Monitoring transmission of systemic risk from shadow banking to regulated banking

Necmi K Avkiran *
Christian Ringle **
Rand Low ***

Abstract

Shadow banking (SB) makes a significant contribution to financing the real economy and is intricately connected with the regulated banking sector (RBS). This article illustrates how transmission of systemic risk from SB to RBS can be modelled in order to enable regulators better manage contagion. After an extensive literature review of articles from the Finance and Law disciplines, we put together a set of indicators that identify causes of systemic risk in SB (grouped into micro and macro-level linkages) and consequences of systemic risk observed in the RBS. This leads to a predictive structural model comprised of two latent exogenous constructs within the SB domain explaining the latent endogenous construct, which in turn, explains the observed consequences of systemic risk in RBS. In a first application of PLS-SEM (partial least squares structural equation modeling) in financial stress testing, we demonstrate how this technique can be used to explain contagion from SB to RBS. Results indicate that around 75% of the variation in systemic risk in RBS can be explained by micro and macro-level linkages traced to SB; the two path coefficients between the exogenous latent constructs and the endogenous latent construct are statistically significant. Analysis of the formative measurement model shows moderate convergent validity and insignificant multicollinearity. The reflective measurement model displays above moderate internal consistency and indicator reliability, and moderate convergent and discriminant validity. Regulators can use the approach illustrated in this article to monitor transmission of systemic risk appreciative of the extent of contagion emanating from micro and macro-level linkages, thus guiding microprudential versus macroprudential regulatory decisions.

JEL classification: E5; F3; G2; L5

Keywords: Systemic risk; shadow banking; regulated banking; contagion; microprudential and macroprudential regulation; structural equation modeling; PLS-SEM

* Send correspondence to Associate Professor Necmi K Avkiran, UQ Business School, The University of Queensland, Brisbane QLD4072, Australia
tel: +(61 7) 334 63282; fax: +(61 7) 334 68166; e-mail: n.avkiran@business.uq.edu.au

** Institute for HRM and Organizations, TUHH - Hamburg University of Technology, Germany

*** UQ Business School, The University of Queensland, Australia
1. Introduction

This article illustrates how transmission of systemic risk from shadow banking (SB) to the regulated banking sector (RBS) can be modelled in an effort to help regulators better monitor and manage contagion. Shadow banking, also known as ‘market-based financing’, includes non-bank channels such as real estate investment trusts, leasing companies, credit guarantee outlets and money market funds. Credit intermediation in SB alters the maturity, quality and liquidity of traditional credit products. SB can be regarded as providing banking intermediation without public liquidity and credit guarantees. According to the UK Financial Stability Board’s (FSB) report, shadow banking makes a significant contribution to financing the real economy; for example, in 2013 shadow banking assets represented 25% of total financial system assets (FSB 2014).

Systemic risk is defined by Gart (1994, p.134) as “…the clear and present danger that problems in financial institutions can be transmitted rapidly to other institutions or markets, inflicting damage on those institutions, their customers, and, ultimately, the economy at large.” In the period leading up to the global financial crisis (GFC) of 2007-09, a large portion of financing of securitized assets was handled by the shadow banking sector (Gennaioli et al. 2013). Thus, the collapse of SB during 2007-09 played an important role in weakening the regulated banking sector that relies on maintaining relationships with firms rather than arm’s length financing often provided by capital markets. Ironically, shadow banking was assumed to be safe partly due to liquidity and credit put options provided by the private sector.¹

Adrian and Ashcraft (2012, p.100) state “The operations of many shadow banking vehicles and activities are symbiotically intertwined with traditional banking and insurance institutions”. Because of the strong interconnectedness between the two banking sectors, SB can become a source of systemic risk – an area of major concern to all regulators. As systemic risk rises, distressed banks reduce lending to clients, who in turn invest less, thus reducing employment. Thus, a main motivation for mitigating systemic risk is the harm caused to citizens when financial institutions fail and the effects of such failures are transferred to the real economy. As part of the interaction between SB and RBS, there also exists a concern that banks might be evading increased regulation by shifting activities to shadow banking. As the Basel III Accord moves towards full implementation by 2019 with a focus on better preparing financial institutions for the next crisis, and the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (DFA) unfolds in the USA, the contribution of SB to systemic risk in RBS needs to be closely monitored.

¹ Gorton and Metrick (2012) provide a comprehensive analysis of the GFC including a timeline of major events, policy responses and real effects of the crisis. Helleiner (2011) also provides a comprehensive account of how the GFC unfolded and maintains that a major cause of the crisis was the transformation of financial systems through new models of securitisation.
Interconnectedness that may start the spread of systematic or non-diversifiable risk carried by various financial institutions can become systemic risk in RBS via direct or indirect linkages with SB. For example, in broad terms, direct linkages are created when shadow banking entities are owned by banks or have dealings with them. On the other hand, indirect linkages can be thought of as the two sectors investing in similar assets or becoming exposed to common counterparties. Other specific examples to interlinkages include backup lines of credit, implicit guarantees to special purpose vehicles (SPVs) and asset management subsidiaries, the outright ownership of securitized assets on bank balance sheets, and credit put options by insurance firms (Adrian and Ashcraft, 2012, p.100). According to FSB (2013, p.21) “These connections create a contagion channel through which stress in one sector can be transmitted to the other, and can be amplified back through feedback loops.”

One of the key findings of Calluzzo and Dong (2015) is that over the period 2005-11 financial markets have become more vulnerable to contagion of systemic risk. Gennaioli et al. (2013) argue that securitization enhances the growth of bank balance sheets by diversifying idiosyncratic risk of loans, but it also raises the level of connectedness among financial institutions, thus concentrating exposure to systematic or market risk, and eventually to systemic risk when multiple institutions fail. At the same time, neglected tail aggregate risks on risky loans – such as the steep fall in house prices prior to the GFC and absence of accurate models to price collateralized debt obligations or loan obligations – can interact with idiosyncratic risk and lead to financial fragility.

Gennaioli et al. (2013) maintain that according to the regulatory arbitrage view, banks pursue securitization using special or structured investment vehicles (SIVs) to circumvent capital requirements. In the period leading up to the GFC, traditional banks’ entry into shadow banking through SIVs and SPVs created strong interdependencies and enabled RBS to engage in almost unrestricted leverage.2 Banks were able to maintain higher leverage and still comply with risk-weighted capital requirements by transforming some assets into highly rated securities. Such a strategy makes banks more vulnerable to shocks. Acharya and Richardson (2009, p.85) link the regulatory arbitrage view to the idea of ‘too-big-to-fail’ (TBTF) where banks take on additional risks, that is, retain tail risks, and provide liquidity guarantees to SIVs or SPVs based on the expectation of a bailout.3 According to Erel et al. (2014), larger banks are likely to participate in higher levels of securitization because their expectations of being bailed out are also higher. FSB (2011, p.5) reports that “Although Basel III closes a number of identified shortcomings, both the incentives for, and the risks associated with, regulatory arbitrage will likely increase as Basel III raises the rigor of bank regulation.” Therefore, the main motivation behind this study is to examine to what extent transmission of systemic risk from SB to RBS can be monitored. Later on we attempt this via partial least squares structural

2 Investment opportunities in shadow banking can be further diversified by structuring a collateralized SIV in tranches of senior, mezzanine and junior, where the latter two tranches are designed to absorb any losses before the senior tranches.

3 A financial institution is often considered TBTF when it has significant connections with other firms either through direct contractual relationships or through its potential to impact markets (Anabtawi and Schwarcz 2013).
equation modeling (PLS-SEM) using data from the US financial system; to the best of our knowledge, this is the first use of PLS-SEM in the field of financial stress testing.

There is a wealth of information on the interconnectedness of the financial system and regulation both in Finance and Law journals. Yet, these disciplines appear to ignore the body of knowledge generated by the other when we examine lists of references in such articles. Further motivated by this observation, we attempt to strike a balance by tapping into both disciplines as we explore the feasibility of monitoring transmission of systemic risk. The rest of the article unfolds with a literature review that describes banking in the USA, continues the discussion on the interconnectedness of the financial system and develops a conceptual framework for predictive modelling of transmission of systemic risk. This is followed by a description of data and an outline of the PLS-SEM method. Following reporting of the results to emerge from the PLS-SEM analysis, some concluding remarks are offered.

2. Literature review

The country focus in the rest of the study is primarily on USA. Thus, we begin this section with an introduction to the US banking systems. There are two separate banking systems in the USA where each is governed by different legal regimes. Those financial institutions that carry a banking charter belong to the traditional depository banking system often evaluated as three tiers, namely, city banks, regional banks and community banks – referred to as the regulated banking sector; most US banks are owned by bank holding companies (BHC) supervised by the Federal Reserve (The Fed). On the other hand, those who do not have a charter belong to the shadow banking system, e.g. investment banks, money market mutual funds (MMMFs), hedge funds, and insurance firms. The key difference between the regulated banks and shadow banks is that the former are allowed to fund their lending activities through insured deposits (capped at US$100,000 per account), whereas the latter are prohibited by federal law to use deposits. Therefore, shadow banks depend on deposit-substitutes in a mostly unregulated and uninsured environment.

Over the last 30 years or so shadow banking has become increasingly dependent on various forms of short-term funding that substitute for functionality of deposits, e.g. over-the-counter (OTC) derivatives (traded outside regulated exchanges), short-term repurchase agreements (repos are regarded as fully secured short-term loans), commercial papers, MMMF shares, prime brokerage accounts and securitized assets. Unfortunately, during a financial crisis, the reliance on deposit-substitutes can have a contagion effect in the wider economy. For example, multinational corporations use MMMFs to fund their day-to-day cash needs. During the GFC, MMMFs were the primary buyers of commercial paper used by financial institutions as well as non-financial corporations such as General Electric and Ford (Jackson 2013). When MMMFs failed, large corporations were unable to sell their commercial paper to raise cash for their operations. Chernenko

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4 MMMFs are intermediaries in short-term credit markets that form a crucial part of shadow banking. In 2010, the Securities and Exchange Commission enacted changes to Rule 2a-7 requiring money market funds to hold higher quality assets of shorter maturities and keep larger buffers of liquid assets (SEC 2010).
and Sunderam (2014) argue that instabilities associated with MMMFs were central to the GFC. An example to a negative spillover is the case where an MMMF adds a risky firm to its portfolio, leading to investors withdrawing funds from that MMMF, and finally limiting of funds available to creditworthy firms financed by the same MMMF. If it were not for the US Federal government’s determined implementation of various guarantees, emergency loans and capital infusions, many non-financial corporations would also have declared bankruptcy alongside financial institutions.

Given externalities or moral hazard problems such as implicit expectations on part of shadow banks to be bailed out in times of crises, it is unlikely that the shadow banking sector will implement optimal protections or fully hedge their risks. Furthermore, Schwarcz (2013) maintains that disintermediation in SB can amplify systemic risk. Therefore, there is a strong argument in favor of regulating how the shadow banking sector relies on deposit-substitutes, and the systemic risk channeled to RBS. Currently, the statutory authority in the USA to regulate deposit-substitutes is inadequate because the existing framework has gaps that can be exploited by the participants in the shadow banking sector. For example, the Dodd-Frank Act provides The Fed with authority to limit short-term debt activities by bank holding companies with over US$50 billion in total assets – yet there are many BHC that are below this threshold (Jackson 2013). Similarly, the Securities and Exchange Commission (SEC) can only oversee MMMFs and some broker-dealers unaffiliated with banks that are members of The Fed. In Finance literature, Beltratti and Stulz (2012), among others, show evidence of fragility for banks financed with short-term funding that is often the domain of SB.

Anabtawi and Schwarcz (2013) maintain that the Dodd-Frank Act has a strong ex ante regulatory bias, i.e. the emphasis is on prevention that is likely to draw opposition from the financial sector and may encourage regulatory arbitrage. The authors make the point that ex ante regulation needs to be accompanied with ex post regulation that brings safety nets as well as mechanisms designed to disrupt the transmission of systemic risk. More importantly, Rixen (2013) states that only about 20% of the rules proposed by DFA have so far been implemented by various US regulatory agencies, and that DFA does not specify targets for capital requirements; devising targets is the responsibility of The Fed and the Financial System Oversight Council (FSOC) established under the Dodd-Frank Act. FSOC also has the responsibility to identify and address threats to financial stability. This study models transmission of systemic risk in an effort to help regulators better predict what is likely to happen in the regulated banking sector we heavily depend on for a well-functioning lifestyle.

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5 Disintermediation can intensify information failure, and thus systemic risk, as it builds on a decentralised structure. Disintermediation can also contribute to agency failure as exemplified by conflicts between middle and senior managers, e.g. middle managers provide value-at-risk analysis to senior managers who are often not qualified or time-poor to double-check submitted work (Schwarcz 2013).

6 The threshold of US$50 billion specified by DFA attempts to define systemic importance in terms of size.
2.1. Interconnectedness of the financial system

The well-known prudential regulation’s main focus is on identifying and mitigating exposure to endogenous crises within individual financial institutions, thus regulating leverage through internal risk management policies overseen by boards of directors. Ellul and Yerramilli (2013) report that bank holding companies with stronger and more independent risk management functions before the GFC had lower tail risk, less impaired loans, better operating performance and higher yearly returns during 2007-08. Importantly, prudential regulation addressed by the Basel II Accord since 2004 at the microeconomic level (and updates under the Basel III Accord since the GFC) has recently been supplemented by the European Systemic Risk Board (ESRB) and the Office of Financial Research (OFR) from the USA working on macroprudential regulation designed to identify and mitigate systemic risks. After all, one of the lessons of the GFC was the acknowledgement that financial institutions are much more interconnected than suggested by the domino model of bank failures.

Macroprudential regulation – an emerging framework – is designed to investigate the interconnectedness between SB and RBS by accounting for counterparty relationships, common models and metrics, correlated exposure to assets, and shared reliance on market utilities (Johnson 2013). Macroprudential policies designed by regulators such as The Fed are in recognition of systemic risk being a negative externality where firms lack private incentives to minimize it (Liang 2013). Macroprudential regulation fills the gaps in prudential regulation by simultaneously focusing attention on institution-specific endogenous factors and network-related exogenous factors that give rise to systemic risk. While the micro and macro-level regulations need to function seamlessly in order to effectively identify systemic risk and mitigate it, this study’s focus is on the ability to identify systemic risk arising from linkages. Thus, we continue by expanding on key linkages between RBS and SB already mentioned in the preceding sections – with a view to laying the groundwork for a systemic risk framework that could enable monitoring contagion.

A good starting point is the article by Anabtawi and Schwarcz (2011) that discusses regulating systemic risk. The authors premise their extensive arguments on the need for regulatory intervention but highlight the absence of an analytical framework that could help the regulators – in particular regarding how systemic risk is transmitted. Anabtawi and Schwarcz (2011) also express strong concern about the market participants being unreliable in interrupting and limiting transmission of systemic risk.

First, Anabtawi and Schwarcz (2011) posit an intra-firm correlation between a firm’s exposure to the risk of low probability adverse events that can cause economic shocks and a firm’s financial integrity. Second, the authors put forward the concept of an inter-firm correlation among financial firms and markets,

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7 ESRB was established in December 2010 and OFR was established with the Dodd-Frank Act enacted in 2010.
8 Counterparty refers to each of the two parties to a bilateral contract. According to Johnson (2013, p.906) “In a derivatives agreement the counterparty described as the buyer generally owns an asset and, therefore, faces risk that the asset may decline in value…The buyer in the derivatives contract seeks protection against the default risk and the seller agrees to cover some percentage or all of the loss that the buyer may experience if the issuer defaults…”
where interaction with the intra-firm correlation can facilitate transmission of otherwise localized economic shocks. An example to *intra-firm* correlation from the GFC is the fall in home prices (a low probability risk) leading to defaulting of asset-backed securities and erosion of the integrity of institutions heavily invested in such securities. An example to *inter-firm* correlation is the failure to fully appreciate the interconnectedness among traditional financial institutions and institutions such as Bear Stearns (failed in 2008), Lehman Brothers (failed in 2008), AIG and other shadow banking institutions. According to Anabtawi and Schwarz (2011, p.1356), “Operating together, however, these correlations create a transmission mechanism that can allow even what might appear to be a modest localized adverse economic shock to generate severe systemic consequences.”

Effective regulation that weakens the above-mentioned correlations can reduce the enormous costs associated with financial crises.

Anabtawi and Schwarz (2011, p.1368) define *complexity* in the financial system as “…the elaborate web of financial and legal relationships that increasingly underlies financial assets, investment securities, and financial markets”. Thus, complexity can make it particularly difficult to appreciate different correlations and how they interact with each other. Overall, complexity detracts from the ability to identify intra-firm correlations because managers find it more difficult to assess risk of various financial products. It also gives rise to information asymmetry between an investor and the originator of an instrument. Under the indirect holding system found in trading of debt and equity securities, financial intermediaries hold securities on behalf of investors, thus making it difficult for others to identify the ultimate owners and related credit risk exposures. Essentially, complexity means cost of risk assessment can outweigh the perceived benefits. Cognitive limitations to processing and assessing complex financial and legal relationships will further discourage in-house analyses, relying instead on credit rating agencies’ simpler and more general assessments.

When we consider the financial system as consisting of a network of institutions that interact at various levels, then complexity is also implicated in the inter-firm correlation. In a network, there is always the potential for a shock to be amplified through feedback loops. For example, during the GFC of 2007-09, the real estate bubble was partially made possible by additional capital flowing into mortgage securities, thus increasing capital availability to write more mortgages, in particular subprime home loans. Essentially, one bubble fed the other, creating a feedback loop. However, the domino model of contagion assumes shocks are transmitted directly between firms that belong to the financial system network but it does not account for the equally important *indirect* transmissions through the impact of firms’ decisions on markets. For example, firms experiencing margin calls are often forced to engage in a fire sale of assets which depresses market prices through a feedback effect. We can also argue that when contagion stops, amplification continues

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9 The financial crisis that started in 2007 turned into the GFC as a result of these correlations combining to transmit economic shocks across many countries because counterparty risks were deemed too high to continue to extend credit. A similar withdrawal by investors simply exacerbated the situation and lack of credit lead to collapses in the real economy. Such a series of events reflects interconnectedness and forms the essence of what gives rise to systemic risk.
through mounting defaults among the institutions indebted to one another (Glasserman and Young 2015). Complexity can also arise from technological innovation, e.g. high frequency algorithmic trading that can add to loss spirals.

Another publication that attempts to make sense of interconnectedness and systemic risk is by Judge (2012) that focuses on financial innovation and resulting complexity that can lead to systemic risk. Judge (2012, p.661) identifies four sources of complexity, “(1) fragmentation, (2) the creation of contingent and dynamic economic interests in the underlying assets, (3) a latent competitive tendency among different classes of investors, and (4) the lengthening of the chain separating an investor from the assets ultimately underlying its investment.” It is then argued that complexity contributes to information loss and stickiness (the latter refers to arrangements in markets that are difficult to modify) – both of which are sources of systemic risk. For example, as a mortgage-backed security is converted into a collateralized debt obligation (CDO), new fragmentation nodes are created with a much more complex arrangement that introduces many more investors with stake in the original mortgage loan. In short, the longer the chain separating an investor from an investment, the more difficult it becomes for investors to exercise due diligence in assessing risk and value.

Rixen (2013) argues that shadow banking is primarily incorporated in lightly regulated offshore financial centers (OFCs). OFCs can be regarded as an extreme expression of jurisdictional competition. OFCs have two main functions in the form of regulatory or tax havens. SPVs and SIVs benefit from regulatory and tax advantages offered by such havens. Rixen (2013, p.438-439) maintains that OFCs can increase financial risk in at least five different ways by (1) making it easier to register SPVs and SIVs, (2) enabling onshore financial institutions to hide risks, (3) raising the incentives for risky behavior, (4) helping avoid quality checks on credit that it is to be securitized, and (5) nurturing the debt bias found in investments.

Summing up interconnectedness, a financial firm’s potential contribution to systemic risk can be viewed as a function of two main variables, namely, the extent its assets are correlated with the market and counterparty relationships. Similarly, complexity in the financial markets can be viewed as leading to information loss and stickiness, and ultimately, systemic risk. Regulators’ main tasks in mitigating systemic risk should be to encourage less fragmentation and shorter chains between investors and investments, monitor existing linkages while looking out for new linkages, and disrupt transmission mechanisms. In the next section, we develop a conceptual framework designed to capture transmission of systemic risk from shadow banking to the regulated banking sector.

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10 An alternative to CDOs would be covered bonds favoured in Europe where the intermediation chain is shorter and they remain direct obligations of the bank issuing them.
2.2. Conceptualizing a predictive model for contagion

We now pull together the linkages between SB and RBS already discussed in order to conceptualize a predictive model for shadow banking’s contribution to systemic risk in the regulated banking sector. According to Johnson (2013, p.886) “Regulation must address the increasing interconnectedness between regulated financial institutions and shadow banking institutions, the economic transactions within the shadow banking system, and regulated financial institutions’ use of shadow banking instruments.” The preceding literature review has revealed the following key potential linkages between SB and RBS that can give rise to systemic risk:

- Excessive leverage in RBS supported by SB, e.g. excessive off-balance sheet securitization undertaken by regulated banks through SIVs and SPVs that handle shadow banking products.
- Questionable credit/liquidity put options by insurance firms covering promised payments in case of insolvency, e.g. if such puts are not robust (i.e. underestimate risks), then in a crisis situation liquidity cannot be sustained because the insurers can themselves become bankrupt.
- Shadow banking deposit-substitutes such as derivatives, short-term repos, commercial paper, MMMF shares, prime brokerage accounts and securitized assets as avenues for investment by RBS as well as multinational corporations, thus creating potentially negative feedback loops, e.g. if an MMMF facility in SB fails, a multinational that is part of the real economy depending on financing daily operations through commercial paper purchased by the MMMF in question can find itself in financial strife, which in turn could affect the multinational’s commercial relationship with banks in RBS.
- Multilayered fragmentation nodes in securitized assets adding to complexity, e.g. the extent of CDOs and similar obligations with tranches and the length of the intermediation chain.
- Associations with offshore financial centers.
- Extent assets of a given institution are correlated with the market, i.e. if there is evidence of herding behavior where most institutions invest in similar assets, then movements in profits/losses are amplified.
- Executive compensation in SB institutions that may encourage excessive risk taking.

According to Weiß et al. (2014), despite a large quantity of empirical literature on systemic risk and the accompanying transmission mechanisms, evidence is inconclusive (Bisias et al. 2012 provide an extensive survey of systemic risk analytics). Yet, tracking systemic risk is a core activity in enabling macroprudential regulation (Jin and De Simone 2014). Starting from the above summary of linkages, Table 1 outlines the causes of systemic risk in SB and consequences of systemic risk in RBS in an effort to draft a list of potential indicators (manifest variables) that can be used for predictive modeling.11 Our indicator-

11 We dub this list of indicators “researchers’ theoretical wish-list” because most of the data on formative indicators and some of the data on the reflective indicators cannot be accessed for various reasons. For example, in addition to commercial databases, we perused individual BHC submissions of FORM 10-K (annual report) required by the Securities and Exchange Commission. We found inconsistent reporting formats and scant useful data. We doubt that regulators are in a better position under the current...
based approach to modeling systemic risk is one favored by regulators such as the Basel Committee and reflects both microprudential and macroprudential perspectives, i.e. intra-firm and inter-firm correlations, or micro-level and macro-level linkages.

We now outline the core hypotheses that will be tested through PLS-SEM:

$H_1$: Systemic risk in shadow banking makes a significant contribution to systemic risk in the regulated banking sector.

$H_{1A}$: Systemic risk sourced from intra-firm correlations or micro-level linkages emanating from shadow banking make a significant contribution to systemic risk in the regulated banking sector.

$H_{1B}$: Systemic risk sourced from inter-firm correlations or macro-level linkages emanating from shadow banking make a significant contribution to systemic risk in the regulated banking sector.

Essentially, $H_1$ tests the main argument mounted so far that there is a substantial transmission of systemic risk from SB to RBS. Similarly, $H_{1A}$ tests the significance of contagion via micro-level linkages, whereas $H_{1B}$ tests the main contention behind the need for macroprudential regulation, that is, contagion via network related exogenous factors or macro-level linkages. Similar to Glasserman and Young (2015), we avoid starting the investigation with a pre-defined network structure or topology because we consider financial networks to be dynamic in nature. According to Calluzzo and Dong (2015) systemic risk within integrated markets is difficult to quantify and dynamically changing. Furthermore, research on how risk is transmitted is still in its early stages due to inadequate data and complex linkages (Liang 2013).

3. Data and method

3.1. Data

We focus on BHCs because most banks in the U.S., particularly those at mature stages of their operations, are owned by bank holding companies (Partnership for Progress 2011). Furthermore, the structures of BHCs allow them to diversify their portfolios and banking activities (Strafford 2011). The working sample of 63 BHCs after removing those with missing values are for the year 2013, and those in the sample represent 82.35% of the cumulative total assets for all the BHCs in that year (sourced from BankScope).

For the purposes of illustrating predictive modelling, we start with seven reflective indicators (selection is partly based on data availability) and ten formative indicators from the potential list originally reporting system – a point raised by the Director at the Office of Financial Stability Policy and Research, Federal Reserve Board (Liang 2013, p.134).
summarized in Table 1. The set of formative indicators is comprised of five indicators of *microprudential* focus capturing intra-firm relationships defining one of the two exogenous constructs, and five indicators of *macroprudential* focus capturing inter-firm relationships defining the other exogenous construct (see Table A1 in Appendix A for details of the selected variables). Summary statistics on the variables reported in Table 2 indicate non-normal data as evidenced by substantial skewness and kurtosis across about half the variables (observed, as well as simulated).

In the absence of data on the formative indicators in the public domain, we simulate such data as detailed in Appendix A by making certain we use the systemic risk levels indicated by the *observed* data on reflective indicators and adjusting for firm size where relevant. Our simulation process for formative indicators starts by dividing each observed potential reflective indicator of a BHC into 3 quantiles (see Appendix A, Table A1, second column). These 3 quantiles are defined as the upper, middle, and lower ranges, i.e. a 3-tiered range. Depending on the number of reflective indicators that each BHC exhibits within these quantiles, a BHC is then assigned to one of eleven systemic risk categories (see Table A2). A random normal distribution for each formative indicator is simulated and bounded by the tiered range as given by a set of rules based upon the systemic risk category of each BHC (see Table A3). The tiered ranges for the formative indicators are defined by the range of maximum and minimum values of formative indicators based upon assumptions in the systemic risk literature for BHCs. Furthermore, certain formative indicators require an additional simulation step to account for firm size captured by total assets. These are formative indicators 4, 5, 7, and 9. In this scenario, each of the original upper, middle and lower ranges for the formative indicator now have 3-quantiles in each range, thus creating 9 quantiles. For example, if a BHC is considered to have a formative indicator that is in the middle range from the first step, and is noted to be in the upper range in terms of firm size, the random simulation will occur in the 6th quantile.

**3.2. Method: Partial least squares structural equation modeling**

For the first time in the field of financial stress studies where a variety of early warning systems are found, we propose to use the iterative OLS regression-based partial least squares path modeling method (Lohmöller 1989; Wold 1982), nowadays often called *partial least squares structural equation modelling* (PLS-SEM). PLS-SEM has become a key multivariate analysis method to estimate complex cause-effect relationship models with latent variables in various disciplines such as accounting (Lee et al. 2011), management information systems (Ringle et al. 2012), marketing (Hair et al. 2012), operations management (Peng and Lai 2012), strategic management (Hair et al. 2012), supply chain management (Kaufmann and Gaeckler 2012).

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12 After the initial testing for indicator reliability, we are left with four reflective indicators for the endogenous construct, and a set of five formative indicators for each of the two exogenous constructs. Thus, the sample size of 63 BHCs passes the rule of thumb commonly applied in PLS-SEM that requires the sample to be at least ‘ten times the maximum number of indicators associated with an outer model (construct)’ (Barclay et al. 1995).

13 Table 1 and Figure 1 in Oet et al. (2013) provide an overview of literature on early warning systems.
2015), and tourism (do Valle and Assaker 2015). For example, popular PLS-SEM applications focus on explaining customer satisfaction and technology acceptance (see Table 1 in Hair et al. 2014b for a breakdown of business disciplines using PLS-SEM). The goal of the non-parametric PLS-SEM is to maximize the explained variance of endogenous latent constructs whereby the assumption of multivariate normality is relaxed. Given the extent of dynamic interconnectedness in the US financial system, we also treat systemic risk as a latent construct representing a phenomenon that cannot be directly observed and avoid defining yet another network topology. The study’s main objective remains one of modeling and understanding the transmission of systemic risk from shadow banking to the regulated banking sector through a first illustration of PLS-SEM in this field.

In this study, PLS-SEM is used to develop a predictive model, that is, starting from known causes of systemic risk in shadow banking captured by formative indicators and estimating the extent we can predict consequences of systemic risk in the regulated banking sector captured by reflective indicators (see Table A1 and the illustrative Figure 1). According to Jöreskog and Wold (1982, p.270) “PLS is primarily intended for causal-predictive analysis in situations of high complexity but low theoretical information.” In summary, use of the PLS-SEM approach is recommended when

- “The goal is predicting key target constructs or identifying key ‘driver’ constructs.
- Formatively measured constructs are part of the structural model. Note that formative measures can also be used with CB-SEM, but doing so requires construct specification modifications (e.g. the construct must include both formative and reflective indicators to meet identification requirements).
- The structural model is complex (many constructs and many indicators).
- The sample size is small and/or the data are non-normally distributed.
- The plan is to use latent variable scores in subsequent analyses.” (Hair et al. 2014a, p.19).

Other advantages of PLS-SEM over its better known cousin – covariance based structural equation modeling (CB-SEM) – are a focus on predicting dependent latent variables (often a key objective in empirical studies) and ability to accommodate indicators with different scales (Hair et al. 2014a). In this context, the distinction between formative and reflective indicators is particularly important:

- Formative indicators are considered causes of the associated exogenous latent constructs. We try to minimize the overlap among them because they are treated as complementary (see the left hand side of Table A1 for formative indicators likely to lead to systemic risk in shadow banking). The exogenous latent constructs illustrated in Figure 1 become the dependent variables in multiple regression where the

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associated formative indicators are the independent variables. A model that only consists of formative indicators is known as a Mode B model (Wold 1982).

- Reflective indicators are consequences or manifestations of the underlying target latent construct i.e. causality is from the construct to the indicator. Because of substantial overlap among the reflective indicators, they are treated as interchangeable, i.e. they are expected to be highly correlated. Reflective indicators likely to capture the systemic risk in the regulated banking sector are indicated on the right hand side of Table A1. The endogenous latent construct becomes the independent variable in single regression runs where the reflective indicators individually become the dependent variable in each run. A model that only consists of reflective indicators is known as a Mode A model (Wold 1982). However, because the illustrative Figure 1 comprises both formative and reflective indicators, it would be classified as a Mode C model (Wold 1982).

Insert Figure 1 about here

PLS-SEM models consist of three main components, namely, the structural or inner model, the measurement or outer model, and the weighting scheme visible in the illustrative Figure 1. A group of manifest variables associated with a latent construct are known as a block, and a manifest variable can only be associated with one construct. According to Monecke and Leisch (2012, p.2) “…latent variable scores are estimated as exact linear combinations of their associated manifest variables and treats them as error free substitutes for the manifest variables…PLS path modeling is a soft-modeling technique with less rigid distributional assumptions on the data.” PLS-SEM requires use of recursive models where there are no circular relationships (Hair et al. 2014a). Figure 2 provides a diagrammatic representation of the PLS-SEM algorithm as described in Monecke and Leisch (2012).

Insert Figure 2 about here

At the beginning of the algorithm, all the manifest variables in the data matrix are scaled to have a zero mean and unit variance. The algorithm estimates factor scores for the latent constructs by an iterative procedure where the first step is to construct each latent construct by the weighted sum of its manifest variables. The inner approximation procedure (step 2) reconstructs each latent construct by its associated latent construct(s), i.e. as a weighted sum of neighboring latent constructs. The outer approximation procedure (step 3) then attempts to locate the best linear combination to express each latent construct by its manifest variables, in the process generating coefficients known as outer weights. While the weights were set to one during initialization, in step 3 weights are recalculated based on latent construct values emerging from the inner approximation in step 2. In step 4, latent constructs are put together again as the weighted sum or linear combination of their corresponding manifest variables to arrive at factor scores. The algorithm terminates when the relative change for the outer weights is less than a pre-specified tolerance (following each step, latent constructs are scaled to have zero mean and unit variance).
As a result the PLS-SEM algorithm provides the latent variable scores, reflective loadings and formative weights in the measurement models, estimations of the path coefficients in the structural model, and the $R$-squared values of endogenous latent variables. These results allow computing many additional results and quality criteria such as Cronbach’s alpha, the composite reliability (preferred in PLS-SEM), the $Q^2$ value of predictive relevance, and $f^2$ effect size (e.g., Chin 1998; Chin 2010; Hair et al. 2013; Hair et al. 2014a) as well as the new HTMT criterion (heterotrait-monotrait ratio of correlations) to assess discriminant validity (Henseler et al. 2015). Recapping, in addition to being robust with skewed data because it transforms non-normal data according to the central limit theorem, PLS-SEM is also considered an appropriate technique when working with small samples (Henseler et al. 2009, Hair et al. 2014a). Literature review in Table 1 in Hair et al. (2014b) lists the top three reasons for PLS-SEM usage as non-normal data, small sample size and presence of formative indicators (all of these conditions exist in this study’s data set).

4. Results

The testing procedure followed is detailed in Appendix B. Essentially, we begin with the ten formative indicators (five for each of the two exogenous constructs) and seven reflective indicators for the endogenous construct detailed in Table A1 in Appendix A. We then run additional tests by individually removing three low-loading reflective indicators (i.e. <0.5) before reporting the final results. The second part of Appendix B shows the results for the final model depicted in Figure 3, which provides a diagrammatic summary of the PLS-SEM results. We used the software SmartPLS 3 (Ringle et al. 2015) for conducting all the PLS-SEM analyses presented in this study.

[Insert Figure 3 about here]

Convergent validity and discriminant validity describe construct validity, i.e. the extent we measure systemic risk as theorized. More importantly, to be able to say we have construct validity, both convergent and discriminant validity have to be established. Convergent validity is the extent an indicator is positively correlated with alternative indicators measuring the same construct. For example, in the reflective measurement model, indicators are considered as reflecting the same endogenous construct, and thus, they are expected to share a high proportion of variance, where ideally the outer loadings exceed 0.7 (Hair et al. 2011), although loadings as low as 0.4 are acceptable in exploratory research such as the current study (Hair et al. 2012). Similarly, we also need to examine the convergent validity of the formative measurement model where we look for evidence that the exogenous constructs are in fact predicting the endogenous latent construct. A sound indication of convergent validity here would be statistically significant path coefficients that lead to a substantial coefficient of determination ($R$-squared) – results that emerge once we closely examine the structural model. On the other hand, discriminant validity measures the extent the endogenous construct is distinct from the exogenous construct(s).
Findings reported in Appendix B indicate moderately strong statistical criteria (see the second set of results reported after removing the three low-loading reflective indicators). Starting with the strongest finding reported under the structural model, $R^2$ (adjusted $R^2$) for our parsimonious model are substantial at 0.756 (0.748), suggesting that the two exogenous constructs theorized are significantly explaining the variation in the endogenous construct, i.e. sources or causes of systemic risk emanating from shadow banking are explaining the consequences of systemic risk observed in the regulated banking sector, thus supporting $H_1$. Continuing with the properties of the structural model, predictive relevance is also satisfactory as measured by a $Q^2$ of 0.316, i.e. a value larger than zero shows that data points for reflective indicators are accurately predicted by the endogenous construct. Equally pleasing is the finding that the two path coefficients of 0.567 and 0.342 between the exogenous latent constructs and the endogenous latent construct are statistically highly significant, thus supporting $H_{1A}$ and $H_{1B}$ (we note that macro-level linkages play a smaller role compared to micro-level linkages). $f^2$ effect size confirms that micro-level linkages explain more of the variation in systemic risk in RBS (0.435 vs 0.159 where both are strong), thus indicating the effect of removing either exogenous construct to be substantial.

Findings summarized in Appendix B on the formative measurement model indicate moderate convergent validity according to the path coefficients already identified above, multi-collinearity is below critical levels (VIF=3.025), and formative indicators are mostly significant. On the other hand, the reflective measurement model displays above moderate internal consistency (composite reliability=0.784) and indicator reliability (mean outer loading of 0.685 with a maximum of 0.849), and moderate convergent validity (AVE=0.482) and discriminant validity (Fornell-Larcker criterion=0.695). These findings on the outer models generate more confidence in our findings on the inner model (structural model) reported above.

5. Concluding remarks

We embarked on this project to illustrate how transmission of systemic risk from SB to RBS can be modelled in order to help regulators monitor contagion. Initially, we identified various micro and macro-level linkages between SB and RBS following an extensive literature review that brought together Finance and Law disciplines. To address an extensive amount of missing data on causes of systemic risk in shadow banking, we opted to simulate formative indicator data by establishing linkages to the observed reflective indicator data. The structural model to emerge consisted of two latent exogenous constructs of micro and macro-level linkages embedded in SB explaining the latent endogenous construct on systemic risk in RBS. Statistically significant results based on PLS-SEM predictive modelling indicate that around 75% of the variation in systemic risk in RBS can be explained by micro and macro-level linkages that can be traced to SB. The significant path coefficients between the two exogenous constructs and the endogenous construct highlight the importance of the more traditional microprudential regulation, as well as macroprudential regulation.
The finding that micro-level linkages have a greater impact on contagion of systemic risk (compared to macro-level linkages) is significant. It suggests that internal risk management within BHCs have a greater role in reducing the likelihood of systemic risk events. Although central banks and other regulators can impose macroprudential frameworks on the markets, these appear to have a lower impact on reducing the likelihood of spread of systemic risk within RBS. Regulators can use the approach illustrated in this article to monitor transmission of systemic risk. As Majerbi and Rachdi (2014) point out in their study of probability of systemic banking crises across a sample of 53 countries, stricter banking regulation, supervision and bureaucratic efficiency generally result in reduced probability of crises.

A more advanced application of the predictive modelling illustrated in this article can incorporate scenario analysis using projected data. That is, once model parameters that are stable over time are identified, projected data on formative indicators representing potential negative developments in SB can be used to predict reflective indicator levels in RBS. Such an extension of this study will require running PLS-SEM over a number of years and observing path coefficients and loadings for various indicators. According to Hair et al. (2014a, p.19) PLS-SEM is highly suited to situations where the intention is to use latent variable scores in subsequent studies.

**Acknowledgements**

We wish to thank Professors Ravi Pappu and Andrew Burton-Jones for reading a pre-submission copy of our article, as well as Keay-shen See and Yong Li for assisting with data collection.
References


Appendix A: The data simulation process

In general, bank holding companies (BHCs) with higher systemic risk levels (as captured by the reflective indicators) should be traced to BHC characteristics (as captured by the formative indicators) with greater importance weights, i.e. greater causes of systemic risk in shadow banking (see Table A1). Predictive PLS-SEM modelling follows from the seventeen variables detailed in Table A1.

Table A1: Indicators of systemic risk with weights and ranges

<table>
<thead>
<tr>
<th>Causes of systemic risk in SB and the corresponding potential formative indicators (simulated)</th>
<th>Consequences of systemic risk in RBS are potential reflective indicators (observed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Level of specific complex derivatives such as collateralized debt obligations (CDOs) or loan obligations (CLOs) with tranches associated with a BHC ($) ((\text{Higher values lead to higher SR}) ) {MICRO}</td>
<td>1. Total regulatory capital ratio {MICRO} ((\text{Higher values lead to higher SR}) ) Tiered range [0 \leq L \leq 13.10; 13.10 \leq M \leq 15.80; 15.80 \leq U \leq 25.60]</td>
</tr>
<tr>
<td>Weight 40% Main range [$0 - 4 billion] Tiered range [0 \leq L \leq 1; 1 \leq M \leq 3; 3 \leq U \leq 4]</td>
<td>2. Non-interest income scaled by interest income {MICRO} ((\text{Higher values lead to higher SR}) ) Tiered range [0.02 \leq L \leq 0.27; 0.27 \leq M \leq 0.71; 0.71 \leq U \leq 6.07]</td>
</tr>
<tr>
<td>2. Repurchase agreements ($) ((\text{Higher values lead to higher SR}) ) {MICRO}</td>
<td>3. Non-performing loans (NPL) scaled by total loans {MICRO} ((\text{Higher values lead to higher SR}) ) Tiered range [0.07 \leq L \leq 0.85; 0.85 \leq M \leq 2.76; 2.76 \leq U \leq 9.46]</td>
</tr>
<tr>
<td>Weight 30% Main range [$0.1 - 2 billion] Tiered range [0.1 \leq L \leq 0.58; 0.58 \leq M \leq 1.5; 1.5 \leq U \leq 2]</td>
<td>4. Bank z-score measured as the ratio of ROA plus the capital-asset ratio, divided by the SD of ROA over six years {MICRO} ((\text{Higher values lead to lower SR}, \text{Reciprocal}) ) Tiered range [0.58 \leq L \leq 0.92; 0.92 \leq M \leq 1.28; 1.28 \leq U \leq 2.26]</td>
</tr>
<tr>
<td>3. For SB institutions associated with a BHC, average duration of executive stock options in years ((\text{Shorter duration leads to higher SR, Reciprocal}) ) {MICRO}</td>
<td>5. Relative efficiency scores based on CPM {MICRO} ((\text{Higher values lead to lower SR}, \text{Reciprocal}) ) Tiered range [0.23 \leq L \leq 0.45; 0.45 \leq M \leq 1.06; 1.06 \leq U \leq 1.42]</td>
</tr>
<tr>
<td>Weight 10% Main range [1 - 10 years] Tiered range [1 \leq L \leq 3.25; 3.25 \leq M \leq 7.75; 7.75 \leq U \leq 10]</td>
<td>6. Financial beta defined as volatility of bank share price relative to the overall stock market {MACRO} ((\text{Higher values lead to higher SR}) ) Tiered range [0.44 \leq L \leq 0.78; 0.78 \leq M \leq 1.09; 1.09 \leq U \leq 1.72]</td>
</tr>
<tr>
<td>4. For SB institutions associated with a BHC, the number of compensation packages linked to a risk-weighted portfolio of firm’s securities adjusted for firm size ((\text{Lower values lead to higher SR}, \text{Reciprocal}) ) {MICRO}</td>
<td>7. See Cohen et al. (2000).</td>
</tr>
<tr>
<td>Weight 10% Main range [0 - 100] Tiered range [0 \leq L \leq 25; 25 \leq M \leq 75; 75 \leq U \leq 100]</td>
<td>8. Given repos appear as N/A in BankScope, a small range has been used.</td>
</tr>
<tr>
<td>Sub-tiered range based on total assets Lower: [0 \leq L \leq 8; 8 \leq M \leq 17; 17 \leq U \leq 25] Middle: [25 \leq L \leq 42; 42 \leq M \leq 59; 59 \leq U \leq 75] Upper: [75 \leq L \leq 83; 83 \leq M \leq 92; 92 \leq U \leq 100]</td>
<td>Tiered range [0.0 \leq L \leq 0.2; 0.2 \leq M \leq 0.5; 0.5 \leq U \leq 1.0]</td>
</tr>
<tr>
<td>5. For SB institutions associated with a BHC, contingent convertible executive bonds adjusted for firm size ($) ((\text{Lower values lead to higher SR}, \text{Reciprocal}) ) {MICRO}</td>
<td>Tiered range [0.0 \leq L \leq 0.2; 0.2 \leq M \leq 0.5; 0.5 \leq U \leq 1.0]</td>
</tr>
<tr>
<td>Weight 10% Main range [$0 - 10 million] Tiered range [0 \leq L \leq 2.5; 2.5 \leq M \leq 7.5; 7.5 \leq U \leq 10]</td>
<td></td>
</tr>
<tr>
<td>Sub-tiered range based on total assets Lower: [0 \leq L \leq 0.8; 0.8 \leq M \leq 1.7; 1.7 \leq U \leq 2.5] Middle: [2.5 \leq L \leq 4; 4 \leq M \leq 6; 6 \leq U \leq 7.5] Upper: [7.5 \leq L \leq 8; 8 \leq M \leq 9; 9 \leq U \leq 10]</td>
<td>Tiered range [0.44 \leq L \leq 0.78; 0.78 \leq M \leq 1.09; 1.09 \leq U \leq 1.72]</td>
</tr>
<tr>
<td>6. Average length of the intermediation chain (complexity of derivatives) from investors to assets measured by the number of counterparties ((\text{Higher values lead to higher SR}) ) {MACRO}</td>
<td></td>
</tr>
<tr>
<td>Weight 40% Main range [2 - 10] Tiered range [2 \leq L \leq 4; 4 \leq M \leq 8; 8 \leq U \leq 10]</td>
<td></td>
</tr>
</tbody>
</table>
7. Number of SB facilities incorporated in OFCs associated with a BHC adjusted for firm size (Higher values lead to higher SR) \{MACRO\}

Weight 25%
Main range [0 - 20]
Tiered range [0<=L<5; 5<=M<15; 15<U<20]
Sub-tiered range based on total assets
   Lower: 0<=L<1.5; 1.5<=M<3.5; 3.5<=U<5
   Middle: 5<=L<8.2; 8.2<=M<11.8; 11.8<=U<15
   Upper: 15<=L<16.5; 16.5<=M<18.5; 18.5<U<20

7. Modified BCBS score approximating domestic systemic importance of banks \{MACRO\}
(Higher values lead to higher SR)
Tiered range
[0.02<=L<0.04; 0.04<=M<0.37; 0.37<U<24.90]

8. Extent financial assets of a given SB institution associated with a BHC are correlated with similar SB institutions (Higher values lead to higher SR) \{MACRO\}

Weight 15%
Main range [0 - 1]
Tiered range [0<=L<0.25; 0.25<=M<0.75; 0.75<U<1]

8. Extent financial assets of a given SB institution associated with a BHC are correlated with similar SB institutions (Higher values lead to higher SR) \{MACRO\}

Weight 15%
Main range [0 - 1]
Tiered range [0<=L<0.25; 0.25<=M<0.75; 0.75<U<1]

9. Number of associations with structured credit vehicles for a given BHC adjusted for firm size (Higher values lead to higher SR) \{MACRO\}

Weight 10%
Main range [2 - 30]
Tiered range [2<=L<9; 9<=M<23; 23<U<30]
Sub-tiered range based on total assets
   Lower: 2<=L<4.2; 4.2<=M<6.8; 6.8<U<9
   Middle: 9<=L<13.5; 13.5<=M<18.5; 18.5<U<23
   Upper: 23<=L<25.2; 25.2<=M<27.8; 27.8<U<30

9. Number of associations with structured credit vehicles for a given BHC adjusted for firm size (Higher values lead to higher SR) \{MACRO\}

Weight 10%
Main range [2 - 30]
Tiered range [2<=L<9; 9<=M<23; 23<U<30]
Sub-tiered range based on total assets
   Lower: 2<=L<4.2; 4.2<=M<6.8; 6.8<U<9
   Middle: 9<=L<13.5; 13.5<=M<18.5; 18.5<U<23
   Upper: 23<=L<25.2; 25.2<=M<27.8; 27.8<U<30

10. Relationship of a BHC with financial performance of its insurer(s) providing put options measured by return on assets (Lower ROA is a proxy for non-robust puts, and thus, higher SR, Reciprocal) \{MACRO\}

Weight 10%
Main range [-10% - 13%]17
Tiered range [-10<=L <-4.25; -4.25<=M<7.25; 7.25<U<13]

Notes: SB, shadow banking; RBS, regulated banking sector; BHC, bank holding company; SR, systemic risk; MACRO, macroprudential perspective; MICRO, microprudential perspective. L, M, and U are notations for Lower (below 25th percentile), Middle (between the 25th and 75th percentile) and Upper (above the 75th percentile) ranges. In the simulation, reciprocals are taken of some of the indicators to bring their meaning in line with the others, i.e. higher levels suggest higher systemic risk. Main ranges for the simulated variables are arbitrary choices. The tiered range for total assets (in USD millions) is comprised of lower (8,735<=L<14,751), middle (14,751<=M<=100,440), and upper (100,440<U<2,415,689), and total assets is used as a proxy for adjusting for firm size.

The simulation process follows the steps outlined below:

A1. Categorize the BHCs into systemic risk level categories as determined by reflective indicators (see second column in Table A1);
A2. Simulate the BHC formative indicators based upon their systemic risk category; and
A3. Account for the impact of firm size in the simulation of formative indicators.

A1: Categorization of BHCs into eight systemic risk categories

Based on seven reflective indicators, we sort the BHCs into eleven categories according to the level of systemic risk in descending order, e.g., Category 1 has the highest systemic risk and Category 11 has the lowest systemic risk. All variables are divided into three-tier range derived from the sample (N=63), e.g. lower (below 25th percentile), middle

17 Maximum value of 13% is based on Cummins et al. (2012).
(between the 25th and 75th percentile) and upper (above the 75th percentile) ranges. The BHC categories are classified as given in Table A2.

### Table A2: BHC systemic risk categories and criteria

<table>
<thead>
<tr>
<th>BHC systemic risk category</th>
<th>Corresponding BHC systemic risk category criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BHC has 7 reflective indicators in the upper ranges</td>
</tr>
<tr>
<td>2</td>
<td>BHC has 6 reflective indicators in the upper ranges</td>
</tr>
<tr>
<td>3</td>
<td>BHC has 5 reflective indicators in the upper ranges</td>
</tr>
<tr>
<td>4</td>
<td>BHC has 4 reflective indicators in the upper ranges</td>
</tr>
<tr>
<td>5</td>
<td>BHC has 3 reflective indicators in the upper ranges</td>
</tr>
<tr>
<td>6</td>
<td>BHC has 2 reflective indicators in the upper ranges</td>
</tr>
<tr>
<td>7</td>
<td>BHC has 1 reflective indicator in the upper ranges</td>
</tr>
<tr>
<td>8</td>
<td>BHC has no reflective indicator in the upper range, but has five or more variables in the middle ranges</td>
</tr>
<tr>
<td>9</td>
<td>BHC has no reflective indicator in the upper range but has three to four variables in the middle ranges</td>
</tr>
<tr>
<td>10</td>
<td>BHC has no reflective indicator in the upper range but has one to two variables in the middle ranges</td>
</tr>
<tr>
<td>11</td>
<td>BHC has no reflective indicator which falls in the upper or middle ranges, i.e. all are in the lower ranges</td>
</tr>
</tbody>
</table>

### A2: Simulation of formative indicators based upon BHC systemic risk category

Starting with the systemic risk category determined as per Table A2, simulations of formative indicators for each BHC in the sample are generated from a random uniform distribution within the minimum and maximum values indicated in Table A1. Table A3 summarizes the simulation process for each formative indicator based on the BHC systemic risk category. All variables are divided into a three-tier range, e.g. lower (below 25th percentile), middle (between the 25th and 75th percentile) and upper (above the 75th percentile) ranges (see Table A1 for the ranges used).
### Table A3: BHC formative indicator simulation process based upon BHC systemic risk categories

<table>
<thead>
<tr>
<th>BHC systemic risk category</th>
<th>BHC category conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Random generation of ten formative indicators in the upper ranges.</td>
</tr>
<tr>
<td>2</td>
<td>Random generation of formative indicators 1, 2, 6, 7 and 8 in the upper ranges; and random generation of the remaining formative indicators in the middle ranges</td>
</tr>
<tr>
<td>3</td>
<td>Random generation of formative indicators 2, 7 and 8 in the upper ranges; and random generation of the remaining formative indicators in the middle ranges</td>
</tr>
<tr>
<td>4</td>
<td>Random generation of formative indicator 8 in the upper range; and random generation of the remaining formative indicators in the middle ranges</td>
</tr>
<tr>
<td>5</td>
<td>Random generation of all the formative indicators in the middle ranges</td>
</tr>
<tr>
<td>6</td>
<td>Random generation of formative indicators 1, 2, 6, 7 and 8 in the middle ranges; and random generation of the remaining formative indicators in the lower ranges</td>
</tr>
<tr>
<td>7</td>
<td>Random generation of formative indicators 2, 6, 7 and 8 in the middle ranges; and random generation of the remaining formative indicators in the lower ranges</td>
</tr>
<tr>
<td>8</td>
<td>Random generation of formative indicators 2, 7 and 8 in the middle ranges; and random generation of the remaining formative indicators in the lower ranges</td>
</tr>
<tr>
<td>9</td>
<td>Random generation of formative indicators 7 and 8 in the middle ranges; and random generation of the remaining formative indicators in the lower ranges</td>
</tr>
<tr>
<td>10</td>
<td>Random generation of formative indicator 8 in the middle range; and random generation of the remaining formative indicators in the lower ranges</td>
</tr>
<tr>
<td>11</td>
<td>Random generation of all the formative indicators in the lower ranges</td>
</tr>
</tbody>
</table>

**A3: Accounting for firm size in the simulation**

For example, formative indicator #4 requires an additional simulation step to reflect its relationship to firm size (total assets). That is, once a BHC’s range for the formative indicator #4 is determined in line with its systemic risk category (e.g. under Category 1, this range is ‘upper’, whereas under Category 3 the range changes to ‘middle’), an additional set of three-tier range within that range is applied based on firm size represented by total assets. To illustrate, during the first set of simulations, if formative indicator #4 falls within the upper range (above the 75th percentile), we will determine if the bank is located in the upper, middle or lower ranges in terms of total assets. Based upon the three-tier range in terms of firm size, a second simulation for formative indicator #4 is run. This additional step is included because larger firms have a greater likelihood of managing more risk-weighted executive compensation packages. A similar treatment is extended to formative indicators #5, 7, and 9.

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18 These ranges describe the ranges of systemic risk. For formative indicators #3, #4, #5 and #10, higher systemic risk will mean that lower values are simulated, i.e. taking reciprocals. For all other formative indicators, higher systemic risk will result in simulation within the higher ranges, respectively.
Appendix B: Procedure followed for predictive model assessment using PLS-SEM in SmartPLS software

(See Table 3 in Hair et al. 2011, and Table 5 in Hair et al. 2012)

INITIAL TEST: This first attempt is based on the variables detailed in Table A1, i.e. ten formative indicators and seven reflective indicators. SmartPLS was set to 300 maximum iterations with a stop criterion of $10^{-7}$, and analysis converged in 36 iterations.

- REFLECTIVE MEASUREMENT MODEL
  - **Internal consistency**: Composite reliability is 0.684; according to Hair et al. (2012), 0.6 is acceptable in exploratory research. Similarly, values above 0.9 are undesirable (Hair et al. 2014a). Overall, we find moderate internal consistency. According to Hair et al. (2012, 2014b), composite reliability is a better measure of internal consistency because it avoids underestimation often seen with Cronbach’s alpha and accommodates differences in indicator reliabilities expected by PLS-SEM, i.e. composite reliability does not assume tau-equivalence.
  - **Indicator reliability**: Outer loadings fall in the range 0.875 – 0.067 and four of them are above 0.5 with a mean value of 0.468. Overall, we find moderate indicator reliability. Hair et al. (2012) state that in exploratory research, loadings as low as 0.4 are acceptable. The three reflective indicators with the low outer loadings of 0.067, 0.141 and 0.403 (‘relative efficiency scores based on CPM’, ‘total regulatory capital ratio’, and ‘non-interest income ratio’, respectively) can be removed as part of the exercise to improve the predictive model.
  - **Convergent validity**: Average variance extracted (AVE) is only 0.290, suggesting low convergent validity. That is, the endogenous construct accounts for less than 50% of the reflective indicators’ variance. AVE greater than 0.5 is desirable.
  - **Discriminant validity**: Fornell-Larcker criterion stands at 0.538 with mostly appropriate cross-loadings.

- FORMATIVE MEASUREMENT MODEL
  - **Convergent validity**: Path coefficients are moderate at 0.587 (MICRO) and 0.348 (MACRO).
  - **Multi-collinearity among indicators**: Variance inflation factor (VIF) is 3.044. Since this number is less than 5, multi-collinearity is not an issue.
  - **Significance and relevance of outer weights**: At 5% level, $p$-values following bootstrapping indicate that the ‘outer weights’ of six out of ten formative indicators are insignificant with ‘number of compensation packages’ with the highest $p$-value of 0.705. Checking ‘outer loadings’ for the insignificant formative indicators, only one indicator is still indicated for potential removal (i.e. a loading less than 0.5), namely, ‘insurer’s return on assets’ (see formative indicator #10 in Table A1). However, eliminating formative indicators should be approached with caution because formative measurement theory expects the indicators to cover the domain of a construct.

- STRUCTURAL MODEL: [N.B. If the outer models, that is, measurement models are not reliable, we can have little confidence in the structural (inner) model.]
  - **Coefficient of determination, $R^2$**: is high at 0.801 (adjusted 0.795). This number indicates that the two exogenous constructs substantially explain the variation in the endogenous construct.

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19 ‘Weight’ is an indicator’s relative contribution. ‘Loading’ is an indicator’s absolute contribution.
Predictive relevance, $Q^2$, is obtained by the sample re-use technique called ‘Blindfolding’ in SmartPLS where omission distance is set to 8 (Hair et al. 2012 recommend a distance between 5 – 10 where the number of observations divided by the omission distance is not an integer). $Q^2$ emerges as 0.175. Since this number is larger than zero, it is indicative of the path model’s predictive relevance in the context of the endogenous construct and the corresponding reflective indicators.

Size and significance of path coefficients: For example, the $p$-value for the path coefficient of 0.587 between the MICRO exogenous construct and the endogenous construct is 0.001; the MACRO path coefficient 0.348 (0.054) is borderline significant.

$f^2$ effect size: $f^2$ measures the importance of the exogenous constructs in explaining the endogenous construct and it re-calculates $R^2$ by omitting one exogenous construct at a time. 0.570 (MICRO) is pleasingly high, indicating a large change in $R^2$ if the exogenous construct on micro-level linkages were to be omitted; 0.200 (MACRO) is lower but still substantial, implying that while the MACRO exogenous construct contributes relatively less to explaining the endogenous construct, both of the exogenous constructs are important. Hair et al. (2014a) provide a rule of thumb where effect size of 0.02 is considered small, 0.15 is medium and 0.35 is large.

REVOMAL OF LOW-LOADING REFLECTIVE INDICATORS:

1. Remove the reflective indicator #5 outlined in Table A1 ‘Relative efficiency scores based on CPM’ and check all other results.
2. If the above removal leads to improvement of statistical criteria, next remove the reflective indicator #1 in Table A1 ‘Total regulatory capital ratio’ before checking the results again.
3. Finally, remove the ‘Non-interest income ratio’ – the reflective indicator #2 in Table A1.

Removing the relative efficiency scores improves internal consistency, convergent validity and discriminant validity of the reflective measurement model; removal also improves the predictive relevance of the structural model (details are available from the corresponding author). We then sequentially remove the ‘Total regulatory capital ratio’ and the ‘Non-interest income ratio’ which leads to further improvements where the analysis converges in 22 iterations. The full report on the fourth test with ten formative and four reflective indicators is presented below:

**REFLECTIVE MEASUREMENT MODEL**

- **Internal consistency**: Composite reliability is much better at 0.784 compared to the initial test. Overall, we now observe above moderate internal consistency.
- **Indicator reliability**: Outer loadings fall in the range 0.849 – 0.529 (mean=0.685). Overall, we find above moderate indicator reliability.
- **Convergent validity**: Average variance extracted (AVE) is now higher at 0.482, suggesting moderate convergent validity.
- **Discriminant validity**: Fornell-Larcker criterion rises to 0.695, again suggesting moderate but improved discriminant validity with appropriate cross-loadings.

**FORMATIVE MEASUREMENT MODEL**

- **Convergent validity**: Path coefficients are still moderate at 0.567 (MICRO) and 0.342 (MACRO).
Multi-collinearity among indicators: Variance inflation factor (VIF) remains under 5 at 3.025.

Significance and relevance of outer weights: At 5% level, \( p \)-values indicate that the ‘outer weights’ of five out of ten formative indicators are insignificant. Checking ‘outer loadings’ for the insignificant formative indicators, two indicators are indicated for potential removal, namely, ‘insurer’s return on assets’ and ‘number of counterparties’. However, we do not remove these formative indicators as they are important components of the theorised exogenous construct on macro-level linkages.

**STRUCTURAL MODEL**

- Coefficient of determination, \( R^2 \), is still high at 0.756 (adjusted 0.748).
- Predictive relevance: \( Q^2 \) rises to 0.316 indicating higher predictive relevance compared to the initial test.
- Size and significance of path coefficients: For example, the \( p \)-value for the path coefficient of 0.567 between the MICRO exogenous construct and the endogenous construct is 0.000; the MACRO path coefficient 0.342 (0.012) is also significant.
- \( f^2 \) effect size: 0.435 (MICRO) is still high. 0.159 (MACRO) is lower compared to the initial test but still of medium magnitude, implying that while both exogenous constructs are significant, the MACRO exogenous construct continues to contribute relatively less to explaining the endogenous construct.
Figure 1: Illustrative representation of a predictive model for shadow banking’s contribution to systemic risk in the regulated banking sector. This is a purely illustrative depiction of PLS-SEM modeling; the actual diagrammatic model representing the results reported is shown in Figure 3. Circles represent the latent variables or constructs that comprise the structural model; left-hand rectangles ($X_1 - X_5$) house the formative indicators theorized as underlying causes of the two exogenous latent constructs (i.e. measurement model for systemic risk in shadow banking); right-hand rectangles ($X_6 - X_{10}$) house the reflective indicators theorized as the consequences of the endogenous or target latent construct (i.e. measurement model for systemic risk in the regulated banking sector). $W_1 - W_{10}$ are the outer weights, and $P_1$ and $P_2$ are the proxies for $Y_1$ and $Y_2$ (exogenous latent constructs) explaining $Y_3$ (endogenous latent construct). The number of indicators represented in Figure 1 is illustrative only and do not represent the actual indicator numbers used (see Figure 3 for the model reported).
Figure 2: Diagram depicting the PLS-SEM algorithm (adapted from Figure 5 in Monecke and Leisch 2012)
Figure 3: Depiction of the final model in SmartPLS software. Expanded variable names are in Table A1. Below we provide names corresponding to the abbreviated variable names (also used in Table 2). RI-MICRO stands for ‘reflective indicator with microprudential perspective’ and RI-MACRO stands for ‘reflective indicator with macroprudential perspective’; similarly, FI-MICRO stands for ‘formative indicator with microprudential perspective’ and FI-MACRO stands for ‘formative indicator with macroprudential perspective’.

Observed reflective indicators

- (RI-MICRO)Non-perLoansRatio: Non-performing loans (NPL)
- (RI-MICRO)BankZscore_Recip: Bank z-score (BZS)
- (RI-MACRO)FinBeta: Financial beta (FB)
- (RI-MACRO)BCBS: Modified BCBS score (CBS)

Simulated formative indicators

- (FI-MICRO)CDO_CLO: Level of specific complex derivatives (CD)
- (FI-MICRO)Repos: Repurchase agreements (RA)
- (FI-MICRO)DurExeStockOpt_Recip: Average duration of executive stock (DES)
- (FI-MICRO)#CompPkg_TA_Recip: # of compensation packages (#CP)
- (FI-MICRO)ContBonds_TA_Recip: Contingent convertible executive bonds (CEB)
- (FI-MACRO)#Counterparties: # of counterparties (#CP)
- (FI-MACRO)#SBfacilitiesOFC_TA: # of SB facilities incorporated in OFCs (#OFC)
- (FI-MACRO)extFinAssSBcorr: Extent financial assets are correlated (FAC)
- (FI-MACRO)#CreditVehicles_TA: # of associations with credit vehicles (#ACV)
- (FI-MACRO)insurerROA_Recip: Insurer’s return on assets (ROA)
Table 1: Potential indicators of systemic risk

<table>
<thead>
<tr>
<th>Causes of systemic risk in SB and the corresponding potential formative indicators</th>
<th>Consequences of systemic risk in RBS are potential reflective indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excessive securitization through special purpose investment vehicles (Gennaioli et al. 2013)</td>
<td>Number of associations with structured credit vehicles for a given BHC ((Higher \ values \ lead \ to \ higher \ SR)) {MACRO}</td>
</tr>
<tr>
<td>Excessive dependence on short-term funding (Baker 2012 and Barr 2012)</td>
<td>* Level of OTC derivatives associated with a BHC ((Higher \ values \ lead \ to \ higher \ SR)) {MICRO}</td>
</tr>
<tr>
<td>Complexity of derivatives (Blyth 2003, and Bryan and Rafferty 2006)</td>
<td>* Repurchase agreements ((Higher \ values \ lead \ to \ higher \ SR)) {MICRO}</td>
</tr>
<tr>
<td>Homogeneity of financial assets in shadow banking (Elsinger et al. 2006)</td>
<td>* Number of compensation packages linked to a risk-weighted portfolio of firm’s securities ((lower \ values \ lead \ to \ higher \ SR)) {MICRO}</td>
</tr>
<tr>
<td>Non-robust (mispriced) credit/liquidity put options (Adrian and Ashcraft 2012)</td>
<td>* Contingent convertible executive bonds ((lower \ values \ lead \ to \ higher \ SR)) {MICRO}</td>
</tr>
<tr>
<td>Incorporation of SB facilities in offshore financial centers (OFCs) (FSB 2011, 2013 and Rixen 2013)</td>
<td>Relationship of a BHC with financial performance of its insurer(s) providing put options measured by return on assets ((lower \ ROA \ is \ a \ proxy \ for \ non-robust \ puts, \ and \ thus, \ higher \ SR)) {MACRO}</td>
</tr>
<tr>
<td>Types of executive compensation (Anabtawi and Schwarcz 2011, Tung 2011, Kaal 2012, and Johnson 2013)</td>
<td>For SB institutions associated with a BHC: * Average duration of executive stock options in years ((shorter \ duration \ leads \ to \ higher \ SR)) {MICRO};</td>
</tr>
<tr>
<td></td>
<td>* Number of compensation packages linked to a risk-weighted portfolio of firm’s securities ((lower \ values \ lead \ to \ higher \ SR)) {MICRO};</td>
</tr>
<tr>
<td></td>
<td>* Contingent convertible executive bonds ((lower \ values \ lead \ to \ higher \ SR)) {MICRO}</td>
</tr>
</tbody>
</table>

Notes: SB, shadow banking; RBS, regulated banking sector; BHC, bank holding company; SR, systemic risk; MACRO, macroprudential perspective; MICRO, microprudential perspective.

20 This variable is currently not available. It is expected to be implemented in the USA as of 2016 (Gibson Dunn Lawyers 2013).
21 See Brämer and Gischer (2013) who illustrate a practical adaptation of the indicator-based method proposed by the Basel Committee on Banking Supervision (2011b).
22 See the core profitability model (CPM) in Avkiran and Cai (2014).
Table 2: Summary statistics and correlations on variables used in all PLS-SEM tests (N=63 BHCs)

<table>
<thead>
<tr>
<th>Observed reflective indicators</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>CV</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total regulatory capital ratio (RCR) b</td>
<td>14.38</td>
<td>14.33</td>
<td>3.58</td>
<td>0.25</td>
<td>0.00</td>
<td>25.62</td>
<td>-1.40</td>
<td>8.30</td>
</tr>
<tr>
<td>Non-interest income (NII) b</td>
<td>0.77</td>
<td>0.44</td>
<td>1.07</td>
<td>1.39</td>
<td>0.02</td>
<td>6.07</td>
<td>3.11</td>
<td>10.82</td>
</tr>
<tr>
<td>Non-performing loans (NPL)</td>
<td>2.01</td>
<td>1.39</td>
<td>1.75</td>
<td>0.87</td>
<td>0.07</td>
<td>9.46</td>
<td>1.86</td>
<td>4.76</td>
</tr>
<tr>
<td>Bank z-score (BZS)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.94</td>
<td>0.00</td>
<td>0.00</td>
<td>2.31</td>
<td>6.39</td>
</tr>
<tr>
<td>Relative efficiency scores (RES) b</td>
<td>1.58</td>
<td>1.37</td>
<td>0.72</td>
<td>0.46</td>
<td>0.70</td>
<td>3.48</td>
<td>0.84</td>
<td>-0.05</td>
</tr>
<tr>
<td>Financial beta (FB)</td>
<td>0.95</td>
<td>0.97</td>
<td>0.27</td>
<td>0.28</td>
<td>0.44</td>
<td>1.71</td>
<td>0.52</td>
<td>0.55</td>
</tr>
<tr>
<td>Modified BCBS score (CBS)</td>
<td>1.59</td>
<td>0.08</td>
<td>4.34</td>
<td>2.73</td>
<td>0.02</td>
<td>24.90</td>
<td>3.59</td>
<td>14.32</td>
</tr>
</tbody>
</table>

Simulated formative indicators

<table>
<thead>
<tr>
<th>Simulated formative indicators</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>CV</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level of specific complex derivatives (CD)</td>
<td>1.19</td>
<td>0.90</td>
<td>0.87</td>
<td>0.73</td>
<td>0.04</td>
<td>2.94</td>
<td>0.56</td>
<td>-0.99</td>
</tr>
<tr>
<td>Repurchase agreements (RA)</td>
<td>1.03</td>
<td>1.01</td>
<td>0.40</td>
<td>0.39</td>
<td>0.21</td>
<td>1.86</td>
<td>-0.07</td>
<td>-0.57</td>
</tr>
<tr>
<td>Average duration of executive stock (DES)</td>
<td>0.14</td>
<td>0.12</td>
<td>0.04</td>
<td>0.33</td>
<td>0.10</td>
<td>0.28</td>
<td>1.84</td>
<td>2.52</td>
</tr>
<tr>
<td>% of compensation packages (%CP)</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.29</td>
<td>0.01</td>
<td>0.03</td>
<td>2.28</td>
<td>5.84</td>
</tr>
<tr>
<td>Contingent convertible executive bonds (CEB)</td>
<td>0.14</td>
<td>0.13</td>
<td>0.03</td>
<td>0.25</td>
<td>0.10</td>
<td>0.26</td>
<td>2.13</td>
<td>4.58</td>
</tr>
<tr>
<td>% of counterparties (%CP)</td>
<td>5.53</td>
<td>5.73</td>
<td>1.62</td>
<td>0.29</td>
<td>0.10</td>
<td>2.26</td>
<td>7.91</td>
<td>-0.39</td>
</tr>
<tr>
<td># of SB facilities incorporated in OFCs (%OFC)</td>
<td>10.11</td>
<td>10.00</td>
<td>2.71</td>
<td>0.27</td>
<td>0.40</td>
<td>15.00</td>
<td>-0.17</td>
<td>-0.42</td>
</tr>
<tr>
<td>Extent financial assets are correlated (FAC)</td>
<td>0.58</td>
<td>0.59</td>
<td>0.18</td>
<td>0.31</td>
<td>0.26</td>
<td>0.96</td>
<td>0.21</td>
<td>-0.73</td>
</tr>
<tr>
<td># of associations with credit vehicles (%ACV)</td>
<td>8.48</td>
<td>7.00</td>
<td>5.25</td>
<td>0.62</td>
<td>2.00</td>
<td>22.00</td>
<td>1.11</td>
<td>0.32</td>
</tr>
<tr>
<td>Insurer’s return on assets (ROA)</td>
<td>0.20</td>
<td>0.10</td>
<td>0.62</td>
<td>3.01</td>
<td>0.70</td>
<td>4.46</td>
<td>5.71</td>
<td>38.10</td>
</tr>
</tbody>
</table>

Panel B: Correlations

| RCR | NII | NPL | BZS | RES | FB | CBS | CD | RA | DES | %CP | CEB | %CP | %OFC | FAC | %ACV | ROA |
|-----|-----|-----|-----|-----|----|-----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| RCR | 1.00 |     |     |     |    |     |    |    |     |     |     |     |     |     |     |     |
| NII | 0.14 | 1.00 |     |     |    |     |    |    |     |     |     |     |     |     |     |     |
| NPL | -0.03 | -0.17 | 1.00 |     |    |     |    |    |     |     |     |     |     |     |     |     |
| BZS | -0.09 | -0.01 | 0.51 | 1.00 |    |     |    |    |     |     |     |     |     |     |     |     |
| RES | -0.20 | -0.22 | 0.30 | 0.18 | 1.00 |    |    |    |     |     |     |     |     |     |     |     |
| FB  | 0.14 | 0.40 | 0.37 | 0.41 | -0.05 | 1.00 |    |    |     |     |     |     |     |     |     |     |
| CBS | 0.15 | 0.35 | 0.06 | -0.05 | -0.31 | 0.48 | 1.00 |    |     |     |     |     |     |     |     |     |
| CD  | 0.17 | 0.31 | 0.42 | 0.26 | -0.03 | 0.58 | 0.53 | 1.00 |    |     |     |     |     |     |     |     |
| RA  | -0.02 | 0.22 | 0.52 | 0.37 | 0.27 | 0.44 | 0.29 | 0.35 | 1.00 |    |     |     |     |     |     |     |
| DES | 0.14 | 0.44 | 0.45 | 0.28 | 0.09 | 0.58 | 0.34 | 0.50 | 0.35 | 1.00 |    |     |     |     |     |     |
| %CP | -0.09 | 0.20 | 0.68 | 0.49 | 0.41 | 0.47 | 0.08 | 0.43 | 0.42 | 0.65 | 1.00 |    |     |     |     |     |
| CEB | -0.06 | 0.07 | 0.70 | 0.49 | 0.43 | 0.50 | 0.13 | 0.41 | 0.43 | 0.58 | 0.92 | 1.00 |    |     |     |     |
| %CP | 0.11 | 0.07 | 0.28 | 0.33 | 0.14 | 0.20 | 0.05 | 0.21 | 0.34 | 0.21 | 0.27 | 0.26 | 0.04 | 1.00 |    |     |
| %OFC | 0.07 | 0.15 | 0.26 | 0.21 | 0.07 | 0.23 | 0.14 | 0.14 | 0.30 | 0.26 | 0.26 | 0.25 | 0.04 | 1.00 |    |     |
| FAC | -0.09 | 0.36 | 0.21 | 0.17 | -0.02 | 0.57 | 0.26 | 0.37 | 0.31 | 0.55 | 0.32 | 0.37 | 0.09 | 0.07 | 1.00 |    |
| %ACV | 0.17 | 0.33 | 0.47 | 0.30 | -0.05 | 0.62 | 0.65 | 0.64 | 0.35 | 0.60 | 0.56 | 0.60 | 0.26 | 0.21 | 0.38 | 1.00 |
| ROA | -0.03 | -0.15 | 0.35 | 0.21 | 0.13 | 0.07 | -0.16 | 0.16 | 0.04 | 0.13 | 0.38 | 0.32 | 0.19 | 0.06 | -0.13 | 0.06 | 1.00 |

Notes: Refer to Table A1 in Appendix A for more details on the variables used.

* Coefficient of variation (std. dev. / mean)

b Removed following the initial PLS-SEM analysis.