.

Tables 2–4 give the equilibrium deposit insurance premium, equilibrium liquidity ratio and 1% ES of the deposit insurer under various parameter values for the case in which banks have failure probabilities of approximately 0.5%, 1% and 2% respectively, depending on the chosen return variance of the loan portfolio. The results illustrate that the equilibrium deposit insurance premium increases with an increase in the asset-specificity of loans and with an increase in return correlations. The latter finding is in line with Acharya et al. (2010), who argue that actuarially fair deposit insurance premia should increase in joint failure risk. Note, however, that even in the worst case scenario, with high return correlations across banks and a high degree of asset-specificity of banks loans, deposit insurance premia remain relatively low (around 0.3%). Since the premium is proportional to the expected systemic loss, this finding indicates that the *expected* systemic loss is (in absolute terms) hardly affected by the potential for firesales for any reasonable combination of parameters. This finding is not surprising, since in our model the surviving banks ensure that the expected return on liquidity does not exceed the expected return on loans. Banks will thus increase their holdings of liquidity in response to an increase in joint failure risk or in the asset-specificity of loans, since such changes increase the expected return on liquidity. This mechanism can clearly be observed in the above-mentioned tables, where liquidity ratios increase when moving from the northwest to the southeast corner of the tables. Even though the average loss of the deposit insurer is hardly affected by the potential for firesales, the same cannot be said for its tail risk, as measured by the 1% ES. Indeed, we find that tail risk is almost

Table 2

Outcomes for a system with 50 equally sized banks with a failure probability of approximately 0.5%.

Variable	Outsider price \ Return correlation	Low (0.00)	Medium (0.25)	High (0.50)
Deposit insurance premium	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.000	0.001	0.001
	Medium (0.50)	0.000	0.001	0.001
	Low (0.25)	0.000	0.001	0.001
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.019	0.030	0.030
	Medium (0.50)	0.023	0.035	0.047
	Low (0.25)	0.024	0.036	0.053
1% Expected shortfall	Book (1.00)	0.000	0.001	0.001
	High (0.75)	0.011	0.023	0.045
	Medium (0.50)	0.018	0.043	0.084
	Low (0.25)	0.018	0.055	0.113

This table presents our quantitative results when analyzing a banking system consisting of 50 equally sized banks with failure probabilities of approximately 0.5%. *Return correlation* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The expected shortfall is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 3

Outcomes for a system with 50 equally sized banks with a failure probability of approximately 1%.

Variable	Outsider price \ Return correlation	Low (0.00)	Medium (0.25)	High (0.50)
Deposit insurance premium	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.000	0.001	0.001
	Medium (0.50)	0.000	0.001	0.002
	Low (0.25)	0.000	0.001	0.002
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.034	0.048	0.056
	Medium (0.50)	0.035	0.056	0.079
	Low (0.25)	0.035	0.057	0.090
1% Expected shortfall	Book (1.00)	0.001	0.001	0.002
	High (0.75)	0.015	0.034	0.065
	Medium (0.50)	0.025	0.064	0.118
	Low (0.25)	0.026	0.080	0.156

This table presents our quantitative results when analyzing a banking system consisting of 50 equally sized banks with failure probabilities of approximately 1%. *Return correlation* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The expected shortfall is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.0172. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

negligible when assets can always be liquidated for their fundamental value, but that it increases sharply with a decrease in the outsider price and an increase in return correlations of loan portfolios. For example, when banks have a 1% failure probability, return correlations are 0.25 and outsiders are willing to pay 50% of the fundamental value of banks' loans, the 1% ES is 5.6% of the size of the banking system as a whole. In the worst-case scenario, with high failure probabilities, return correlations and asset specificity, the 1% ES is no less than 20% of the size of the system. This contrasts sharply with the case in which loans are always sold for their fundamental value, in which case the 1% ES is smaller than 0.1% of the size of the system. We find this effect for a wide range of parameter values, which suggests that systemic risk is likely to be heavily underestimated when it is assumed that banks' assets can always be sold for their fundamental value.

4.3. The role of concentration

The numerical analysis so far has only dealt with a banking system consisting of a large number banks of equal size, whereas in reality many financial systems are dominated by a few large banks. This fact is relevant in the context of our model, since the probability of a firesale is likely to be an increasing function of the concentration of a banking system. Indeed, when the system is dominated by a few large banks, the failure of a single bank might already constitute a systemic event and lead to a firesale. As such, we would expect the firesale mechanism to have a stronger effect on systemic risk in a more concentrated banking system. We analyze whether this is the case by repeating the simulation procedure for (i) a system with 10 equally sized banks, (ii) a system

Table 4

Outcomes for a system with 50 equally sized banks with a failure probability of approximately 2%.

Variable	Outsider price \ Return correlation	Low (0.00)	Medium (0.25)	High (0.50)
Deposit insurance premium	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.001	0.001	0.002
	Medium (0.50)	0.001	0.002	0.002
	Low (0.25)	0.001	0.002	0.003
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.050	0.076	0.099
	Medium (0.50)	0.051	0.090	0.119
	Low (0.25)	0.051	0.094	0.144
1% Expected shortfall	Book (1.00)	0.001	0.002	0.005
	High (0.75)	0.020	0.049	0.087
	Medium (0.50)	0.031	0.091	0.162
	Low (0.25)	0.032	0.107	0.201

This table presents our quantitative results when analyzing a banking system consisting of 50 equally sized banks with failure probabilities of approximately 1%. *Return correlation* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The expected shortfall is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.0195. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 5

Outcomes for a system with 10 equally sized banks with a failure probability of approximately 1%.

Variable	Outsider price \ Return correlation	Low (0.00)	Medium (0.25)	High (0.50)
Deposit insurance premium	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.001	0.002	0.002
	Medium (0.50)	0.002	0.002	0.003
	Low (0.25)	0.002	0.003	0.003
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.079	0.080	0.079
	Medium (0.50)	0.080	0.084	0.089
	Low (0.25)	0.081	0.086	0.104
1% Expected shortfall	Book (1.00)	0.002	0.002	0.003
	High (0.75)	0.027	0.051	0.074
	Medium (0.50)	0.041	0.102	0.152
	Low (0.25)	0.050	0.135	0.197

This table presents our quantitative results when analyzing a banking system consisting of 10 equally sized banks with failure probabilities of approximately 1%. *Return correlation* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The expected shortfall is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

with 10 banks of heterogeneous size, and (iii) a system with two banks of equal size.¹⁶ Tables 5–7 report the results for the case in which banks have a failure probability of approximately 1%. As expected, the effect of the firesale mechanism on systemic tail risk generally increases with an increase in the degree of concentration in the banking system, even though liquidity ratios also increase due to the higher probability of a firesale. Indeed, in the worst-case scenario the increase in liquidity ratios is so large, that it more than compensates the increase in the probability of a firesale, so that the effect of the firesale mechanism on tail risk becomes smaller with an increase in concentration. In all other cases, however, concentration increases tail risk. For instance, tail risk in the case with a medium degree of asset-specificity and return correlations increases from 5.6% in the 50-bank case, to 8.4% in the 10-bank case, to 12.1% and 13.7% in the case of 10 heterogeneous banks and 2 equal banks, respectively. Another interesting finding is that for the heterogeneous bank case, we find an almost perfectly negative correlation between a bank's size and its equilibrium liquidity ratio. This finding indicates that, *ceteris paribus*, a bank's optimal liquidity ratio is a negative function of its size that is close to linear. Intuitively this outcome makes sense, since a large bank knows that its asset portfolio choice will affect the expected price of liquidated loans. Hence, the larger is a bank, the stronger will be incentive to choose a strategically low liquidity ratio in an attempt to lower the expected price of liquidated loans.

¹⁶ To obtain 10 banks of heterogeneous size, we take 10 random draws from a generalized Pareto distribution with the location parameter set to 0 and the shape parameter set to 1 and normalize the values so that they sum to 1. We obtain a vector of bank sizes in which the largest bank has a market share of 29.3%, whereas the smallest bank has a market share of 3.8%.

Table 6

Outcomes for a system with 10 unequally sized banks with a failure probability of approximately 1%.

Variable	Outsider price \ Return correlation	Low (0.00)	Medium (0.25)	High (0.50)
Deposit insurance premium	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.002	0.002	0.002
	Medium (0.50)	0.002	0.003	0.003
	Low (0.25)	0.003	0.003	0.003
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.080	0.081	0.078
	Medium (0.50)	0.113	0.121	0.152
	Low (0.25)	0.131	0.144	0.167
1% Expected shortfall	Book (1.00)	0.000	0.003	0.003
	High (0.75)	0.074	0.080	0.096
	Medium (0.50)	0.147	0.157	0.170
	Low (0.25)	0.159	0.167	0.183

This table presents our quantitative results when analyzing a banking system consisting of 10 banks of heterogeneous size with failure probabilities of approximately 1%. *Return correlation* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The expected shortfall is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

Table 7

Outcomes for a system with 2 equally sized banks with a failure probability of approximately 1%.

Variable	Outsider price \ Return correlation	Low (0.00)	Medium (0.25)	High (0.50)
Deposit insurance premium	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.005	0.005	0.006
	Medium (0.50)	0.004	0.005	0.005
	Low (0.25)	0.004	0.004	0.004
Liquidity ratio	Book (1.00)	0.000	0.000	0.000
	High (0.75)	0.009	0.009	0.005
	Medium (0.50)	0.140	0.137	0.138
	Low (0.25)	0.193	0.192	0.191
1% Expected shortfall	Book (1.00)	0.005	0.005	0.005
	High (0.75)	0.131	0.143	0.171
	Medium (0.50)	0.213	0.221	0.241
	Low (0.25)	0.295	0.302	0.319

This table presents our quantitative results when analyzing a banking system consisting of equally sized banks of with failure probabilities of approximately 1%. *Return correlation* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The deposit insurance premium is expressed as a ratio (in terms of total deposits). The liquidity ratio is defined as aggregate liquidity relative to the size of the banking system (in terms of total assets). The expected shortfall is also expressed relative to the size of the banking system. Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.01553. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

4.4. The role of liquidity

Overall, our findings suggest that taking LGDs as exogenously given is likely to heavily understate systemic tail risk. They also suggest that liquidity ratios are an important determinant of systemic risk through their effect on liquidation prices and that in concentrated financial systems, banks have an incentive to strategically choose low liquidity ratios. As a last exercise, therefore, we exogenously set the aggregate liquidity ratio equal to 0.2 and repeat the simulation procedure described above. This scenario resembles a situation in which banks are forced to hold at least 20% of their assets in liquid form, and are allowed to use this liquidity to purchase liquidated loans in case of bank failures. As shown in Table 8, tail risk is indeed substantially reduced by this policy. Indeed, when the system consists of at least 10 banks, the 1% ES is never above 5% of the size of the banking system for any reasonable combination of parameters. As such, our analysis indicates an important role for time-varying liquidity requirements in macroprudential regulation. More specifically, financial institutions should be required to hold a relatively large amount of liquidity during 'normal times'. By lowering the liquidity requirement during times of systemic distress, financial institutions can then be allowed to use their liquidity buffer to clear the market for liquidated loans of failed banks. This should significantly lower the severity of firesales and thereby reduce systemic risk.

5. Conclusion

This study has analyzed how the possibility that bank loans are liquidated at firesale prices affects systemic risk, where systemic risk is defined as the risk that creditors of financial institutions incur significant losses as a result of the joint failure of multiple institutions. While other studies using this definition of systemic risk assume that liquidation prices are deterministic and thereby

Table 8

Expected 1% shortfall for the different banking systems when liquidity-to-asset ratios are exogenously set to 0.2 and banks have failure probabilities of approximately 1%.

Banking system	Outsider price \ Return correlation	Low (0.00)	Medium (0.25)	High (0.50)
50 equally sized banks	Book (1.00)	0.000	0.000	0.001
	High (0.75)	0.000	0.001	0.007
	Medium (0.50)	0.000	0.001	0.010
	Low (0.25)	0.000	0.001	0.011
10 equally sized banks	Book (1.00)	0.001	0.001	0.001
	High (0.75)	0.001	0.002	0.011
	Medium (0.50)	0.001	0.003	0.018
	Low (0.25)	0.001	0.003	0.021
10 unequally sized banks	Book (1.00)	0.001	0.001	0.001
	High (0.75)	0.018	0.019	0.025
	Medium (0.50)	0.026	0.029	0.041
	Low (0.25)	0.026	0.030	0.047
2 equally sized banks	Book (1.00)	0.001	0.001	0.001
	High (0.75)	0.057	0.058	0.057
	Medium (0.50)	0.114	0.114	0.114
	Low (0.25)	0.167	0.168	0.168

This table presents the 1% expected shortfall of the different banking systems when liquidity-to-asset ratios are exogenously set to 0.2 and failure probabilities are approximately 1%. *Return correlation* refers to the assumed asset return correlations between banks. *Outsider price* refers to the ratio between the value that outsiders are assumed to attach to banks' assets and the book value of these assets. The expected shortfall is expressed relative to the size of the banking system (in terms of total assets). Returns of banks are assumed to be multivariate normally distributed with means of 0.01 and standard deviations of 0.072. All banks are assumed to have a debt-to-assets ratio of 0.97 and to value each other's assets at their book value.

take losses given default (LGDs) as exogenously given, we endogenize LGDs by explicitly modeling liquidation prices. In addition, we model the portfolio decision of banks with regard to the choice between loans and liquidity, thereby endogenizing the amount of aggregate liquidity in the system, and show how this affects systemic risk.

Our analysis indicates that systemic risk is likely to be underestimated when LGDs are assumed to be exogenous. Furthermore, we show that the degree of underestimation increases in the correlation of financial institutions' loan portfolio returns, the degree of asset-specificity of loans, and the degree of concentration in the banking system. Moreover, even for intermediate return correlations and a reasonable degree of asset-specificity, tail risk is severely underestimated when LGDs are taken as exogenous. As such, the analysis in this study illustrates the importance of modeling LGDs when measuring systemic risk. In addition, our findings indicate that liquidity is not only important due to liquidity risk (i.e. the risk that a financial institution might fail because of illiquidity), but that it also indirectly affects systemic risk through its effect on LGDs during systemic events.

A policy prescription following from the analysis would be to introduce time-varying liquidity requirements. Financial institutions should be required to hold a relatively large amount of liquidity during normal times, so that liquidity requirements can be lowered during times of systemic distress. The resulting liquidity buffer allows surviving financial institutions to clear the market for liquidated loans during times of systemic distress, thereby reducing the probability and severity of firesales and limiting systemic risk.

Acknowledgment

Laura Spierdijk gratefully acknowledges financial support by a Vidi grant (452.11.007) in the 'Vernieuwingsimpuls' program of the Netherlands Organization for Scientific Research (NWO). The usual disclaimer applies.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.jempfin.2017.09.012>.

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