



Research Paper

# Monitoring transmission of systemic risk: application of partial least squares structural equation modeling in financial stress testing

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## ABSTRACT

Regulators need a method that is versatile, is easy to use and can handle complex path models with latent (not directly observable) variables. In a first application of partial least squares structural equation modeling (PLS-SEM) in financial stress testing, we demonstrate how PLS-SEM can be used to explain the transmission of systemic risk. We model this transmission of systemic risk from shadow banking to the regulated banking sector (RBS) using a set of indicators (directly observable variables) that are sources of systemic risk in shadow banking and consequences of systemic risk measured in the RBS. Procedures for predictive model assessment using PLS-SEM are outlined in clear steps. Statistically significant results based on predictive modeling indicate that around 75% of the variation in systemic risk in the RBS can be explained by microlevel and macrolevel linkages that can be traced to shadow banking (we use partially simulated data). The finding that microlevel linkages have a greater impact on the contagion of systemic risk highlights the type of significant insight that can be generated through PLS-SEM. Regulators can use PLS-SEM to monitor the

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transmission of systemic risk, and the demonstrated skills can be transferred to any topic with latent constructs.

**Keywords:** structural equation modeling; partial least squares; path model; contagion of systemic risk; shadow banking; bank holding companies.

## 1 INTRODUCTION

According to Calluzzo and Dong (2015), it is difficult to quantify systemic risk in integrated markets, and doing so changes dynamically. Further, research on how risk is transmitted is still in its early stages due to inadequate data and complex linkages (Liang 2013). We examine the exposure of US bank holding companies (BHCs) to systemic risk sourced from shadow banking (SB), where SB is comprised of less regulated transactions, also known as market-based financing, through nonbank channels such as real estate investment trusts, leasing companies, credit guarantee outlets and money market funds.

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Given the intricate and often changing connections between SB and the regulated banking sector (RBS), we refrain from defining yet another network topology designed to explain the transmission of systemic risk (examples of network topology can be found in Boss *et al* (2004), Hu *et al* (2012), Oet *et al* (2013), Caccioli *et al* (2014), Hautsch *et al* (2014) and Levy-Carciente *et al* (2015)). Instead, we work with a set of key indicators (directly measurable variables) identified as capturing the sources of systemic risk in SB and the consequences of systemic risk in the RBS.

From a regulator perspective, as connections change in a complex cause–effect environment, it is easier to add or remove indicators from a predictive contagion model, rather than redefine another network topology. As Acharya *et al* (2013, p. 76) point out, “The analysis of network effects in a stress test is extremely complex, even if all of the data on positions [is] available”. The statistical method in this paper is more versatile and easier to use, compared with network-based analyses. It better accommodates data characteristics often found in the real world, such as multivariate nonnormality.

This paper illustrates how the transmission of systemic risk from SB to the RBS can be modeled using partial least squares structural equation modeling (PLS-SEM) in an effort to help regulators better monitor and manage contagion. PLS-SEM is a nonparametric approach based on ordinary least squares (OLS) regression, designed to maximize the explained variance in latent constructs, eg, systemic risk that cannot be directly observed or measured but can be observed indirectly through related indicators.

In addition to being robust with skewed data, PLS-SEM is considered an appropriate technique when working with composite models (Henseler *et al* 2014; Sarstedt *et al*

2016). A variance-based SEM technique, such as PLS-SEM, has particular advantages when it comes to composite modeling over its better-known cousin, covariance-based structural equation modeling (CB-SEM) (Henseler *et al* 2009; Hair *et al* 2014; Hair *et al* 2017a; Sarstedt *et al* 2014).<sup>1</sup> The prediction-oriented character and the capability to deal with complex models highlights PLS-SEM as the method of choice in a wide range of disciplines (Wold 1982; Lohmöller 1989; Cepeda Carrión *et al* 2016; Richter *et al* 2016a).

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The results of various review and overview studies across different business research disciplines, including accounting (Lee *et al* 2011; Nitzl 2016), family business (Sarstedt *et al* 2014), management information systems (Hair *et al* 2016; Ringle *et al* 2012), marketing (Hair *et al* 2012b; Henseler *et al* 2009; Richter *et al* 2016b), operations management (Peng and Lai 2012), supply chain management (Kaufmann and Gaeckler 2015), strategic management (Hair *et al* 2012a) and tourism (do Valle and Assaker 2016), support the rising popularity of PLS-SEM. Beside its wide application in business research, the use of PLS-SEM as published in journal articles reveals that it has recently expanded into fields such as biology, engineering, environmental and political science, medicine and psychology (see, for example, Willaby *et al* 2015).

Gart (1994, p. 134) defines systemic risk as the clear hazard that difficulties with the operations of financial institutions can be quickly transferred to others, including markets, and cause economic damage. In the period leading up to the global financial crisis (GFC) of 2007–9, a large portion of the financing of securitized assets was handled by the SB sector (Gennaioli *et al* 2013). The collapse of SB during these years therefore played an important role in weakening the RBS. According to the Financial Stability Board's (FSB's) report, SB makes a significant contribution to financing the real economy; for example, in 2013, SB assets represented 25% of total financial system assets (Financial Stability Board 2014).

Because of the interconnectedness between SB and the RBS (Adrian and Ashcraft 2012), SB can become a source of systemic risk: a major concern to all regulators. A main motivation for mitigating systemic risk is minimizing a negative impact on the real economy. As systemic risk rises, distressed banks reduce lending to clients, who in turn invest less, which reduces employment. As part of the interaction between SB and the RBS, there is a concern that banks might be evading increased regulation by shifting activities to SB (Gennaioli *et al* 2013). As the Basel III Accord moves toward full implementation by 2019, with a focus on better preparing financial institutions

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<sup>1</sup> CB-SEM can be used to investigate relationships or linkages among latent constructs indicated by multiple variables or measures, but it expects multivariate normal distribution and large samples. CB-SEM follows a confirmatory approach to multivariate analysis, where the researcher theorizes about causal relations among the variables of interest. For a highly readable introduction to CB-SEM, see Lei and Wu (2007).

for the next crisis, and the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 (DFA) unfolds in the United States, the contribution of SB to systemic risk in the RBS needs to be closely monitored.

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 SB through SIVs and special purpose vehicles (SPVs) created strong interdependencies and enabled the RBS to engage in almost unrestricted leverage. Banks were able to maintain higher leverage and still comply with risk-weighted capital requirements by transforming assets into highly rated securities. Such a strategy makes banks more vulnerable to shocks. The FSB (2011, p. 5) reports that while Basel III addresses a number of failings, regulatory arbitrage is likely to rise as bank regulation becomes tighter. The main motivation behind this study is to examine to what extent the transmission of systemic risk from SB to the RBS can be monitored. To the best of our knowledge, this is the first use of PLS-SEM in the field of financial stress testing.

Despite extensive empirical literature on systemic risk and the accompanying transmission mechanisms, Weiß *et al* (2014) state that the 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). Our indicator-based approach to modeling systemic risk is favored by international regulators such as the Basel Committee on Banking Supervision (BCBS) and reflects microprudential as well as macroprudential perspectives (microlevel and macrolevel linkages). Similar to Glasserman and Young (2015), we avoid starting the investigation with a predefined network structure or topology, because we consider financial networks to be dynamic.

There is a wealth of information on the interconnectedness of the financial system and regulation in finance and law journals. However, both of these disciplines appear to ignore the body of knowledge generated by the other when we examine the references in such articles. Motivated by this observation, we attempt to strike a balance by tapping into both disciplines as we explore the feasibility of monitoring the transmission of systemic risk. The rest of this paper unfolds with a conceptual framework that develops assumptions to be tested. This is followed by an outline of the PLS-SEM method and a description of data. After reporting the results, we offer concluding remarks.

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## 2 CONCEPTUAL FRAMEWORK

There are two banking systems in the United States, and each is governed by a different legal regime. Financial institutions that carry a banking charter belong to the tradi-

tional depository banking system often evaluated as three tiers, namely city banks, regional banks and community banks. These are referred to as the RBS; most US banks are owned by BHCs supervised by the Federal Reserve (Fed). Those who do not have a charter belong to the SB system, such as investment banks, money market mutual funds (MMMFs), hedge funds and insurance firms. One of the key differences between regulated banks and shadow banks is that the former are allowed to fund their lending activities through insured deposits (capped at US\$250 000 per account), whereas federal law prohibits the latter from using deposits. Shadow banks therefore depend on deposit substitutes in a mostly unregulated and uninsured environment.

Over the last thirty years or so, SB has become increasingly dependent on various forms of short-term funding that substitute for functionality of deposits, such as 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. During a financial crisis, the reliance on deposit substitutes can have a contagious 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 nonfinancial 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 and Sunderam (2014) argue that instabilities associated with MMMFs were central to the GFC, and Bengtsson (2013) provides similar evidence from Europe.

Given externalities or moral hazards such as implicit expectations on the part of institutions to be bailed out in crises, it is unlikely that either banking sector will implement optimal protection or fully hedge their risks. There is a strong argument in favor of regulating how the SB sector relies on deposit substitutes and the systemic risk channeled to the RBS. In the finance literature, scholars such as Beltratti and Stulz (2012) have shown evidence of fragility in banks financed with the short-term funding that is often the domain of SB.

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This study models the transmission of systemic risk using PLS-SEM in an effort to help regulators to better predict what is likely to happen in the RBS we heavily depend on for a well-functioning society. Thus, the first assumption is as follows.

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(A<sub>1</sub>) Systemic risk in SB makes a significant contribution to systemic risk in the RBS.

The well-known prudential regulation's main focus is on identifying and mitigating exposure to endogenous crises at individual financial institutions, regulating leverage through internal risk management policies overseen by boards of directors. Ellul and Yerramilli (2013) report that BHCs with stronger and more independent risk

management functions before the GFC had lower tail risk, less impaired loans, better operating performance and higher annual returns in 2007–8. Importantly, prudential regulation addressed by the Basel Accords has recently been supplemented by the European Systemic Risk Board (ESRB) and the Office of Financial Research (OFR) from the United States working on macroprudential regulation designed to identify and mitigate systemic risks.

Macroprudential regulation – an emerging framework – is designed to investigate the interconnectedness between SB and the 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 recognize systemic risk as a negative externality, where firms lack private incentives to minimize it (Liang 2013). Macroprudential regulation complements prudential regulation by simultaneously focusing attention on institution-specific endogenous factors and network-related exogenous factors that give rise to systemic risk.

We continue by expanding on key linkages between SB and the RBS, with a view to laying the groundwork for a predictive systemic risk framework that could enable monitoring contagion. A good starting point is an 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, particularly regarding how systemic risk is transmitted. Anabtawi and Schwarcz (2011) express a strong concern about the market participants being unreliable in terms of interrupting and limiting the transmission of systemic risk.

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First, Anabtawi and Schwarcz (2011) posit an intrafirm correlation between a firm's exposure to the risk of low-probability adverse events that can cause economic shocks and harm a firm's financial integrity. Second, the authors put forward the concept of an interfirm correlation among financial firms and markets, where interaction with the intrafirm correlation can facilitate the transmission of otherwise localized economic shocks. An example of intrafirm 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 that are heavily invested in such securities. An example of interfirm 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 SB institutions.

According to Anabtawi and Schwarcz (2011, p. 1356), intrafirm and interfirm correlations give rise to a transmission mechanism that can take a local adverse economic shock and convert it to strong systemic concerns. Effective regulation that weakens the abovementioned correlations can reduce the cost associated with financial crises. Following our first assumption, our second and third assumptions are defined below.

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- (A<sub>1A</sub>) Systemic risk sourced from intrafirm correlations or microlevel linkages emanating from SB makes a significant contribution to systemic risk in the RBS.
- (A<sub>1B</sub>) Systemic risk sourced from interfirm correlations or macrolevel linkages emanating from SB makes a significant contribution to systemic risk in the RBS.

Another publication that attempts to make sense of interconnectedness and systemic risk is by Judge (2012), which focuses on financial innovation and the 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. 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 SB is primarily incorporated in lightly regulated offshore financial centers (OFCs). SPVs and SIVs benefit from regulatory and tax advantages offered by OFCs. Rixen (2013, pp. 438–439) maintains that OFCs can increase financial risk in at least five 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 in investments.

In summary, 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. Starting from the above discussion of linkages, Table 1 outlines the sources of systemic risk in SB and the consequences of systemic risk in the RBS in an effort to draft a list of potential indicators (manifest variables) that can be used for predictive modeling.

### 3 METHOD AND DATA

#### 3.1 Partial least squares structural equation modeling

For the first time in the field of financial stress studies, we use the iterative OLS regression-based PLS-SEM (Lohmöller 1989; Wold 1982). PLS-SEM has become a key multivariate analysis method to estimate complex models with relationships

TABLE 1 Potential indicators of systemic risk. [Table continues on next page.]

Sources of systemic risk in SB and the corresponding potential formative indicators	Consequences of systemic risk in RBS are potential reflective indicators
Excessive securitization through special purpose investment vehicles (Gennaioli <i>et al</i> 2013)	<p><b>Number of associations with structured credit vehicles</b> for a given BHC (<i>higher values lead to higher SR</i>) {MACRO}</p> <ul style="list-style-type: none"> <li>• Countercyclical capital buffer percentages, eg, 0-2.5% of risk weighted assets (BCBS 2011a) {MACRO}*</li> </ul>
Excessive dependence on short-term funding (Baker 2012; Barr 2012)	<p>• Level of OTC derivatives associated with a BHC (US\$) (<i>Higher values lead to higher SR</i>) {MICRO}</p> <ul style="list-style-type: none"> <li>• <b>Repos</b> (US\$) (<i>higher values lead to higher SR</i>) {MICRO}</li> <li>• MMMFs (US\$) (<i>Higher values lead to higher SR</i>) {MICRO}</li> </ul>
Complexity of derivatives (Blyth 2003; Bryan and Rafferty 2006)	<p>• <b>Level of specific complex derivatives</b> such as collateralized debt obligations (CDOs) or loan obligations (CLOs) with tranches associated with a BHC (US\$) (<i>higher values lead to higher SR</i>) {MICRO}</p> <ul style="list-style-type: none"> <li>• <b>Average length of the intermediation chain</b> from investors to assets, measured by the number of counterparties (<i>higher values lead to higher SR</i>) {MACRO}</li> </ul>
Nonrobust (mispriced) credit/liquidity put options (Adrian and Ashcraft 2012)	<p>• <b>Relationship of a BHC with financial performance of its insurer(s)</b> providing put options measured by return on assets (<i>lower ROA is a proxy for nonrobust puts and higher SR</i>) {MACRO}</p> <ul style="list-style-type: none"> <li>• <b>Bank z-score measured as the ratio of ROA plus the capital-asset ratio, divided by the SD of ROA over six years</b>, distance to default (Laeven and Levine 2009; Erel <i>et al</i> 2014) {MICRO}</li> <li>• Spread of bank bonds defined as the difference between ten-year A-rated bond yield and ten-year US Treasury yield (Oet <i>et al</i> 2011, 2013; Bianco <i>et al</i> 2012) {MACRO}</li> </ul>



TABLE 1 Continued.

Sources of systemic risk in SB and the corresponding potential formative indicators	Consequences of systemic risk in RBS are potential reflective indicators
Incorporation of SB facilities in OFCs (FSB 2011, 2013; Rixen 2013)	<p><b>Number of SB facilities incorporated in OFCs</b> associated with a BHC (<i>higher values lead to higher SR</i>) {MACRO}</p> <ul style="list-style-type: none"> <li>• <b>Financial beta</b> defined as volatility of bank share price relative to the overall stock market (Oet <i>et al</i> 2011, 2013; Bianco <i>et al</i> 2012) {MACRO}</li> </ul>
Types of executive compensation (Anabtawi and Schwarcz 2011; Tung 2011; Kaal 2012; Johnson 2013)	<p><i>For SB institutions associated with a BHC:</i></p> <ul style="list-style-type: none"> <li>• <b>Average duration of executive stock options</b> in years (<i>shorter duration leads to higher SR</i>) {MICRO};</li> <li>• <b>Number of compensation packages</b> linked to a risk-weighted portfolio of firm's securities (<i>lower values lead to higher SR</i>) {MICRO};</li> <li>• <b>Contingent convertible executive bonds</b> (US\$) (<i>lower values lead to higher SR</i>) {MICRO}</li> </ul> <p>Results of annual stress testing required by Dodd-Frank Act (Barr 2012) {MACRO}</p> <ul style="list-style-type: none"> <li>• Stressed value-at-risk (VaR) required by Basel Accords (BCBS 2011a) {MACRO}</li> <li>• <b>Modified BCBS' score</b> approximating domestic systemic importance of banks {MACRO}**</li> <li>• <b>Relative efficiency scores</b> based on CPM {MICRO}***</li> </ul>
Homogeneity of financial assets in SB (Eisinger <i>et al</i> 2006)	<p><b>Extent of financial assets of a given SB institution associated with a BHC</b> are correlated with similar SB institutions (<i>higher values lead to higher SR</i>) {MACRO}</p>

SB: shadow banking; RBS: regulated banking sector; BHC: bank holding company; SR: systemic risk; MACRO: macroprudential perspective; MICRO: microprudential perspective; indicators used are in bold. \* This variable is currently not available. It was expected to be implemented in the United States as of 2016 (Gibson Dunn Lawyers 2013). \*\* Brämer and Gischer (2013) illustrate a practical adaptation of the indicator-based method proposed by the BCBS (2011b). \*\*\* See the core profitability model (CPM) in Avkiran and Cai (2014).

between latent variables in various disciplines. For example, popular PLS-SEM applications focus on explaining customer satisfaction and loyalty, or technology acceptance and use (Hair *et al* (2014, Table 1) provides a breakdown of business disciplines that use PLS-SEM). The goal of the nonparametric PLS-SEM method is to maximize the explained variance of endogenous latent constructs (a latent construct explained by other latent constructs in the PLS path model), whereby the assumption of multivariate normality is relaxed. For instance, Hair *et al* (2011, 2012b, 2014, 2017a, 2018) introduce users to PLS-SEM, while, for example, Lohmöller (1989) and Moncke and Leisch (2012) provide a step-by-step explanation of the mathematics behind its algorithm.

Given the extent of dynamic interconnectedness in the US financial system, we treat the transmission of systemic risk as a set of latent constructs representing phenomena that cannot be directly observed or measured. Figure 1 represents a predictive model. This study's main objective remains one of predictive modeling and understanding the transmission of systemic risk from SB to the RBS through a foundational illustration of PLS-SEM in this field.

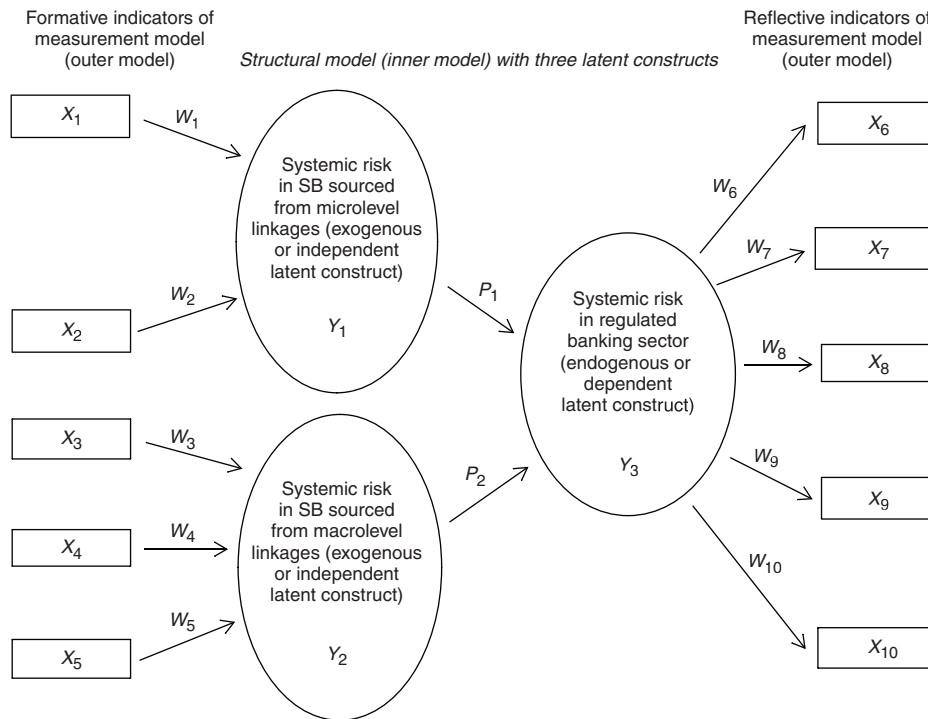
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We start with known sources of systemic risk in SB captured by formative indicators, and estimate the extent to which we can predict consequences of systemic risk in the RBS captured by reflective indicators (see Table 1 and Figure 1). According to 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, using the PLS-SEM approach is recommended when (1) the objective is explaining and predicting target constructs and/or detecting important driver constructs, (2) the structural model has formatively measured constructs, (3) the model is complex (with many constructs and indicators), (4) the researcher is working with a small sample size (due to a small population size) and/or data is nonnormal, and (4) the researcher intends to use latent variable scores in follow-up studies (Hair *et al* 2017a; Rigdon 2016). The latter case has been demonstrated by importance-performance map analyses (Ringle and Sarstedt 2016) or the combination of PLS-SEM results with agent-based simulation (Schubring *et al* 2016).

Some other advantages of PLS-SEM over CB-SEM are its focus on predicting dependent latent variables (Evermann and Tate 2016; Shmueli *et al* 2016), which is often a key objective in empirical studies, and its ability to accommodate indicators with different scales. In this context, the distinction between formative and reflective indicators is particularly important (Hair *et al* 2011, 2012b; Sarstedt *et al* 2016).

- Formative indicators form the associated exogenous latent constructs. We try to minimize the overlap among them because they are treated as complementary (Table 1's left-hand column contains potential formative indicators likely to lead to systemic risk in SB). The exogenous latent constructs in Figure 1 are

**FIGURE 1** Illustrative representation of a predictive model for SB's contribution to systemic risk in the RBS.



This is an 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 forming the two exogenous latent constructs (measurement model for systemic risk in SB); right-hand rectangles ( $X_6$ – $X_{10}$ ) house the reflective indicators theorized as the consequences of the endogenous or target latent construct (measurement model for systemic risk in the RBS).  $W_1$ – $W_{10}$  are the outer weights, and  $P_1$  and  $P_2$  are the proxies or path coefficients 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 does not represent the actual indicator numbers used (the actual model is reported in Figure 3).

formed by the associated indicators, and the outer weights result from a multiple regression, with the construct as a dependent variable and its associated formative indicators as independent variables.

- Reflective indicators are consequences or manifestations of the underlying target latent construct, meaning causality is from the construct to the indicator. Because of substantial overlap among the reflective indicators, they are treated as interchangeable, meaning they are expected to be highly correlated. Poten-

tial reflective indicators likely to capture the systemic risk in the RBS are indicated in the right-hand column of Table 1. The endogenous latent construct in Figure 1 becomes the independent variable in single regression runs to determine the outer loadings, where the reflective indicators individually become the dependent variable in each run.

PLS-SEM models consist of two main components, namely the structural or inner model and the measurement or outer model, visible in Figure 1. A group of manifest variables (indicators) associated with a latent construct is 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 treat 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 the use of recursive models, where there are no circular relationships (Hair *et al* 2017a); nonrecursive models with circular relationships may use the latent variable scores and, in a second stage, estimate the circular relationships by using, for example, the two-stage least squares method (see, for example, Bollen 2001).

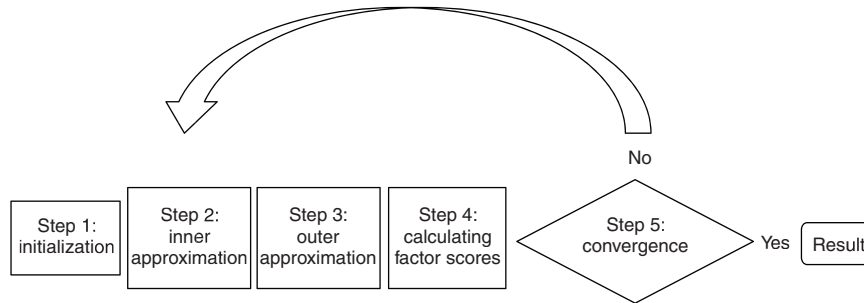
Figure 2 provides a diagrammatic representation of the PLS-SEM algorithm as described in Monecke and Leisch (2012). At the beginning of the algorithm, all the manifest variables in the data matrix are scaled to have a zero mean and unit variance. The algorithm estimates factor scores for the latent constructs 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), 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 prespecified tolerance (following each step, latent constructs are scaled to have zero mean and unit variance).

The PLS-SEM algorithm provides latent variable scores, reflective loadings and formative weights in the measurement models, estimations of path coefficients in the

**FIGURE 2** Diagram depicting the PLS-SEM algorithm (adapted from Monecke and Leisch (2012, Figure 5)).



structural model, and  $R^2$  values of endogenous latent variables. These results allow computing many additional results and quality criteria, such as Cronbach's alpha, the composite reliability,  $f^2$  effect sizes,  $Q^2$  values of predictive relevance (see, for example, Chin 1998; Tenenhaus *et al* 2005; Chin 2010; Hair *et al* 2017a) and the new HTMT criterion (heterotrait–monotrait ratio of correlations) to assess discriminant validity (Henseler *et al* 2015).

Nevertheless, PLS-SEM has been criticized for giving biased parameter estimates because it does not explicitly model measurement error, despite employing bootstrapping to estimate standard errors for parameter estimates (Gefen *et al* 2011). This potential shortcoming can be restated as PLS-SEM parameter estimates based on limited information not being as efficient as those based on full information estimates (Sohn *et al* 2007). Alternatively, CB-SEM is able to model measurement error structures via a factor analytic approach; however, the downside is covariance among the observed variables that need to conform to overlapping proportionality constraints, meaning measurement errors are assumed to be uncorrelated (Jöreskog 1979).

Further, CB-SEM assumes homogeneity in the observed population (Wu *et al* 2012). Unless latent constructs are based on highly developed theory and the measurement instrument is refined through multiple stages, such constraints are unlikely to hold. Therefore, secondary data – often found in business databases – is unlikely to satisfy expected constraints. In such a situation, CB-SEM that relies on common factors would be the inappropriate choice, and PLS-SEM that relies on weighted composites would be more appropriate because of its less restrictive assumptions. Further, using formative indicators is problematic in CB-SEM because it gives rise to identification problems and reduces the ability of CB-SEM to reliably capture measurement error (Petter *et al* 2007). Those interested in further critique/rebuttal of PLS-SEM are

invited to read Henseler *et al* (2014), Marcoulides *et al* (2012), Rigdon (2016) and Sarstedt *et al* (2016).

Recapping, in addition to being robust with skewed data because it transforms nonnormal 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* 2017a). However, this argument is relevant when the sample size is small due to a small population size. Otherwise, using large data sets and normally distributed data are advantageous when using PLS-SEM. The literature review in Hair *et al* (2014, Table 1) lists the top three reasons for PLS-SEM usage as (1) nonnormal data, (2) small sample size and (3) presence of formative indicators (all of these conditions exist in this study's data set).

Against this background of stated reasons, it is important to consider the arguments for and against the use of PLS-SEM that Rigdon (2016) puts forward. In summary, good reasons for using PLS-SEM are

- (1) to explain and predict the key target construct of the model,
- (2) to estimate complex models,
- (3) the inclusion of formatively measured constructs,
- (4) small populations and relatively small sample sizes, and/or
- (5) the use of secondary data.

Finally, PLS-SEM provides determinate latent variable scores, which can be employed in complementary methods (see, for example, Ringle and Sarstedt 2016; Schubring *et al* 2016).

### 3.2 Data

We dub the list of indicators found in Table 1 the “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 US Securities and Exchange Commission. We found inconsistent reporting formats and scant useful data for the project at hand.

We focus on BHCs because most banks in the United States, and particularly those at mature stages of operation, are owned by BHCs (Partnership for Progress 2011). The structures of BHCs allow them to diversify their portfolios and banking activities (Strafford 2011). Our working sample of sixty-three 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 modeling, we start with seven reflective indicators and ten formative indicators from the potential list first summarized in Table 1 (see also Table A1 in the online appendix). The set of formative indicators is comprised of five indicators of microprudential focus capturing intrafirm relationships defining one of the two exogenous constructs, and five indicators of macroprudential focus capturing interfirm relationships defining the other exogenous construct (see the left-hand column of Table A1 in the online appendix, where the first five formative indicators are microprudential and the next five are macroprudential). In the run-up to the GFC of 2007–9, Acharya *et al* (2010) argue that the SB system was used to organize the manufacture of systemic tail risk (based on securitization) with inadequate capital in place; it is challenging for regulators to supervise this type of risk-taking by financial institutions.

After the initial run of PLS-SEM, we are left with four reflective indicators for the endogenous construct (two indicators of microprudential and two indicators of macroprudential perspective), and the same set of ten formative indicators for the two exogenous constructs.<sup>2</sup> As the maximum number of arrows pointing at a latent variable (in the measurement models or in the structural model) is five, we would need at least  $5 \times 10 = 50$  observations to technically estimate the model (according to the ten-times rule of Barclay *et al* (1995)). Following the more rigorous recommendations from a power analysis (Hair *et al* 2016, p. 26, Exhibit 1.7), at least forty-five observations are needed to detect a minimum  $R^2$  value of 25% at a significance level of 5% and a statistical power level of 80%. Therefore, the sample size of sixty-three BHCs passes both technical minimum sample size requirements for estimating the underlying PLS path model. Summary statistics on the variables reported in Table 2 indicate nonnormal 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 data such as that detailed in the online appendix by ensuring we use the systemic risk levels indicated by the observed data on reflective indicators, adjusting for firm size where relevant. Our simulation process for formative indicators starts by dividing each observed potential reflective indicator of a BHC into three quantiles (see the online appendix, Table A1, second column). These quantiles are defined as the upper, middle and lower ranges. Depending on the number of reflective indicators that each BHC exhibits in these quantiles, a BHC is assigned to one of eleven systemic risk categories (see Table A2 in the online appendix). The list of BHCs assigned to each systemic risk category is given in Table A3 (available online).

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<sup>2</sup> The reflective indicators “relative efficiency scores based on CPM”, “total regulatory capital ratio”, and “noninterest income ratio” are sequentially removed because of their low outer loadings and the observed improvement in statistical criteria once they are omitted.

**TABLE 2** Summary statistics and correlations on variables used in all PLS-SEM tests ( $N = 63$  BHCs). [Table continues on next page.]

(a) Summary statistics										
	Mean	Median	SD	CV <sup>a</sup>	Min.	Max.	Skew.	Kurtosis		
<i>Observed reflective indicators</i>										
1. Total regulatory capital ratio (RCR) <sup>b</sup>	14.3766	14.3300	3.5822	0.2491	0.0000	25.6200	-1.3991	8.2999		
2. Noninterest income (NII) <sup>b</sup>	0.7669	0.4445	1.0677	1.3920	0.0194	6.0739	3.1101	10.8240		
3. Nonperforming loans (NPLs)	2.0053	1.3900	1.7451	0.8702	0.0700	9.4600	1.8585	4.7642		
4. Bank z-score (BZS)	0.0005	0.0003	0.0005	0.9375	0.0000	0.0027	2.3059	6.3931		
5. Relative efficiency scores (RESs) <sup>b</sup>	1.5797	1.3734	0.7217	0.4568	0.7036	3.4820	0.8405	-0.0460		
6. Financial beta (FB)	0.9488	0.9650	0.2667	0.2810	0.4424	1.7139	0.5159	0.5501		
7. Modified BCBS score (CBS)	1.5873	0.0820	4.3401	2.7343	0.0228	24.9039	3.5877	14.3240		
<i>Simulated formative indicators</i>										
1. Level of specific complex derivatives (CD)	1.1863	0.9047	0.8666	0.7305	0.0430	2.9411	0.5643	-0.9885		
2. Repurchase agreements (RAs)	1.0297	1.0107	0.4005	0.3889	0.2094	1.8557	-0.0745	-0.5724		
3. Average duration of executive stock (DES)	0.1381	0.1209	0.0449	0.3254	0.1013	0.2819	1.8351	2.5231		
4. # of compensation packages (#CP)	0.0138	0.0120	0.0039	0.2889	0.0101	0.0312	2.2837	5.8411		
5. Contingent convertible executive bonds (CEB)	0.1385	0.1295	0.0339	0.2451	0.1014	0.2600	2.1280	4.5771		
6. # of counterparties (#CP)	5.5298	5.7266	1.6230	0.2935	2.2560	7.9147	-0.3859	-0.9434		
7. # of SB facilities incorporated in OFCs (#OFC)	10.1111	10.0000	2.7126	0.2682	4.0000	15.0000	-0.1662	-0.4193		
8. Extent that financial assets are correlated (FAC)	0.5822	0.5856	0.1816	0.3119	0.2577	0.9632	0.2088	-0.7347		
9. # of associations with credit vehicles (#ACV)	8.4761	7.0000	5.2451	0.6188	2.0000	22.0000	1.1121	0.3193		
10. Insurer's return on assets (ROA)	0.2049	0.1032	0.6174	3.0131	-0.6998	4.4647	5.7099	38.0971		



TABLE 2 Continued.

(b) Correlations

	RCR	NII	NPL	BZS	RES	FB	CBS	CD	RA	DES	#Comp	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							
#Comp	-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	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

Refer to Table A1 in the online appendix for more details on the variables. <sup>a</sup>Coefficient of variation (standard deviation (SD)/mean). <sup>b</sup>Removed following the initial PLS-SEM analysis.

A random normal distribution for each formative indicator is simulated and bounded by the tiered range, as given by a set of rules based on the systemic risk category of each BHC (Table A3). The tiered ranges for the formative indicators are defined by the range of maximum and minimum values of formative indicators based on assumptions in the systemic risk literature for BHCs. Further, 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 has three quantiles each, creating nine quantiles. For example, if a BHC is considered to have a formative indicator that is in the middle range from step 1, and it is noted to be in the upper range in terms of firm size, the random simulation will occur in the sixth quantile. For more details on the simulation process, please see Section A2 of the online appendix.

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## 4 MODEL ESTIMATION AND RESULTS

Initially, we model ten formative indicators (five for each of the two exogenous constructs) and seven reflective indicators for the endogenous construct (see Table 1 and Table A1 in the online appendix). We then execute an additional run of PLS-SEM by removing three low-loading reflective indicators before reporting the final results. The reduced model in Figure 3 provides a diagram of the PLS-SEM final results. We used the software SmartPLS 3 (Ringle *et al* 2015) to conduct all the PLS-SEM analyses in this study.

### 4.1 Procedure followed for predictive model assessment using PLS-SEM

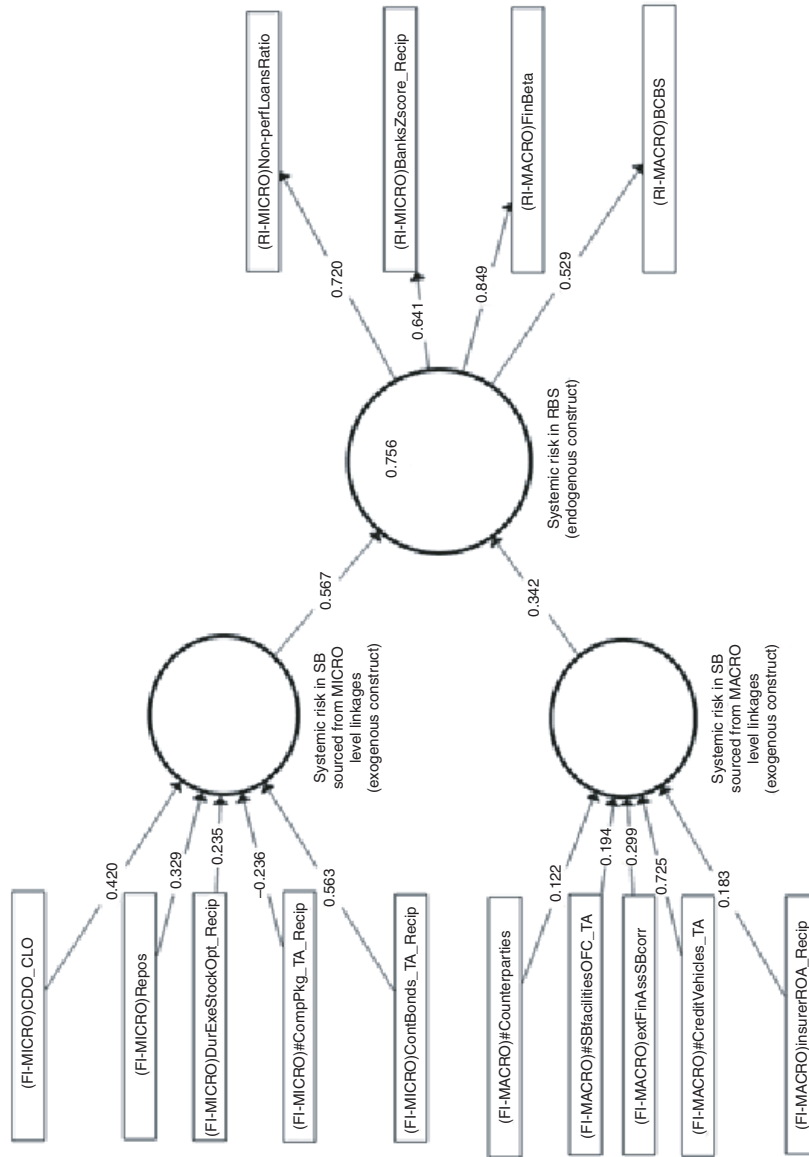
SmartPLS was set to 300 maximum iterations, with a stop criterion of  $10^{-7}$  and analysis converged in thirty-six iterations. Hair *et al* (2017a, Exhibit 4.1) contains an outline of the procedure used below.

#### *Reflective measurement model*

*Indicator reliability.* Hair *et al* (2012b) state that in exploratory research, loadings as low as 0.4 are acceptable. Outer loadings fall in the range 0.067–0.875. The three reflective indicators with the outer loadings of 0.067, 0.141 and 0.403 (“relative efficiency scores based on CPM”, “total regulatory capital ratio” and “noninterest income ratio”) are removed, as their indicator reliability is at relatively low levels. As a result of using the reduced model, outer loadings rise with a narrower range of 0.529–0.849. The rest of the testing is based on the reduced model.

*Internal consistency.* According to Hair *et al* (2017a), we use Cronbach’s alpha as our lower boundary and composite reliability as our upper boundary to determine

FIGURE 3 Depiction of the reduced model in SmartPLS software (expanded variable names are in Table 3 and Table A1).



**TABLE 3** Abbreviated variable names.

(a) Four observed reflective indicators	
(RI-MICRO)Non-perLoansRatio	Nonperforming loans (NPL)
(RI-MICRO)BankZscore_Recip	Bank <i>z</i> -score (BZS)
(RI-MACRO)FinBeta	Financial beta (FB)
(RI-MACRO)BCBS	Modified BCBS score (CBS)*
(b) Ten simulated formative indicators	
(FI-MICRO)CDO_CLO	<i>Level of specific complex derivatives (CD)</i>
(FI-MICRO)Repos	<i>Repurchase agreements (RA)</i>
(FI-MICRO)DurExeStockOpt_Recip	<i>Average duration of executive stock (DES)</i>
(FI-MICRO)#CompPkg_TA_Recip	<i># of compensation packages (#CP)</i>
(FI-MICRO)ContBonds_TA_Recip	<i>Contingent convertible executive bonds (CEB)</i>
(FI-MACRO)#Counterparties	<i># of counterparties (#CP)</i>
(FI-MACRO)#SBfacilitiesOFC_TA	<i># of SB facilities incorporated in OFCs (#OFC)</i>
(FI-MACRO)extFinAssSBcorr	<i>Extent that financial assets are correlated (FAC)</i>
(FI-MACRO)#CreditVehicles_TA	<i># of associations with credit vehicles (#ACV)</i>
(FI-MACRO)insurerROA_Recip	<i>Insurer's return on assets (ROA)</i>

Here, 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". \* An alternative approach would be to use systemic risk scores by the Fed. See Benoit *et al* (2017) for systemic risk scoring used by the BCBS.

internal consistency; the formulas for Cronbach's alpha and composite reliability are shown in Hair *et al* (2017a, pp. 111–112). Cronbach's alpha is 0.627 and composite reliability is 0.784; 0.6 is acceptable in exploratory research (Hair *et al* 2012b). Similarly, values above 0.95 are undesirable (Hair *et al* 2017a). Overall, we establish internal consistency at a satisfactory level.

*Convergent validity.* Average variance extracted (AVE) greater than 0.5 is preferred.

When examining reflective indicator loadings, it is desirable to see higher loadings in a narrow range, indicating that all items explain the underlying latent construct, meaning convergent validity (Chin 2010). AVE is 0.482, suggesting that the endogenous construct accounts for 48.2% of the reflective indicators' variance. Even though the AVE does not exceed the critical value of 0.5, we consider the result of 0.482 to be close enough to assume that convergent validity has been established. AVE could be increased above 0.5 by removing reflective indicators, but such an action is not recommended when the starting point is four indicators, because of its theoretical impact on the reflective measurement model.

*Discriminant validity.* For reflective constructs, we aim to establish discriminant validity. Since the PLS path model only has one reflectively measured latent variable, we do not address this issue, for example, by applying the HTMT criterion.

### *Formative measurement model*

*Convergent validity.* Convergent validity is the degree to which a measure correlates positively with other measures (eg, reflective) of the same construct, using different indicators. When evaluating the convergent validity of formative measurement models in PLS-SEM, we use redundancy analysis (Chin 1998) to test whether the formatively measured construct is highly correlated with a reflective measure of the same construct (Hair *et al* 2017a). Since we do not have such reflective items of the formatively measured constructs in this study or a single-item measure of the same construct, we cannot conduct the redundancy analysis. We only find that the sign of the relationship between the formatively measured exogenous constructs and the reflectively measured endogenous construct is high and positive as expected, with path coefficients of 0.567 for MICRO and 0.342 for MACRO. Also as expected, the correlation between the formatively measured constructs is positive. We can therefore, at least to some extent, substantiate convergent validity.

*Multicollinearity among indicators.* When collinearity exists, standard errors and variances are inflated. A variance inflation factor (VIF) of one means there is no correlation among the predictor variable examined and the rest of the predictors; therefore, the variance is not inflated. If the VIF is higher than five, the researcher should consider removing the corresponding indicator, or combining the collinear indicators into a new composite indicator. In this case, the VIF is 3.025. Since this number is less than five, multicollinearity is not an issue.

*Significance and relevance of outer weights.* At a 5% probability of error level, the bootstrap confidence intervals indicate that the outer weights' (an indicator's relative contribution) significance of five out of ten formative indicators cannot be established. Checking outer loadings (an indicator's absolute contribution) for these formative indicators, only two indicators are candidates for potential removal, namely "insurer's return on assets" and "number of counterparties". We do not remove these formative indicators, as they are important components of the theorized exogenous construct on macrolevel linkages.

### *Structural model*

Establishing substantial measurement model(s) is a prerequisite for assessing the structural model. The latter provides confidence in the structural (inner) model. Analysis of the structural model is an attempt to find evidence supporting the theoretical/

conceptual model, meaning the theorized/conceptualized relationships between the latent variables.

*Size and significance of path coefficients.* The 95% bootstrap confidence intervals indicate that the path coefficient of 0.567 between the MICRO exogenous construct and the endogenous construct is significant; the MACRO path coefficient of 0.342 is also significant.

*Predictive accuracy, coefficient of determination.* The  $R^2$  value is high, at 0.756 (adjusted to 0.748). This number indicates that the two exogenous constructs substantially explain the variation in the endogenous construct. According to Hair *et al* (2011, 2017a), as a rough rule of thumb, 0.25 is weak, 0.50 is moderate and 0.75 is substantial.

*Assessing the “effect sizes”.*  $f^2$  measures the importance of the exogenous constructs in explaining the endogenous construct, and it recalculates  $R^2$  by omitting one exogenous construct at a time. A 0.435 (MICRO) is pleasingly high, indicating a large change in  $R^2$  if the exogenous construct on microlevel linkages were to be omitted; a 0.159 (MACRO) is lower but still substantial, implying that while the MACRO exogenous construct contributes relatively less to explaining the endogenous construct, both exogenous constructs are important. Hair *et al* (2017a) provide a rule of thumb, whereby an effect size of 0.02 is considered small, 0.15 is medium and 0.35 is large. The formula for effect size can be found in Hair *et al* (2017a, p. 201).

*Predictive relevance,  $Q^2$ .* This is obtained by the sample reuse technique called “blindfolding” in SmartPLS, where omission distance is set to eight (Hair *et al* (2012b) recommend a distance between five and ten, where the number of observations divided by the omission distance is not an integer). For example, setting the omission distance to eight, every eighth data point is omitted and parameters are estimated with the remaining data points. Omitted data points are considered missing values and replaced by mean values (Hair *et al* 2017a). In turn, estimated parameters help predict the omitted data points, and the difference between the actual omitted data points and predicted data points becomes the input in our calculation of  $Q^2$ . In this case,  $Q^2$  emerges as 0.316. 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.

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*Assessing the relative impact of predictive relevance ( $q^2$ ).* Following from the above analysis of predictive relevance,  $q^2$  effect size can be calculated by excluding the exogenous constructs one at a time (see Hair *et al* (2017a, p. 207) for the formula). According to Hair *et al* (2013, 2017a), an effect size of 0.02 is considered small, 0.15

is moderate and 0.35 is large. The effect sizes following the respective exclusion of exogenous constructs are MACRO (0.0190) and MICRO (0.0833). The numbers indicate the dominance of MICRO in predicting systemic risk in the RBS.

In summary, our systematic evaluation of PLS-SEM results supports the establishment of substantial constructs via their measurement models, on which we build the analysis of the structural model. For the reflectively measured construct (systemic risk in the RBS), we can say we have construct validity (the extent we measure systemic risk as theorized) if both convergent and discriminant validity have been 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. 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, our current study included (Hair *et al* 2012b). For the formatively measured constructs, we also need to examine the convergent validity by means of the redundancy analysis. Due to the lack of additional indicators we need for conducting the redundancy analysis, we could not carry out such an assessment in this study. However, we find that collinearity between indicators is not a critical issue and establish the significance and relevance of outer weights.

Based on the findings, we assess the PLS-SEM results of the structural model. Starting with the strongest finding reported under the structural model,  $R^2$  and adjusted  $R^2$  for our parsimonious model are substantial at 0.756 and 0.748, respectively, suggesting that the two exogenous constructs theorized significantly explain the variation in the endogenous construct. This means sources of systemic risk emanating from SB explain the consequences of systemic risk observed in the RBS, 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, meaning 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, supporting  $H_{1A}$  and  $H_{1B}$  (we note that microlevel linkages play a larger role compared with macrolevel linkages). The  $f^2$  effect sizes of MICRO (0.435) and MACRO (0.159) suggest that microlevel linkages explain more of the variation in systemic risk in the RBS. A similar finding, but at a lower level, holds for the  $q^2$  effect sizes of predictive relevance.

As a result, we establish reliable and valid PLS-SEM results that allow us to substantiate our assumptions regarding the structural model. We find that the exogenous latent variables MICRO and MACRO explain 75.6% of the target construct (sys-

Are you not referring here to the things labeled  $A_{1A}$  and  $A_{1B}$  earlier?

temic risk in RBS), whereby MICRO is the somewhat more important explanatory construct. Also, we establish predictive relevance of the PLS path model.

## 4.2 Robustness testing

Hwang and Takane (2004, 2014) introduced generalized structured component analysis (GSCA) as an alternative to PLS-SEM (see Hair *et al* 2017b). We apply GSCA as a robustness test because it belongs to the same family of methods. PLS-SEM and GSCA are both variance-based methods, appropriate for predictive modeling, and they substitute components for factors. GSCA uses a global optimization function in parameter estimation with least squares (Hwang *et al* 2010). We restate that CB-SEM is not a meaningful alternative to PLS-SEM under the conditions of the current study, where the sample size is small, formative indicators are present and the study is exploratory rather than confirmatory.

GSCA maximizes the average or the sum of explained variances of linear composites, where latent variables are determined as weighted components or composites of observed variables. GSCA follows a global least squares optimization criterion, which is minimized to generate the model parameter estimates. GSCA is not scale-invariant and it standardizes data. GSCA retains the advantages of PLS-SEM, such as fewer restrictions on distributional assumptions, unique component score estimates and avoidance of improper solutions with small samples (Hwang and Takane 2004; Hwang *et al* 2010).

We use the web-based GSCA software GeSCA ([www.sem-gesca.org](http://www.sem-gesca.org)) for robustness testing of the reduced model with ten formative indicators across two exogenous constructs and four reflective indicators attached to the reflective measurement model (Hair *et al* 2017b). As can be seen in Table 4, the PLS-SEM results are confirmed by GSCA. For example, AVE is identical; outer loadings are of a similar magnitude across the four reflective indicators; both path coefficients are also of a similar magnitude in the structural model; and the coefficients of determination are close to each other, with GSCA giving a slightly larger  $R^2$ .

## 5 CONCLUDING REMARKS

We embarked on this project to illustrate how the transmission of systemic risk from SB to the RBS can be modeled using PLS-SEM, to help regulators monitor contagion without resorting to complex network topologies. To the best of our knowledge, using PLS-SEM in financial stress testing is the first such application. We have taken care to detail the procedure to be followed and how to interpret the results correctly. Behavioral finance is bound to provide a wealth of opportunities to apply PLS-SEM.

Following a literature review of finance and law disciplines, we identified various

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**TABLE 4** Robustness testing of PLS-SEM with GSCA.

	PLS-SEM	GSCA
<i>Measurement model</i>		
Average variance extracted (AVE)	0.482	0.482
<i>Outer loadings of reflective indicators</i>		
Nonperforming loans	0.720	0.743
Bank <i>z</i> -score	0.641	0.646
Financial beta	0.849	0.835
Modified BCBS score	0.529	0.513
<i>Structural model (path coefficients)</i>		
MICRO	0.567	0.561
MACRO	0.342	0.368
Coefficient of determination ( $R^2$ )	0.756	0.765

microlevel and macrolevel linkages between SB and the RBS. To address an extensive amount of missing data on sources of systemic risk in SB, we opted to simulate formative indicator data by establishing mathematical linkages to the observed reflective indicator data. The structural model to emerge consisted of two latent exogenous constructs of microlevel and macrolevel linkages embedded in SB, explaining the latent endogenous construct on systemic risk in the RBS. Based on partially simulated data, statistically significant results from PLS-SEM predictive modeling indicate that around 75% of the variation in systemic risk in the RBS can be explained by microlevel and macrolevel linkages that can be traced to SB.

While based on partially simulated data, the finding that microlevel linkages have a greater impact on the contagion of systemic risk (compared with macrolevel linkages) highlights the type of significant insight that can be generated through PLS-SEM. It suggests that internal risk management in BHCs has 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 in the RBS. This finding is in line with the Dodd–Frank Act, which calls for stricter prudential regulation of systemically important financial institutions.

Regulators can use the approach in this paper to monitor the transmission of systemic risk. As Majerbi and Rachdi (2014) aptly point out in their study of the probability of systemic banking crises across a sample of fifty-three countries, stricter banking regulation, supervision and bureaucratic efficiency generally result in the reduced probability of crises. However, Hirtle *et al* (2016) draw a distinction between regulation and supervision, defining the latter as out-of-sight monitoring to identify

unsound banking practices, which serves to complement regulation, ie, rules governing banks. Further, continued focus on transmission of systemic risk is warranted by the empirical evidence reported in Fink and Schüller (2015), where emerging market economies are shown to be negatively affected by systemic financial stress emanating from the United States.

Benoit *et al* (2016) conduct an extensive survey on systemic risk. The authors define systemic risk as a concept along the lines of “hard-to-define-but-you-know-it-when-you-see-it”. They continue to highlight that regulators need systemic risk measures that capture properly identified economic interactions in a timely manner, and that can be used in regulation. The authors highlight the fact that policy makers need reliable tools to monitor the escalation of systemic risks. They end their article with the comment that the search for a global risk measure that incorporates different sources of systemic risk and generates a single metric is still not over.

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An extension of the study can include testing the stability of parameters over time. Other potential extensions may focus on smaller financial crises such as the eurozone sovereign debt crisis (2011–12) as well as the US debt ceiling crisis in 2011 (and to a lesser extent 2013). For example, the majority of redemptions resulted from flight-to-liquidity during the US debt ceiling crisis in 2011 (Gallagher and Collins 2016). A new model may be designed to understand the contribution of such actions to systemic risk. As the Basel III Accord is rolled out, it is feasible to collect data (post-2019) on additional variables, such as the thirty-day liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), and run PLS-SEM.

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PLS-SEM is appropriate where (a) the nature of the underlying theory is predictive and exploratory rather than confirmative, (b) the types of latent constructs modeled include formative and reflective models and (c) the sample size is small due to a relatively small population, and the data exhibits nonnormal data characteristics. Against this background, we would like to reiterate the versatile, easy-to-use nature of PLS-SEM compared with network topologies and encourage others to use PLS-SEM in prediction-oriented and exploratory research.

## DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper. This paper uses the statistical software SmartPLS 3 ([www.smartpls.com](http://www.smartpls.com)). Ringle acknowledges a financial interest in SmartPLS.

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