ARE COMPETITIVE BANKING SYSTEMS REALLY MORE STABLE?

by

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Abstract

This study replicates Schaeck, Čihák, and Wolfe (2009), henceforth SCW. SCW conclude that (i) concentration and competition (as measured by Panzar and Rosse's H-statistic) represent two separate dimensions of the banking sector, with (ii) greater competition being associated with greater financial stability. Using their data, we are able to exactly reproduce their original results. However, when we use current vintage data for the variables in their dataset, from both the same and alternative data sources, we find that H-statistic fails to attain significance at the 5-percent level. We obtain this result even though we use the same estimation procedures and variable specifications as SCW, along with their original values for H-statistic and concentration. Additional tests, such as expanding the timeframe from 1980-2005 to 1980-2011, employing more recent data for H-statistic and concentration, or using the z-score as an alternative measure of financial distress, further confirm this result. Further, not only are the estimates statistically insignificant, but they are economically insignificant, with small effect magnitudes. Our paper suggests that competition may not positively contribute to financial stability after all.

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1. INTRODUCTION

This paper investigates key findings reported by Schaeck, Čihák and Wolfe (2009), henceforth SCW, in their influential *Journal of Money, Credit, and Banking* article, "Are Competitive Banking Systems More Stable?" Over the last twenty years there has been increasing interest in the relationship between conditions in the financial sector and country-level economic performance. Of particular interest is whether competition in the financial sector contributes to the likelihood that a country will be vulnerable to banking sector distress.

Competition is a complex phenomenon and its measurement has evolved over time.[1] Earlier literature on bank behavior equated greater concentration with decreased competition, with concentration commonly measured by the "concentration ratio", defined as the proportion of assets held by a given number (usually three or five) of financial institutions. However, subsequent research has argued that concentration is not a good measure of competition in the banking sector.

Based on the New Empirical Industrial Organization, more recent literature has proposed other, non-structural measures of competition. A prominent measure in this class is the H-statistic, which uses bank level data to gauge the ability of banks to pass on increases in input prices (Panzar and Rosse, 1987). The greater the elasticity of banking revenues to input prices, the less competitive the banking sector. Claessens and Laeven (2004) were the first to highlight that bank concentration was not negatively related to competition, as measured by the H-statistic. Beck et al. (2006) confirmed that concentration "insufficiently" measured competitiveness in the banking sector. However, they did not measure competition directly, instead proxying it with measures of regulatory policies and institutions that impeded competition.

[1] For a critical review of the literature on competition in the banking sector, see Berger et al. (2004) and Leon (2014).

SCW improved upon Beck et al. (2006) by incorporating a direct measure of competition, the H-statistic, to study the relationship between competition and banking stability. They analysed 38 "systemic crises" from a sample of 45 countries over the period 1980-2005. They reported evidence to support two conclusions. First, they found that the more competitive the banking sector, as measured by the H-statistic, the less likely it is to experience a "systemic crisis" (to be defined below). Second, they found that when the concentration ratio is included in an equation with the H-statistic variable, both are statistically significant.

SCW is widely cited. At the time of this writing (February 2018), it had received 570 Google Scholar cites, and 118 Web of Science citations. One reason for its wide influence is because the authors demonstrated that their results were robust to a wide variety of estimation and specification approaches. SCW use two different estimation procedures. They check for compositional robustness in the sample by altering the countries and time periods used in the analysis. They modify variable specifications to control for macroeconomic dynamics and banking sector development. They control for cross-country differences in regulatory environments. Throughout this battery of robustness checks, SCW consistently find that competition and concentration are both significantly and negatively associated with systemic crises.

Our replication of SCW proceeds as follows. In Section 2, we demonstrate that we can exactly reproduce SCW's key findings using their original data. In Section 3, we compare currently available data for their variables from the same and alternative data sources, and find substantial differences. The next three sections conduct a variety of robustness checks. Section 4 investigates the effect of replacing SCW's control variables with current vintage data, while still restricting ourselves to the same sample period as SCW's original analysis (1980-2005). Section 5 extends the sample period to 1980-2011 and re-estimates SCW's models, incorporating currently available values for H-statistic and concentration where available.

Section 6 employs a different measure of financial stability, the z-score, and investigates whether SCW's conclusions are robust using this alternative measure. Across these different investigations, we consistently find that H-statistic is not significant at the 5-percent level. Further, the associated effect sizes are economically small in magnitude. As a result, we conclude that there is insufficient evidence to support the hypothesis that competition promotes financial stability.

Our findings with respect to concentration are mixed. When we update the control variables but use SCW's values for *Concentration*, we confirm their findings that greater concentration in the banking sector reduces the likelihood of a systemic crisis. However, when we expand the sample timeframe, update the concentration values, and use the z-score as an alternative measure of financial duress, the results vacillate, so that we can even find that concentration is negatively associated with financial stability.

The last section of our analysis goes beyond SCW and investigates the inclusion of two alternative measures of competition: the Lerner index (Fernandez de Guevara, Maudos, and Perez, 2007; Maudos and Solis, 2011) and the Boone indicator (Boone, 2008). This analysis does not produce much additional insight. We continue to find little evidence that competition plays a role in contributing to countries' financial stability. We note that all of the data and programs necessary to reproduce the results from this paper can be downloaded from the public website *Dataverse*.[2]

2. REPRODUCTION OF SCW'S KEY RESULTS

The dependent variable in SCW's analysis is "systemic crisis." This is a dummy variable that takes the value 1 for a given country in a given year if any of the following four criteria hold (SCW, page 717):

1. "emergency measures such as deposit freezes or bank holidays are implemented,"

[2] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FMWRQJX .

2. “large-scale bank nationalizations take place,”
3. “nonperforming assets reach at least 10% of total assets,” or
4. “fiscal cost of the rescue operations reach 2% of gross domestic product (GDP)”.

The key explanatory variables are *H-statistic* and *Concentration*, described above, which measure competition and concentration in a country’s banking sector. The H-statistic takes the value 1 when the banking sector is characterized by competition. It takes values between 0 and 1 when the sector is monopolistically competitive, and is negative in the case of monopoly. Thus, increases in the H-statistic are associated with greater competition in the banking industry.

Two estimation procedures are used. SCW use duration analysis to measure the determinants of “time to failure”; that is, the number of years from the start of the sample until a systemic crisis occurs. If no systemic crisis occurs for a given country, the spell is treated as being right-censored. A variable that is positively associated with stability will have a positive coefficient in this analysis, as it will take longer for a systemic crisis to occur. SCW also estimate a logit model. A variable that positively contributes to stability will have a negative coefficient in this analysis, as an increase in this variable will be associated with a lower probability of a crisis occurring.

SCW include a large number of control variables. To address macroeconomic determinants of financial stability, they include lagged GDP growth, inflation, the real interest rate, exchange rate depreciation, terms of trade, real credit growth, and a variable to measure “moral hazard” associated with generous deposit insurance. They include a set of dummy variables to control for legal origin of the country, as previous research has linked this to the contractual environment underlying the banking sector. Finally, a set of regional dummy variables are included as general controls for economic development.

SCW’s main results are reported in Table 3 of their paper. The first four columns of their Table 3 report various specifications of the duration model. Column (1) reports the results of estimating the model with control variables but no competition or concentration variables. Column (2) adds the competition variable (*H-statistic*). Column (3) adds the concentration variable to the specification in Column (2). Column (4) adds an interaction term for the competition and concentration variables to Column (3). Columns (5) through (8) do the same for the logit model. As SCW's main conclusions focus on the coefficients of *H-statistic* and *Concentration*, we will focus our attention on Columns (2), (3), (6), and (7) in SCW's Table 3.

The first step in our replication study consists of reproducing SCW's key results. As SCW graciously provided their data and Stata do files, this proved to be straightforward. TABLE 1 reports the results of estimating the duration model using the variable specifications of Column (2) and (3) in SCW's Table 3 with the data and do files they provided us. TABLE 2 does the same for the logit models of Columns (6) and (7) in SCW's Table 3. The tables confirm that we are able to exactly reproduce their main findings.

Since SCW provide a discussion of the estimated coefficients of the respective control variables, we do not do that here. Instead, we focus on the competition and concentration variables. When the competition variable (*H-statistic*) stands alone, the duration model produces an estimate of 1.6977, which is significant at the 10 percent level. The positive coefficient indicates that greater competition in a country's banking sector is associated with a longer time before a systemic crisis occurs. When both competition and concentration variables are included in the model, both coefficients are positive and statistically significant. The concentration variable is significant at the 1 percent level, while the competition variable increases to 2.3482 and is now significant at the 5 percent level. The fact that both *H-statistic* and *Concentration* are statistically significant lead SCW to conclude that these two variables "describe different characteristics of banking systems" (page 725), with the *H-statistic* capturing the effect of competition, and *Concentration* capturing advantages of being large-sized.

TABLE 2 repeats the replication exercise for the two logit models.[3] When the competition variable stands alone, the associated coefficient is negative and statistically significant at the 5 percent level. When the concentration variable is added to the specification, both competition and concentration variables achieve statistical significance at the 5 percent level. As a negative coefficient here implies a lower probability of a crisis, these estimates are consistent with the corresponding duration model estimates from TABLE 1.[4]

3. UPDATING THE CONTROL VARIABLES

Having determined that we are able to exactly reproduce SCW's results, we next want to check the robustness of their results. The first step involves using current vintages of SCW's data to see if their results persist with revised, and thus presumably, more accurate data values. It is wellknown that macroeconomic data can vary, sometimes substantially, across different vintages (Ciccone and Jarocinski, 2010; van Bergeijk, 2016). As approximately ten years have passed since SCW obtained their data, it is possible that subsequent data revisions could produce different results. The Data Appendix in SCW identifies the sources they used for all the variables in their analysis. For example, SCW used the World Development Indicators (WDI) to obtain values for GDP growth, inflation, and terms of trade. They used International Financial Statistics (IFS) for depreciation.

We found numerous cases where current vintage data differ substantially from SCW's original dataset. FIGURE 1 gives some examples. The figure produces four screen shots of data that allow one to compare SCW's original data with updated data from the same data source, as well as from alternative data sources.

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[3] In contrast to their duration model estimates, SCW report heteroskedasticity robust, rather than cluster robust, standard errors for their logit estimates. We follow suit in our replication of their work in TABLE 2. However, our subsequent analysis uses cluster robust standard errors when estimating logit models. In most cases this reduced standard errors, enhancing statistical significance.

[4] It is worth noting that, while not reported by SCW, their estimated logit models have poor sensitivity. There are 30 crises included in the dataset used to produce the estimates in Column (7). The model only correctly predicts (Prob>0.50) three of them.

For example, Panel A reports values for *GDP growth (lag)* for Indonesia for the years 1980-2005. The source of these data is the World Development Indicator dataset (WDI), so that the first two columns ("Original" and "WDI") allow a side-by-side comparison of the data used by SCW and current vintage data from the same source. The last column presents values for lagged GDP growth as reported in the International Financial Statistics dataset (IFS), which allows a comparison from an alternative data source.

One immediately notes a large number of "missing values" in SCW's dataset. However, these "missing values" should not be misinterpreted. In some cases they are missing from SCW's dataset because SCW deleted observations during "crisis years." In their words (page 717): "As most crises run over multiple years, we follow the approach in the literature (Demirgüç-Kunt and Detragiache 2002) and remove observations classified as crisis after the initial year of the crisis." Our analysis follows the same practice.

The main takeaway from Panel A is that the original and updated data can differ greatly. For example, lagged GDP growth for Indonesia in 1980 is 1.63% in SCW's original dataset, but 7.09% when we access the current vintage of this variable from the same source (WDI). When we go to an alternative source, the IFS, we find a value (6.26%) that is different from both the original dataset and WDI, but is closer to the latter. Similarly, for 1981, SCW's original data has lagged GDP growth of -0.58%, with WDI currently reporting a value of 8.72% for this year, and IFS reporting 9.88%.

Another example is given in Panel B, which reports inflation rates for Brazil from 1980-2005. The first two columns of inflation data report values from SCW's dataset and the currently available values for these years from the WDI, which is the same source that SCW used for this variable. The last two columns report current vintage values from alternative data sources -- IFS and DataMarket -- where in this case the latter values are identical to the WDI data. The original data are surely wrong, as Brazil was experiencing well-known hyperinflation in the 1980 and early 1990s. Panels C and D repeat the exercise for depreciation and terms of trade for Austria and Columbia, respectively. They provide further examples of substantial differences in values between SCW's and current vintage data.

An interesting data scenario can be found in Panel C during the years 1999-2005. This is an example where SCW's dataset contains values for variables for which corresponding values are unavailable at either the updated, same data source (in this case, IFS), or the alternative data sources (WDI and DataMarket). Note that a puzzling, abrupt shift is discernable in SCW's original series after 1998 for Austria. Another thing to note from Panels C and D is that sometimes data are available from one data source for a given year, but not another. For example, DataMarket does not have depreciation values for Austria for the years 1980-1991 (cf. Panel C), while IFS and WDI do; and WDI does not have a value for terms of trade for Columbia in 1980, while DataMarket does.

This highlights two dimensions of using a more recent vintage of data. First, the more recent vintage can result in different variable values for the same observations. Second, it can also alter the set of observations available for estimation. Our analysis studies both facets.

TABLE 3 highlights the first facet, looking at the differences in variable values for the same observations across the two different vintages of data. To be included in the table, observations must have been used in SCW's estimation of the Column (3) model, while also being currently available.

The top panel of TABLE 3 reports descriptive statistics for lagged GDP growth from three data sources: SCW's original dataset ("Original"), and current vintages of WDI and IFS. An asterisk is placed next to WDI to indicate that this is the source cited by SCW for their data. The original data have a mean lagged growth rate of -0.197% over the 699 observations for which we have observations from all three data sources. For the exact same observations, the current vintages of the WDI and IFS data produce mean lagged growth rates of 3.556% and 3.679%, respectively.

As the table demonstrates, similar differences are found for other variables. Where there are alternative data sources, these generally accord closely with each other, so that the original data are an outlier. This does not mean that SCW did anything wrong, as the data in their dataset may have been the best available at the time they collected it. However, it does mean that using the most current vintage of data should give a more accurate measure of the true values of the control variables. The next section investigates whether SCW's key findings persist when the values of the control variables are updated.

4. ROBUSTNESS CHECK #1: Reestimation of Models Using Current Vintage Data

TABLE 4 reports the results of estimating the Column (2), (3), (6) and (7) models using current vintage data for the same sample period as SCW (1980-2005), and a common set of observations. Unlike in TABLE 3, where observations had to be the same for just one variable; in TABLE 4, we require the original and updated datasets to have a common set of observations for the full set of control variables. Observations must both have been used in the estimation of the original model in SCW (e.g., Column 2 model, Column 3 model, etc.), and be available in the current vintage of data for each of the control variables. We continue to use SCW's values for *H-statistic* and *Concentration,* as we were unable to obtain a more recent vintage of data for these variables for the 1980-2005 sample period.

Our analysis constructs two sets of common observations. The first set ("Common Observations 1", see Panel A) restricts itself to the same data source as SCW. So, if SCW used WDI for lagged GDP growth, the updated dataset only takes lagged GDP growth values from WDI. The second set of common observations ("Common Observations 2", see Panel B) uses more recent vintage data from whatever data source provides the most observations. Thus, if

SCW used WDI for terms of trade, but DataMarket has more total observations for terms of trade than WDI, then we take our updated values from DataMarket.

The benefit of using common observations is that it allows us to zero in on the effect of updating variable values for the duration and logit estimates, holding constant the sample of observations. The cost is a substantial reduction in the number of observations. Whereas the original results reported by SCW used 701 observations for the duration models, and 707 observations for the logit models; the number of observations drops to 222 and 218 respectively for the dataset "Common Observations 1", and to 474/479 for "Common Observations 2".

For each set of common observations, we first estimate the respective duration or logit model using SCW's original data ("Original Data"), and then estimate the same model with the same observations, but with current vintage data for the control variables (either "Updated Data – Same Sources" or "Updated Data – Multiple Sources"). This allows us to concentrate on the effect of the updated variable values on the respective model estimates.

We first focus on *H-statistic*. Using SCW's values for the control variables, but restricting the observations to "Common Observations 1," the estimated coefficients for *H-statistic* are consistent with SCW's estimates for the full sample. The estimates for *H-statistic* in Columns (2), (3), (6) and (7) are 2.7960, 1.9825, -5.9893, and -5.4947. All but one are significant at the 5-percent level. The corresponding estimates from the full samples in TABLES 1 and 2 are 1.6977, 2.3482, -2.3116 and -2.9703. Similarly, all but one are significant at the 5-percent level. The results for the "Common Observations 2" subsample are similar, with all four estimates significant at the 5-percent level.

In contrast, when we use current vintage data for the control variables (see "Updated Data – Same Sources" and "Updated Data – Multiple Sources"), while the signs and approximate sizes of the estimated coefficients are the same, none of the estimates are different from zero at the 5-percent level of significance. Note that the loss in significance cannot be solely attributed to the smaller sample sizes, since many of the coefficients are significant using SCW's original data, even with the reduced number of observations.

The effects of updating the variables for common observations are less pronounced for *Concentration*. As with *H-statistic*, the signs and sizes of the estimates are consistent with those reported in TABLES 1 and 2. However, statistical significance depends on the subsample. In the "Common Observations 1" subsample, all the estimated coefficients for *Concentration* are insignificant at the 5-percent level using both SCW's original values and current vintage data. For the "Common Observations 2" subsample, they are all significant, save one (cf. Panel B, Column 3, "Original Data").

As noted above, the second dimension of using a different vintage of data is that it changes the sample of observations available for estimation. Some of the country/year observations in SCW's original data have missing values in the current vintages of these data sources. Other country/year observations with missing values in SCW's original data now appear in these same data sources. TABLE 5 reports the estimates of Models (2), (3), (6) and (7) using the maximum number of observations over the same time period as SCW's original study (1980-2005). As before, we use two approaches for updating the data: Panel A restricts itself to updating data from the same sources as SCW. Panel B searches for updated values across several data sources, and chooses the data source that allows the maximum sample size. The resulting sample sizes for the duration and logit models when data are updated from the same sources are 327 and 331, respectively. When the data are updated using multiple sources, the associated sample sizes are 679 and 682.

The change in the samples due to using current vintage data has important consequences for SCW's findings about competition. The coefficient estimates for *H-statistic* are everywhere statistically insignificant at the 5-percent level, and much smaller in absolute size than the estimates reported by SCW. For example, the associated estimates in Panel A are 0.9160, 0.3447, -0.5822 and -0.0653. The corresponding estimates from TABLES 1 and 2 are 1.6977, 2.3482, -2.3116 and -2.9703. In contrast, the results for *Concentration* are statistically significant and larger in absolute value.

To summarize, TABLES 4 and 5 report on two facets associated with using current vintage data for the control variables in SCW's study: (i) changes in values for the same observations; and (ii) sample differences due to the availability of updated data for SCW's study period, 1980-2005. The clearest results have to do with the competition variable, *H-statistic*. Updating the data for the same observations produces estimates that are of the same sign and approximate size as SCW. However, the associated estimates become statistically insignificant. These effects are exacerbated when different vintages of data alter the set of sample observations. The associated estimates are much smaller in absolute value. If one considers the more recent vintage of data to be higher quality than the data used by SCW, then it follows that these results nullify SCW's findings about competition and financial stability.

The evidence regarding *Concentration* is less clear. The signs and sizes of the respective estimates are similar to those reported by SCW. However, while generally significant, there were instances where the estimates did not achieve statistical significance (cf. Panel A, TABLE 4).

5. ROBUSTNESS CHECK #2: Extending the Time Period

SCW studied the time period 1980-2005. In this next section, we investigate the effect of extending this time period to 2011, which is the last year of the updated catalogue of systemic crises compiled by Laeven and Valencia (2013). One benefit of this extension is that it allows us to include the years of the Global Financial Crisis (GFC). Having a better understanding of the factors that allowed banking systems to withstand the severe stresses of the GFC is of great interest. Further, it allows us to address the following question: Suppose SCW had carried out their analysis more recently, over this extended time period – would they have reached the same conclusions about competition and concentration?

We are able to obtain current vintage *H-statistic* values from the Global Financial Development Database, but only starting from 2010. The situation for *Concentration* is somewhat better, with current vintage values available starting in 1996, also from the Global Financial Development Database. Outside those years, the only available values for these variables come from SCW.

An issue arises straightaway with how to best represent the competition and concentration conditions that prevail for a given country and time period. SCW chose to use a constant value for each country over the entire sample period, 1980-2005. Here is how they supported that decision for *H-statistic*:

> "While our data start in 1980, the information on the H-statistic is only available starting in 1998. We therefore assume it to be constant over the sampling period. There are several justifications for this: First, the regulatory and supervisory environment, which is a major determinant for the degree of competition, has not undergone major changes (Barth, Caprio, and Levine 2001, and reaffirmed by Barth, Caprio, and Levine 2006). By extension, we argue that the level of competition has similarly not seen much change over time. Second, in cases where the regulatory environment has changed, it was modified toward less rather than more regulation (Beck, Demirgüç-Kunt, and Levine 2007). This tends to bias our results against finding a positive relationship between competition and the risk of a crisis" (page 720).

They used the same approach for *Concentration*, averaging the "proportion of total assets held by the three largest institutions in a country" over the sample period, and using that constant, average value to characterize concentration in a country's banking sector over the entirety of the 1980-2005 period.

This approach of assuming a constant competition and concentration environment is obviously more difficult to defend given an even longer time period, especially one that encompasses the GFC. Unfortunately, data availability restricts our ability to investigate this question for the variable *H-statistic*, as updated data are available only from 2010.

We are in a better position with respect to *Concentration*, where annual data exist for 1996 onwards. To check whether the GFC systematically affected banking sector concentration, we estimated a regression model (not reported) with country fixed effects and a dummy variable for the GFC years (2008-2010). The associated GFC dummy was insignificant, with a t-statistic of -0.14 (p-value = 0.885). This provides some confidence that country-level, concentration conditions were not systematically impacted by the GFC.

This still leaves open the question of how best to incorporate the current vintage values for *H-statistic* and *Concentration.* We employ three approaches. First, we follow SCW's approach of using a constant value for each country over the entire time period. We take the country-specific, constant values of *H-statistic* and *Concentration* from SCW's data set and apply it to each year, 1980-2011. Second, we average the values for *H-statistic* and *Concentration* over the time periods where we have updated data (2010-2011 and 1996-2011, respectively). We then use a combination approach where we use SCW's values for those periods when we don't have updated data, and the averaged values for those years when we do. For example, for *H-statistic,* we use SCW's data for the years 1980-2009, and the average of the updated *H-statistic* values for the period 2010-2011. For *Concentration*, we use SCW's data for the years 1980-1995, and the average of the updated *Concentration* values for the period 1996-2011. This produces two periods, different for each variable, where the country-level value of that variable is constant over the respective period. The third approach is similar, except rather than using averaged values over the periods where we have updated data (2010-2011 and 1996-2011, respectively), we use the time-varying values of these variables for these years. These three approaches are represented in Panels A, B, and C of TABLE 6.

Extending the sample period does nothing to change our conclusion with respect to competition. The coefficient for *H-statistic* remains relatively small and statistically insignificant across every model and all three approaches for handling the updated values of the competition and concentration variables.[5]

As was true in the previous robustness check, the results for *Concentration* are again mixed. In Panel A, the estimated coefficient is similar in size to previous estimates and statistically significant at the 1-percent level. In Panel B, the estimated coefficients are smaller, and significant at the 10-, but not the 5-percent level. And in Panel C, the estimates are smaller still, and no longer significant even at the 10-percent level.

So which approach to handling the updated values is best? From a practical perspective, it doesn't make a difference for evaluating *H-statistic*, as the results are consistent across all three panels. Unfortunately, that is not the case for *Concentration.* On the one hand, the estimates in Panel A generally have the best goodness of fit as measured by the information criteria AIC and SIC. On the other hand, it is difficult to believe that a single, constant value for each of competition and concentration is appropriate for the entire 32 years of the sample period. Accordingly, for the later purpose of estimating effect sizes, we balance goodness of fit and flexibility in variable values and focus on the estimates in Panel B.

6. ROBUSTNESS CHECK #3: Using a Different Measure of Financial Stability

SCW's approach to estimating the determinants of cross-country financial stability relies on the compilation of episodes of systemic banking crises compiled by Demirgüç-Kunt and Detragiache (2005). While these data are widely used for studying financial stability, there are other measures that have been used in the literature. One widely used measure is z-score. In this section, we further explore the relationship between financial stability, competition and concentration using z-score as our dependent variable.

[5] As a further robustness check, we excluded the GFC and post-GFC years from the analysis and re-estimated the models in TABLE 6 using the shortened sample period, 1980-2007. The results are reported in the Appendix and show little change.

Z-score is a measure of bank risk that is usually measured at the level of individual banks. It uses readily available accounting data to measure the probability of default for a bank. It relates the bank's capital level to variability in its returns to capture the amount of variability in returns that can be absorbed by its capital without making the bank insolvent. The variability in returns is typically measured by the standard deviation of Return on Assets (ROA), while the returns are measured as the ratio of equity capital to assets plus ROA. It is assumed that the bank becomes insolvent when its capital level falls to zero. The theoretical foundations of z-score are developed in Roy (1952), Boyd and Graham (1986), Hannan and Hanweck (1988), and Boyd, Graham, and Hewitt (1993).

A country-level measure of z-score can be calculated analogously to the bank-level measure. It is estimated by $z\text{-}score = \frac{ROA+(\frac{Equity}{Assets})}{stdev(ROA)}$, where *ROA*, *Equity*, and *Assets* are country level aggregates, and *stdev(ROA)* is the standard deviation of *ROA.* Increases in z-score indicate a lower probability of default, and thus a greater degree of financial stability. Examples of research that have used z-score in cross-country studies of financial stability are Uhde and Heimeshoff (2009) and Yeyati and Micco (2007).

Our empirical analysis draws on z-score data for 1999-2015 from the Global Financial Development Database. As a measure of the probability of a country's banking system defaulting, it takes values bounded between 0 and 1. FIGURE 2 provides a histogram of the z-score values used in our subsequent analysis, along with descriptive statistics. The variable ranges from a minimum of 0.0140 to a maximum of 0.3076, with a mean value of 0.1134. To accommodate the fact that the data are probabilities, the subsequent analysis employs a fractional logistic regression procedure.

Once again, we are faced with the choice between constant and time-varying values for the variables *H-statistic* and *Concentration*. As current vintage *H-statistic* data are only available for the year 2010-2015, we use SCW's (constant) value for the period 1999-2009. For 2010-2015, we consider two approaches. The first approach ("Constant Values: Two Periods") uses a constant value for *H-statistic* based on the average of this variable over 2010-2015. The second approach ("Mixed Constant, Time-Varying Values") allows it to vary over time during this period. As we have time-varying values for *Concentration* for the whole sample period, we decide to divide the years into two periods, 1999-2007 and 2008-2015. This divides the sample into two, roughly equal halves, and corresponds to (i) pre-GFC and (ii) GFC and post-GFC periods. The first approach ("Constant Values: Two Periods") uses a constant for each of the two periods, where the constant equal the average of *Concentration* over the respective time periods. The second approach ("Mixed Constant, Time-Varying Values") uses the time-varying values for the entire sample period.

TABLE 7 reports our results. As before, we estimate a specification with just *H-statistic* (Columns 1 and 3) and a specification with both *H-statistic* and *Concentration* (Columns 2 and 4). For both variables, positive coefficient estimates indicate that the variables are positively associated with default risk, and thus negatively associated with financial stability. Looking across all four sets of estimates, we see that the coefficient for *H-statistic* is everywhere statistically insignificant, with estimates that alternate signs depending on the treatment of time-varying values. The results for *Concentration* are similar with regard to statistical significance. Interestingly, and in contrast to earlier estimates, the coefficients suggest a negative association between concentration in the banking sector and financial stability. However, we cannot reject the possibility that no association exists.

Little has been said up to now about the economic significance of the estimates for *H-statistic* and *Concentration.* Accordingly, we want to translate the estimates of TABLES 6 and 7 into economically meaningful numbers. This is not a problem for the logit and fractional logistic regression results of TABLES 6 and 7. However, interpretation is somewhat more challenging for the duration model estimates in TABLE 6.

One possibility is to estimate the marginal impact of *H-statistic* and *Concentration* on the length of time until a systemic crisis occurs. However, this requires that we have great confidence in our procedures' ability to accurately estimate the unobserved endings of right-censored spells. An alternative approach is to estimate the effect of these variables on survival rates. Survival rates are the probabilities of surviving to a given duration. In our context, it is the probability that a country goes a given number of years without experiencing a systemic crisis.

Another challenge with estimating marginal effects concerns the units of *H-statistic* and *Concentration*. A useful approach is to put the changes in these variables on a common scale in order to facilitate comparison. Accordingly, we calculate three different survival rate curves: one evaluated at an *H-statistic/Concentration* value equal to its 25th percentile value, another evaluated at the 50th percentile value, and the third evaluated at the 75th percentile; with all other variables set equal to their sample means. This way we can both compare the effects of changes in *H-statistic* with similar changes in *Concentration*, and get an insight into the economic significance of each variable by observing how changes from the 25th to the 50th to the 75th percentile values affects the respective survival rate curves.

FIGURE 3 reports survival probabilities by duration length (in years) for *H-statistic* and *Concentration*. The respective probabilities are based on the duration model estimates from TABLE 6, Panel B, Column 3. We focus on the survival rate at 20 years, both because it is supported by a relatively large number of country observations, and because it allows for sufficient elapsed time so that the influence of the variables can be observed.

For a wide range of both *H-statistic* and *Concentration* values, the probability of a country going 20 years without a systemic crisis is greater than 0.50. There is a clear difference in the economic significance of competition (as measured by *H-statistic*) and concentration. An increase in the *H-statistic* variable from its 25th to its 75th percentile has only a relatively small effect on the survival probability. At the 20 year mark, the difference amounts to less than a few percentage points. In contrast, the same change in the value of the *Concentration* variable has about ten times the effect. In this case, statistical significance and economic significance tell similar stories.

TABLE 8 reports the results of a comparable exercise for the logit model of TABLE 6, Panel B, Column (7), and the fractional logistic regression model of TABLE 7, Panel A, Column (2). In the former case, the probability represents the probability of a systemic crisis. In the latter case, it represents the probability of default of a country's banking system. The economic interpretation of the estimated coefficients for *H-statistic* is similar to what we observed with survival probabilities. An increase in the *H-statistic* variable from its 25th percentile to 75th percentile value reduces the probability of a crisis by a tenth of a percentage point (-0.0010), and reduces the probability of a default by less than 2/10ths of a percentage point (-0.0017). We conclude that the influence of *H-statistic* on financial stability is not only statistically insignificant, but also economically insignificant.

The story for *Concentration* is different, and ambiguous. In absolute value, the effect of the same change in *Concentration* values is between 10 and 20 times larger compared to *H-statistic* (-0.0196 versus -0.0010, and 0.0171 versus -0.0017, respectively). However, the coefficient for *Concentration* is insignificant in TABLE 7, and has the opposite sign compared to TABLE 6. The latter is reflected in the fact that the effect of an increase in the value of *Concentration* from its 25th to 75th percentile is estimated to lower the probability of a crisis by 1.72 percentage points (cf. Panel A), while increasing the probability of a default by almost the same amount (1.71 percentage points, cf. Panel B). However, we note that the latter effect is measured with greater imprecision, as the underlying coefficient estimate is statistically insignificant.

7. INVESTIGATING ALTERNATIVE MEASURES OF COMPETITION

The previous analysis has been unable to provide evidence that competition, as measured by *H-Statistic*, is positively associated with financial stability. While many studies like SCW have used H-statistic as a measure of competition, it has some serious limitations. One of the main problems is the econometric identification and interpretation associated with this measure. In a long-run equilibrium, H-statistic equals 1 for competitive firms and is non-positive for profit-maximizing monopolists. However, theoretical studies have shown that the H-statistic can be positive for a monopolist (Spierdijk and Shaffer, 2015) and negative in a competitive market (Shaffer, 1983 and Bikker et al., 2012). Thus, higher values of H-statistic do not necessarily imply greater competition.

To address these short-comings, we explore the relationship between competition and stability using two alternative measures. While there is no consensus regarding the best measure of competition, using different alternatives allows us to evaluate the robustness of the competition-stability hypothesis. The Lerner index is an alternative measure of competition that is widely used in the literature. Similar to the H-statistic, the Lerner index is another first-generation, non-structural measure that captures market power. Whereas H-statistic measures the ability of firms to pass on input price increases to their customers, the Lerner index measures competition by estimating the ratio of the price of total assets over their marginal cost (Beck, De Jonghe, and Schepens, 2013; Fernandez de Guevara, Maudos, and Perez, 2007; Maudos and Solis, 2011). Increases in the Lerner index are associated with diminished competition.

The Lerner index is popular as it does not impose stringent data requirements for its calculation and is easy to interpret. It is also flexible since one does not need to define the relevant market, and it allows the measurement of market power separately for different markets (geographic or by products). Moreover, it can also be calculated with a limited number of observations, which is particularly important since competitive concerns become more relevant when numbers of firms is limited. However, the Lerner index is not free from criticism. It is often criticized on theoretical grounds as it is a measure of market power and not competition. Stiglitz (1987, 1989), Bulow and Klemperer (2002) and others have shown that an increase in the intensity of competition can co-exist with an increase in the average price-cost margin or market power. Oliver et al. (2006) point out that the Lerner index can over-estimate market power since banks can enjoy higher margins even when they spend relatively more of their resources for granting credits.

Another measure is the Boone indicator. It is a non-structural measure of competition developed to capture the dynamics of the market. The Boone indicator measures the degree of competition based on profit-efficiency and is calculated as the elasticity of profits to marginal costs (Boone, 2008; Duygun, Shaban, and Weyman-Jones, 2015; and Schaeck and Čihák, 2014). Like the Lerner index, larger (less negative) values of Boone indicate a less competitive industry.

The main advantage of the Boone indicator is that the relationship between costs and profits is continuous and monotonic. Moreover, this method only requires information about profits (or market shares) and costs, and does not require any information on prices. This is a great advantage, particularly for developing country studies, where data are limited. But the Boone indicator also has its limitations. The model used to calculate the Boone indicator assumes that efficiency is one dimensional and observable, ignoring other aspects. One can argue that efficiency gains may not be translated into lower costs or higher profits in the short term. Thus, year-to-year changes in the Boone indicator may not reflect profit efficiency.

A list of papers that use the respective measures to measure competition in the banking sector is given below:

- H-statistic: Molyneux, Lloyd-Williams and Thornton (1994); Bikker and Haaf (2002); Claessens and Laeven (2004); Casu and Girardone (2006); Matthews, Murinde and Zhao (2007); Yeyati and Micco (2007); Schaeck, Čihák and Wolfe (2009); Maudos and Solıs (2011); Schaeck and Čihák (2012); Weill (2013); Bolt and Humphrey (2015); Leon (2015).

- Lerner index: Shaffer (1983); Fernandez de Guevara, Maudos, and Perez (2007); Lopez and Saurina (2007); Schaeck and Čihák (2008); Berger, Klapper and Turk-Ariss (2009); Beck, De Jonghe and Schepens (2013); Weill (2013); Fu, Lin and Molyneux (2014); Love and Peria (2014); Mirzaei and Moore (2014); Bolt and Humphrey (2015); Diallo (2015); Jiménez, Kasman and Kasman (2015); Leon (2015).

- Boone indicator: Schaeck and Čihák (2008); Schaeck and Čihák (2012); Love and Peria (2014); Mirzaei and Moore (2014); Schaeck and Čihák (2014); Diallo (2015); Duygun, Shaban and Weyman-Jones (2015); Kasman and Kasman (2015); Leon (2015).

Our empirical analysis utilizes the Lerner index and Boone indicator values from the Global Financial Development Database, available via the World Bank's website.

Since all three measures are constructed to measure competition in the banking sector, it is of interest to see how closely they correlate. TABLE 9 provides pairwise correlations for the three competition measures. Given the different periods of data availability – 2010-2015, 1996-2015 and 1999-2015 for the (current vintage) *H-statistic*, *Lerner*, and *Boone* variables, respectively – there are different numbers of observations for each pair of correlations.

As expected, the *Lerner* and *Boone* measures are each negatively correlated with *H-statistic*, since the first two of these variables are decreasing in degree of competition, while *H-statistic* is increasing. Noteworthy is the loose association between the variables. All three pairwise correlations are rather low, with no single correlation exceeding 0.11 in absolute value (*Lerner/H-statistic* has the largest correlation). Further, none of the pairwise correlations are statistically significant at the 5-percent level, and only *Lerner/H-statistic* is significant at the 10-percent level (barely).

These results highlight that while all three measures have the intention of measuring the same thing, they are picking up, at best, different aspects of competition in a country's banking sector. For this reason it is of interest to see whether including *Lerner* and *Boone* in our analysis produces a different perspective on the relationship between competition and financial stability.

TABLE 9 also reports pairwise correlations between the three competition measures and concentration. A problem is immediately apparent, as *Concentration* is positively and significantly related to both *H-statistic* and *Boone*. This is perturbing because *H-statistic* and *Boone* are inverse measures of competition, with increases in the former and decreases in the latter indicating greater competition. Accordingly, one would expect the two measures to also have inverse relationships with concentration.

A possible explanation for these incongruous results are that the two correlation results cover different time periods, with the *Boone/Concentration* correlation encompassing the time period included in the *H-statistic/Concentration* correlation. When we restrict the observations to span the same time periods (Obs = 270), the *Boone/Concentration* correlation becomes insignificant and negligible in size, with a p-value of 0.881. This highlights the time inconstancy of this correlation, and underscores the problem with using *Concentration* as a measure of competition.

TABLES 10 and 11 repeat the analyses of TABLES 6 and 7, adding the *Lerner* and *Boone* variables to the respective specifications, with everything else held constant. As before, we have the issue of how much time-varying behavior of the variables we should incorporate into our analysis. In TABLE 10, which covers the period 1980-2011, we again employ three approaches, with *H-statistic* and *Concentration* handled exactly as they were in TABLE 6. For the "Constant Values: Whole Period" approach, *Lerner* and *Boone* are set equal to their average value over the periods for which their data are available: 1996-2011 and 1999-2011, respectively. For the "Constant Values: Two Periods" approach, *Lerner* uses the 1996 value for 1980-1996 and the country average for 1997-2011; while *Boone* uses the 1999 value for

1980-1999, and the country average for 2000-2011. And for the "Mixed Constant and Time-Varying Values," *Lerner* uses the 1996 value for 1980-1996 and time-varying value for 1997-2011; while *Boone* uses the 1999 value for 1980-1999, and time-varying values for 2000-2011.

We first focus on the results for *Lerner* and *Boone*, and then discuss whether the addition of these variables to the specifications of TABLES 6 and 7 affect previous assessments of *H-statistic* and *Concentration.* If increased competition was associated with greater financial stability, we would expect *Lerner* and *Boone* to have negative coefficients in Columns (2) and (3) of TABLE 10, positive coefficients in Columns (6) and (7) of TABLE 10, and positive coefficients for all columns in TABLE 11.

Unfortunately, the estimates for *Lerner* are inconsistent across the different columns, panels, and tables. In Panel A of TABLE 10, the sign of the estimated coefficients indicate that increases in *Lerner*, i.e., decreases in competition, are associated with shorter times until the onset of crises (Columns 2 and 3), and a higher probability of a crisis occurring (Columns 6 and 7). This suggests that competition is positively associated with financial stability. However, none of the estimates are significant.

In Panel B, the signs reverse themselves, suggesting that competition, at least as measured by *Lerner,* is negatively associated with financial stability, though only one of the estimated coefficients (Column 3) is significant at the 5-percent level. These results are weakly confirmed in Panel C, where the signs are the same as in Panel B, though none of the coefficients are different from zero at the 5-percent significance level.

TABLE 11 presents our last set of results regarding *Lerner*. The signs of the estimated coefficients differ depending on how we incorporate time-varying behavior in the respective variables, with the estimates from Columns (3) and (4) being highly significant. The latter estimates indicate that decreased competition lowers the probability of default. In summary, of the 16 estimated coefficients in TABLES 10 and 11, only three are significant at the 5-percent level. These three, and the majority of the insignificant estimates, suggest that increased competition contributes to financial instability.

The results for *Boone* are similar, but even weaker, than the results for *Lerner.* Across both tables and all panels and columns, the estimated signs for *Boone* are identical to those for *Lerner*. However, only one of those estimates is significant at the 5-percent level. In TABLE 10, Panel A, Column (3), the associated coefficient indicates that competition, as measured by the Boone indicator, is positively associated with financial stability[6].

With respect to *H-statistic* and *Concentration,* the inclusion of the additional two competition variables strengthens our previous findings with respect to *H-statistic*, while providing further contradictory evidence regarding the role of *Concentration*. Across both tables, and all panels and columns, the estimated coefficients for *H-statistic* are always statistically insignificant at the 5-percent level. The results for *Concentration* remain unchanged with the addition of *Lerner* and *Boone*, with one, major exception. The estimated coefficient for *Concentration* is statistically significant in TABLE 11, and that at the 1-percent level. Further, the associated sign of those estimates indicates that greater concentration is associated with a higher probability of default, and thus, contributes to financial instability.

8. CONCLUSION

Schaeck, Čihák and Wolfe (2009), henceforth SCW, ask whether "competitive banking systems are more stable" in their influential *Journal of Money, Credit, and Banking* study. They summarize their findings as follows (SCW, page 711):

> Using the Panzar and Rosse H-statistic as a measure of competition in 45 countries, we find that more competitive banking systems are less prone to experience a systemic crisis and exhibit increased time to crisis. This result holds even when we control for banking system concentration, which is associated with higher probability of a crisis and shorter time to crisis. Our

[6] Using bank-level data, Diallo (2015) also reaches a similar conclusion. He finds that bank competition as measured by the Boone indicator, the Lerner and the adjusted Lerner indices is detrimental for bank stability. Our paper improves upon that by considering a larger time period, additional robustness tests and highlighting the differences between concentration and competition.

> results indicate that competition and concentration capture different characteristics of banking systems, meaning that concentration is an inappropriate proxy for competition. The findings suggest that policies promoting competition among banks, if well executed, have the potential to improve systemic stability.

Our study reproduces the results of SCW using their original data, and then examines whether their results are robust to a number of changes. First, we re-estimate their models using current vintage data over the same time period analyzed by SCW. Second, we expand the time frame of the study to take into account more recent catalogues of systemic crises around the world. Third, we use an alternative measure of financial stability, the z-score. And, finally, we investigate whether two alternative measures of competition, the Lerner index and the Boone indicator, can provide corroborating evidence about the relationship between competition and banking sector stability.

Our analysis produces one consistent result, and a number of ambiguous, at times, conflicting results. We consistently find that the variable *H-statistic* is insignificantly associated with financial stability. In none of our estimates does it ever attain significance at the 5-percent level. All that is required to obtain this result is to use the current vintage of data for SCW's control variables, retaining SCW's estimation procedures and variable specifications, and using their values for *H-statistic* and *Concentration.* Additional robustness checks such as expanding the sample timeframe, or using an alternative measure of financial distress, only confirm this initial finding. Further, not only are the estimates statistically insignificant, but the effects sizes are small and economically inconsequential. As a result, we are unable to find evidence supporting SCW's conclusion that competition, as measured by *H-statistic*, positively contributes to financial stability.

Our findings with respect to banking sector concentration are mixed. When we update the control variables but use SCW's values for *Concentration*, we confirm their findings that greater concentration in the banking sector reduces the likelihood of a systemic crisis.

However, when we expand the sample timeframe, update the concentration values, and use an alternative measure of financial duress, the results change, so that we can even find that concentration is negatively associated with financial stability.

Lastly, when we include two alternative measures of banking sector competition, the Lerner index and the Boone indicator, we find that the respective competition measures are usually insignificant. The few cases where the estimates are significant do not produce a consistent result.

The failure to find consistent results for many of our variables -- so that estimates vary in significance, size, and even sign depending on the estimation procedure, variable specification, time period, and measure of financial stability -- is unsatisfying. At the same time, it should not be too surprising that we are unable to produce one-size-fits-all empirical relationships for all countries and time periods. Systemic crises are complex phenomena depending on the interplay of many economic actors and environmental conditions that may not be adequately controlled for by a relatively small set of control variables.

Perhaps the more surprising result is that any of our results should maintain consistency in the face of such a large battery of tests and checks. In this sense, our consistent finding of a lack of evidence that competition is systematically related to financial stability is an important contribution. It prevents policy makers from making costly changes to promote competition in their banking sectors when these are not likely to produce positive results. And it frees up researchers to investigate alternative determinants of banking sector durability that may better inform future policy initiatives.

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TABLE 1
Replication of Key Duration Models with Authors' Data

Variable	*Column (2)*		*Column (3)*	
	Original	*Replication*	*Original*	*Replication*
GDP growth (lag)	-0.0594 (0.0365)	-0.0594 (0.0365)	-0.0592 (0.0377)	-0.0592 (0.0377)
Inflation	-0.1693 (0.3200)	-0.1693 (0.3200)	-0.1907 (0.3457)	-0.1907 (0.3457)
Real interest rate	-0.0251** (0.0121)	-0.0251** (0.0121)	-0.0224* (0.0114)	-0.0224** (0.0114)
Depreciation	0.0533* (0.0275)	0.0533* (0.0275)	0.0524* (0.0289)	0.0524* (0.0289)
Terms of trade	-0.3126*** (0.0697)	-0.3126*** (0.0697)	-0.3043*** (0.0746)	-0.3043*** (0.0746)
Credit growth	-0.0008** (0.0004)	-0.0008** (0.0004)	-0.0008*** (0.0003)	-0.0008*** (0.0003)
Moral hazard index	-0.4363** (0.1785)	-0.4363** (0.1785)	-0.4215* (0.2279)	-0.4215* (0.2279)
German legal origin	-0.5967 (1.0905)	-0.5967 (1.0905)	-0.8851 (1.0288)	-0.8851 (1.0288)
French legal origin	-1.0421** (0.4511)	-1.0421** (0.4511)	-1.3532*** (0.3887)	-1.3532*** (0.3887)
Scandinavian legal origin	0.6542 (1.0942)	0.6542 (1.0942)	-0.0875 (1.1386)	-0.0875 (1.1386)
Africa dummy	-1.5102** (0.6586)	-1.5102** (0.6586)	-1.8586*** (0.6682)	-1.8586*** (0.6682)
Other dummy	-1.1901* (0.6368)	-1.1901* (0.6368)	-1.5535** (0.6481)	-1.5535** (0.6481)
Latin America dummy	-0.5069 (0.7557)	-0.5069 (0.7557)	-0.4322 (0.6853)	-0.4322 (0.6853)
H-statistic	1.6977* (0.8804)	1.6977* (0.8804)	2.3482** (0.9700)	2.3482** (0.9700)
Concentration	----	----	3.0834*** (0.9595)	3.0834*** (0.9595)
Observations	701	701	701	701

NOTE: This table reports the replication of Columns (2) and (3) of Table 3 in SCW (page 722). The data for the replication were provided by SCW, as were the Stata do files used to produce the replications. Estimates are derived from a duration model that assumes that survival times are exponentially distributed. Survival times are measured in years as time to a systemic crisis. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

TABLE 2
Replication of Key Logit Models with Authors' Data

Variable	*Column (6)*		*Column (7)*	
	Original	*Replication*	*Original*	*Replication*
GDP growth (lag)	-0.2554*** (0.0773)	-0.2554*** (0.0773)	-0.2640*** (0.0842)	-0.2640*** (0.0842)
Inflation	0.5328* (0.2985)	0.5328* (0.2985)	0.5125 (0.3154)	0.5125 (0.3154)
Real interest rate	0.0306 (0.0193)	0.0306 (0.0193)	0.0290 (0.0222)	0.0290 (0.0222)
Depreciation	0.0273 (0.0653)	0.0273 (0.0653)	0.0151 (0.0685)	0.0151 (0.0685)
Terms of trade	0.2680*** (0.0609)	0.2680*** (0.0609)	0.2388*** (0.0655)	0.2388*** (0.0655)
Credit growth	0.0006 (0.0006)	0.0006 (0.0006)	0.0006 (0.0006)	0.0006 (0.0006)
Moral hazard index	0.5596 (0.3550)	0.5596 (0.3550)	0.4734 (0.3803)	0.4734 (0.3803)
German legal origin	0.2724 (1.2038)	0.2724 (1.2038)	0.5139 (1.1809)	0.5139 (1.1809)
French legal origin	0.8124 (0.6748)	0.8124 (0.6748)	1.2292** (0.6031)	1.2292** (0.6031)
Scandinavian legal origin	0.1937 (0.9042)	0.1937 (0.9042)	1.1016 (0.8323)	1.1016 (0.8323)
Africa dummy	0.6712 (0.9422)	0.6712 (0.9422)	1.0718 (0.9226)	1.0718 (0.9226)
Other dummy	0.5525 (0.6716)	0.5525 (0.6716)	0.9495 (0.7398)	0.9495 (0.7398)
Latin America dummy	-0.7543 (0.8183)	-0.7543 (0.8183)	-0.8618 (0.8182)	-0.8618 (0.8182)
H-statistic	-2.3116** (1.0644)	-2.3116** (1.0644)	-2.9703** (1.2328)	-2.9703** (1.2328)
Concentration	----	----	-3.4672** (1.4747)	-3.4672** (1.4747)
Observations	707	707	707	707

NOTE: This table reports the replication of Columns (6) and (7) of Table 3 in SCW (page 722). The data for the replication were provided by SCW, as were the Stata do files used to produce the replications. Estimates come from maximum likelihood estimation of a logit model, where the dependent variable takes the value 1 if there has been a systemic crisis for that country in that year, and 0 otherwise. The numbers in parentheses below estimated coefficients are heteroskedasticity robust standard errors, as per SCW's analysis. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

TABLE 3
Descriptive Statistics for Original and Updated Data (Common Observations)

Variable	*Data Source*	*N*	*Mean*	*Std. Dev.*	*Min*	*Max*
GDP growth (lag)	*Original*	699	-0.197	3.731	-17.333	25.572
	WDI*	699	3.556	3.399	-13.128	21.829
	IFS	699	3.679	3.797	-8.857	52.554
Inflation	*Original*	691	1.854	1.166	-4.257	6.439
	WDI*	691	15.085	45.013	-0.929	625.802
	IFS	691	15.169	44.896	-4.410	620.840
	DataMarket	691	15.085	45.013	-0.929	625.802
Depreciation	*Original*	332	2.835	2.546	-4.760	8.868
	IFS*	332	0.083	0.250	-0.282	3.219
	WDI	332	0.083	0.250	-0.282	3.219
	DataMarket	332	0.083	0.250	-0.282	3.219
Terms of trade	*Original*	404	4.626	0.197	3.931	5.305
	WDI*	404	0.312	10.945	-46.653	67.797
	DataMarket	404	1.409	15.754	-63.605	169.845
Real interest rate†	*Original*	591	2.159	16.931	-312.233	41.110
	WDI	591	7.231	9.505	-35.078	76.428
	DataMarket	591	7.225	9.505	-35.078	76.428
Credit growth†	*Original*	698	108.092	282.845	-811.882	3393.340
	WDI	698	15.887	93.366	-1605.175	541.081
	GDD	698	15.759	93.416	-1605.175	541.081
Moral hazard index†	*Original*	544	1.664	0.259	0.000	1.940
	DID	544	0.289	2.774	-11.862	4.618

<u>NOTE</u>: The values in the table allow comparison of descriptive statistics across data sources for key variables in SCW's analysis. "Original" refers to the data provided by SCW. The other

data sources are World Development Indicators ("WDI"), International Financial Statistics ("IFS"), Global Financial Development Database ("GDD"), Deposit Insurance Database ("DID") and DataMarket. For each variable, we selected the maximum number of observations for which data were available for all data sources listed for that variable. This insured that differences were due solely to different values across data sources, and not because different observations were used to calculate the descriptive statistics. An asterisk indicates that the respective data source was used by SCW.

† We did not use SCW's data sources for these three variables when it came time for updating. The reasons are given below.

Real interest rate. SCW state that they sourced real interest rate data from International Financial Statistics (IFS). They state that real interest rates were calculated as "nominal interest rate minus the rate of inflation". However, IFS reports various interest rates and inflation rates. The available interest rates are Central Bank policy rate, money market rate, Treasury bill rate, deposit rate, lending rate and government bond rates. Inflation rate data are available for both the consumer price index and the GDP deflator. Not knowing the exact series that SCW used to calculate their real interest data, we instead used the variables identified as "real interest rate" in WDI and DataMarket for the purposes of updating.

Credit growth. Credit growth is based on the amount of domestic credit loaned to the private sector. SCW used IFS data in their paper. However, these data are not currently available from IFS. Therefore, we used domestic credit to private sector data from the WDI and GDD databases when updating.

Moral hazard index. SCW obtained data for their moral hazard index from Demirguc-Kunt and Detragiache's (2002) Deposit Insurance Database. These data were updated by Demirguc-Kunt, Kane and Laeven (2014), and we draw from this latter source when calculating updated values for this variable.

TABLE 4
Replication of Key Models Using Updated Data/Common Observations

Variable	*Duration models* (2)	(3)	*Logit models* (6)	(7)
A. COMMON OBSERVATIONS 1				
Original Data				
H-statistic	2.7960** (1.2908)	1.9825 (1.7485)	-5.9893*** (2.2759)	-5.4947** (2.2470)
Concentration	----	5.7003 (3.9084)	----	-4.3380 (3.7786)
Observations	222	222	218	218
Updated Data – Same Sources				
H-statistic	3.9171 (3.1742)	3.3610 (3.3713)	-4.6618 (3.4343)	-4.1897 (3.8093)
Concentration	----	3.9562 (2.6326)	----	-4.3421* (2.3198)
Observations	222	222	218	218
B. COMMON OBSERVATIONS 2				
Original Data				
H-statistic	2.5688** (1.1370)	2.6843** (1.2699)	-3.8997*** (1.3488)	-4.6277*** (1.4535)
Concentration	----	4.8737* (2.6118)	----	-5.3242** (2.2109)
Observations	474	474	479	479
Updated Data – Multiple Sources				
H-statistic	2.9316* (1.5956)	3.5204 (2.2027)	-3.1329* (1.6277)	-3.7062* (2.1125)
Concentration	----	4.4773*** (1.5671)	----	-4.9514*** (1.4539)
Observations	474	474	479	479

NOTE: The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722 and 723). Only the competition and concentration coefficients are reported. All datasets used in the table consist of subsamples of the observations used to estimate the original specifications in SCW. The table consists of two panels. The top panel updates variable values using the same data sources as SCW. The bottom panel expands the number of data sources, choosing the one that maximizes the number of observations available for estimation. Each panel (A and B) consists of two parts. Both parts within a panel use the identical set of observations. The only difference is the top part uses SCW's original data, while the bottom part of the panel uses updated values of the control variables. Note that there are variables values that are available in SCW's original dataset, for which updated values are not available; and variables for which current values are available, but for which values are missing in SCW's original dataset. For this reason, the number of observations in each panel is less than the original number of observations used by SCW. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

TABLE 5
Replication of Key Models Using Updated Data: 1980-2005

Variable	***Duration models***		***Logit models***	
	(2)	***(3)***	***(6)***	***(7)***
A. SAME SOURCES (1980-2005)				
H-statistic	0.9160 (1.2239)	0.3447 (1.3776)	-0.5822 (0.7937)	-0.0653 (0.9521)
Concentration	-	4.4016** (1.8738)	-	-4.3776** (1.7657)
Observations	327	327	331	331
B. MULTIPLE SOURCES (1980-2005)				
H-statistic	0.2551 (0.9266)	0.3110 (0.9797)	-0.0580 (0.9519)	-0.1678 (1.0370)
Concentration	-	4.6350*** (1.4047)	-	-4.9581*** (1.5135)
Observations	679	679	682	682

NOTE: The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722). Only the competition and concentration coefficients are reported. Panels A and B are identical to Panels A and B in Table 5, except that all available observations are used, even if the observations were not included in SCW's original analysis. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

TABLE 6
Replication of Key Models Using Updated Data: 1980-2011

Variable	*Duration models*		*Logit models*	
	(2)	*(3)*	*(6)*	*(7)*
A. CONSTANT *H-Statistic* AND *Concentration* VALUES: WHOLE PERIOD				
H-statistic	0.1285 (0.8489)	0.1201 (0.9120)	0.0251 (0.8696)	-0.0028 (0.9769)
Concentration	-	4.4092*** (1.2183)	-	-4.6377*** (1.3097)
Observations	803	803	802	802
B. CONSTANT *H-Statistic* AND *Concentration* VALUES: TWO PERIODS				
H-statistic	0.2899 (0.8437)	0.3480 (0.7830)	-0.2841 (0.8067)	-0.4065 (0.7630)
Concentration	-	2.6524* (1.3919)	-	-2.7918* (1.4608)
Observations	803	803	802	802
C. MIXED CONSTANT, TIME-VARYING *H-Statistic* AND *Concentration* VALUES				
H-statistic	0.2827 (0.8375)	0.3157 (0.7948)	-0.2836 (0.8048)	-0.3192 (0.7722)
Concentration	-	1.3664 (1.1118)	-	-0.8524 (1.1031)
Observations	803	803	802	802

NOTE: The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722). All three sets/panels of estimates use multiple sources to achieve maximum number of observations with updated data, even if the observations were not included in SCW's original analysis. The values of the control variables across the three panels are identical. The values for *H-statistic* and *Concentration* differ as follows: Panel A uses SCW's (constant) values for the entire time period (1980-2011). Panels B and C accommodate the availability of updated *H-statistic* and *Concentration* data for the years 2010-2011 and 1996-2011, respectively. Panel B uses two sets of constant values for each variable. For *H-Statistic*, it uses SCW's value for 1980-2009 and the country average of *H-statistic* for 2010-2011. For *Concentration*, it uses SCW's value for 1980-1995, and the country average of *Concentration* for 1996-2011. Panel C differs from Panel B in that it uses the time-varying, updated values for these variables whenever possible. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

TABLE 7
Replication Using Z-Score as the Dependent Variable: 1999-2015

Variable	A. CONSTANT *H-Statistic* AND *Concentration* VALUES: TWO PERIODS		B. MIXED CONSTANT, TIME-VARYING *H-Statistic* AND *Concentration* VALUES	
	(1)	*(2)*	*(3)*	*(4)*
H-statistic	-0.0253 (0.3974)	-0.0544 (0.3919)	0.0192 (0.3492)	0.0039 (0.3549)
Concentration	-	0.5832 (0.3904)	-	0.4770 (0.3098)
Observations	384	384	384	382

NOTE: Unlike previous tables, the column headings do not refer to the models in SCW, because the dependent variable is different. TABLE 7 uses the variable Z-score as its measure of financial stability. All other control variables remain the same. We use two approaches to handle the issue of time-varying values for *H-statistic* and *Concentration.* Panel A uses two sets of constant variables for each variable. For *H-statistic*, it uses the SCW's *H-statistic* value for the period 1999-2009, and the country average of *H-statistic* for 2010-2015. For *Concentration*, it uses the country averages for 1999-2007 and 2008-2015, respectively. Panel B maximizes the use of time-varying values. For *H-statistic*, it uses the SCW's *H-statistic* value for the period 1999-2009, and the time-varying values of *H-statistic* for 2010-2015. For *Concentration*, it uses time-varying values over the entire, 1999-2015 period. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country.

TABLE 8
Effect Size Estimates: Evaluating Predicted Probabilities at the
25th, 50th, and 75th Percentile Values of *H-statistic* and *Concentration*

	Obs	***H-statistic***	***Concentration***
A. PROBABILITY OF A CRISIS (from TABLE 6, Panel B, Column 7)			
25th Percentile	803	0.0257	0.0371
50th Percentile	803	0.0254	0.0283
75th Percentile	803	0.0247	0.0175
Δ (75th-25th)	---	*-0.0010*	*-0.0196*
B. PROBABILITY OF A DEFAULT (from TABLE 7, Panel A, Column 2)			
25th Percentile	384	0.1107	0.1020
50th Percentile	384	0.1102	0.1058
75th Percentile	384	0.1090	0.1191
Δ (75th-25th)	---	*-0.0017*	*+0.0171*

NOTE: The predicted probabilities for Panel A are derived from the estimated Logit model of TABLE 6, Panel B, Column (7). The dependent variable in that equation is the binary variable indicating a systemic crisis. The predicted probabilities for Panel B are derived from the estimated fractional logit model of TABLE 7, Panel A, Column (2). The dependent variable in that equation is the country's z-score. All probabilities are calculated at the mean values of the regression covariates, except for the variable of interest (*H-statistic* or *Concentration*) which are evaluated at their 25th, 50th, and 75th percentile values (ascending order).

TABLE 9
Pairwise Correlations for the Three Competition Variables and Concentration

	H-statistic	***Lerner***	***Boone***	***Concentration***
H-statistic	--- --- Obs = 270	--- --- ---	--- --- ---	
Lerner	-0.1070 *p-value = 0.095* Obs = 245	--- --- Obs = 737	--- --- ---	
Boone	-0.0436 *p-value = 0.476* Obs = 270	-0.0073 *p-value = 0.843* Obs = 735	--- --- Obs = 761	
Concentration	0.1807 *p-value = 0.003* Obs = 270	0.0113 *p-value = 0.760* Obs = 732	0.0968 *p-value = 0.008* Obs = 756 ------------------- 0.0092 *p-value = 0.881* Obs = 270	--- --- Obs = 757

NOTE: The competition measures *H-statistic, Lerner,* and *Boone* are described in the text. Number of pairwise observations differ because the availability of updated, time-varying observations differ as follows: *H-statistic*: 2010-2015; *Lerner*: 1996-2015; *Boone*: 1999-2015.

TABLE 10
Replication of Key Models Using Updated Data and Additional Competition Variables: 1980-2011

Variable	*Duration models*		*Logit models*	
	(2)	*(3)*	*(6)*	*(7)*
A. CONSTANT VALUES: WHOLE PERIOD				
H-statistic	-0.4568 (0.9483)	-0.6599 (1.1343)	0.6520 (0.9236)	0.9250 (1.1771)
Lerner	-3.6815 (2.7352)	-3.8679 (3.2869)	4.0123 (2.8382)	4.7302 (3.5410)
Boone	-0.5113 (0.4157)	-1.0771** (0.5173)	0.6351 (0.5073)	1.2416* (0.7544)
Concentration	-	4.8944*** (1.3272)	-	-5.2185** (1.4834)
Observations	803	803	802	802
B. CONSTANT VALUES: TWO PERIODS				
H-statistic	1.1101 (1.0461)	1.0641 (0.9770)	-0.3897 (0.9105)	-0.5457 (0.8427)
Lerner	5.6094* (2.9749)	6.1103** (2.7840)	-0.5487 (3.6257)	-1.1863 (3.4246)
Boone	0.6088 (1.0289)	0.3009 (1.0397)	-0.4325 (1.1504)	-0.1566 (1.1735)
Concentration	-	3.1853* (1.6804)	-	-2.8637* (1.4716)
Observations	803	803	802	802
C. MIXED CONSTANT and TIME-VARYING VALUES				
H-statistic	0.5999 (0.9218)	0.6229 (0.8774)	-1.1331 (1.0930)	-1.1656 (1.0683)

Variable	*Duration models*		*Logit models*	
	(2)	***(3)***	***(6)***	***(7)***
Lerner	2.1977 (2.5525)	2.5437 (2.6875)	-5.2821* (3.1450)	-5.6882* (3.2988)
Boone	0.3247 (0.9225)	0.1372 (0.8901)	-0.9467 (1.1125)	-0.7443 (1.1183)
Concentration	-	1.5530 (1.2306)	-	-1.2420 (1.2679)
Observations	803	803	802	802

NOTE: TABLE 10 uses the same data, variables, and estimation procedures as TABLE 6 except that it adds the competition variables *Lerner* and *Boone* to the respective specifications. The values of the control variables across the three panels are identical. The values for *H-statistic* and *Concentration* in each of the three panels are the same as in TABLE 6 (see note there). The values for *Lerner* and *Boone* are set as follows. Panel A uses constant values for these variables for the entire time period (1980-2011), where *Lerner* and *Boone* are set equal to their average value over the periods for which their data are available: 1996-2011 and 1999-2011, respectively. Panel B uses two sets of constant values for each variable. *Lerner* uses the 1996 value for 1980-1996 and the country average for 1997-2011. *Boone* uses the 1999 value for 1980-1999, and the country average for 2000-2011. Panel C differs from Panel B in that it uses the time-varying values for these variables whenever possible. Note that increases in *H-statistic* are associated with greater competition while increases in *Lerner* and *Boone* are associated with decreased competition. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

TABLE 11
Replication Using Z-Score as the Dependent Variable and Additional Competition Variables: 1999-2015

Variable	**A. CONSTANT VALUES: TWO PERIODS**		**B. MIXED CONSTANT AND TIME-VARYING VALUES**	
	(1)	***(2)***	***(3)***	***(4)***
H-statistic	0.0028 (0.1639)	-0.0296 (0.1613)	-0.1635 (0.1512)	-0.1793 (0.1500)
Lerner	0.0061 (0.0235)	0.0142 (0.0211)	-0.0680*** (0.0199)	-0.0598*** (0.0208)
Boone	0.1760 (0.1194)	0.1262 (0.1204)	-0.0035 (0.0659)	-0.0252 (0.0565)
Concentration	-	0.5779*** (0.1409)	-	0.5117*** (0.1575)
Observations	384	384	376	374
AIC	228.4416	230.1708	223.3076	223.6320
SIC	295.6025	301.2824	290.1106	294.2686

NOTE: TABLE 11 uses the same data, variables, and estimation procedures as TABLE 7 except that it adds the competition variables *Lerner* and *Boone* to the respective specifications. The values of the control variables across the two panels are identical. The values for *H-statistic* and *Concentration* in each of the panels are the same as in TABLE 7 (see note there). The values for *Lerner* and *Boone* are set as follows. Panel A uses two sets of constant variables for each variable. For both *Lerner* and *Boone*, it uses the country average of these variables for the periods 1999-2007 and 2008-2015, respectively. Panel B uses the time-varying values of these variables for the entire period. Note that increases in *H-statistic* are associated with greater competition while increases in *Lerner* and *Boone* are associated with decreased competition. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.

FIGURE 1
Comparison of Selected Data Values from Alternative Sources

A. Variable = *GDP growth (lag)*

Country	Year	Original	WDI*	IFS
INDONESIA	1980	1.63	7.09	6.26
INDONESIA	1981	-0.58	8.72	9.88
INDONESIA	1982	-7.04	8.15	7.93
INDONESIA	1983	7.35	1.10	2.25
INDONESIA	1984	-1.28	8.45	4.19
INDONESIA	1985	-3.69	7.17	6.97
INDONESIA	1986	2.49	3.48	2.46
INDONESIA	1987	-0.66	5.96	5.88
INDONESIA	1988	1.06	5.30	4.93
INDONESIA	1989	2.73	6.36	5.78
INDONESIA	1990	-0.08	9.08	7.46
INDONESIA	1991	-0.07	9.00	7.24
INDONESIA	1992	-1.71	8.93	6.95
INDONESIA	1993			
INDONESIA	1994			
INDONESIA	1995			
INDONESIA	1996	-0.75	8.40	8.22
INDONESIA	1997	-2.94	7.64	7.82
INDONESIA	1998			
INDONESIA	1999			
INDONESIA	2000			
INDONESIA	2001			
INDONESIA	2002			
INDONESIA	2003			
INDONESIA	2004			
INDONESIA	2005			

B. Variable = *Inflation*

Country	Year	Original	WDI*	IFS	DataMarket
BRAZIL	1980	4.5	87.3	91.2	87.3
BRAZIL	1981	4.7	107.2	104.7	107.2
BRAZIL	1982	4.7	104.8	101.9	104.8
BRAZIL	1983	4.9	140.2	136.4	140.2
BRAZIL	1984	5.4	212.8	204.4	212.8
BRAZIL	1985	5.4	231.7	249.5	231.7
BRAZIL	1986	5.0	145.3	147.5	145.3
BRAZIL	1987	5.3	204.1	204.8	204.1
BRAZIL	1988	6.5	651.1	648.7	651.1
BRAZIL	1989				
BRAZIL	1990				
BRAZIL	1991	6.0	414.2	414.2	414.2
BRAZIL	1992	6.9	968.2	974.1	968.2
BRAZIL	1993				
BRAZIL	1994				
BRAZIL	1995				
BRAZIL	1996				
BRAZIL	1997				
BRAZIL	1998				
BRAZIL	1999	1.7	8.0	8.5	8.0
BRAZIL	2000	2.1	5.5	6.2	5.5
BRAZIL	2001	2.0	8.1	9.0	8.1
BRAZIL	2002	2.3	9.9	10.6	9.9
BRAZIL	2003	2.7	14.0	13.7	14.0
BRAZIL	2004	2.1	7.8	8.0	7.8
BRAZIL	2005	2.0	7.5	7.2	7.5

FIGURE 1
Comparison of Selected Data Values from Alternative Sources (continued)

C. Variable = *Depreciation*

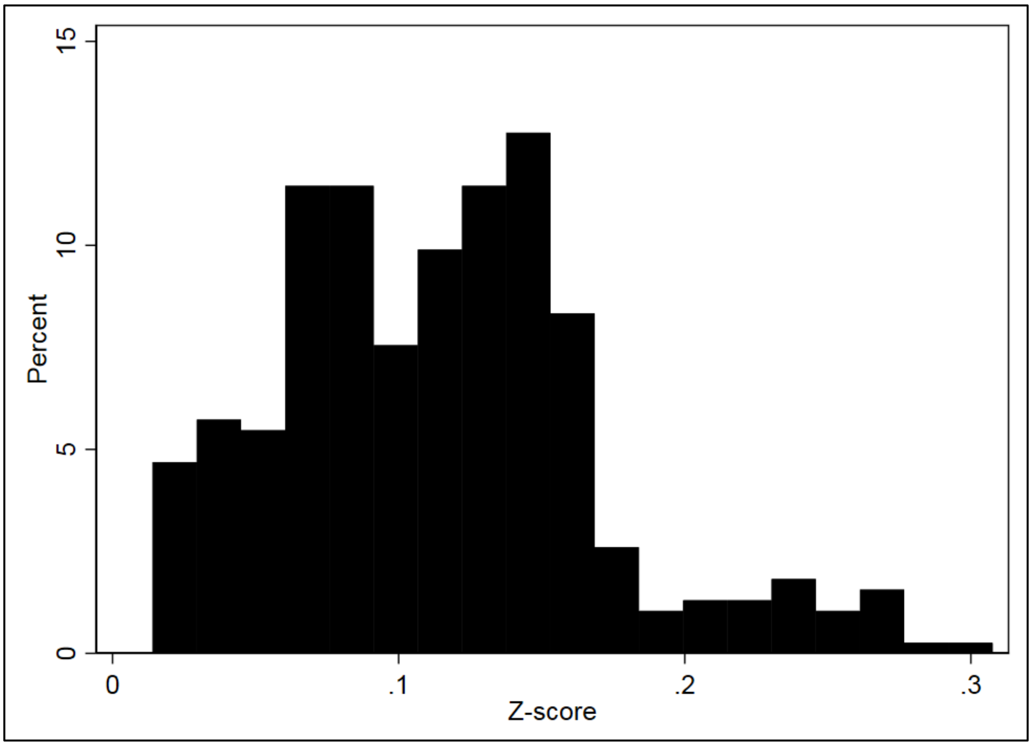
Country	Year	Original	IFS*	WDI	DataMarket
AUSTRIA	1980	2.625	-0.032	-0.032	
AUSTRIA	1981	2.765	0.231	0.231	
AUSTRIA	1982	2.815	0.071	0.071	
AUSTRIA	1983	2.962	0.053	0.053	
AUSTRIA	1984	3.093	0.114	0.114	
AUSTRIA	1985	2.850	0.034	0.034	
AUSTRIA	1986	2.618	-0.262	-0.262	
AUSTRIA	1987	2.420	-0.172	-0.172	
AUSTRIA	1988	2.531	-0.023	-0.023	
AUSTRIA	1989	2.469	0.072	0.072	
AUSTRIA	1990	2.368	-0.141	-0.141	
AUSTRIA	1991	2.369	0.027	0.027	
AUSTRIA	1992	2.430	-0.059	-0.059	-0.059
AUSTRIA	1993	2.497	0.058	0.058	0.058
AUSTRIA	1994	2.395	-0.018	-0.018	-0.018
AUSTRIA	1995	2.311	-0.117	-0.117	-0.117
AUSTRIA	1996	2.394	0.050	0.050	0.050
AUSTRIA	1997	2.536	0.153	0.153	0.153
AUSTRIA	1998	2.464	0.014	0.014	0.014
AUSTRIA	1999	-0.005			
AUSTRIA	2000	0.072			
AUSTRIA	2001	0.126			
AUSTRIA	2002	-0.048			
AUSTRIA	2003	-0.233			
AUSTRIA	2004	-0.309			
AUSTRIA	2005	-0.165			

D. Variable = *Terms of trade*

Country	Year	Original	WDI*	DataMarket
COLOMBIA	1980	4.72		3.85
COLOMBIA	1981	4.59	-11.86	-12.16
COLOMBIA	1982	4.62	2.55	2.88
COLOMBIA	1983			
COLOMBIA	1984			
COLOMBIA	1985			
COLOMBIA	1986	4.87	25.60	22.74
COLOMBIA	1987	4.55	-27.23	-17.64
COLOMBIA	1988	4.50	-5.50	-5.62
COLOMBIA	1989	4.48	-1.78	-0.69
COLOMBIA	1990	4.40	-7.85	-2.34
COLOMBIA	1991	4.45	5.49	2.16
COLOMBIA	1992	4.33	-11.58	-1.93
COLOMBIA	1993	4.36	3.57	2.24
COLOMBIA	1994	4.51	15.70	0.00
COLOMBIA	1995	4.46	-4.43	0.15
COLOMBIA	1996	4.50	3.48	-1.84
COLOMBIA	1997	4.50	0.10	0.96
COLOMBIA	1998	4.41	-8.21	-10.15
COLOMBIA	1999	4.49	7.71	2.06
COLOMBIA	2000			
COLOMBIA	2001	4.51	-5.75	-7.47
COLOMBIA	2002	4.49	-1.86	0.84
COLOMBIA	2003	4.52	2.91	2.69
COLOMBIA	2004	4.53	7.47	6.12
COLOMBIA	2005			

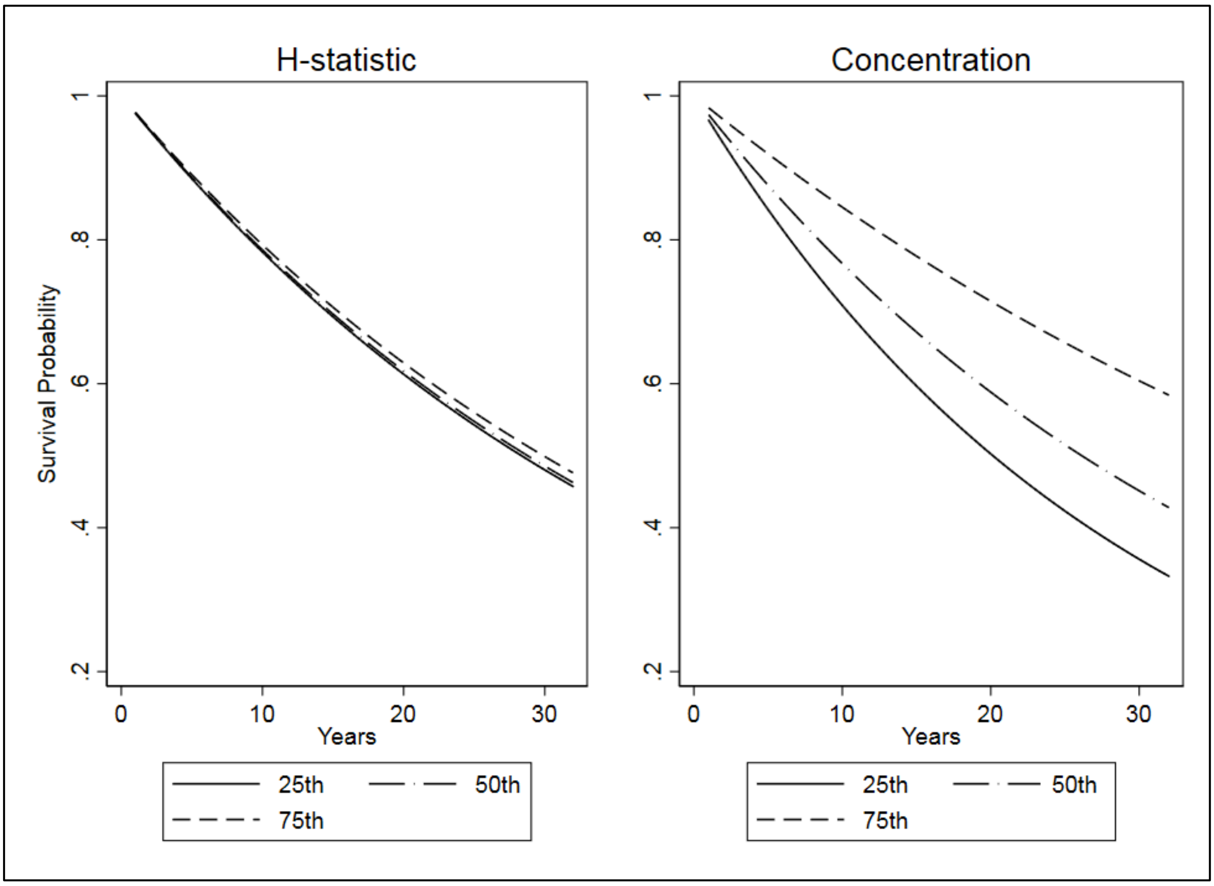
NOTE: The values in the table allow comparison of variable values across data sources for selected variables, countries, and years. “Original” refers to the data provided by SCW. The other data sources are World Development Indicators (“WDI”), and International Financial Statistics (“IFS”). An asterisk indicates that the respective data source was used by SCW.

FIGURE 2
Histogram and Descriptive Statistics for Z-Score



Mean	*Std. Dev.*	*Min*	*Max*	*Obs*
0.1134	0.0559	0.014	0.3076	384

FIGURE 3
Survival Rates Evaluated at the 25th, 50th, and 75th Percentile Values of *H-statistic* and *Concentration*



NOTE: Survival rates are calculated from the duration model results of Panel B, TABLE 6, Column (3). The associated probabilities calculated at the mean values of all variables other than the variable of interest: *H-statistic* and *Concentration*, respectively. The latter variables are set equal to their 25th, 50th, and 75th percentile values (ascending order).

APPENDIX
Replication of Key Models Using Updated Data: 1980-2007

Variable	*Duration models*		*Logit models*	
	(2)	*(3)*	*(6)*	*(7)*
A. CONSTANT *H-Statistic* AND *Concentration* VALUES: WHOLE PERIOD				
H-statistic	0.2380 (0.8646)	0.1974 (0.9241)	-0.0787 (0.8771)	-0.0965 (0.9879)
Concentration	-	4.6680*** (1.2643)	-	-4.9014*** (1.3642)
Observations	731	731	732	732
B. CONSTANT *H-Statistic* AND *Concentration* VALUES: TWO PERIODS				
H-statistic	0.2380 (0.8646)	0.1819 (0.8269)	-0.0787 (0.8771)	-0.0311 (0.8572)
append Concentration	-	3.5186*** (1.2614)	-	-3.6476*** (1.3552)
Observations	731	731	732	732
C. MIXED CONSTANT, TIME-VARYING *H-Statistic* AND *Concentration* VALUES				
H-statistic	0.2380 (0.8646)	0.2620 (0.8226)	-0.0787 (0.8771)	-0.1105 (0.8298)
Concentration	-	2.1741** (1.0443)	-	-1.6310 (1.077)
Observations	731	731	732	732

NOTE: The column headings indicate that the respective estimates refer to estimating the models in Columns (2), (3), (6) and (7) from Table 3 in SCW (page 722). All three sets/panels of estimates use multiple sources to achieve maximum number of observations with updated data, even if the observations were not included in SCW's original analysis. The values of the control variables across the three panels are identical, as is the value for *H-statistic.* In the latter case, we use SCW's (constant) values for the entire period (1980-2007). The three panels differ in how we incorporate time-varying behavior in *Concentration.* Panel A uses SCW's (constant) values for the entire time period (1980-2007). Panel B uses SCW's value for 1980-1995, and the country average of *Concentration* for 1996-2007. Panel C uses SCW's value for 1980-1995, and time-varying values for 1996-2007. The numbers in parentheses below estimated coefficients are cluster robust standard errors, clustered on country. *, **, and ***, indicate significance at the 10-, 5-, and 1-percent significance levels.