Bankers need new clothes: bank capital, leverage, and default probability adjustment through the macroeconomic cycle

First version: September 2015

This version: September 2016

Abstract

We assess the quantitative implications of the recent proposal for more robust bank capital adequacy (Admati and Hellwig, 2013; Myerson, 2014). Our theoretical proof and evidence are consistent with the central thesis that banks become more stable by increasing its equity capital cushion to absorb large losses in times of severe financial stress. This analysis thus contributes to the ongoing policy debate on total bank capital adequacy. Our study also helps design an analytical solution for the default probability adjustment through the macroeconomic cycle. This analysis poses a challenge to DeAngelo and Stulz's (2015) model of high optimal bank leverage.

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Introduction

The U.S. Basel Final Rule[1] stipulates that the default probability should be the "bank's empirically based best estimate of the long-run average of one-year default rates for the exposures in the segment, capturing the average default experience for exposures in the segment over a mix of economic conditions (including downturn conditions) [that are] sufficient to provide a reasonable estimate of the average one-year default rate over the economic cycle for the segment". The core idea pertains to how the risk model developer incorporates the joint non-linear effect of macroeconomic risk covariates into the default probability function to measure the through-the-cycle (TTC) probability of default (PD). The conventional industry practice is to plug the long-term average macroeconomic risk covariates into the non-linear default probability function to compute the "TTC1 PD". In comparison, an alternative approach would be to calculate each long-term average "TTC0 PD" based on the point-in-time (PIT) macroeconomic fluctuations through at least one complete business cycle. To the best of our knowledge, the extant literature does not provide an evaluation of these different approaches for the default probability adjustment through the macroeconomic cycle under the new Basel bank capital regime.

For bank capital management, PIT default probabilities include all available and pertinent information as of a given date to estimate the propensity for the borrower to default on the loan over the one-year period. This information includes not only the bank's expectations about the borrower's long-run credit risk trend but also the macroeconomic and idiosyncratic shifts in the borrower's credit risk profile. As a result, PIT default probabilities respond immediately to all the news that affects the borrower's default risk. For this reason, PIT default probabilities are highly volatile and procyclical in contrast to TTC default probabilities. Relative to PIT default probabilities, TTC default probabilities show less volatility and procyclicality over the business cycle. TTC default probabilities primarily reflect the borrower's long-term persistent default risk trend and thus do not contain the short-term transient changes in default risk that are likely to reverse with the passage of time. As TTC default probabilities are stable over the macroeconomic cycle, the Basel capital accord requires banks to use TTC default probabilities for regulatory capital measurement. This major distinction between PIT and TTC default probabilities affects how the bank incorporates macroeconomic risk covariates into the highly non-linear default probability model. The resultant default probability quantification contributes to the joint determination of bank equity capital.

There are several advantages of greater equity capital for banks. First, the main purpose of stricter equity capital regulation is to ensure that each bank is able to contain significant losses in its asset value while the bank continues to honor deposit withdrawals and other debt obligations (Admati and Hellwig, 2013; Demirguc-Kunt, Detragiache, and Merrouche, 2013; Aginer and Demirguc-Kunt, 2014). In this light, higher equity capitalization reduces bank risk and increases its long-term

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[1] Department of the Treasury, Federal Reserve System, Federal Deposit Insurance Corporation, and Office of Thrift Supervision. (2007). Risk-based capital standards, advanced capital adequacy framework of Basel II. *Federal Register* **72**(235): 69308. Available online at http://www.gpo.gov/fdsys/pkg/FR-2007-12-07/pdf/07-5729.pdf.

survival probability. Second, a larger equity capital buffer requires bank owners to retain an active interest in the financial enterprise. This active interest induces bank owners to improve the bank's risk management practices with fewer excessive risk-taking incentives due to both limited-liability and bailout expectations (Allen, Carletti, and Marquez, 2011; Coval and Thakor, 2005; Holmstrom and Tirole, 1997; Myerson, 2014). Third, greater equity capitalization would result in the choice of less risky portfolios through the lens of moral hazard because each bank has to contain large reductions in its asset value while there would be little incentive to transfer risk to another party (Keeley, 1990; Calomiris and Kahn, 1991; Acharya, Mehran, and Thakor, 2014). To the extent that discretionary regulatory forbearance counterproductively induces banks to increase their leverage, this high leverage funds excessively risky assets whose default probabilities significantly correlate with one another. The resultant equilibrium outcome is a suboptimal balance between asset substitution and debt discipline on managerial rent protection. This rationale suggests an important role for greater equity capitalization that helps resolve the moral hazard problem. In addition to the above, another reason for greater equity capital concerns the fact that higher equity capital requirements lead to higher endogenously determined bank survival probabilities at the interim point in time (Mehran and Thakor, 2010). This increase in survival likelihood suggests better cash-flow benefits from monitoring bank management in subsequent periods. Higher future profitability helps enhance bank value in the cross-section. Mehran and Thakor's (2010) empirical analysis of gains and synergies from bank mergers and acquisitions confirms a positive relation between equity capital and bank value, the latter of which can be measured in terms of total bank value and its components such as acquisition value, goodwill, and net present value to the target bank's shareholders.

This literature review suggests that the benefits of greater equity capital requirements for banks should outweigh the costs. Although many proponent of the compelling case for more robust total bank capital adequacy offer qualitative perspectives on this important policy issue (e.g. Admati and Hellwig (2013); Kashyap, Stein, and Hanson (2010); Myerson (2014)), we know little about the quantitative implications of this recent proposal. In other words, the econometrician has yet to test for the effect of changes in major risk parameters on the typical bank's equity capital ratio. This test requires a deeper analysis of the default probability adjustment through the macroeconomic cycle. To the extent that the TTC1 PD computation tends to underestimate the true TTC0 PD adjustment, this latter adjustment emerges as a topical subject for bank capital analysis.

Our current study first derives the mathematical result and then uses Monte Carlo simulation to demonstrate that there is a significant difference between the TTC0 and TTC1 PD estimates. Insofar as the vast majority of individual PDs land in the convex region of the highly non-linear PD function, the mathematical notion of Jensen's inequality suggests that the TTC1 PDs would be much lower than the TTC0 PDs. It is important to note that the TTC0 PD adjustment by brute force can be computationally intensive. For the sheer volume of a typical bank's retail and wholesale portfolios, it can be prohibitively costly to carry out the TTC0 PD adjustment by brute force. For this reason, we propose a convenient approximation, TTC2 and TTC3, via the higher-order Taylor-series expansion. Our empirical analysis suggests that this approximation is closer to the TTC0 PD origin by a full order of magnitude.

Our analytical result suggests that the conventional industry practice introduces a downward bias in the default probability adjustment for bank capital measurement. In contrast to the TTC1 PD adjustment, both the TTC0 PD adjustment by brute force and the TTC2 and TTC3 PD alternative methods result in higher default probabilities. This evidence has important implications in the context of the recent proposal for banks to hold more equity capital (Admati, DeMarzo, Hellwig, and Pfleiderer, 2011; Admati and Hellwig, 2013; Kashyap, Stein, and Hanson, 2010; Myerson, 2014). Specifically, our results bolster the case for revisiting the newly introduced 3%-6% equity capital requirement under the Basel bank capital regime. In contrast to this rather lenient regulatory equity capital requirement, our empirical results suggest that the typical bank's equity capital as a proportion of the total asset base should be as high as 22%-26%. This broad range is consistent with the qualitative implications of the recent proposal for banks to substantially raise their equity capital ratios that would become more commensurate with financial risk exposure that such banks would face in a rare severe macroeconomic recession (e.g. Admati and Hellwig (2013); Kashyap, Stein, and Hanson (2010); Myerson (2014)). Also, our analysis can be extended to help design a macroeconometric stress test for bank capital management. Overall, our research advocates support for more robust total capital adequacy. This endeavor thus serves as a scientific microfoundation for the central thesis that banks can become more stable by holding a greater capital cushion to absorb large losses in times of severe financial stress.

Several recent studies connect the credit risk model with macroeconomic variables (Duffie, Saita, and Wang, 2007; Duffie, Eckner, Horel, and Saita, 2009; Koopman, Kraussel, Lucas, and Monteiro, 2009; Koopman, Lucas, and Schwaab, 2011). Bangia, Diebold, Kronimus, Schagen, and Schuermann (2002) and Nickel, Perraudin, and Varotto (2000) empirically find that macroeconomic fluctuations have a significant effect on credit rating transitions. Also, Pesaran, Schuermann, Treutler, and Weiner (2006) link the macroeconomic covariates contemporaneously with global equity returns. Pesaran et al assess the impact of macro shocks on the average loss distribution for each credit portfolio and then demonstrate that these macro shocks have an asymmetric and non-proportional effect on default risk due to the highly non-linear nature of the credit risk model. In this context, the extant literature does not distinguish the manner in which macroeconomic risk factors enter the default probability model. In particular, there is virtually no guidance on how the risk model developer should incorporate the joint non-linear effect of macroeconomic risk factors into the default probability adjustment through the business cycle. In relation to the distinction between TTC and PIT default probabilities, one can condition the default probability model on a set of long-term average macroeconomic risk covariates to design the TTC credit risk metric; alternatively, one can also use the long-term average credit risk metric of the PIT default probabilities over at least a complete macroeconomic cycle. In this paper, we investigate this important issue and assess these alternative approaches to integrating macroeconomic risk factors into the default probability model.

Several other studies examine the TTC properties of external credit rating measures as well as how credit rating agencies achieve rating stability over time (Carey and Hrycay, 2001; Loeffler, 2004, 2005; Altman and Rijken, 2004 and 2006). The major credit rating agencies focus on the permanent credit risk component when they assign exposures to credit risk grades. Altman and Rijken (2006) suggest that credit rating agencies tend to slowly adjust their credit rating assignment while this slow adjustment is the most important source of rating stability. Further, Loeffler (2005) suggests that the slow adjustment can be explained by the desire to avoid subsequent credit rating reversals. Building on Fama and French's (1988) model of the effect of both permanent and transitory components on stock prices, Loeffler (2004) imposes a stress scenario on the transitory component when one forecasts future asset prices. Carey and Hrycay (2001) note that the TTC approach entails estimating default risk over a long time horizon subject to an explicit worst-case scenario. In this view, the conventional practice of plugging long-run average macroeconomic risk factors into the default probability model may be too lenient to be consistent with the spirit of the TTC default probability requirement set out in the Basel capital framework. As a result, we need to revisit the current default probability adjustment and its quantitative implications for bank capital management.

The current U.S. federal agencies propose a target equity capital ratio in the range of 3%-5% for bank holding companies and up to 6% for U.S. systemically important financial institutions that receive the protection of federal deposit insurance.[2] With a unique set of plausible risk parameters, our Monte Carlo analysis suggests that the equity capital ratio for a typical bank should be substantially higher. While most estimates of the value-at-risk capital ratios land in the intermediate range of about 13%-19%, most estimates of the conditional value-at-risk capital ratios land in the range of 15%-23%. When the econometrician conservatively increases asset correlation from 15% to 35% for a severe downturn scenario, ceteris paribus, the equity capital ratio can be as high as 22%-26%. This quantitative evidence supports the recent proposal by Admati and Hellwig (2013), Admati (2014), Kashyap, Stein, and Hanson (2010), and Myerson (2014) to introduce a 20%-30% bank capital requirement. Our evidence lends credence to a scientific basis for the socially optimal introduction of substantially heightened equity capital requirements for banks in particular as well as financial institutions in general. This fresh strand of quantitative research can become part of our financial risk toolkit in due course.

Overall, our analysis poses an important challenge to the central prediction of DeAngelo and Stulz's (2015) baseline model of high bank leverage. Through the lens of financial risk management, the typical bank should substantially raise its equity capital cushion to counteract severe losses in times of extreme financial stress. From this normative perspective, high bank leverage cannot be socially optimal because the typical bank runs the risk of not being able to absorb large financial losses in a rare macroeconomic downturn such as the recent Global Financial Crisis. In contrast to DeAngelo and Stulz's (2015) emphasis on the important role that most banks play in producing aggregate liquid claims, our current study points out that

[2] Department of the Treasury, Federal Reserve System, and Federal Deposit Insurance Corporation. (2007). Regulatory capital rules: regulatory capital, supervisory revisions to the supplementary leverage ratio. *Federal Register* **79**(187): 57726. Available online at http://www.gpo.gov/fdsys/pkg/FR-2014-09-26/pdf/2014-22083.pdf.

the typical bank's high leverage ratio suggests an insufficient equity capital buffer for extreme loss absorption in a rare but plausible economic recession. Our empirical analysis corroborates the recent proposal for most banks to substantially raise their equity capital positions due to precautionary concerns (Admati, DeMarzo, Hellwig, and Pfleiderer, 2011; Admati and Hellwig, 2013; Kashyap, Stein, and Hanson, 2010; Myerson, 2014).

We organize the remainder of this paper in the following order. Section 1 describes the Taylor series expansion of the logit model with macroeconomic fluctuations. This mathematical derivation provides the theoretical foundation for our Monte Carlo simulation of the different TTC PD adjustments through the macroeconomic cycle. Section 2 offers the comparative statics for the relationship between PD and asset correlation. Section 3 places the current study in the context of the recent literature and then clarifies our main contributions. Section 4 describes our Monte Carlo simulation of default probabilities for a synthetic risky asset portfolio based on the asymptotic single risk factor model. In this section, we describe how we use Monte Carlo simulation to gauge the equity capital requirements for the baseline and alternative TTC PD adjustments. Section 5 discusses the quantitative results in light of the non-trivial difference in capital requirements between the TTC1 PD status quo and its alternatives such as TTC0, TTC2, and TTC3. Section 6 concludes the current study in the context of the recent proposal for banks to substantially raise their equity capital. This section offers a few comments and suggestions for future research.

1. A general default probability model with systematic macro fluctuations

Our narrative characterizes the Taylor series expansion of the logit model with macroeconomic fluctuations. This general expansion provides a higher-order analytic solution to the default probability adjustment through the macroeconomic cycle under the Basel capital framework. In effect, the solution better approximates the long-term average of the point-in-time default probabilities in contrast to the default probability based on the long-run average macroeconomic factors. Not only does this Taylor series expansion adequately correct for the highly non-linear nature of the default probability function, but this expansion also raises the capital output by an order of magnitude insofar as most of the default probabilities land in the convex region of the logit default function. To the extent that the macroeconomic fluctuations have a non-trivial impact on the default probability estimation, the difference in the bank's capital output can be quite substantial. This analytical result is applicable to the through-the-cycle (TTC) probability of default (PD) adjustment for both a bank's wholesale and retail loan portfolios.

Under the Basel capital framework[3], the TTC PD "would be the bank's empirically based best estimate of the long-run average of one-year default rates for the exposures in the segment, capturing the average default experience for exposures in the segment over a mix of economic conditions (including economic downturn conditions) that are sufficient to provide a reasonable estimate of the average one-year default rate over the economic cycle for the segment". It is thus consistent with this Basel requirement to compute the TTC PD as the long-term average of the point-in-time PDs in stark contrast to the default probability based on the long-run average macroeconomic covariates. We derive the Taylor series expansion of this TTC PD requirement:

$$PD_{TTC0} = \left(\frac{1}{t}\right)\sum_{s=1}^{t} PD_s$$

$$= \left(\frac{1}{t}\right)\sum_{s=1}^{t}\left\{\lambda(w+\bar{z}) + (z_s-\bar{z})\frac{d\lambda(w+\bar{z})}{dz} + \frac{1}{2}(z_s-\bar{z})^2\frac{d\lambda^2(w+\bar{z})}{dz^2} + \frac{1}{6}(z_s-\bar{z})^3\frac{d\lambda^3(w+\bar{z})}{dz^3} + o(w+\bar{z})\right\}$$

$$= \lambda(w+\bar{z}) + \left(\frac{1}{t}\right)\sum_{s=1}^{t}(z_s-\bar{z})\frac{d\lambda(w+\bar{z})}{dz} + \frac{1}{2}\left(\frac{1}{t}\right)\sum_{s=1}^{t}(z_s-\bar{z})^2\frac{d\lambda^2(w+\bar{z})}{dz^2} + \frac{1}{6}\left(\frac{1}{t}\right)\sum_{s=1}^{t}(z_s-\bar{z})^3\frac{d\lambda^3(w+\bar{z})}{dz^3} + \ldots$$

$$= \lambda(w+\bar{z}) + \frac{1}{2}\left(\frac{1}{t}\right)\sum_{s=1}^{t}(z_s-\bar{z})^2\frac{d\lambda^2(w+\bar{z})}{dz^2} + \frac{1}{6}\left(\frac{1}{t}\right)\sum_{s=1}^{t}(z_s-\bar{z})^3\frac{d\lambda^3(w+\bar{z})}{dz^3} + \ldots$$

$$= PD_{TTC1} + \frac{1}{2}\left(\frac{1}{t}\right)\sum_{s=1}^{t}(z_s-\bar{z})^2\frac{d\lambda^2(w+\bar{z})}{dz^2} + \frac{1}{6}\left(\frac{1}{t}\right)\sum_{s=1}^{t}(z_s-\bar{z})^3\frac{d\lambda^3(w+\bar{z})}{dz^3} + \ldots$$

$$= PD_{TTC1} + \frac{1}{2}\operatorname{var}(z)\frac{d\lambda^2(w+\bar{z})}{dz^2} + \frac{1}{6}\,skew(z)\operatorname{var}(z)^{3/2}\frac{d\lambda^3(w+\bar{z})}{dz^3} + \ldots \qquad \textbf{Eq(1)}$$

where PD_{TTC0} denotes the TTC0 PD or the long-run average of the point-in-time PDs through the cycle, PD_{s} denotes the point-in-time PD at time $s=\{1,2,3\ldots t\}$, $\lambda(.)$ is the logit transformation of a linear combination of covariates into the default probability metric, w is a linear combination of non-macroeconomic covariates such as the current loan-to-value ratio and

[3] Department of the Treasury, Federal Reserve System, Federal Deposit Insurance Corporation, and Office of Thrift Supervision. (2007). Risk-based capital standards, advanced capital adequacy framework of Basel II. *Federal Register* **72**(235): 69308. Available online at http://www.gpo.gov/fdsys/pkg/FR-2007-12-07/pdf/07-5729.pdf.

the FICO score, z is a linear combination of macroeconomic covariates such as the unemployment rate and the house price variation, $o(.)$ is the error from the higher-order Taylor series approximation, $var(z)$ and $skew(z)$ are the respective variance and skewness of the linear combination of macro fluctuations. For the sake of mathematical simplicity, we consider up to the third-order Taylor series expansion. We observe from Eq(1) that PD_{TTC1} is equivalent to the first-order approximation of PD_{TTC0}. The higher-order terms involve both the variance and skewness of macroeconomic factors and the second-order and third-order derivatives of the logit function with respect to the linear combination of macroeconomic fluctuations. For our current analysis, we consider both the second-order and third-order Taylor series to derive PD_{TTC2} and PD_{TTC3}. These second-order and third-order terms better approximate the long-run average of the point-in-time PDs (i.e. $PD_{\mathrm{TTC2}} \approx PD_{\mathrm{TTC0}}$ and $PD_{\mathrm{TTC3}} \approx PD_{\mathrm{TTC0}}$):

$$PD_{TTC2} \quad = PD_{TTC1} + \frac{1}{2}\operatorname{var}(z)\frac{d\lambda^2(w+\bar{z})}{dz^2} \qquad \textbf{Eq(2)}$$

$$PD_{TTC3} \quad = PD_{TTC1} + \frac{1}{2}\operatorname{var}(z)\frac{d\lambda^2(w+\bar{z})}{dz^2} + \frac{1}{6}skew(z)\operatorname{var}(z)^{3/2}\frac{d\lambda^3(w+\bar{z})}{dz^3} \qquad \textbf{Eq(3)}$$

We now turn to the derivatives of the logit function. We first derive the first derivative of the logit function and then use this result to derive the higher-order derivatives. As the logit function of a random variable h, $\lambda(h)$ follows the form below:

$$\lambda(h) \quad = \left\{\frac{\exp(h)}{1+\exp(h)}\right\} \qquad \textbf{Eq(4)}$$

where the random variable h is a linear combination of both macroeconomic and borrower-specific covariates. The next step is to derive the first derivative of the logit function $\mathrm{d}\lambda(h)/\mathrm{d}h$ through the use of the chain rule:

$$\frac{d\lambda(h)}{dh} \quad = \left\{\frac{\exp(h)}{1+\exp(h)}\right\} + \left\{-\frac{\exp(h)\exp(h)}{(1+\exp(h))^2}\right\}$$

$$= \left\{ \frac{\exp(h)(1+\exp(h)) - \exp(2h)}{(1+\exp(h))^2} \right\}$$

$$= \left\{ \frac{\exp(h)}{1+\exp(h)} \right\} \left\{ \frac{1}{1+\exp(h)} \right\}$$

$$= \lambda(h)(1-\lambda(h))$$

$$= \lambda(h) - \lambda(h)^2 \qquad \textbf{Eq(5)}$$

We make use of the above analytical result in Eq(5) to derive the second-order and third-order derivatives of the logit function $d^2\lambda(h)/dh^2$ and $d^3\lambda(h)/dh^3$:

$$\frac{d^2\lambda(h)}{dh^2} = \left(\lambda(h) - \lambda(h)^2\right) - 2\lambda(h)\left(\lambda(h) - \lambda(h)^2\right)$$

$$= \lambda(h) - \lambda(h)^2 - 2\lambda(h)^2 + 2\lambda(h)^3$$

$$= 2\lambda(h)^3 - 3\lambda(h)^2 + \lambda(h)$$

$$= \lambda(h)\left(2\lambda(h)^2 - 3\lambda(h) + 1\right)$$

$$= \lambda(h)(1-\lambda(h))(1-2\lambda(h)) \qquad \textbf{Eq(6)}$$

$$\frac{d^3\lambda(h)}{dh^3} = 6\lambda(h)^2\left(\lambda(h)-\lambda(h)^2\right)-6\lambda(h)\left(\lambda(h)-\lambda(h)^2\right)$$

$$= 6\lambda(h)^3 - 6\lambda(h)^4 - 6\lambda(h)^2 + 6\lambda(h)^3 + \lambda(h) - \lambda(h)^2$$

$$= -6\lambda(h)^4 + 12\lambda(h)^3 - 7\lambda(h)^2 + \lambda(h)$$

$$= \lambda(h)\left(\lambda(h) - 6\lambda(h)^3 + 12\lambda(h)^2 - 7\lambda(h) + 1\right)$$

$$= \lambda(h)(1-\lambda(h))\left(1-6\lambda(h)+6\lambda(h)^2\right) \qquad \textbf{Eq(7)}$$

We substitute the second-order and third-order derivatives in Eq(6) and Eq(7) into Eq(3) to complete the higher-order Taylor series expansion of the long-run average of the point-in-time PDs through the cycle:

$$PD_{TTC0} \approx PD_{TTC1} + \frac{1}{2}\mathrm{var}(z)\frac{d\lambda^2(w+\bar{z})}{dz^2} + \frac{1}{6}skew(z)\mathrm{var}(z)^{3/2}\frac{d\lambda^3(w+\bar{z})}{dz^3}$$

$$= PD_{TTC1} + \frac{1}{2}\mathrm{var}(z)PD_{TTC1}(1-PD_{TTC1})(1-2PD_{TTC1})$$

$$+ \frac{1}{6}skew(z)\mathrm{var}(z)^{3/2}\, PD_{TTC1}(1-PD_{TTC1})\left(1-6PD_{TTC1}+6PD_{TTC1}^2\right) \qquad \textbf{Eq(8)}$$

We can observe from Eq(8) that the Taylor series expansion better approximates the long-run average of the point-in-time PDs through the cycle, i.e. $PD_{TTC3} \approx PD_{TTC0}$, by incorporating both the variance and skewness of macroeconomic factors. Not only does this Taylor series expansion correct for the highly non-linear nature of the logit default probability function, but this expansion also raises the capital output by an order of magnitude insofar as most of the default probabilities land in the convex region of the logit function. To the extent that the macroeconomic factors serve as important risk covariates in the default probability estimation, the difference in equity capital output can be substantial. The analytical result applies to the TTC PD adjustments for both a bank's wholesale and retail loan portfolios.

2. Comparative statics for the close relation between default probability and asset correlation

We develop a simple and intuitive model to derive the comparative statics for the bank's equity capital curve as a function of both PD and asset correlation. These comparative statics arise from maximizing the primal-dual objective function that characterizes the wedge between the bank's equity capital curve and its envelope. The equity capital function embeds both PD and asset correlation as the major risk parameters. While the former determines the borrower's propensity to default on his or her risky asset with respect to the macroeconomic shocks and asset-specific attributes, the latter governs the relative likelihood that the rare but plausible extreme default event may occur. This characterization applies the envelope theorem to deduce an inequality that sheds light on the empirical relation between PD and asset correlation.

We define $\kappa^*(\lambda)= \kappa^*(\rho^*(\lambda), \lambda)$ as the envelope for the numerous capital curves $\kappa(\rho(\lambda), \lambda)$ for all possible default probabilities λ where $\kappa(.)$ is the equity capital curve as a concave and twice-differentiable function of both PD and asset correlation, $\rho(.)$ is the asset correlation function of PD, and λ is the asset-specific default probability (PD). This characterization suggests $\kappa(\rho(\lambda), \lambda)\leq \kappa^*(\lambda) = \kappa^*(\rho^*(\lambda), \lambda)$. Then we can define the primal-dual objective function $Q(\rho(\lambda), \lambda)$ as the difference between $\kappa(\rho(\lambda), \lambda)$ and $\kappa^*(\lambda)$:

$$Q(\rho(\lambda),\lambda)=\kappa(\rho(\lambda),\lambda)-\kappa^*(\lambda) \qquad \textbf{Eq(9)}$$

This primal-dual objective function reaches its maximum value of zero when $\rho(\lambda)=\rho^*(\lambda)$ such that $Q(\rho^*(\lambda), \lambda)= \kappa^*(\rho^*(\lambda), \lambda)-\kappa^*(\lambda)=0$. The first-order condition holds when the partial derivatives $\partial\kappa(\rho(\lambda), \lambda)/\partial\lambda$ and $\partial\kappa^*(\lambda)/\partial\lambda$ are equal to each other:

$$\frac{\partial Q(\rho(\lambda),\lambda)}{\partial\lambda}=\frac{\partial\kappa(\rho(\lambda),\lambda)}{\partial\lambda}-\frac{\partial\kappa^*(\lambda)}{\partial\lambda}=0 \Leftrightarrow \frac{\partial\kappa(\rho(\lambda),\lambda)}{\partial\lambda}=\frac{\partial\kappa^*(\lambda)}{\partial\lambda} \qquad \textbf{Eq(10)}$$

In addition to the above, the first-order condition holds when $\rho(\lambda)=\rho^*(\lambda)$ for different default probabilities λ. The sufficient second-order conditions suggest that the Hessian matrix of second partial derivatives of $Q(\rho(\lambda), \lambda)$ with respect to $\rho(\lambda)$ and λ is negative definite:

$$H = \begin{vmatrix} \frac{\partial^2 Q}{\partial \rho^2} & \frac{\partial^2 Q}{\partial \rho \partial \lambda} \\ \frac{\partial^2 Q}{\partial \lambda \partial \rho} & \frac{\partial^2 Q}{\partial \lambda^2} \end{vmatrix} = \begin{vmatrix} \frac{\partial^2 \kappa}{\partial \rho^2} & \frac{\partial^2 \kappa}{\partial \rho \partial \lambda} \\ \frac{\partial^2 \kappa}{\partial \lambda \partial \rho} & \frac{\partial^2 \kappa}{\partial \lambda^2} - \frac{\partial^2 \kappa^*}{\partial \lambda^2} \end{vmatrix} \quad \textbf{Eq(11)}$$

$$\left(\frac{\partial^2 \kappa}{\partial \rho^2} \right) < 0 \quad \textbf{Eq(12)}$$

$$\left(\frac{\partial^2 \kappa}{\partial \rho \partial \lambda} \right) \left(\frac{\partial^2 \kappa}{\partial \lambda \partial \rho} \right) > 0 \quad \textbf{Eq(13)}$$

$$\left(\frac{\partial^2 \kappa}{\partial \rho^2} \right) \left(\frac{\partial^2 \kappa}{\partial \lambda^2} - \frac{\partial^2 \kappa^*}{\partial \lambda^2} \right) - \left(\frac{\partial^2 \kappa}{\partial \rho \partial \lambda} \right) \left(\frac{\partial^2 \kappa}{\partial \lambda \partial \rho} \right) > 0 \Leftrightarrow \left(\frac{\partial^2 \kappa^*}{\partial \lambda^2} - \frac{\partial^2 \kappa}{\partial \lambda^2} \right) > 0 \quad \textbf{Eq(14)}$$

We use implicit differentiation to derive the second partial derivative $\partial^2\kappa^*(\lambda)/\partial\lambda^2$:

$$\begin{aligned} \left(\frac{\partial^2 \kappa^*}{\partial \lambda^2} \right) &= \left(\frac{\partial^2 \kappa(\rho^*(\lambda), \lambda)}{\partial \lambda^2} \right) \\ &= \left\{ \partial \left(\frac{\partial \kappa}{\partial \rho} \frac{\partial \rho^*}{\partial \lambda} \right) \Big/ \partial \lambda \right\} + \left(\frac{\partial^2 \kappa}{\partial \lambda^2} \right) \\ &= \left(\frac{\partial^2 \kappa}{\partial \rho \partial \lambda} \right) \left\{ \frac{\partial \rho^*}{\partial \lambda} \right\} + \left(\frac{\partial^2 \kappa}{\partial \lambda^2} \right) \quad \textbf{Eq(15)} \end{aligned}$$

where the last equality holds by Young's theorem and the partial derivative $\partial\rho^*/\partial\lambda$ in curly brackets is the marginal change in asset correlation with respect to a marginal change in default probability λ. This latter partial derivative is the theoretical relation between PD and asset correlation. Substituting Eq(14) into Eq(15) yields the inequality below:

$$\left(\frac{\partial^2\kappa^*}{\partial\lambda^2}-\frac{\partial^2\kappa}{\partial\lambda^2}\right)=\left(\frac{\partial^2\kappa}{\partial\rho\partial\lambda}\right)\left\{\frac{\partial\rho^*}{\partial\lambda}\right\}>0$$ **Eq(16)**

Eq(16) offers a major economic insight into the marginal relation between PD and correlation. The theoretical association between PD and asset correlation (i.e. the partial derivative $\partial\rho^*/\partial\lambda$ in curly brackets) should be in the same direction as the marginal effect of PD on the first-order envelope response of equity capital to asset correlation $\partial(\partial\kappa/\partial\rho)/\partial\lambda=\partial^2\kappa/\partial\rho\partial\lambda$. Then we can deduce the theoretical association between PD and asset correlation from this second-order cross-partial derivative:

$$\left(\frac{\partial^2\kappa}{\partial\rho\partial\lambda}\right)>0\Leftrightarrow\left\{\frac{\partial\rho^*}{\partial\lambda}\right\}>0$$ **Eq(17)**

$$\left(\frac{\partial^2\kappa}{\partial\rho\partial\lambda}\right)<0\Leftrightarrow\left\{\frac{\partial\rho^*}{\partial\lambda}\right\}<0$$ **Eq(18)**

Several recent studies shed light on the appropriate size of asset correlation for incorporating some margin of econometric conservatism in the risk capital quantification. A general rule of thumb suggests that an asset correlation value of 15% may reflect a lack of conservatism in the value-at-risk equity capital ratio (Hansen, Van Vuuren, Ramadurai, and Verde, 2008). In contrast, Zhang, Zhu, and Lee (2008) find that the magnitude of default-implied asset correlation is significantly higher than what some prior research suggests. There is a close alignment between Zhang, Zhu, and Lee’s (2008) default-implied asset correlation and the Basel benchmark. Also, Cai, Levy, and Patel (2009) empirically find that global asset correlation seems to be more volatile than what the conventional Basel systematic risk correlation suggests. Lopez (2004) empirically finds a negative relation between PD and asset correlation, whereas, Dietsch and Petey (2004) and Lee, Wang, and Zhang (2009) provide contradictory evidence on the empirical nexus between PD and asset correlation. Specifically, Lee, Wang, and Zhang (2009) report that there is no significantly negative association between PD and asset correlation for corporate exposures while there is a reliably positive relation between PD and asset correlation for commercial real estate and retail exposures. A significantly positive association between PD and asset correlation appears in several more recent studies for North America, Europe, Japan, and emerging markets as well as a wide variety of asset classes such as public and private corporate exposures, small-to-medium enterprise exposures, commercial real estate exposures, residential first mortgages, home equity loans, auto loans, credit cards, consumer loans, student loans, and sovereign exposures (Huang, Lanfranconi, Patel, and Pospisil, 2012; Lanfranconi, Patel, Huang, Levy, and Pospisil, 2013; Lanfranconi, Pospisil, Kaplin, Levy, and

Patel, 2014; Huang, Lanfranconi, Lee, Levy, Mitrovic, Ozkanoglu, Pospisil, Patel, and Yang, 2015; Huang, Pospisil, and Hong, 2015). All of these studies suggest that this area is an important aspect of financial risk model design under the new Basel capital regime.

Our mathematical derivation provides a simple and intuitive theoretical prediction of the marginal relation between PD and asset correlation. The theoretical relation between PD and asset correlation should be in the same direction as the marginal effect of PD on the first-order envelope response of equity capital to asset correlation. When this latter first-order envelope response is positive, we expect to see a positive relation between PD and asset correlation. When this first-order envelope response is negative, we expect to see a negative nexus between PD and asset correlation. In sum, the non-linear negative relation between PD and asset correlation first proposed by Lopez (2004) and then set out in the Basel capital framework arises as a special case of our sufficiently general theoretical proof. Several empirical studies confirm this economic thread (e.g. Lee et al (2009); Huang et al (2012); Lanfranconi et al (2014)).

3. Conceptual connections between the current study and the prior capital structure literature

In the absence of bankruptcy costs, taxes, and other market frictions, Modigliani and Miller (1958) analytically posit that a firm's market value is independent of the mix of debt and equity. At its core, this capital-structure irrelevance proposition has been the baseline model for corporate finance. The conditions are so stringent that they are not meant to be an accurate representation of reality. Alternatively, this model allows the econometrician to be precise about which deviations from the above conditions is at work (Kashyap, Stein, and Hanson, 2010). For instance, the tax shields from debt create an incentive for the firm to lever up while high leverage inadvertently raises the firm's bankruptcy and distress costs. On balance, these forces offset each other at least to some extent and result in an optimal leverage ratio in the canonical trade-off model of capital structure (Leland, 1994; Leland and Toft, 1996).[4]

A body of more recent empirical literature assesses the speed of partial adjustment toward the optimal target leverage ratio. This literature suggests a wide array of econometric techniques for testing the relative speed of partial adjustment toward target leverage. Examples are the Fama-MacBeth cross-sectional regressions (Fama and French, 2002; Baker and Wurgler, 2002; Welch, 2004), mean-differencing panel regressions (Flannery and Rangan, 2006), dynamic GMM panel regressions (Antoniou, Guney, and Paudyal, 2008), and long-differencing panel regressions (Huang and Ritter, 2009). These empirical

4 Some recent evidence highlights the importance of financial flexibility in the form of both available debt capacity and share issuance that can exert a first-order impact on corporate capital structure (DeAngelo, DeAngelo, and Whited, 2011; McLean, 2011; Denis and McKeon, 2012).

studies indicate a broad gamut of speed estimates from 3 years to 20 years. Leverage is highly persistent[5] across quartiles (Lemmon, Roberts, and Zender, 2008; DeAngelo and Roll, 2015), so the econometrician needs the use of Hahn, Hausman, and Kuersteiner's (2007) long-differencing panel regressions to account for this persistence. Specifically, Huang and Ritter (2009) find empirical support for the dynamic trade-off model with slow target leverage adjustment speed estimates from 5 years to 7 years ceteris paribus. Notwithstanding this recent strand of empirical literature on corporate capital structure, no capital-structure theory adequately explains persistently high bank leverage, slow convergence toward target bank leverage, and a modest effect of higher bank capital on loan growth and equity cost estimation (Berrospide and Edge, 2010; Francis and Osborne, 2009).

Berrospide and Edge (2011) empirically find that a typical U.S. bank with an 11% equity capital ratio and a target ratio of 10% would grow the balance sheet by no more than 0.6%. The same set of evidence suggests that this typical bank would shrink its capital by 1% in the subsequent year relative to an otherwise substantially similar bank with zero capital surplus. Francis and Osborne (2009) report that the reduction in U.K. aggregate loan supply in response to a 1% increase in bank equity capital is only 1.2%. In other words, a typical British bank that increases its equity capital from 10% to 11% would face a 1.2% decline in aggregate loan supply ceteris paribus. Francis and Osborne (2009) infer from their evidence that the countercyclical capital requirement would have constrained bank credit growth with a concomitant increase in bank equity capital and consequently better systemic stability at the start of the global financial crisis in late-2007.

[5] An alternative theoretical model of corporate capital structure is the pecking-order theory. In this theory of Myers (1984) and Myers and Majluf (1984), there is no optimal corporate capital structure. If there is an optimum, the cost of deviating from this optimum is insignificant in contrast to the cost of raising external finance. Raising external finance is costly because corporate managers have better information about the corporation's recent prospects. Due to this information asymmetry, outside investors rationally discount the firm's stock price when the firm issues equity in lieu of debt. To avoid this discount, corporate managers regard equity as the last resort. The Myers-Majluf firm first uses up internal funds, then uses up debt, and finally resorts to equity. In the absence of valuable investment opportunities, the firm retains profits and builds up financial slack to avoid having to raise external finance in the future. A firm raises debt to fund its valuable investment projects if there is insufficient internal finance to support these projects. Following the pecking order, a firm adjusts the debt ratio due to the need for external funds, but not because of an attempt to reach an optimal mix of debt and equity (Myers, 1984; Myers and Majluf, 1984; Shyam-Sunder and Myers, 1999).

Contrary to the prediction of the pecking-order model, Fama and French (2002) find a significantly positive association between the target and future leverage wedges. This evidence suggests the existence of an optimal debt ratio in stark contrast to the prediction of the pecking order theory. However, the mean reversion of leverage is 7%-10% per year for dividend payers and 15%-18% per year for dividend non-payers. This rather slow speed of mean reversion toward target leverage bolsters the dynamic trade-off model with a soft target debt ratio. Further, Fama and French (2005) find that net equity issues are commonplace (i.e. equity is not a last resort). Since equity issues are ubiquitous, most equity issuers are not under financial duress. Fama and French (2005) infer that the pecking order model breaks down at least partly because there are many ways for firms to issue equity with low transaction costs and modest information asymmetries. Any forces that result in equity issuance not as a last resort invalidate the pecking order model. The more recent capital structure literature acknowledges the view that both the trade-off and pecking-order models of capital structure each represent at least some element of truth (Fama and French, 2005; Huang and Ritter, 2009). In essence, the horse race between these theories tells us little about the fact that banks maintain high leverage in spite of their exposure to severe losses in turbulent times of financial stress.

Why is the proportion of equity capital as a percentage of the asset base for banks much lower than the typical counterpart for non-financial companies? Our subsequent simulation suggests that a bank's equity capital ratio should be substantially higher to absorb severe losses in times of financial stress. Specifically, both the value-at-risk and conditional value-at-risk equity capital ratios exceed the newly proposed 3%-6% hurdle by an order of magnitude. When the econometrician raises asset correlation from 15% to 35% in the baseline simulation, the value-at-risk and conditional value-at-risk equity capital ratios jump to 22%-26%. This evidence lands in the broader range of 20%-30% that Admati and Hellwig (2013), Kashyap, Stein, and Hanson (2010), Hanson, Kashyap, and Stein (2011), and Myerson (2014) suggest from a qualitative perspective. Although we do not attempt to pursue perfect accuracy in our simulation, this analysis sheds fresh light on the broad gamut of equity capital ratios that would be commensurate with a typical bank's exposure to extreme losses in a severe financial downturn. As a result, banks should consider a positive tilt toward greater equity usage in their capital structure decisions.

A bank's value-at-risk or conditional value-at-risk fluctuates procyclically over time as total loan supply amplifies during a credit boom and declines during a credit bust. These boom-bust fluctuations arise as a consequence of how banks manage their leverage decisions in reaction to volatile macroeconomic conditions (Adrian and Shin, 2013). Also, leverage tends to move procyclically to the extent that debt overhang creates several implications for corporate investment (Korteweg, 2010; Ivashina and Scharfstein, 2010; Admati and Hellwig, 2013: 245). First, overleverage prevents a corporation from investing in valuable investment projects because some debt covenants prohibit such engagement.[6] In this light, debt overhang can have a first-order impact on corporate investment. Second, excessive debt usage creates moral hazard, propagates default contagion, and sometimes forces banks to tilt toward highly risky investment projects (Admati and Hellwig, 2013; Admati, 2014; Myerson, 2014). To restore corporate liquidity, banks have a perverse incentive to take on too much leverage due to the view that it might be easier for banks to strengthen their equity capital positions via fire sales of unprofitable non-core assets (Brunnermeier, 2009). A wave of fire sales breeds massive asset price depreciation and default contagion within the financial sector. Third, what banks need to hedge their asset portfolios against macro shocks is the use of countercyclical capital buffers, dynamic loan-loss provisions, and contingent convertible instruments (Dewatripont and Tirole, 2012). The above discussion sheds light on the importance of higher moments in the bank's default probability adjustment through the macro cycle. To the extent that deeper recessions tend to follow more credit-intensive expansions (Jorda, Schularick, and Taylor, 2013), banks should recharge their capital cushions by curtailing dividend payout and discretionary share buyback after a substantial deterioration in stock valuation (Acharya, Gujral, Kulkarni, and Shin, 2011). These macro hedges help complement one another in the pursuit of better systemic stability that results from greater bank equity usage.

[6] For instance, banks with more deposit debt reduced their loan syndicates by less than did banks without as much access to this stable source of finance during the global financial crisis of 2008 (Ivashina and Scharfstein, 2010).

4. Monte Carlo simulation of the asymptotic single risk factor model

We simulate the default probabilities for a synthetic asset portfolio. Then we build an empirical default probability model based on the observable systematic and idiosyncratic risk factors. Not only does this analytic approach allow us to assess the relative accuracy of the empirical default probability model, but this approach also helps gauge the impact of each TTC PD adjustment on the resultant bank capital requirement. Our Monte Carlo simulation rests upon the standard derivation of the asymptotic single risk factor model. To quantify a bank's credit risk, we start with the distribution of the bank's asset value over the chosen one-year time horizon (Merton, 1974; Vasicek, 1987, 1991, 2002; Gordy, 2003; Gordy and Howells, 2006; Bohn and Stein, 2009: 410-414). In this context, the company's asset value is the stochastic process:

$$\ln A_t = \ln A_0 + \left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma\sqrt{t}e \qquad \textbf{Eq(19)}$$

where A_0 and A_t denote the asset values observed at the respective start and end of the time horizon t=1, μ is the typically positive asset value drift, σ is the asset volatility, and the firm-specific error term e is a weighted average of a common systematic random factor m and an idiosyncratic random factor ε. The latter property gives rise to the standard setup of the asymptotic single risk factor model (Vasicek, 1987, 2002; Gordy and Howells, 2006; Bohn and Stein, 2009: 410-414):

$$e = \sqrt{\rho}m + \sqrt{1-\rho}\varepsilon \qquad \textbf{Eq(20)}$$

where ρ measures the percentage of the company's asset return variance due to the systematic risk factor m that converges toward a standard normal random variable $m \sim N(0,1)$, and $\varepsilon \sim N(0,1)$ is the idiosyncratic risk factor that serves as a standard normal random variable. A default event occurs when the firm-specific return error term falls below the default trigger threshold $e<d=N^{-1}(udp)$ where d denotes the default trigger threshold, $N^{-1}(.)$ is the cumulative normal inverse distribution function, and udp is the unconditional default probability. We decompose the systematic and idiosyncratic risk factors m and e into their observable and unobservable components through the use of correlation values φ and ξ. This specification is similar to Koopman et al's (2011) use of an unobservable frailty factor:

$$m = \sqrt{\phi}m_o + \sqrt{1-\phi}m_u \qquad \textbf{Eq(21)}$$

$$\varepsilon = \sqrt{\xi}\varepsilon_o + \sqrt{1-\xi}\varepsilon_u \qquad \textbf{Eq(22)}$$

where $m_o \sim N(0,1)$ and $m_u \sim N(0,1)$ are the respective observable and unobservable components of the systematic risk factor, $\varepsilon_o \sim N(0,1)$ and $\varepsilon_u \sim N(0,1)$ are the respective observable and unobservable components of the idiosyncratic risk factor, and the parameters φ and ξ are the correlation values for linking the respective observable and unobservable components of the systematic or idiosyncratic risk factor. It is important to note that we interpret the observable component of the systematic risk factor as the joint macroeconomic risk factor. In practice, the house price variation, the unemployment rate, the GDP growth rate and so forth serve as proxies for this joint macroeconomic risk factor. In contrast, the unobservable component of the systematic risk factor can be viewed as the sector-specific risk factor that cannot be easily identified in the empirical data. Likewise, we can identify the observable component of the idiosyncratic risk factor in terms of several loan-level and borrower-specific risk drivers such as the FICO score and the current loan-to-value ratio. The unobservable component of the idiosyncratic risk factor subsumes all other unidentifiable loan-level and borrower-specific drivers. This decomposition allows us to embed the observable variation in the systematic and idiosyncratic risk factors in a logit regression model of default probabilities. In the subsequent sections, we estimate an empirical logit regression model to score the point-in-time default probabilities for each annual cohort. These PIT PDs can then be used to score the TTC0 PDs in comparison to the TTC1 PDs that are based on the long-run average macroeconomic risk realizations. Our goal is to compare the TTC0 and TTC1 PDs as well as the alternative TTC2 and TTC3 PDs in the context of bank capital management.

With the above model setup, we then expand the empirical default rate below:

$$
\begin{aligned}
edr &= \Pr(e < d) \\
&= \Pr\left(\sqrt{\rho}m + \sqrt{1-\rho}\varepsilon < d\right) \\
&= \Pr\left(\varepsilon < \frac{d - \sqrt{\rho}m}{\sqrt{1-\rho}}\right) \\
&= N\left(\frac{d - \sqrt{\rho}m}{\sqrt{1-\rho}}\right) \\
&= N\left(\frac{N^{-1}(udp) - \sqrt{\rho}m}{\sqrt{1-\rho}}\right) \qquad \textbf{Eq(23)}
\end{aligned}
$$

Eq(20), Eq(21), Eq(22), and Eq(23) describe our Monte Carlo simulation of empirical default rates for a synthetic portfolio. For computational simplicity, we set the asset correlation value ρ=15%[7] and the unconditional default probability *udp*=5% for the synthetic loan portfolio. With no *a priori* expectation about the correlation values φ and ξ, we set both φ=50% and ξ=50% to assign equal weights to the respective observable and unobservable components. To ensure consistency with the spirit of the long-term TTC PD requirement set out in the Basel capital accord, we focus on the 1,000-year multi-period horizon. For each of the 1,000 annual cohorts, we simulate a single systematic risk factor as a standard normal random variable in conjunction with 10,000 idiosyncratic standard normal random variables. Eq(20) helps compute the residual realizations for the 10,000 loans. If the residual realization is less than $N^{-1}(udp)=N^{-1}(5\%)=-1.64485362695$, this realization triggers a default event. For each of the 1,000 annual cohorts, the synthetic empirical default rate is thus the number of default events divided by the total number of loans. Then we run this simulation for 1,000 annual cohorts. This replication is equivalent to simulating the empirical default likelihood for a given asset over 1,000 years in accordance with the Basel capital framework that focuses on the one-in-a-thousand-year rare event.

In order to arrive at the consistent results, we set the random seed at $exp(\pi)$. In the subsequent sections, we run the k-means clustering segmentation from 5 segments to 100 segments in increments of a single segment. This segmentation seeks to meet the Basel Final Rule[8] that the through-the-cycle default probability needs to be the "bank's empirically based best estimate of the long-term average of one-year default rates for the exposures in the segment…". This latter phrase requires each bank to concoct a clustering algorithm to group individual default probabilities into a reasonable number of segments. Then we can calculate the bank's regulatory capital requirement based on this algorithmic segmentation.[9] For the k-means

[7] The Basel capital framework specifies various asset correlation values for different retail and wholesale loan portfolios. The asset correlation value for a given portfolio of exposures is an estimate of the degree to which any unanticipated changes in the financial conditions of the underlying obligors of the exposures are correlated. For a portfolio of exposures with the same risk parameters, a larger asset correlation value generally suggests less diversification within the portfolio, greater overall systematic risk, and a higher risk capital requirement. For instance, the asset correlation values are 15% for residential retail mortgages, 4% for retail revolving exposures such as credit cards, 3% to 13% for retail other exposures, 12% to 18% for wholesale high-value commercial real estate exposures, and 12% to 24% for wholesale other exposures.

[8] Department of the Treasury, Federal Reserve System, Federal Deposit Insurance Corporation, and Office of Thrift Supervision. (2007). Risk-based capital standards, advanced capital adequacy framework of Basel II. *Federal Register* **72**(235): 69308. Available online at http://www.gpo.gov/fdsys/pkg/FR-2007-12-07/pdf/07-5729.pdf.

[9] Under the new Basel bank capital framework, a bank must group its retail exposures into multiple segments with homogeneous risk characteristics. The U.S. regulatory agencies believe that a bank may use the internal models, including the loan-level risk parameter estimates such as PD and LGD, to group exposures into the resultant segments with homogeneous risk attributes. In contrast to the conventional decision tree method, we design a new algorithmic model for credit portfolio segmentation. This new model identifies the optimal number of segments, sorts the individual loan exposures into the various segments, and then leads to a greater degree of risk homogeneity in comparison to the baseline equal-bin and quantile-bin schemes. We analyze the Monte Carlo asset correlations for the synthetic asset segments over time to better assess the implications for bank capital measurement. The k-means clustering algorithmic model for credit portfolio segmentation results in some capital relief that serves as an incentive for the bank to invest in this algorithmic segmentation. This positive outcome accords with the principle of statistical conservatism set out in the Basel bank capital framework. Lastly, our algorithmic segmentation applies to the cardinal wholesale commercial loan masterscale for the main risk parameters such as PD and LGD.

clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met all the time. The k-means algorithmic segmentation maximizes the Calinski-Harabasz ratio of inter-group variance to intra-group variance. In other words, the optimal k-means algorithmic segmentation selects the centroids for different PD segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous PD estimates with close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC equity capital requirements for each segment.

We extend Eq(23) to compute the common equity capital ratio κ as a percentage of the total asset balance or the exposure at default (EAD)[10]:

$$\kappa = \left(N\left(\frac{N^{-1}(PD) + \sqrt{\rho} N^{-1}(\alpha)}{\sqrt{1-\rho}} \right) - PD \right) LGD \qquad \textbf{Eq(24)}$$

where $N(.)$ is the cumulative normal distribution function, PD is the empirical default probability based on the logit regression model, LGD=56.8% is the flat downturn LGD[11], ρ=15% is the asset correlation value, and α=99.9% is the confidence interval. Eq(24) allows us to calculate the asset-equivalent or size-weighted-average capital risk weight for each segment.[12] This capital risk weight can be viewed as a measure of the bank's financial leverage that reflects the relative proportion of common equity in the total asset base. We compare and contrast the equity capital results for the alternative TTC0, TTC1, TTC2, and TTC3 PD adjustments. Our primary objective is to ferret out a scientific reason for the potential downward bias in the PD estimation that can arise from the conventional Basel TTC requirement.

In addition to the value-at-risk equity capital ratio, we compute the conditional value-at-risk equity capital ratio. This latter equity capital ratio covers the average extreme loss that is conditional upon the occurrence of a rare event that the potential

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[10] Department of the Treasury, Federal Reserve System, Federal Deposit Insurance Corporation, and Office of Thrift Supervision. (2007). Risk-based capital standards, advanced capital adequacy framework of Basel II. *Federal Register* **72**(235): 69308. Available online at http://www.gpo.gov/fdsys/pkg/FR-2007-12-07/pdf/07-5729.pdf.

[11] Qi and Yang (2008) provide this estimate of the flat downturn LGD for residential mortgages. To the best of our knowledge, this flat downturn LGD is the highest measure of default loss percentage in the financial risk literature. For the basic purpose of econometric conservatism, we use this measure to calculate the capital requirement κ as a percentage of the total asset base.

[12] We refer to κ as the equity capital ratio. This equity capital ratio κ differs from the conventional asset risk weight κ_0 as $\kappa_0=\kappa/8\%$. For our purposes, we can conceptualize the equity capital ratio κ as one minus the leverage ratio insofar as the outstanding loan balance is the only drawn amount or the exposure at default. The exceptions are corporate, home equity, and other lines of credit that allow the debtor to progressively borrow more up to the full amount of credit line commitment. At any rate, our focus on the equity capital ratio κ helps simplify the analysis to the ubiquitous use of the total asset base as the exposure at default.

loss exceeds the value-at-risk metric. To this end, we replace $N^{-1}(\alpha)$ with the conditional value-at-risk correction to modify the equity capital computation below:

$$R = \frac{\exp\left\{-\frac{\left(N^{-1}(\alpha)\right)^2}{2}\right\}}{\alpha\sqrt{2\pi}} \qquad \textbf{Eq(25)}$$

$$\kappa = \left(N\left(\frac{N^{-1}(PD)+\sqrt{\rho}R}{\sqrt{1-\rho}}\right)-PD\right)LGD \qquad \textbf{Eq(26)}$$

For estimating the default probability model, we run a logit regression model of the binary default event on the observable systematic and idiosyncratic risk factors m_o and ε_o (Campbell et al, 2008: Koopman et al, 2011). Then we can use the logit regression model with both m_o and ε_o to score the point-in-time PDs for each of the 1,000 annual cohorts:

$$PD = \left(\frac{1}{1+\exp\left\{-\left(\beta_o+\beta_m m_o+\beta_\varepsilon\varepsilon_o+v\right)\right\}}\right) \qquad \textbf{Eq(27)}$$

where PD is the point-in-time PD, m_o and ε_o are the respective observable systematic and idiosyncratic risk factors, v is the residual term, and β_o, β_m, and β_ε are the logit coefficients for the panel estimation of Eq(27). This logit model allows us to compute each TTC0 PD as the long-term average measure of the point-in-time PDs for each of the 10,000 synthetic assets. Then we compare this TTC0 PD to the TTC1 PD that takes into account a linear combination of the long-term average macroeconomic risk covariates. In addition, we compute the TTC2 and TTC3 PD approximations set out in Eq(2), Eq(3), and Eq(8). Lastly, we use Eq(24) and Eq(26) to gauge the value-at-risk or conditional value-at-risk equity capital ratio as a percentage of the total asset balance or the exposure at default (EAD).

5. Default probability and equity capital evidence with algorithmic segmentation

For a synthetic loan portfolio of 10,000 risky assets, we simulate each asset's default experience over 1,000 annual cohorts. Our next step is to run the logit regression of each binary default realization on the observable components of systematic macroeconomic and sector-specific idiosyncratic risk factors. With the maximum-likelihood logit coefficient estimates, we compute the default probability for each risky asset in a given year. This point-in-time (PIT) method allows us to compute the TTC0 PD for each risky asset as the long-run average of PIT PDs over multiple macroeconomic cycles. Also, we carry out similar calculations to gauge the TTC1, TTC2, and TTC3 PDs for each risky asset. While the TTC1 PD is equal to the default probability function of a given set of long-term average observable systematic macroeconomic and sector-specific idiosyncratic risk factors, we use the TTC2 and TTC3 PD adjustments to approximate the TTC0 PD origin. These TTC PD estimates serve as inputs in the regulatory capital formulae with 99.9% confidence. For better econometric conservatism, we quantify both the value-at-risk and conditional value-at-risk equity capital ratios (i.e. we express each capital estimate as a proportion of the total asset base). At the core of this quantitative analysis, we are interested in the extent to which the capital estimates vary in response to changes in the key risk parameters such as the TTC PD estimates, the asset correlation value, and the correlation values for the observable and unobservable parts of each of the systematic and idiosyncratic risk factors. One of the primary purposes of this quantitative analysis is to assess whether the TTC2 and TTC3 PD adjustments adequately correct for the TTC1 capital underestimation bias relative to the TTC0 capital ratio in accordance with the spirit of the TTC regulatory requirement set out in the Basel capital framework. Further, our sensitivity analysis helps isolate the standalone effect of each input on the capital estimates. This analysis contributes to a better triangulation that sheds fresh light on whether asset correlation in particular, and default contagion in general, causes most gyrations in the equity capital curves. In essence, the above twin objectives require the use of a reasonably accurate default probability model.

5.1 Monte Carlo simulation and k-means algorithmic segmentation

Table 1 presents the key parameter values for the Monte Carlo simulation of default probabilities based on the asymptotic single risk factor model. We set the baseline correlation values ρ=15%, φ=50%, and ξ=50%. For the subsequent sensitivity analysis of bank capital estimates, we consider different sets of correlation permutations: ρ={15%, 20%, 25%, 30%, 35%}, φ={40%, 45%, 50%, 55%, 60%}, and ξ={40%, 45%, 50%, 55%, 60%}. With 5 separate sets of equity capital estimates for each baseline correlation permutation, we end up with 15 sets of logit regressions, PD estimates, and equity capital results.

Figure 1 displays the time-series plots of both the systematic risk factor and its observable and unobservable components over 1,000 annual cohorts. Figure 1 indicates that the systematic risk factor moves in tandem with the joint gyrations in the observable and unobservable components. The majority of the systematic, macroeconomic, and sector-specific risk factors land within the 95% confidence interval around zero. Only the first of these latter random variables, the observable part of systematic risk is one of the explanatory variables in the logit default probability model. This observable variable captures a linear combination of systematic macroeconomic fluctuations such as GDP growth, unemployment, house price variation, and so forth. The other explanatory variable is the observable part of idiosyncratic risk that represents a linear combination of asset-specific attributes such as FICO, loan-to-value, debt-to-income, and so forth. In brief, these variables help develop a reasonably accurate logistic default probability model for our subsequent equity capital analysis.

Table 2 presents the logit regression results for these 15 sets of Monte Carlo simulation. The observable systematic macro and sector-specific idiosyncratic risk factors are econometrically significant predictors of binary default occurrence. Each of the logit coefficients β_m and β_ε is significantly negative (p-value<0.01). The concordance percentage indicates the extent to which the logit model correctly captures binary default occurrence. Table 2 shows that all the concordance percentages are greater than 88% across the board while the vast majority of these concordance percentages are 90%+. This evidence bolsters our use of the logit default probability model for bank equity capital quantification. This financial risk application is central to our quantitative analysis of a typical bank's baseline and alternative equity capital needs.

Figure 2 provides the stereoscopic visualization of default probability (PD), confidence level (α), and value-at-risk equity capital (κ). We can observe from this visualization that the value-at-risk or conditional value-at-risk capital requirement is a highly non-linear quasi-concave function of the default probability measure. At each confidence level, the equity capital ratio first increases with PD up to some threshold and then decreases with PD. This watershed appears to be between 25% and 40%. This non-linear trend highlights an important part of the equity capital formula: the equity capital cushion covers only the large financial losses above and beyond the average loss, the latter of which simply equates PD times LGD. Thus, the equity capital ratio first increases with PD as the marginal increase in financial risk exposure incurs large losses that in turn outweigh the average reserve for asset impairment. As PD increases, the likely loss severity declines up to some point at which the sum of additional losses equates the average loss provision. When PD rises above this watershed, the average loss provision more than fully offsets any marginal loss. In this latter case, the equity capital requirement decreases as the asset exposures exhibit much greater default likelihood in the highest PD segments.

Figure 2 indicates that the conditional value-at-risk capital curve consistently embeds an overlay on top of the value-at-risk capital curve. Also, the former exhibits a faster speed of capital deterioration than the latter toward the right tail of the PD spectrum. Thus, the conditional value-at-risk equity capital requirement typically exceeds the value-at-risk equity capital requirement up to some PD threshold while the former declines more quickly than the latter beyond this PD threshold. In sum, the asset-equivalent conditional value-at-risk equity capital ratio consistently outweighs the value-at-risk counterpart. Our subsequent analysis demonstrates this latter point throughout Tables 3 to 8.

5.2 Baseline PD and capital evidence

Figure 3 displays the point-in-time PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. Panels A to E present this information for the different asset correlation permutations ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%. Within each panel, the left-hand side shows the TTC0 PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. The long-term average TTC1 PD is lower than the long-term average TTC0, TTC2, and TTC3 PDs by an order of magnitude. For instance, the baseline set of risk parameters {ρ, φ, ξ}={15%, 50%, 50%} yields the long-run average TTC0, TTC2, and TTC3 PDs near 5.30%, whereas, the long-run average TTC1 PD is no greater than 4.65%. Thus, the TTC1 approach substantially underestimates the TTC0 PD and equity capital results that better accord with the spirit of the Basel TTC regulatory requirement. The right-hand side of each panel magnifies the fine neighborhood of the long-term average TTC0, TTC2, and TTC3 PDs. We observe from this chart that the long-run average TTC3 PD better approximates the long-run average TTC0 PD than the TTC2 counterpart. At any rate, the TTC2 and TTC3 PD approximations are both sufficiently close to the TTC0 origin. Our subsequent analysis suggests that these higher-order approximations are accurate enough for the equity capital differences to be reasonably minimal.

Figure 4 shows the TTC0, TTC1, TTC2, and TTC3 PD histograms and Calinski-Harabasz variance ratios with quantile-bin (QB), equal-bin (EB), and k-means (KM) algorithmic segmentation. Panels A to E display all this quantitative information for different asset correlation permutations ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%. The Calinski-Harabasz chart displays that KM segmentation consistently achieves the highest ratio of inter-group variance to intra-group variance up to at least 30 segments in comparison to the QB and EB methods. In terms of the QB, EB, and KM PD histograms, the latter exhibit smoother curves that are similar to their corresponding empirical kernel density charts. This smooth evidence arises from the computational power of KM algorithmic segmentation that allows for changes in both PD band width and frequency to optimize the ratio of inter-to-intra-group PD heterogeneity. In essence, KM algorithmic segmentation yields smoother PD histograms across the panels {TTC0, TTC1, TTC2, TTC3}={top-left, top-right, bottom-left, bottom-right}.

Table 3 summarizes the TTC0, TTC1, TTC2, and TTC3 PD, value-at-risk, and conditional value-at-risk across the 30 KM segments. Panels A to E present this information for the different asset correlation permutations ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%. Each panel comprises a pair of subsidiary tables that encapsulate the TTC0, TTC1, TTC2, and TTC3 results. The first subsidiary table shows that both the TTC0 value-at-risk and conditional value-at-risk equity capital ratios consistently exceed the TTC1 counterparts across all of the 30 PD segments. This evidence suggests that the current approach to integrating macroeconomic risk factors into the highly non-linear default probability function results in a large capital underestimation bias. Furthermore, the second subsidiary table suggests that the TTC2 and TTC3 value-at-risk and conditional value-at-risk equity capital ratios closely approximate the TTC0 counterparts across the vast majority of the 30 PD segments. This latter evidence provides confidence that our Taylor-series expansion adequately accounts for the higher moments of a linear combination of macroeconomic risk factors (i.e. its variance and skewness). Thus, our alternative TTC approximation helps fill the gap between TTC0 and TTC1 to better gauge PD, value-at-risk, and conditional value-at-risk.

Table 4 shows the baseline asset-equivalent value-at-risk and conditional value-at-risk equity capital ratios for the different asset correlation permutations ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%. When we vary the asset correlation value from 15% to 35% in increments of 5%, the TTC0 value-at-risk equity capital ratios range from 9.74% to 22.05%. In addition, the TTC0 conditional value-at-risk equity capital ratios range from 11.92% to 26.66% within the same baseline model. However, the TTC1 value-at-risk equity capital ratios grossly underestimate the TTC0 counterparts by 101 to 415 basis points. In contrast, our alternative TTC capital approximation is closer to the TTC0 origin by an order of magnitude. The TTC2 and TTC3 capital underestimation bias is no more than 73 basis points (<3% of the total equity capital amount). From a pragmatic perspective, we prefer to recommend the introduction of econometric conservatism to the extent that the law of inadvertent consequences counsels caution. While most estimates of the value-at-risk equity capital ratios are in the intermediate range of about 13%-19%, most estimates of the conditional value-at-risk equity capital ratios are in the range of 15%-23%. When we conservatively increase asset correlation from 15% to 35% for a severe downturn scenario, ceteris paribus, the equity capital cushion can be as high as 22%-26%. These quantitative results support the recent proposal by Admati and Hellwig (2013), Admati (2014), Kashyap, Stein, and Hanson (2010), and Myerson (2014) to introduce a 20%+ equity capital requirement for banks. Our evidence lends credence to a scientific basis for the socially optimal introduction of substantially heightened equity capital requirements for banks in particular as well as financial institutions in general. This fresh strand of quantitative research can become part of our financial risk toolkit in due course.

Figures 5 and 6 show the TTC0, TTC1, TTC2, and TTC3 value-at-risk and conditional value-at-risk equity capital ratios across the 30 KM segments. We can infer at least three empirical results from this diagrammatical representation. First, the equity capital ratios exhibit a concave positive relation with PD across the first 20-25 segments. Beyond the watershed, the equity capital ratios decline at a fast rate toward the last 5 segments. A concave hump exists across the board, and higher asset correlation raises the height of this hump. This phenomenon magnifies the cross-sectional variation in equity capital. Second, it is easy to observe that the TTC1 equity capital ratios underestimate the true TTC0 counterparts. This evidence is more pronounced for the special case of ρ=30%. Third, it is difficult to identify any peculiar empirical association between PD and asset correlation. For an invariant equity capital ratio, higher asset correlation seems to correspond to the lower PD segments. However, this capital-invariance assumption does not hold in a dynamic equilibrium context. The value-at-risk and conditional value-at-risk capital ratios gyrate in response to changes in both asset correlation and PD segmentation. In this more realistic dynamic view, equity capital movements adjust in accordance with changes in both asset correlation and portfolio composition. The empirical relation between PD and asset correlation can be positive, negative, or ambiguous. In fact, this empirical relation largely depends upon how equity capital requirements dynamically react to the joint changes in asset correlation and PD segmentation.

This latter discussion echoes the mathematical derivation of a sufficiently general microfoundation for the empirical nexus between PD and asset correlation set out in Section 2. From the viewpoint of financial regulators, the worst-case scenario arises from a significantly positive relation between PD and asset correlation during a severe macroeconomic recession. In this case, the unpropitious rise in asset correlation exacerbates a portfolio tilt toward the higher PD segments. In response, higher financial risk exposure manifests in the bank's equity capital requirement. This economic thread helps explain why our default probability model better captures a dynamic equilibrium increase in the bank's equity capital requirement once we relax the capital-invariance assumption to characterize a positive relation between PD and asset correlation. This thread reinforces the central thesis that banks can become more stable by holding more equity capital to counteract extreme losses in times of financial stress.

5.3 Alternative PD and capital evidence

Figure 7 displays the point-in-time PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. Panels A to E present this information for the alternative correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. Within each panel, the left-hand side plots the TTC0 PD time-series and the long-run average TTC0, TTC1, TTC2, and TTC3 PDs. The long-term average TTC1 PD is lower than the long-term average TTC0, TTC2, and TTC3 PDs by an order of magnitude. For instance, the baseline set of risk parameters {ρ, φ, ξ}={15%, 50%, 50%} yields the long-run mean TTC0, TTC2, and TTC3 PDs near 5.30%, whereas, the long-run average TTC1 PD is lower than 4.65%. Hence, the TTC1 approach substantially underestimates the TTC0 PD and equity capital results that better accord with the spirit of the Basel TTC regulatory requirement. The right-hand side of each panel magnifies the fine neighborhood of the long-term average TTC0, TTC2, and TTC3 PDs. We can observe from this informative chart that the long-term average TTC3 PD sometimes slightly overestimates the long-term average TTC0 PD while the long-term average TTC2 PD underestimates the long-run average TTC0 PD. Moreover, the long-run average TTC3 PD better approximates the long-run average TTC0 PD than the TTC2 counterpart. At any rate, the TTC2 and TTC3 PD approximations are both sufficiently close to the TTC0 origin. Our subsequent analysis suggests that these higher-order approximations are accurate enough for the equity capital differences to be reasonably minimal.

Figure 8 shows the TTC0, TTC1, TTC2, and TTC3 PD histograms and Calinski-Harabasz variance ratios with quantile-bin (QB), equal-bin (EB), and k-means (KM) algorithmic segmentation. Panels A to E display all this quantitative information for alternative correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. The Calinski-Harabasz plot displays that KM segmentation consistently achieves the highest ratio of inter-group variance to intra-group variance up to at least 30 segments in comparison to the QB and EB methods. In terms of the QB, EB, and KM PD histograms, the latter exhibit smoother curves that are similar to their corresponding empirical kernel density charts. This smooth evidence arises from the computational power of KM segmentation that permits changes in both PD band width and frequency to optimize the ratio of inter-to-intra-group PD heterogeneity. In brief, KM algorithmic segmentation yields smoother PD histograms across the panels {TTC0, TTC1, TTC2, TTC3}={top-left, top-right, bottom-left, bottom-right}.

Table 5 summarizes the TTC0, TTC1, TTC2, and TTC3 PD, value-at-risk, and conditional value-at-risk across the 30 KM segments. Panels A to E present this information for the alternative correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. Each panel comprises a pair of subsidiary tables that encapsulate the TTC0, TTC1, TTC2, and TTC3 results. The first subsidiary table shows that both the TTC0 value-at-risk and conditional value-at-risk equity capital ratios consistently exceed the TTC1 counterparts across all of the 30 PD segments. This evidence suggests that the current approach to integrating macroeconomic risk factors into the highly non-linear default probability function results in a large capital underestimation bias. Furthermore, the second subsidiary table suggests that the TTC2 and TTC3 value-at-risk and conditional value-at-risk equity capital ratios closely approximate the TTC0 counterparts across the vast majority of the 30 PD segments. This latter evidence provides confidence that our Taylor-series expansion adequately accounts for the higher moments of a linear combination of macroeconomic factors (i.e. its variance and skewness). Thereby, our alternative TTC approximation helps fill the gap between TTC0 and TTC1 to better gauge PD, value-at-risk, and conditional value-at-risk.

Table 6 summarizes the asset-equivalent value-at-risk and conditional value-at-risk equity capital ratios for the alternative correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. When we vary the systematic risk macro correlation value from 40% to 60% in increments of 5%, the TTC0 value-at-risk equity capital ratios hover around 9.72%-9.77%. In addition, the TTC0 conditional value-at-risk equity capital ratios hover around 11.90%-11.92%. Thus, the TTC0 equity capital requirements appear insensitive to whether the observable and unobservable components of the systematic risk factor highly correlate with each other.

The TTC1 value-at-risk equity capital ratios underestimate the TTC0 counterparts by 80 to 134 basis points. In comparison, our alternative TTC capital approximation is closer to the TTC0 origin by a full order of magnitude. The TTC2 and TTC3 capital underestimation bias is no more than 12 basis points (<1% of the total equity capital amount). Our alternative TTC approximation performs well relative to the TTC0 origin.

Figures 9 and 10 show the TTC0, TTC1, TTC2, and TTC3 value-at-risk and conditional value-at-risk equity capital ratios across the 30 KM segments. We can observe from these charts that the equity capital curves almost overlap although these curves reflect different correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. This evidence is no surprise because our logit default probability model is reasonably accurate with 90%+ concordance percentages. Insofar as this model predicts binary default occurrence correctly most of the time, whether the observable systematic macro factor significantly correlates with the unobservable counterpart does not matter. In summary, the value-at-risk and conditional value-at-risk equity capital ratios do not vary much in response to this alternative set of correlation permutations.

Figure 11 displays the point-in-time PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. Panels A to E present this information for the alternative correlation permutations ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}. Within each panel, the left-hand side plots the TTC0 PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. The long-term average TTC1 PD is lower than the long-term average TTC0, TTC2, and TTC3 PDs by an order of magnitude. For instance, the baseline set of risk parameters {ρ, φ, ξ}={15%, 50%, 50%} yields the long-run mean TTC0, TTC2, and TTC3 PDs near 5.30%, whereas, the long-run average TTC1 PD is lower than 4.65%. Hence, the TTC1 approach substantially underestimates the TTC0 PD and equity capital results that better accord with the spirit of the Basel TTC regulatory requirement. The right-hand side of each panel magnifies the fine neighborhood of the long-term average TTC0, TTC2, and TTC3 PDs. We can observe from this informative chart that the long-term average TTC3 PD sometimes slightly overestimates the long-term average TTC0 PD while the long-term average TTC2 PD underestimates the long-run average TTC0 PD. Moreover, the long-run average TTC3 PD better approximates the long-run average TTC0 PD than the TTC2 counterpart. At any rate, the TTC2 and TTC3 PD approximations are both sufficiently close to the TTC0 origin. Our subsequent analysis suggests that these higher-order approximations are accurate enough for the equity capital differences to be reasonably minimal.

Figure 12 shows the TTC0, TTC1, TTC2, and TTC3 PD histograms and Calinski-Harabasz variance ratios with equal-bin (EB), quantile-bin (QB), and k-means (KM) algorithmic segmentation. Panels A to E present this quantitative information for alternative correlation permutations ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}. The Calinski-Harabasz plot displays that KM segmentation consistently achieves the highest ratio of inter-group variance to intra-group variance up to at least 30 segments in comparison to the QB and EB methods. In terms of the QB, EB, and KM PD histograms, the latter exhibit smoother curves that are similar to their corresponding empirical kernel density charts. This smooth evidence arises from the computational power of KM segmentation that permits changes in both PD band width and frequency to optimize the ratio of inter-to-intra-group PD heterogeneity. In brief, KM algorithmic segmentation yields smoother PD histograms across the panels {TTC0, TTC1, TTC2, TTC3}={top-left, top-right, bottom-left, bottom-right}.

Table 7 summarizes the TTC0, TTC1, TTC2, and TTC3 PD, value-at-risk, and conditional value-at-risk across the 30 KM segments. Panels A to E present this information for the alternative correlation permutations ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}. Each panel comprises a pair of subsidiary tables that contain the TTC0, TTC1, TTC2, and TTC3 results. The first subsidiary table shows that both the TTC0 value-at-risk and conditional value-at-risk equity capital ratios consistently exceed the TTC1 counterparts across all the 30 PD segments. This evidence suggests that the current approach to integrating macroeconomic risk factors into the highly non-linear default probability function results in a serious capital underestimation bias. Moreover, the second subsidiary table reflects that the TTC2 and TTC3 value-at-risk and conditional value-at-risk equity capital ratios closely approximate the TTC0 counterparts across the vast majority of the 30 segments. This latter evidence provides confidence that our Taylor-series expansion adequately accounts for the higher moments of a linear combination of macro risk factors (i.e. its variance and skewness). Hence, our alternative TTC approximation helps close the wedge between TTC0 and TTC1 to better estimate PD, value-at-risk, and conditional value-at-risk.

Table 8 summarizes the asset-equivalent value-at-risk and conditional value-at-risk equity capital ratios for the alternative correlation permutations ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}. When the idiosyncratic risk correlation value increases from 40% to 60% in increments of 5%, the TTC0 value-at-risk equity capital ratio declines from 10.78% to 8.68% while the TTC0 conditional value-at-risk equity capital ratio decreases from 13.08% to 10.61%. Further, the TTC1 equity capital ratios underestimate the TTC0 counterparts by 100 to 122 basis points. In comparison, our alternative TTC capital approximation is closer to the TTC0 origin by an order of magnitude. The TTC2 and TTC3 capital underestimation bias is no more than 11 basis points (<1% of the total equity capital amount). Our alternative TTC approximation performs well relative to the TTC0 origin.

Figures 13 and 14 show the TTC0, TTC1, TTC2, and TTC3 value-at-risk and conditional value-at-risk equity capital ratios across the 30 KM segments. When the idiosyncratic risk correlation value increases from 40% to 60% in increments of 5%, we observe a fair bit of credit migration from the high PD segments to the low PD segments. This increase in idiosyncratic risk correlation suggests that the econometrician faces less uncertainty around the idiosyncratic risk factor. As a result, this reduction in idiosyncratic uncertainty represents lower model risk. A plausible economic interpretation indicates that this lower model risk translates into a tangible benefit in the form of equity capital relief. In essence, the bank requires a lower equity capital cushion when the logit default probability model more accurately captures idiosyncratic risk through higher correlation between the observable and unobservable components of the idiosyncratic risk factor.

6. Conclusion

We have developed an analytical solution for the default probability adjustment through the macroeconomic cycle. This adjustment corrects for the capital underestimation bias due to the highly non-linear nature of the default probability model. Our results bolster the case for a non-trivial bank capital overlay on the Basel minimum equity capital requirement that one calculates from the use of long-term average macroeconomic risk factors. This major contribution adds to the literature on bank capital management by advocating support for more robust total capital adequacy. Our conclusion is thus consistent with the recent proposal for banks to hold more equity capital (Admati, DeMarzo, Hellwig, and Pfleiderer, 2011; Admati and Hellwig, 2013; Kashyap, Stein, and Hanson, 2010; Myerson, 2014). Banks should have a structural shift in the mix of debt and equity in the total asset base, and the resultant move toward a greater use of equity capital helps lower the bank's leverage ratio. Hence our study provides a scientific basis for the central thesis that banks become more stable by holding a greater equity capital cushion to absorb severe losses in times of financial stress.

Our results substantiate the case for revisiting the newly proposed 3%-6% equity capital requirement under the Basel bank capital regime. In contrast to this rather lenient regulatory equity capital requirement, our empirical results suggest that the typical bank's equity capital ratio should be as high as 22%-26%. This range is consistent with the qualitative implications of the recent proposal for banks to substantially increase their equity capital ratios that would become more commensurate with financial risk exposure that these banks might face in a severe recession (e.g. Admati and Hellwig (2013); Kashyap, Stein, and Hanson (2010); Myerson (2014)). Also, our analysis can be extended to help design a macroeconometric stress test for bank equity capital management. Overall, our work advocates support for more robust total equity capital adequacy. This endeavor serves as a scientific microfoundation for the central thesis that banks can become more stable by holding a greater equity capital buffer to absorb large losses in times of severe financial stress.

Overall, our analysis poses an important challenge to the central prediction of DeAngelo and Stulz's (2015) baseline model of high bank leverage. Through the lens of financial risk management, the typical bank should substantially raise its equity capital cushion to counteract severe losses in times of extreme financial stress. From this normative perspective, high bank leverage cannot be socially optimal because the typical bank runs the risk of not being able to absorb large financial losses in a rare macroeconomic downturn such as the recent Global Financial Crisis. In contrast to DeAngelo and Stulz's (2015) emphasis on the important role that most banks play in producing aggregate liquid claims, our current study points out that the typical bank's high leverage ratio suggests an insufficient equity capital buffer for extreme loss absorption in a rare but plausible economic recession. Our empirical analysis corroborates the recent proposal for most banks to substantially raise their equity capital positions due to precautionary concerns (Admati, DeMarzo, Hellwig, and Pfleiderer, 2011; Admati and Hellwig, 2013; Kashyap, Stein, and Hanson, 2010; Myerson, 2014).

Our research sheds light on the quantitative design of the countercyclical capital buffer. The countercyclical capital buffer can be set to be commensurate with the higher-order Taylor series in the default probability adjustment. To the extent that macroeconomic fluctuations exert a first-order impact on the non-linear default probability adjustment, the countercyclical capital buffer that the bank's capital management committee would demand can manifest in the higher-order derivatives in the default probability function. We await future policy research to assess whether this countercyclical capital buffer fits better in the Pillar 1 minimum capital requirement or the Pillar 2 supervisory review under the Basel bank capital regime.

The evidence also points to the pragmatic use of asymmetric tweaks such as the maximum loan-to-value or debt-to-income ratios for dampening the financial market bubble through the credit channel of monetary transmission. To the extent that the loan-to-value or debt-to-income ratio serves as a pivotal default risk driver, setting a cap on the total mortgage quantum, for instance, helps curtail the housing price bubble that tends to precede a subsequent economic downturn. This alternative macroprudential policy instrument can thus help mute the borrower's asymmetric response to macroeconomic fluctuations in an upturn. In addition to the design of the countercyclical equity capital buffer, this alternative macroprudential policy instrument helps an expansionary economy cast an anchor windward to better prepare for the next recession.

Future research can extend our Monte Carlo simulation of the asymptotic single risk factor model to analyze the extent to which the pervasive macroeconomic, systematic, and idiosyncratic risk factors affect the time-series variation in the capital shortfall that is due to procyclicality risk. This research helps us better develop the theoretical basis of macroeconometric stress tests. In turn, this development connects the procyclical capital shortfall to the bank's internal risk management for total capital adequacy.

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Table 1: Parameter values for the Monte Carlo simulation

This table summarizes the major parameters for the Monte Carlo simulation of empirical default probabilities for a synthetic portfolio of 10,000 risky asset exposures over 1,000 annual cohorts. For each of these annual cohorts, the synthetic empirical default probability is the number of default events divided by the total number of risky asset exposures. Replicating this simulation for 1,000 annual cohorts is equivalent to simulating the empirical default likelihood for a given risky asset exposure over 1,000 years in accordance with the Basel capital framework that focuses on the one-in-a-thousand-year rare stress event. We use a simple and intuitive logit regression model to estimate default likelihood for the individual risky asset exposures with the inclusion of the observable systematic and idiosyncratic risk factors (both of which arise from the initial Monte Carlo simulation). In order to arrive at the consistent quantitative evidence, we set the random seed at $exp(\pi)$. We employ the k-means clustering algorithm from 5 segments to 100 segments in increments of a single segment. This algorithmic segmentation helps gauge the central tendency of default probabilities within each segment. These default probabilities serve as key inputs in the computation of value-at-risk and conditional value-at-risk capital requirements across the optimally chosen 30 k-means segments. With the baseline and alternative numerical values for asset correlation, systematic risk correlation, and idiosyncratic risk correlation, we can carry out sensitivity analysis to examine the extent to which both the value-at-risk and conditional value-at-risk capital requirements vary in response to marginal changes in these major parameters.

Major parameter for Monte Carlo simulation of value-at-risk capital	**Numerical value or range of each parameter for Monte Carlo analysis**
Random seed	exp(π)
Asset correlation ρ	{$\underline{15\%}$, 20%, 25%, 30%, 35%}
Systematic risk factor m	m~N(0,1)
Systematic correlation φ	{40%, 45%, $\underline{50\%}$, 55%, 60%}
Observable systematic risk factor m_o	$m_o \sim N(0,1)$
Unobservable systematic risk factor m_u	$m_u \sim N(0,1)$
Idiosyncratic risk factor ε	$\varepsilon \sim N(0,1)$
Idiosyncratic correlation ξ	{40%, 45%, $\underline{50\%}$, 55%, 60%}
Observable idiosyncratic risk factor ε_o	$\varepsilon_o \sim N(0,1)$
Unobservable idiosyncratic risk factor ε_u	$\varepsilon_u \sim N(0,1)$
Number of asset exposures	10,000
Number of annual cohorts	1,000
Minimum number of segments	5
Maximum number of segments	100
Number of iterations for k-means segmentation	100

Table 2: Logit regression summary with different parameter values

This table encapsulates the logit regression results for the baseline and alternative versions of the quasi-maximum likelihood estimation of default probabilities for the risky asset exposures. In total, there are 5 sets of baseline logit regressions for 5 different asset correlation values from 15% to 35% in increments of 5%, as well as 10 sets of alternative logit regressions for 5 different systematic risk correlation values from 40% to 60% in increments of 5% and 5 different idiosyncratic risk correlation values from 40% to 60% in increments of 5%. In each logit regression, we first separately include only one of the observable systematic and idiosyncratic risk factors and then include both factors as explanatory variables. Each set of logit regression results reports the logit coefficients, their respective standard errors, the McFadden pseudo-R^2s and the concordance percentages. The logit model allows us to compute each TTC0 default probability as the long-run average measure of the point-in-time default probabilities for each of the 10,000 synthetic risky assets. Then we compare this TTC0 default probability to the TTC1 default probability that takes into account a linear combination of the long-term average macro risk covariates. We gauge the TTC2 and TTC3 default probabilities via the higher-order Taylor-series expansion of the non-linear logit default likelihood function. These default probabilities serve as inputs in the subsequent computation of equity capital ratios.

Baseline logit model ρ ={15%,20%,25%,30%,35%}			
Parameter permutation	(1)	(2)	(3)
ρ =15%, φ =50%, ξ =50%			
β_o	-3.013	-4.136	-4.426
stderr(β_o)	0.002	0.003	0.003
β_m	-0.579		-0.760
stderr(β_m)	0.001		0.002
β_ε		-1.830	-1.949
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.1%	28.8%	34.0%
Concordance percentage	65.7%	88.2%	90.8%
ρ =20%, φ =50%, ξ =50%			
β_o	-3.069	-4.034	-4.414
stderr(β_o)	0.002	0.003	0.003
β_m	-0.677		-0.878
stderr(β_m)	0.001		0.002
β_ε		-1.736	-1.883
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	5.5%	26.8%	33.8%
Concordance percentage	67.7%	87.1%	90.7%
ρ =25%, φ =50%, ξ =50%			
β_o	-3.128	-3.939	-4.403
stderr(β_o)	0.002	0.003	0.003
β_m	-0.766		-0.982
stderr(β_m)	0.001		0.002
β_ε		-1.645	-1.816
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	7.0%	24.9%	33.5%
Concordance percentage	70.5%	86.1%	90.6%
ρ =30%, φ =50%, ξ =50%			
β_o	-3.187	-3.847	-4.390
stderr(β_o)	0.002	0.003	0.003
β_m	-0.849		-1.075
stderr(β_m)	0.001		0.002
β_ε		-1.556	-1.746
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	8.5%	22.9%	33.3%
Concordance percentage	72.3%	85.0%	90.5%
ρ =35%, φ =50%, ξ =50%			
β_o	-3.247	-3.762	-4.379
stderr(β_o)	0.002	0.002	0.003
β_m	-0.928		-1.160
stderr(β_m)	0.002		0.002
β_ε		-1.471	-1.677
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	10.0%	21.1%	33.1%
Concordance percentage	74.0%	83.8%	90.4%

Alternative #1 model φ ={40%,45%,50%,55%,60%}			
Parameter permutation	(1)	(2)	(3)
ρ =15%, φ =40%, ξ =50%			
β_o	-2.982	-4.130	-4.356
stderr(β_o)	0.002	0.003	0.003
β_m	-0.517		-0.673
stderr(β_m)	0.001		0.002
β_ε		-1.828	-1.921
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	3.3%	28.7%	32.9%
Concordance percentage	63.7%	88.1%	90.3%
ρ =15%, φ =45%, ξ =50%			
β_o	-2.997	-4.132	-4.391
stderr(β_o)	0.002	0.003	0.003
β_m	-0.549		-0.718
stderr(β_m)	0.001		0.002
β_ε		-1.829	-1.935
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	3.7%	28.8%	33.5%
Concordance percentage	64.4%	88.2%	90.6%
ρ =15%, φ =50%, ξ =50%			
β_o	-3.013	-4.136	-4.426
stderr(β_o)	0.002	0.003	0.003
β_m	-0.579		-0.760
stderr(β_m)	0.001		0.002
β_ε		-1.830	-1.949
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.1%	28.8%	34.0%
Concordance percentage	65.7%	88.2%	90.8%
ρ =15%, φ =55%, ξ =50%			
β_o	-3.028	-4.137	-4.462
stderr(β_o)	0.002	0.003	0.003
β_m	-0.609		-0.802
stderr(β_m)	0.001		0.002
β_ε		-1.830	-1.962
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.5%	28.8%	34.6%
Concordance percentage	66.3%	88.1%	91.0%
ρ =15%, φ =60%, ξ =50%			
β_o	-3.044	-4.137	-4.495
stderr(β_o)	0.002	0.003	0.003
β_m	-0.636		-0.843
stderr(β_m)	0.001		0.002
β_ε		-1.829	-1.974
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.9%	28.8%	35.1%
Concordance percentage	67.1%	88.1%	91.2%

Alternative #2 model ξ ={40%,45%,50%,55%,60%}			
Parameter permutation	(1)	(2)	(3)
ρ =15%, φ =50%, ξ =40%			
β_o	-3.019	-3.834	-4.068
stderr(β_o)	0.002	0.003	0.003
β_m	-0.583		-0.710
stderr(β_m)	0.001		0.002
β_ε		-1.555	-1.638
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.1%	22.9%	27.9%
Concordance percentage	65.8%	85.0%	88.1%
ρ =20%, φ =50%, ξ =45%			
β_o	-3.016	-3.975	-4.235
stderr(β_o)	0.002	0.003	0.003
β_m	-0.581		-0.734
stderr(β_m)	0.001		0.002
β_ε		-1.688	-1.787
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.1%	25.8%	30.9%
Concordance percentage	65.7%	86.6%	89.4%
ρ =25%, φ =50%, ξ =50%			
β_o	-3.013	-4.136	-4.426
stderr(β_o)	0.002	0.003	0.003
β_m	-0.579		-0.760
stderr(β_m)	0.001		0.002
β_ε		-1.830	-1.949
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.1%	28.8%	34.0%
Concordance percentage	65.7%	88.2%	90.8%
ρ =30%, φ =50%, ξ =55%			
β_o	-3.011	-4.305	-4.632
stderr(β_o)	0.002	0.003	0.004
β_m	-0.578		-0.790
stderr(β_m)	0.001		0.002
β_ε		-1.974	-2.116
stderr(β_ε)		0.002	0.002
McFadden pseudo-R^2	4.1%	31.7%	37.1%
Concordance percentage	65.4%	89.6%	92.0%
ρ =35%, φ =50%, ξ =60%			
β_o	-3.011	-4.497	-4.870
stderr(β_o)	0.002	0.003	0.004
β_m	-0.577		-0.824
stderr(β_m)	0.001		0.002
β_ε		-2.129	-2.298
stderr(β_ε)		0.002	0.003
McFadden pseudo-R^2	4.0%	34.7%	40.3%
Concordance percentage	65.7%	90.9%	93.1%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel A-(i): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1675	0.00%	0.11%	0.24%	1.18%	2.68%	1786	0.00%	0.09%	0.19%	0.99%	2.30%
2	1174	0.24%	0.36%	0.50%	2.81%	4.50%	1206	0.19%	0.29%	0.41%	2.41%	3.92%
3	931	0.50%	0.65%	0.81%	4.25%	6.13%	997	0.41%	0.53%	0.68%	3.69%	5.50%
4	677	0.81%	0.97%	1.14%	5.57%	7.62%	804	0.68%	0.83%	1.02%	5.04%	7.11%
5	555	1.14%	1.31%	1.50%	6.80%	9.01%	685	1.02%	1.20%	1.43%	6.44%	8.75%
6	487	1.50%	1.69%	1.91%	7.99%	10.40%	582	1.43%	1.65%	1.90%	7.89%	10.38%
7	457	1.91%	2.13%	2.37%	9.23%	11.77%	481	1.91%	2.15%	2.44%	9.29%	11.96%
8	389	2.37%	2.61%	2.88%	10.43%	13.09%	434	2.44%	2.73%	3.03%	10.71%	13.46%
9	347	2.88%	3.15%	3.45%	11.63%	14.42%	335	3.03%	3.33%	3.65%	11.99%	14.86%
10	371	3.45%	3.75%	4.09%	12.83%	15.74%	261	3.65%	3.98%	4.31%	13.26%	16.15%
11	289	4.10%	4.45%	4.83%	14.07%	17.09%	257	4.31%	4.63%	4.99%	14.38%	17.36%
12	262	4.84%	5.23%	5.62%	15.31%	18.35%	221	5.00%	5.36%	5.77%	15.50%	18.57%
13	256	5.63%	6.03%	6.48%	16.45%	19.56%	203	5.77%	6.19%	6.63%	16.66%	19.76%
14	217	6.48%	6.93%	7.45%	17.59%	20.76%	174	6.64%	7.09%	7.60%	17.78%	20.93%
15	224	7.46%	7.99%	8.62%	18.77%	22.02%	160	7.62%	8.11%	8.71%	18.90%	22.11%
16	198	8.63%	9.26%	10.00%	20.01%	23.28%	188	8.73%	9.33%	10.00%	20.07%	23.28%
17	199	10.03%	10.76%	11.54%	21.24%	24.44%	145	10.01%	10.68%	11.42%	21.18%	24.35%
18	180	11.56%	12.34%	13.24%	22.34%	25.49%	160	11.47%	12.21%	13.14%	22.26%	25.44%
19	163	13.25%	14.14%	15.12%	23.38%	26.42%	115	13.22%	14.10%	15.06%	23.36%	26.39%
20	129	15.13%	16.12%	17.21%	24.29%	27.21%	127	15.14%	16.05%	17.18%	24.27%	27.20%
21	140	17.31%	18.38%	19.59%	25.11%	27.86%	95	17.26%	18.42%	19.81%	25.12%	27.91%
22	96	19.65%	20.89%	22.29%	25.76%	28.32%	109	19.92%	21.39%	23.00%	25.87%	28.40%
23	113	22.40%	23.90%	25.56%	26.27%	28.57%	80	23.03%	24.64%	26.66%	26.35%	28.59%
24	90	25.69%	27.40%	29.53%	26.53%	28.50%	79	26.76%	28.77%	30.81%	26.55%	28.40%
25	94	29.72%	31.94%	34.24%	26.44%	27.98%	84	30.93%	33.05%	35.75%	26.36%	27.73%
26	83	34.29%	36.59%	39.84%	25.96%	26.89%	60	36.27%	38.82%	41.85%	25.60%	26.40%
27	75	40.03%	43.37%	47.99%	24.67%	24.60%	52	42.13%	45.22%	50.07%	24.22%	23.91%
28	74	48.75%	53.99%	60.54%	21.60%	19.91%	65	50.29%	55.27%	61.88%	21.17%	19.34%
29	38	61.35%	67.89%	75.11%	16.21%	13.24%	38	62.78%	69.90%	77.56%	15.33%	12.02%
30	17	76.42%	84.58%	94.51%	8.30%	3.07%	17	78.89%	86.73%	95.68%	7.19%	2.42%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel A-(ii): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1785	0.00%	0.12%	0.25%	1.21%	2.75%	1785	0.00%	0.12%	0.25%	1.21%	1.61%
2	1202	0.25%	0.38%	0.53%	2.89%	4.64%	1202	0.25%	0.38%	0.53%	2.90%	3.70%
3	978	0.53%	0.68%	0.86%	4.38%	6.39%	978	0.53%	0.68%	0.86%	4.39%	5.49%
4	757	0.86%	1.05%	1.25%	5.87%	8.09%	757	0.87%	1.05%	1.26%	5.88%	7.25%
5	603	1.26%	1.46%	1.69%	7.30%	9.67%	603	1.26%	1.47%	1.69%	7.31%	8.90%
6	480	1.69%	1.91%	2.16%	8.64%	11.15%	480	1.69%	1.92%	2.16%	8.65%	10.42%
7	452	2.16%	2.40%	2.68%	9.93%	12.59%	452	2.16%	2.41%	2.69%	9.94%	11.88%
8	372	2.68%	2.96%	3.27%	11.21%	14.02%	372	2.69%	2.96%	3.28%	11.23%	13.30%
9	395	3.28%	3.59%	3.93%	12.52%	15.44%	395	3.28%	3.60%	3.94%	12.54%	14.74%
10	299	3.94%	4.28%	4.65%	13.79%	16.78%	299	3.95%	4.29%	4.66%	13.81%	16.12%
11	251	4.66%	5.05%	5.42%	15.04%	18.05%	251	4.68%	5.06%	5.44%	15.06%	17.47%
12	254	5.43%	5.82%	6.25%	16.17%	19.25%	254	5.45%	5.83%	6.26%	16.18%	18.66%
13	221	6.26%	6.69%	7.19%	17.30%	20.45%	221	6.27%	6.70%	7.20%	17.31%	19.86%
14	203	7.19%	7.69%	8.22%	18.45%	21.61%	203	7.21%	7.70%	8.23%	18.46%	21.05%
15	174	8.23%	8.76%	9.35%	19.54%	22.71%	174	8.25%	8.78%	9.37%	19.56%	22.17%
16	160	9.38%	9.95%	10.65%	20.60%	23.79%	159	9.39%	9.97%	10.65%	20.61%	23.24%
17	184	10.67%	11.35%	12.09%	21.67%	24.81%	184	10.66%	11.35%	12.10%	21.68%	24.31%
18	145	12.10%	12.85%	13.68%	22.65%	25.73%	146	12.11%	12.86%	13.69%	22.66%	25.27%
19	156	13.70%	14.53%	15.49%	23.57%	26.58%	156	13.72%	14.54%	15.51%	23.58%	26.16%
20	111	15.51%	16.48%	17.55%	24.44%	27.32%	111	15.52%	16.49%	17.56%	24.45%	26.97%
21	138	17.59%	18.64%	19.87%	25.19%	27.92%	138	17.60%	18.65%	19.88%	25.19%	27.63%
22	96	19.93%	21.20%	22.64%	25.83%	28.37%	96	19.94%	21.20%	22.64%	25.83%	28.17%
23	113	22.75%	24.28%	25.97%	26.31%	28.58%	113	22.75%	24.28%	25.97%	26.31%	28.51%
24	90	26.11%	27.83%	29.98%	26.54%	28.47%	90	26.10%	27.83%	29.96%	26.54%	28.57%
25	94	30.18%	32.39%	34.68%	26.41%	27.91%	94	30.16%	32.37%	34.65%	26.41%	28.23%
26	83	34.73%	37.00%	40.19%	25.90%	26.81%	83	34.70%	36.96%	40.15%	25.90%	27.51%
27	75	40.37%	43.62%	48.09%	24.61%	24.57%	75	40.33%	43.58%	48.04%	24.62%	25.93%
28	74	48.82%	53.88%	60.23%	21.64%	20.03%	74	48.77%	53.84%	60.19%	21.66%	22.56%
29	39	61.02%	67.71%	76.06%	16.28%	12.77%	39	60.99%	67.69%	76.06%	16.29%	16.76%
30	16	77.04%	84.94%	94.57%	8.11%	3.04%	16	77.04%	84.95%	94.58%	8.11%	8.23%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel B-(i): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1448	0.00%	0.12%	0.23%	1.73%	3.83%	1745	0.00%	0.10%	0.20%	1.49%	3.41%
2	1096	0.23%	0.35%	0.49%	3.86%	6.21%	1205	0.20%	0.30%	0.42%	3.43%	5.62%
3	878	0.49%	0.63%	0.77%	5.69%	8.23%	1009	0.42%	0.54%	0.68%	5.14%	7.64%
4	698	0.77%	0.92%	1.09%	7.29%	10.11%	763	0.68%	0.83%	0.99%	6.82%	9.56%
5	625	1.08%	1.26%	1.46%	8.89%	11.95%	620	0.99%	1.15%	1.33%	8.42%	11.36%
6	538	1.46%	1.66%	1.87%	10.50%	13.72%	505	1.33%	1.51%	1.71%	9.94%	13.04%
7	459	1.88%	2.09%	2.33%	12.03%	15.39%	455	1.71%	1.90%	2.12%	11.38%	14.65%
8	420	2.33%	2.57%	2.83%	13.51%	16.97%	383	2.12%	2.34%	2.59%	12.82%	16.23%
9	367	2.83%	3.09%	3.37%	14.91%	18.47%	391	2.59%	2.83%	3.11%	14.24%	17.78%
10	327	3.38%	3.66%	3.93%	16.30%	19.84%	310	3.12%	3.40%	3.73%	15.69%	19.37%
11	284	3.93%	4.20%	4.49%	17.47%	21.07%	301	3.74%	4.07%	4.42%	17.20%	20.90%
12	234	4.50%	4.80%	5.14%	18.63%	22.30%	262	4.42%	4.77%	5.18%	18.58%	22.37%
13	246	5.15%	5.49%	5.87%	19.84%	23.54%	243	5.18%	5.59%	6.06%	19.99%	23.84%
14	249	5.88%	6.25%	6.67%	21.01%	24.74%	209	6.07%	6.53%	7.04%	21.42%	25.24%
15	210	6.68%	7.10%	7.61%	22.19%	25.95%	181	7.07%	7.58%	8.17%	22.78%	26.59%
16	227	7.61%	8.12%	8.72%	23.40%	27.17%	190	8.19%	8.77%	9.39%	24.10%	27.81%
17	202	8.74%	9.36%	10.06%	24.68%	28.39%	147	9.40%	10.01%	10.69%	25.27%	28.89%
18	200	10.08%	10.80%	11.55%	25.92%	29.49%	160	10.74%	11.42%	12.27%	26.38%	29.94%
19	180	11.56%	12.30%	13.14%	26.98%	30.42%	115	12.34%	13.14%	14.01%	27.49%	30.84%
20	165	13.15%	14.00%	14.92%	27.95%	31.22%	127	14.09%	14.91%	15.94%	28.38%	31.58%
21	129	14.93%	15.86%	16.96%	28.78%	31.87%	95	16.01%	17.07%	18.34%	29.20%	32.18%
22	159	17.00%	18.12%	19.63%	29.52%	32.39%	109	18.44%	19.77%	21.24%	29.90%	32.56%
23	125	19.68%	21.18%	22.93%	30.13%	32.63%	80	21.27%	22.74%	24.59%	30.31%	32.60%
24	131	22.97%	24.71%	27.05%	30.41%	32.43%	79	24.68%	26.52%	28.41%	30.41%	32.26%
25	100	27.11%	29.48%	31.68%	30.22%	31.71%	84	28.51%	30.47%	32.97%	30.12%	31.43%
26	96	31.88%	34.09%	37.26%	29.57%	30.33%	62	33.46%	35.94%	39.11%	29.19%	29.78%
27	78	37.45%	40.69%	45.07%	28.01%	27.72%	54	39.17%	42.34%	46.98%	27.53%	26.99%
28	74	45.78%	50.69%	56.88%	24.67%	22.78%	62	47.24%	51.98%	58.96%	24.17%	21.81%
29	39	57.65%	64.26%	72.57%	18.86%	15.05%	37	59.37%	66.41%	74.18%	17.84%	14.21%
30	16	73.56%	81.92%	92.65%	9.98%	4.15%	17	75.60%	84.27%	94.53%	8.72%	3.09%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel B-(ii): Parameter permutations with ρ={15%, <u>20%</u>, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	TTC2 default probability computation across different bins						TTC3 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1654	0.00%	0.13%	0.26%	1.83%	4.08%	1654	0.00%	0.13%	0.26%	1.83%	4.10%
2	1183	0.26%	0.39%	0.54%	4.13%	6.62%	1183	0.26%	0.39%	0.54%	4.14%	6.64%
3	925	0.54%	0.69%	0.85%	6.07%	8.77%	925	0.54%	0.70%	0.86%	6.09%	8.79%
4	672	0.86%	1.02%	1.19%	7.78%	10.65%	672	0.86%	1.02%	1.19%	7.80%	10.68%
5	552	1.19%	1.36%	1.55%	9.34%	12.37%	552	1.20%	1.37%	1.56%	9.36%	12.40%
6	479	1.55%	1.74%	1.95%	10.80%	14.03%	479	1.56%	1.75%	1.96%	10.83%	14.05%
7	430	1.95%	2.17%	2.40%	12.27%	15.61%	430	1.96%	2.18%	2.41%	12.30%	15.64%
8	400	2.40%	2.63%	2.89%	13.68%	17.15%	400	2.41%	2.64%	2.90%	13.71%	17.18%
9	343	2.89%	3.16%	3.46%	15.09%	18.71%	343	2.91%	3.17%	3.47%	15.11%	18.74%
10	387	3.46%	3.77%	4.11%	16.54%	20.25%	387	3.48%	3.78%	4.13%	16.57%	20.28%
11	298	4.11%	4.46%	4.83%	17.98%	21.72%	298	4.13%	4.47%	4.84%	18.01%	21.75%
12	251	4.84%	5.22%	5.60%	19.38%	23.10%	251	4.86%	5.24%	5.61%	19.41%	23.13%
13	254	5.61%	5.99%	6.41%	20.62%	24.37%	254	5.62%	6.01%	6.43%	20.65%	24.40%
14	220	6.42%	6.84%	7.33%	21.85%	25.61%	220	6.44%	6.86%	7.35%	21.87%	25.63%
15	204	7.33%	7.82%	8.34%	23.06%	26.78%	204	7.35%	7.84%	8.36%	23.09%	26.80%
16	174	8.36%	8.87%	9.45%	24.20%	27.86%	174	8.38%	8.90%	9.47%	24.23%	27.88%
17	160	9.47%	10.03%	10.70%	25.28%	28.89%	160	9.49%	10.05%	10.72%	25.31%	28.91%
18	186	10.73%	11.38%	12.11%	26.35%	29.84%	186	10.75%	11.41%	12.13%	26.37%	29.86%
19	147	12.12%	12.85%	13.65%	27.31%	30.67%	147	12.14%	12.87%	13.67%	27.33%	30.68%
20	160	13.70%	14.48%	15.46%	28.19%	31.42%	160	13.72%	14.51%	15.49%	28.20%	31.42%
21	123	15.54%	16.52%	17.58%	29.02%	32.02%	123	15.56%	16.54%	17.60%	29.03%	32.03%
22	144	17.62%	18.71%	20.22%	29.67%	32.47%	144	17.64%	18.73%	20.23%	29.67%	32.47%
23	120	20.25%	21.77%	23.52%	30.21%	32.63%	120	20.26%	21.78%	23.53%	30.21%	32.63%
24	131	23.57%	25.36%	27.76%	30.42%	32.35%	131	23.58%	25.36%	27.75%	30.42%	32.35%
25	100	27.83%	30.23%	32.44%	30.15%	31.55%	100	27.82%	30.21%	32.41%	30.15%	31.56%
26	96	32.64%	34.82%	37.92%	29.43%	30.14%	96	32.61%	34.78%	37.87%	29.43%	30.15%
27	78	38.11%	41.22%	45.40%	27.86%	27.60%	78	38.06%	41.16%	45.33%	27.88%	27.63%
28	74	46.06%	50.68%	56.52%	24.67%	22.94%	74	45.99%	50.61%	56.45%	24.70%	22.97%
29	39	57.26%	63.65%	71.89%	19.14%	15.41%	39	57.19%	63.61%	71.88%	19.16%	15.41%
30	16	72.90%	81.56%	92.72%	10.17%	4.11%	16	72.89%	81.57%	92.74%	10.16%	4.10%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel C-(i): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	TTC0 default probability computation across different bins						TTC1 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1183	0.00%	0.12%	0.23%	2.32%	5.08%	1672	0.00%	0.10%	0.20%	2.06%	4.68%
2	1037	0.23%	0.34%	0.47%	4.92%	8.03%	1218	0.20%	0.30%	0.42%	4.56%	7.51%
3	848	0.47%	0.61%	0.76%	7.20%	10.61%	1011	0.42%	0.54%	0.68%	6.71%	9.99%
4	817	0.76%	0.91%	1.08%	9.28%	13.00%	756	0.68%	0.82%	0.97%	8.72%	12.25%
5	621	1.08%	1.26%	1.44%	11.32%	15.16%	624	0.97%	1.13%	1.30%	10.59%	14.32%
6	516	1.45%	1.63%	1.83%	13.12%	17.08%	514	1.30%	1.47%	1.65%	12.36%	16.25%
7	456	1.83%	2.02%	2.25%	14.78%	18.89%	461	1.65%	1.84%	2.04%	14.03%	18.04%
8	417	2.25%	2.47%	2.71%	16.42%	20.60%	379	2.04%	2.25%	2.48%	15.63%	19.80%
9	397	2.71%	2.95%	3.22%	17.98%	22.25%	419	2.48%	2.72%	2.99%	17.26%	21.55%
10	340	3.22%	3.49%	3.80%	19.51%	23.87%	320	2.99%	3.26%	3.58%	18.90%	23.29%
11	390	3.80%	4.11%	4.46%	21.07%	25.44%	308	3.59%	3.91%	4.23%	20.57%	24.92%
12	301	4.46%	4.81%	5.18%	22.57%	26.91%	263	4.23%	4.56%	4.94%	22.06%	26.45%
13	253	5.19%	5.56%	5.94%	24.00%	28.25%	246	4.94%	5.32%	5.75%	23.56%	27.93%
14	260	5.95%	6.32%	6.75%	25.25%	29.46%	210	5.76%	6.19%	6.66%	25.05%	29.35%
15	230	6.76%	7.18%	7.69%	26.48%	30.66%	181	6.69%	7.16%	7.69%	26.45%	30.67%
16	238	7.70%	8.22%	8.82%	27.75%	31.86%	189	7.71%	8.24%	8.80%	27.78%	31.84%
17	204	8.82%	9.43%	10.10%	29.00%	32.95%	148	8.81%	9.37%	9.99%	28.95%	32.87%
18	199	10.13%	10.80%	11.50%	30.16%	33.88%	160	10.03%	10.65%	11.42%	30.04%	33.84%
19	180	11.51%	12.21%	12.99%	31.11%	34.64%	115	11.48%	12.21%	13.00%	31.11%	34.65%
20	164	13.01%	13.79%	14.65%	31.95%	35.26%	127	13.07%	13.81%	14.75%	31.96%	35.29%
21	131	14.66%	15.52%	16.55%	32.65%	35.72%	96	14.81%	15.78%	17.00%	32.73%	35.79%
22	159	16.59%	17.63%	19.02%	33.23%	36.01%	112	17.03%	18.27%	19.68%	33.36%	36.03%
23	125	19.06%	20.44%	22.04%	33.65%	35.99%	82	19.79%	21.10%	22.75%	33.70%	35.94%
24	131	22.08%	23.66%	25.80%	33.73%	35.54%	80	22.94%	24.63%	26.24%	33.69%	35.47%
25	100	25.86%	28.02%	30.03%	33.32%	34.62%	82	26.51%	28.28%	30.88%	33.28%	34.39%
26	99	30.21%	32.32%	35.40%	32.49%	32.98%	66	31.05%	33.60%	36.61%	32.17%	32.56%
27	78	35.56%	38.56%	43.10%	30.71%	30.01%	53	36.93%	40.19%	44.36%	30.16%	29.47%
28	72	43.25%	47.79%	54.06%	27.23%	24.98%	56	44.65%	49.01%	55.56%	26.71%	24.24%
29	39	54.39%	60.83%	69.60%	21.24%	16.95%	36	56.70%	63.08%	71.90%	20.12%	15.71%
30	15	70.20%	79.01%	90.32%	11.73%	5.48%	16	73.01%	81.99%	93.07%	10.10%	3.93%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel C-(ii): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	TTC2 default probability computation across different bins						TTC3 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1185	0.00%	0.11%	0.21%	2.16%	4.79%	1185	0.00%	0.11%	0.21%	2.17%	4.81%
2	1038	0.21%	0.31%	0.43%	4.63%	7.62%	1038	0.21%	0.31%	0.44%	4.65%	7.65%
3	852	0.43%	0.56%	0.69%	6.82%	10.11%	852	0.44%	0.56%	0.70%	6.84%	10.15%
4	815	0.70%	0.83%	1.00%	8.82%	12.44%	815	0.70%	0.84%	1.01%	8.85%	12.47%
5	617	1.00%	1.17%	1.34%	10.81%	14.57%	617	1.01%	1.17%	1.35%	10.84%	14.61%
6	516	1.34%	1.51%	1.70%	12.58%	16.48%	516	1.35%	1.52%	1.71%	12.62%	16.53%
7	459	1.70%	1.89%	2.11%	14.23%	18.31%	459	1.71%	1.90%	2.12%	14.27%	18.36%
8	426	2.11%	2.32%	2.56%	15.90%	20.07%	426	2.12%	2.33%	2.57%	15.94%	20.12%
9	394	2.56%	2.79%	3.06%	17.49%	21.75%	394	2.57%	2.81%	3.07%	17.53%	21.80%
10	345	3.06%	3.32%	3.63%	19.06%	23.42%	345	3.07%	3.34%	3.65%	19.11%	23.46%
11	380	3.63%	3.94%	4.27%	20.65%	25.03%	380	3.65%	3.95%	4.29%	20.69%	25.07%
12	297	4.28%	4.62%	5.00%	22.18%	26.56%	297	4.30%	4.64%	5.02%	22.23%	26.61%
13	253	5.01%	5.38%	5.76%	23.67%	27.96%	253	5.03%	5.40%	5.79%	23.71%	28.00%
14	259	5.76%	6.15%	6.58%	24.98%	29.23%	259	5.79%	6.17%	6.61%	25.02%	29.27%
15	230	6.59%	7.02%	7.55%	26.27%	30.50%	230	6.62%	7.05%	7.58%	26.31%	30.54%
16	239	7.57%	8.10%	8.74%	27.62%	31.78%	239	7.60%	8.13%	8.77%	27.66%	31.81%
17	203	8.74%	9.38%	10.08%	28.95%	32.94%	203	8.77%	9.41%	10.12%	28.98%	32.96%
18	200	10.11%	10.83%	11.57%	30.18%	33.93%	200	10.14%	10.86%	11.61%	30.20%	33.95%
19	180	11.59%	12.33%	13.17%	31.18%	34.72%	180	11.62%	12.36%	13.21%	31.20%	34.74%
20	165	13.19%	14.03%	14.95%	32.06%	35.35%	165	13.22%	14.06%	14.99%	32.08%	35.36%
21	129	14.97%	15.89%	16.98%	32.77%	35.79%	129	15.00%	15.92%	17.02%	32.78%	35.80%
22	158	17.02%	18.13%	19.59%	33.33%	36.03%	158	17.05%	18.16%	19.61%	33.34%	36.03%
23	125	19.63%	21.12%	22.81%	33.70%	35.93%	125	19.66%	21.14%	22.83%	33.70%	35.93%
24	132	22.85%	24.55%	26.80%	33.69%	35.36%	132	22.86%	24.56%	26.80%	33.69%	35.36%
25	100	26.87%	29.09%	31.13%	33.15%	34.32%	100	26.86%	29.07%	31.10%	33.15%	34.33%
26	98	31.32%	33.39%	36.36%	32.23%	32.65%	98	31.29%	33.34%	36.30%	32.24%	32.67%
27	79	36.45%	39.42%	43.72%	30.42%	29.75%	79	36.39%	39.35%	43.63%	30.45%	29.79%
28	74	43.86%	48.19%	54.21%	27.06%	24.91%	74	43.77%	48.09%	54.11%	27.11%	24.95%
29	38	55.08%	60.62%	69.16%	21.34%	17.19%	38	54.99%	60.55%	69.13%	21.38%	17.20%
30	14	71.04%	79.01%	90.34%	11.74%	5.47%	14	71.02%	79.02%	90.37%	11.73%	5.45%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel D-(i): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1065	0.00%	0.13%	0.25%	3.22%	6.93%	1090	0.00%	0.07%	0.14%	2.12%	4.83%
2	990	0.25%	0.37%	0.50%	6.53%	10.59%	1023	0.14%	0.21%	0.29%	4.49%	7.62%
3	835	0.50%	0.64%	0.79%	9.31%	13.65%	832	0.29%	0.37%	0.46%	6.56%	10.04%
4	771	0.79%	0.94%	1.11%	11.78%	16.33%	773	0.46%	0.55%	0.65%	8.45%	12.21%
5	624	1.11%	1.28%	1.46%	14.02%	18.72%	611	0.65%	0.75%	0.86%	10.24%	14.24%
6	541	1.47%	1.65%	1.86%	16.09%	20.94%	538	0.86%	0.97%	1.09%	11.93%	16.18%
7	518	1.86%	2.07%	2.31%	18.09%	23.05%	507	1.09%	1.22%	1.36%	13.62%	18.07%
8	458	2.31%	2.55%	2.81%	20.04%	25.04%	440	1.36%	1.51%	1.67%	15.32%	19.95%
9	446	2.82%	3.08%	3.37%	21.91%	26.90%	460	1.66%	1.84%	2.04%	17.04%	21.85%
10	369	3.37%	3.66%	3.99%	23.66%	28.63%	403	2.04%	2.25%	2.48%	18.84%	23.78%
11	395	3.99%	4.32%	4.66%	25.34%	30.21%	446	2.46%	2.73%	3.02%	20.70%	25.76%
12	309	4.67%	5.01%	5.39%	26.88%	31.64%	334	3.02%	3.31%	3.63%	22.62%	27.65%
13	253	5.39%	5.77%	6.13%	28.31%	32.88%	337	3.62%	3.96%	4.33%	24.46%	29.45%
14	259	6.14%	6.50%	6.91%	29.51%	33.98%	284	4.33%	4.69%	5.13%	26.19%	31.17%
15	231	6.92%	7.33%	7.81%	30.67%	35.03%	277	5.14%	5.58%	6.10%	27.97%	32.83%
16	236	7.83%	8.32%	8.89%	31.85%	36.05%	218	6.11%	6.62%	7.17%	29.69%	34.30%
17	203	8.90%	9.46%	10.09%	32.97%	36.94%	217	7.18%	7.77%	8.38%	31.22%	35.59%
18	194	10.11%	10.74%	11.35%	33.97%	37.66%	184	8.38%	9.04%	9.67%	32.58%	36.66%
19	179	11.39%	12.02%	12.76%	34.77%	38.24%	161	9.67%	10.43%	11.22%	33.75%	37.59%
20	174	12.78%	13.53%	14.35%	35.48%	38.67%	157	11.25%	12.24%	13.15%	34.89%	38.36%
21	132	14.38%	15.18%	16.14%	36.04%	38.93%	121	13.18%	14.24%	15.46%	35.75%	38.85%
22	158	16.17%	17.12%	18.37%	36.44%	38.99%	122	15.56%	16.82%	18.27%	36.39%	38.99%
23	125	18.41%	19.68%	21.14%	36.66%	38.75%	97	18.35%	19.84%	21.74%	36.66%	38.66%
24	132	21.17%	22.64%	24.60%	36.55%	38.09%	116	21.91%	24.07%	26.22%	36.39%	37.68%
25	100	24.66%	26.62%	28.45%	35.95%	37.02%	67	26.30%	28.76%	31.14%	35.47%	36.10%
26	99	28.62%	30.53%	33.34%	34.99%	35.28%	56	31.23%	33.89%	37.32%	33.95%	33.64%
27	79	33.48%	36.28%	40.52%	33.10%	32.22%	61	38.04%	42.14%	46.64%	30.76%	29.30%
28	73	40.65%	44.95%	51.05%	29.53%	27.08%	31	47.42%	51.44%	56.81%	26.48%	24.08%
29	38	51.95%	57.57%	66.13%	23.41%	19.04%	23	57.45%	62.70%	69.62%	20.73%	17.12%
30	14	67.98%	75.89%	87.48%	13.58%	7.10%	14	71.75%	80.03%	91.19%	11.28%	5.00%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel D-(ii): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	TTC2 default probability computation across different bins						TTC3 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1156	0.00%	0.12%	0.24%	3.10%	6.74%	1156	0.00%	0.13%	0.24%	3.11%	6.77%
2	1042	0.24%	0.35%	0.48%	6.35%	10.34%	1042	0.24%	0.35%	0.49%	6.38%	10.38%
3	845	0.48%	0.61%	0.76%	9.09%	13.38%	845	0.49%	0.62%	0.77%	9.13%	13.43%
4	819	0.76%	0.91%	1.08%	11.53%	16.12%	819	0.77%	0.92%	1.09%	11.58%	16.17%
5	617	1.08%	1.26%	1.44%	13.87%	18.55%	617	1.09%	1.27%	1.45%	13.92%	18.61%
6	524	1.44%	1.62%	1.81%	15.92%	20.70%	524	1.45%	1.63%	1.82%	15.97%	20.76%
7	471	1.81%	2.01%	2.23%	17.82%	22.72%	471	1.83%	2.02%	2.25%	17.88%	22.78%
8	421	2.23%	2.45%	2.69%	19.68%	24.59%	421	2.25%	2.47%	2.70%	19.74%	24.65%
9	397	2.69%	2.93%	3.19%	21.40%	26.34%	397	2.71%	2.95%	3.21%	21.46%	26.40%
10	340	3.19%	3.46%	3.76%	23.06%	28.03%	340	3.21%	3.48%	3.79%	23.12%	28.09%
11	390	3.77%	4.07%	4.41%	24.74%	29.66%	390	3.79%	4.10%	4.44%	24.80%	29.72%
12	301	4.42%	4.76%	5.13%	26.35%	31.16%	301	4.44%	4.79%	5.16%	26.41%	31.21%
13	253	5.14%	5.51%	5.89%	27.85%	32.50%	253	5.17%	5.54%	5.92%	27.91%	32.55%
14	260	5.90%	6.27%	6.70%	29.15%	33.69%	260	5.93%	6.30%	6.73%	29.20%	33.74%
15	230	6.71%	7.13%	7.64%	30.41%	34.85%	230	6.74%	7.17%	7.68%	30.46%	34.89%
16	236	7.66%	8.17%	8.78%	31.69%	35.96%	236	7.70%	8.21%	8.82%	31.73%	35.99%
17	204	8.78%	9.39%	10.07%	32.91%	36.93%	204	8.82%	9.43%	10.11%	32.94%	36.96%
18	197	10.09%	10.78%	11.48%	34.00%	37.72%	197	10.13%	10.82%	11.52%	34.03%	37.74%
19	182	11.50%	12.21%	13.01%	34.87%	38.32%	182	11.54%	12.25%	13.06%	34.89%	38.33%
20	165	13.02%	13.83%	14.69%	35.60%	38.73%	165	13.07%	13.87%	14.74%	35.62%	38.74%
21	132	14.72%	15.61%	16.66%	36.15%	38.97%	132	14.77%	15.65%	16.70%	36.16%	38.97%
22	158	16.70%	17.74%	19.12%	36.53%	38.96%	158	16.74%	17.78%	19.15%	36.53%	38.95%
23	125	19.16%	20.56%	22.15%	36.66%	38.60%	125	19.19%	20.59%	22.17%	36.66%	38.59%
24	132	22.18%	23.78%	25.88%	36.42%	37.77%	132	22.21%	23.79%	25.89%	36.42%	37.77%
25	100	25.94%	28.01%	29.91%	35.65%	36.53%	100	25.94%	28.00%	29.89%	35.65%	36.54%
26	96	30.08%	31.94%	34.58%	34.58%	34.78%	96	30.06%	31.91%	34.52%	34.59%	34.81%
27	80	34.74%	37.44%	41.42%	32.67%	31.80%	80	34.68%	37.36%	41.32%	32.70%	31.85%
28	75	41.49%	45.48%	50.96%	29.29%	27.13%	75	41.39%	45.36%	50.83%	29.34%	27.20%
29	38	51.75%	56.79%	64.73%	23.81%	19.81%	38	51.61%	56.68%	64.67%	23.87%	19.84%
30	14	66.55%	74.83%	87.29%	14.16%	7.21%	14	66.50%	74.83%	87.34%	14.16%	7.18%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel E-(i): Parameter permutations with ρ={15%, 20%, 25%, 30%, <u>35%</u>}, φ=50%, and ξ=50%

Baseline logit model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	937	0.00%	0.15%	0.27%	4.29%	9.08%	1599	0.00%	0.12%	0.22%	3.66%	8.16%
2	943	0.27%	0.39%	0.53%	8.37%	13.46%	1250	0.22%	0.33%	0.45%	7.53%	12.35%
3	818	0.53%	0.67%	0.82%	11.67%	16.96%	1029	0.45%	0.58%	0.71%	10.66%	15.76%
4	716	0.82%	0.98%	1.13%	14.48%	19.79%	762	0.71%	0.85%	1.00%	13.38%	18.67%
5	577	1.13%	1.28%	1.45%	16.75%	22.25%	640	1.00%	1.15%	1.31%	15.81%	21.23%
6	575	1.45%	1.63%	1.82%	18.99%	24.57%	530	1.31%	1.47%	1.65%	18.04%	23.56%
7	486	1.83%	2.02%	2.22%	21.12%	26.64%	499	1.65%	1.83%	2.04%	20.15%	25.74%
8	430	2.23%	2.43%	2.66%	22.99%	28.52%	423	2.04%	2.25%	2.48%	22.20%	27.78%
9	413	2.66%	2.89%	3.13%	24.80%	30.26%	423	2.48%	2.71%	2.97%	24.12%	29.70%
10	398	3.14%	3.38%	3.66%	26.50%	31.89%	316	2.97%	3.24%	3.52%	26.03%	31.49%
11	345	3.66%	3.93%	4.25%	28.13%	33.42%	315	3.53%	3.81%	4.12%	27.78%	33.10%
12	399	4.25%	4.57%	4.92%	29.72%	34.87%	268	4.12%	4.43%	4.79%	29.40%	34.62%
13	313	4.93%	5.28%	5.67%	31.23%	36.20%	246	4.80%	5.16%	5.56%	30.99%	36.03%
14	288	5.68%	6.08%	6.49%	32.66%	37.37%	209	5.57%	5.98%	6.46%	32.50%	37.34%
15	290	6.50%	6.90%	7.37%	33.89%	38.41%	209	6.47%	6.95%	7.45%	33.95%	38.48%
16	264	7.40%	7.89%	8.44%	35.10%	39.37%	185	7.46%	7.97%	8.54%	35.19%	39.45%
17	233	8.45%	9.00%	9.61%	36.20%	40.16%	165	8.58%	9.13%	9.74%	36.31%	40.24%
18	207	9.62%	10.24%	10.90%	37.15%	40.79%	114	9.75%	10.36%	11.03%	37.23%	40.84%
19	219	10.92%	11.58%	12.35%	37.92%	41.25%	139	11.06%	11.72%	12.53%	37.99%	41.29%
20	193	12.38%	13.16%	13.94%	38.56%	41.51%	96	12.58%	13.36%	14.35%	38.63%	41.55%
21	137	14.00%	14.78%	15.68%	38.98%	41.59%	112	14.37%	15.37%	16.50%	39.08%	41.56%
22	159	15.70%	16.60%	17.75%	39.22%	41.45%	82	16.59%	17.65%	18.98%	39.26%	41.27%
23	125	17.78%	18.95%	20.28%	39.24%	41.02%	80	19.13%	20.50%	21.81%	39.11%	40.65%
24	132	20.31%	21.65%	23.44%	38.96%	40.20%	77	22.03%	23.34%	25.09%	38.65%	39.67%
25	100	23.49%	25.27%	26.93%	38.20%	39.01%	60	25.46%	27.28%	29.48%	37.64%	38.02%
26	99	27.09%	28.83%	31.39%	37.15%	37.22%	50	29.69%	31.86%	35.28%	36.08%	35.47%
27	81	31.52%	34.16%	38.09%	35.18%	34.14%	54	35.63%	38.86%	42.62%	33.16%	31.88%
28	71	38.25%	42.14%	47.68%	31.64%	29.25%	32	43.35%	47.38%	53.00%	29.07%	26.40%
29	38	48.51%	53.84%	62.05%	25.74%	21.43%	25	53.56%	59.53%	67.44%	22.70%	18.43%
30	14	63.87%	71.93%	84.18%	15.86%	8.98%	11	69.79%	78.81%	88.86%	12.01%	6.32%

Table 3: TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel E-(ii): Parameter permutations with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

Baseline logit model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1111	0.00%	0.14%	0.27%	4.23%	9.06%	1111	0.00%	0.14%	0.27%	4.26%	9.11%
2	1057	0.27%	0.39%	0.53%	8.37%	13.51%	1057	0.27%	0.39%	0.54%	8.41%	13.57%
3	859	0.53%	0.68%	0.84%	11.74%	17.11%	859	0.54%	0.68%	0.84%	11.79%	17.17%
4	826	0.84%	1.00%	1.18%	14.63%	20.21%	826	0.84%	1.00%	1.19%	14.70%	20.28%
5	617	1.18%	1.36%	1.54%	17.30%	22.87%	617	1.19%	1.37%	1.56%	17.37%	22.95%
6	530	1.55%	1.73%	1.93%	19.58%	25.16%	530	1.56%	1.74%	1.95%	19.66%	25.24%
7	463	1.93%	2.13%	2.35%	21.65%	27.24%	463	1.95%	2.15%	2.37%	21.72%	27.32%
8	424	2.35%	2.58%	2.81%	23.61%	29.13%	424	2.37%	2.60%	2.83%	23.69%	29.21%
9	398	2.82%	3.06%	3.32%	25.42%	30.88%	398	2.84%	3.08%	3.34%	25.49%	30.95%
10	345	3.32%	3.59%	3.89%	27.13%	32.53%	345	3.35%	3.61%	3.92%	27.21%	32.60%
11	392	3.90%	4.21%	4.54%	28.84%	34.09%	392	3.93%	4.23%	4.58%	28.91%	34.16%
12	301	4.55%	4.89%	5.25%	30.43%	35.48%	301	4.58%	4.92%	5.28%	30.50%	35.54%
13	253	5.26%	5.63%	5.99%	31.88%	36.69%	253	5.29%	5.66%	6.03%	31.95%	36.75%
14	257	6.00%	6.36%	6.77%	33.11%	37.73%	257	6.04%	6.40%	6.81%	33.17%	37.78%
15	231	6.78%	7.19%	7.68%	34.27%	38.71%	231	6.82%	7.23%	7.72%	34.33%	38.75%
16	236	7.69%	8.19%	8.77%	35.43%	39.62%	236	7.74%	8.24%	8.82%	35.48%	39.66%
17	206	8.79%	9.37%	10.03%	36.51%	40.39%	203	8.84%	9.41%	10.06%	36.54%	40.41%
18	197	10.05%	10.71%	11.38%	37.44%	40.96%	198	10.08%	10.74%	11.42%	37.47%	40.98%
19	182	11.39%	12.07%	12.83%	38.15%	41.35%	182	11.43%	12.11%	12.87%	38.17%	41.36%
20	165	12.84%	13.61%	14.43%	38.70%	41.55%	167	12.89%	13.66%	14.48%	38.71%	41.56%
21	132	14.45%	15.29%	16.29%	39.07%	41.57%	132	14.51%	15.35%	16.34%	39.08%	41.56%
22	158	16.32%	17.31%	18.60%	39.25%	41.33%	158	16.38%	17.36%	18.65%	39.25%	41.32%
23	125	18.64%	19.96%	21.45%	39.17%	40.75%	125	18.69%	20.00%	21.49%	39.16%	40.74%
24	132	21.49%	22.98%	24.96%	38.72%	39.71%	131	21.53%	23.00%	24.86%	38.72%	39.74%
25	100	25.01%	26.95%	28.73%	37.74%	38.32%	101	24.98%	26.94%	28.73%	37.74%	38.33%
26	96	28.90%	30.63%	33.10%	36.53%	36.47%	96	28.89%	30.61%	33.05%	36.54%	36.50%
27	78	33.24%	35.66%	38.88%	34.56%	33.75%	78	33.19%	35.59%	38.77%	34.59%	33.80%
28	77	39.39%	43.05%	48.10%	31.20%	29.03%	77	39.28%	42.90%	47.93%	31.27%	29.12%
29	38	48.80%	53.31%	60.47%	26.02%	22.31%	38	48.63%	53.15%	60.36%	26.10%	22.37%
30	14	62.15%	70.40%	83.58%	16.72%	9.32%	14	62.06%	70.37%	83.63%	16.73%	9.29%

Table 4: Baseline asset-equivalent value-at-risk and conditional value-at-risk capital requirements

This table summarizes the asset-equivalent weighted-average value-at-risk and conditional value-at-risk bank capital requirements or equity capital ratios for all the baseline permutations of both TTC adjustments (TTC0, TTC1, TTC2, and TTC3) and asset correlation values (from 15% to 35% in increments of 5%). Across the value-at-risk and conditional value-at-risk panels, the TTC1 adjustments consistently introduce non-trivial downward biases in the asset-equivalent weighted-average equity capital ratios relative to the TTC0 brute-force adjustments and the TTC2/TTC3 higher-order Taylor-series approximations. The more accurate TTC0, TTC2, and TTC3 asset-equivalent weighted-average value-at-risk and conditional value-at-risk bank capital requirements land in the range of 9.66% to 26.66% across the entire spectrum of asset correlation values. The quantitative results that favor the recent proposal for substantially heighted bank capital requirements indicate equity capital ratios from 22% to 26%+ when the prudent econometrician raises the asset correlation value to 35% to account for potential default contagion in times of extreme financial stress. This evidence resonates with the central thesis that the typical bank should hold a much larger capital cushion to absorb severe losses in a financial downturn.

Baseline equity capital	ρ =15%	ρ =20%	ρ =25%	ρ =30%	ρ =35%
Value-at-risk capital					
TTC0	9.74%	12.60%	15.59%	18.75%	22.05%
TTC1	8.73%	10.97%	13.21%	15.52%	17.90%
TTC2	9.66%	12.43%	15.27%	18.23%	21.28%
TTC3	9.67%	12.44%	15.29%	18.27%	21.33%
Conditional value-at-risk capital					
TTC0	11.92%	15.41%	19.05%	22.83%	26.66%
TTC1	10.83%	13.67%	16.57%	19.33%	22.63%
TTC2	11.87%	15.27%	18.67%	22.27%	25.93%
TTC3	11.17%	15.29%	18.70%	22.31%	25.98%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel A-(i): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	TTC0 default probability computation across different bins						TTC1 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1541	0.00%	0.11%	0.22%	1.14%	2.54%	1784	0.00%	0.10%	0.21%	1.08%	2.46%
2	1112	0.22%	0.33%	0.46%	2.66%	4.25%	1208	0.21%	0.32%	0.45%	2.57%	4.16%
3	877	0.46%	0.59%	0.73%	3.99%	5.74%	994	0.45%	0.58%	0.74%	3.91%	5.79%
4	672	0.73%	0.87%	1.02%	5.18%	7.12%	805	0.74%	0.90%	1.10%	5.31%	7.44%
5	568	1.02%	1.17%	1.35%	6.33%	8.46%	687	1.10%	1.29%	1.53%	6.75%	9.12%
6	511	1.35%	1.53%	1.72%	7.50%	9.79%	582	1.53%	1.77%	2.03%	8.23%	10.78%
7	434	1.72%	1.92%	2.13%	8.66%	11.07%	481	2.03%	2.29%	2.59%	9.65%	12.37%
8	387	2.13%	2.34%	2.57%	9.77%	12.30%	434	2.60%	2.90%	3.21%	11.09%	13.88%
9	370	2.57%	2.81%	3.07%	10.89%	13.56%	335	3.21%	3.52%	3.86%	12.38%	15.28%
10	337	3.06%	3.36%	3.63%	12.07%	14.82%	260	3.86%	4.20%	4.53%	13.65%	16.56%
11	354	3.63%	3.96%	4.33%	13.23%	16.20%	255	4.54%	4.87%	5.24%	14.76%	17.75%
12	280	4.33%	4.71%	5.12%	14.50%	17.56%	223	5.24%	5.61%	6.04%	15.88%	18.96%
13	328	5.10%	5.60%	6.09%	15.86%	19.04%	204	6.05%	6.48%	6.94%	17.03%	20.15%
14	276	6.10%	6.64%	7.21%	17.23%	20.49%	174	6.95%	7.41%	7.93%	18.14%	21.30%
15	239	7.23%	7.81%	8.47%	18.58%	21.87%	160	7.95%	8.45%	9.07%	19.24%	22.45%
16	217	8.48%	9.15%	9.92%	19.90%	23.20%	188	9.09%	9.70%	10.38%	20.39%	23.59%
17	200	9.94%	10.70%	11.48%	21.20%	24.40%	145	10.39%	11.07%	11.82%	21.48%	24.63%
18	183	11.50%	12.29%	13.19%	22.31%	25.46%	160	11.87%	12.63%	13.58%	22.52%	25.67%
19	164	13.20%	14.10%	15.06%	23.36%	26.40%	115	13.65%	14.55%	15.51%	23.58%	26.59%
20	130	15.10%	16.09%	17.19%	24.28%	27.21%	127	15.60%	16.51%	17.65%	24.45%	27.35%
21	140	17.29%	18.36%	19.58%	25.10%	27.86%	95	17.73%	18.90%	20.30%	25.26%	28.01%
22	96	19.64%	20.88%	22.29%	25.76%	28.32%	109	20.41%	21.88%	23.50%	25.96%	28.45%
23	113	22.40%	23.91%	25.58%	26.27%	28.57%	80	23.53%	25.13%	27.15%	26.40%	28.59%
24	90	25.71%	27.44%	29.58%	26.53%	28.49%	79	27.25%	29.25%	31.29%	26.55%	28.35%
25	94	29.78%	32.01%	34.33%	26.44%	27.97%	84	31.40%	33.51%	36.19%	26.32%	27.65%
26	83	34.38%	36.71%	39.99%	25.94%	26.86%	60	36.70%	39.23%	42.23%	25.53%	26.30%
27	75	40.18%	43.56%	48.22%	24.63%	24.53%	52	42.50%	45.55%	50.34%	24.13%	23.82%
28	74	48.99%	54.27%	60.87%	21.51%	19.77%	65	50.56%	55.46%	61.97%	21.10%	19.30%
29	38	61.68%	68.24%	75.47%	16.05%	13.06%	38	62.86%	69.87%	77.44%	15.34%	12.08%
30	17	76.77%	84.84%	94.61%	8.16%	3.02%	17	78.76%	86.56%	95.54%	7.28%	2.50%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel A-(ii): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1729	0.00%	0.12%	0.25%	1.23%	2.75%	1721	0.00%	0.12%	0.25%	1.23%	2.75%
2	1167	0.25%	0.37%	0.52%	2.88%	4.62%	1171	0.25%	0.37%	0.52%	2.88%	4.61%
3	992	0.52%	0.67%	0.85%	4.36%	6.34%	985	0.52%	0.67%	0.85%	4.36%	6.32%
4	714	0.85%	1.03%	1.21%	5.79%	7.93%	718	0.85%	1.02%	1.21%	5.78%	7.92%
5	584	1.21%	1.41%	1.62%	7.11%	9.43%	579	1.21%	1.40%	1.61%	7.10%	9.41%
6	497	1.62%	1.83%	2.06%	8.40%	10.86%	490	1.61%	1.82%	2.04%	8.37%	10.82%
7	434	2.06%	2.29%	2.54%	9.65%	12.23%	432	2.05%	2.28%	2.52%	9.61%	12.17%
8	390	2.54%	2.80%	3.07%	10.87%	13.57%	393	2.52%	2.78%	3.06%	10.82%	13.54%
9	352	3.08%	3.39%	3.67%	12.12%	14.90%	363	3.06%	3.37%	3.67%	12.09%	14.89%
10	336	3.68%	3.99%	4.36%	13.28%	16.26%	319	3.67%	3.97%	4.32%	13.23%	16.18%
11	273	4.37%	4.74%	5.13%	14.55%	17.59%	274	4.32%	4.68%	5.07%	14.46%	17.49%
12	287	5.14%	5.57%	5.99%	15.81%	18.89%	280	5.07%	5.49%	5.92%	15.71%	18.79%
13	240	5.99%	6.46%	6.93%	17.01%	20.14%	260	5.91%	6.39%	6.88%	16.92%	20.08%
14	212	6.93%	7.44%	7.99%	18.18%	21.37%	220	6.89%	7.42%	7.97%	18.16%	21.35%
15	196	8.00%	8.55%	9.19%	19.34%	22.56%	197	7.99%	8.55%	9.19%	19.34%	22.56%
16	179	9.20%	9.84%	10.56%	20.50%	23.72%	180	9.20%	9.84%	10.57%	20.51%	23.73%
17	186	10.59%	11.29%	12.03%	21.63%	24.76%	186	10.60%	11.30%	12.04%	21.64%	24.77%
18	146	12.04%	12.78%	13.61%	22.62%	25.69%	146	12.06%	12.79%	13.63%	22.62%	25.70%
19	157	13.62%	14.45%	15.42%	23.54%	26.55%	157	13.63%	14.46%	15.43%	23.54%	26.55%
20	111	15.43%	16.40%	17.45%	24.41%	27.29%	111	15.44%	16.40%	17.46%	24.41%	27.29%
21	138	17.50%	18.53%	19.76%	25.16%	27.90%	138	17.50%	18.54%	19.77%	25.16%	27.90%
22	96	19.82%	21.08%	22.52%	25.81%	28.35%	96	19.83%	21.09%	22.52%	25.81%	28.35%
23	113	22.63%	24.15%	25.85%	26.30%	28.58%	113	22.63%	24.15%	25.84%	26.30%	28.58%
24	90	25.98%	27.72%	29.87%	26.54%	28.47%	90	25.98%	27.71%	29.86%	26.54%	28.47%
25	94	30.07%	32.30%	34.62%	26.42%	27.92%	94	30.06%	32.29%	34.60%	26.42%	27.93%
26	83	34.66%	36.97%	40.21%	25.90%	26.80%	83	34.65%	36.94%	40.18%	25.91%	26.81%
27	75	40.40%	43.71%	48.28%	24.59%	24.51%	75	40.37%	43.68%	48.25%	24.60%	24.52%
28	74	49.03%	54.20%	60.67%	21.53%	19.85%	74	49.00%	54.17%	60.65%	21.54%	19.86%
29	39	61.47%	68.21%	76.54%	16.07%	12.53%	39	61.45%	68.20%	76.54%	16.07%	12.53%
30	16	77.51%	85.25%	94.65%	7.95%	3.00%	16	77.51%	85.26%	94.65%	7.95%	2.99%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel B-(i): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1558	0.00%	0.11%	0.22%	1.13%	2.54%	1785	0.00%	0.09%	0.20%	1.04%	2.38%
2	1127	0.22%	0.33%	0.46%	2.66%	4.26%	1207	0.20%	0.31%	0.43%	2.49%	4.04%
3	877	0.46%	0.59%	0.73%	4.00%	5.77%	996	0.43%	0.55%	0.71%	3.80%	5.64%
4	673	0.73%	0.87%	1.03%	5.20%	7.14%	804	0.71%	0.87%	1.06%	5.17%	7.28%
5	549	1.03%	1.18%	1.36%	6.35%	8.48%	686	1.06%	1.25%	1.48%	6.59%	8.94%
6	518	1.36%	1.53%	1.73%	7.52%	9.81%	582	1.48%	1.71%	1.97%	8.06%	10.58%
7	421	1.73%	1.92%	2.13%	8.67%	11.07%	481	1.97%	2.22%	2.52%	9.47%	12.17%
8	404	2.13%	2.35%	2.59%	9.80%	12.36%	434	2.52%	2.82%	3.12%	10.90%	13.67%
9	382	2.59%	2.85%	3.12%	10.97%	13.67%	335	3.12%	3.42%	3.76%	12.19%	15.07%
10	350	3.12%	3.43%	3.72%	12.21%	14.99%	260	3.76%	4.09%	4.42%	13.46%	16.35%
11	336	3.72%	4.04%	4.41%	13.37%	16.35%	255	4.42%	4.75%	5.11%	14.57%	17.55%
12	272	4.42%	4.78%	5.18%	14.63%	17.66%	223	5.12%	5.48%	5.90%	15.69%	18.77%
13	287	5.18%	5.61%	6.03%	15.88%	18.95%	204	5.91%	6.33%	6.78%	16.84%	19.96%
14	238	6.04%	6.50%	6.97%	17.06%	20.19%	174	6.80%	7.25%	7.76%	17.96%	21.12%
15	225	6.97%	7.50%	8.06%	18.24%	21.44%	160	7.78%	8.28%	8.89%	19.07%	22.28%
16	208	8.08%	8.68%	9.35%	19.46%	22.71%	188	8.91%	9.52%	10.20%	20.23%	23.43%
17	190	9.36%	10.07%	10.79%	20.70%	23.90%	145	10.20%	10.88%	11.62%	21.33%	24.49%
18	198	10.79%	11.60%	12.44%	21.85%	25.02%	160	11.67%	12.42%	13.36%	22.39%	25.56%
19	170	12.46%	13.35%	14.23%	22.95%	26.01%	115	13.44%	14.33%	15.29%	23.47%	26.49%
20	153	14.24%	15.26%	16.36%	23.92%	26.92%	127	15.37%	16.28%	17.42%	24.36%	27.28%
21	156	16.38%	17.76%	19.02%	24.91%	27.73%	95	17.50%	18.66%	20.06%	25.19%	27.96%
22	121	19.05%	20.50%	22.16%	25.68%	28.31%	109	20.17%	21.64%	23.25%	25.92%	28.43%
23	116	22.29%	23.87%	25.58%	26.26%	28.57%	80	23.28%	24.89%	26.91%	26.37%	28.59%
24	90	25.71%	27.42%	29.56%	26.53%	28.49%	79	27.01%	29.01%	31.05%	26.55%	28.38%
25	94	29.76%	31.98%	34.29%	26.44%	27.97%	84	31.17%	33.29%	35.97%	26.34%	27.69%
26	83	34.34%	36.65%	39.92%	25.95%	26.87%	60	36.49%	39.03%	42.05%	25.56%	26.35%
27	75	40.11%	43.47%	48.11%	24.65%	24.56%	52	42.32%	45.39%	50.21%	24.17%	23.86%
28	74	48.87%	54.14%	60.71%	21.55%	19.84%	65	50.43%	55.37%	61.94%	21.13%	19.32%
29	38	61.52%	68.07%	75.29%	16.13%	13.15%	38	62.83%	69.89%	77.51%	15.33%	12.05%
30	17	76.59%	84.71%	94.56%	8.23%	3.04%	17	78.83%	86.65%	95.61%	7.23%	2.46%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel B-(ii): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1783	0.00%	0.12%	0.25%	1.24%	2.79%	1783	0.00%	0.12%	0.25%	1.24%	2.80%
2	1203	0.25%	0.38%	0.54%	2.94%	4.70%	1203	0.25%	0.38%	0.54%	2.94%	4.70%
3	979	0.54%	0.69%	0.87%	4.43%	6.46%	979	0.54%	0.69%	0.88%	4.44%	6.47%
4	757	0.88%	1.06%	1.27%	5.93%	8.16%	757	0.88%	1.07%	1.27%	5.94%	8.17%
5	603	1.27%	1.48%	1.70%	7.36%	9.73%	603	1.28%	1.48%	1.71%	7.37%	9.74%
6	480	1.71%	1.93%	2.18%	8.69%	11.21%	480	1.71%	1.94%	2.18%	8.70%	11.23%
7	452	2.18%	2.42%	2.70%	9.98%	12.65%	452	2.18%	2.43%	2.71%	9.99%	12.66%
8	372	2.70%	2.98%	3.29%	11.26%	14.07%	372	2.71%	2.98%	3.30%	11.27%	14.09%
9	395	3.30%	3.61%	3.95%	12.56%	15.48%	395	3.30%	3.62%	3.96%	12.58%	15.49%
10	299	3.96%	4.30%	4.67%	13.82%	16.81%	299	3.97%	4.31%	4.68%	13.84%	16.83%
11	251	4.68%	5.06%	5.44%	15.07%	18.08%	251	4.69%	5.07%	5.45%	15.08%	18.09%
12	254	5.45%	5.84%	6.26%	16.19%	19.27%	254	5.46%	5.85%	6.28%	16.20%	19.29%
13	221	6.27%	6.70%	7.20%	17.31%	20.46%	221	6.29%	6.71%	7.21%	17.33%	20.48%
14	203	7.20%	7.69%	8.22%	18.45%	21.61%	203	7.21%	7.70%	8.23%	18.47%	21.62%
15	174	8.24%	8.76%	9.35%	19.54%	22.71%	174	8.25%	8.78%	9.36%	19.56%	22.72%
16	160	9.38%	9.95%	10.64%	20.60%	23.78%	159	9.39%	9.96%	10.64%	20.61%	23.78%
17	184	10.67%	11.33%	12.08%	21.66%	24.80%	184	10.65%	11.34%	12.08%	21.67%	24.80%
18	145	12.08%	12.83%	13.65%	22.64%	25.72%	146	12.09%	12.84%	13.67%	22.65%	25.72%
19	156	13.68%	14.50%	15.46%	23.56%	26.56%	156	13.69%	14.51%	15.47%	23.56%	26.57%
20	111	15.47%	16.44%	17.50%	24.43%	27.30%	111	15.49%	16.45%	17.51%	24.43%	27.31%
21	138	17.55%	18.59%	19.82%	25.17%	27.91%	138	17.56%	18.60%	19.83%	25.18%	27.91%
22	96	19.88%	21.14%	22.58%	25.82%	28.36%	96	19.89%	21.15%	22.58%	25.82%	28.36%
23	113	22.69%	24.22%	25.91%	26.30%	28.58%	113	22.69%	24.22%	25.91%	26.30%	28.58%
24	90	26.05%	27.78%	29.93%	26.54%	28.47%	90	26.04%	27.77%	29.91%	26.54%	28.47%
25	94	30.13%	32.35%	34.65%	26.42%	27.92%	94	30.11%	32.33%	34.63%	26.42%	27.92%
26	83	34.70%	36.98%	40.20%	25.90%	26.81%	83	34.68%	36.96%	40.17%	25.90%	26.81%
27	75	40.39%	43.67%	48.19%	24.60%	24.54%	75	40.35%	43.63%	48.15%	24.61%	24.55%
28	74	48.93%	54.05%	60.46%	21.58%	19.94%	74	48.89%	54.01%	60.43%	21.60%	19.95%
29	39	61.25%	67.97%	76.30%	16.17%	12.65%	39	61.22%	67.95%	76.30%	16.18%	12.65%
30	16	77.28%	85.10%	94.61%	8.03%	3.02%	16	77.28%	85.11%	94.62%	8.03%	3.01%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel C-(i): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1675	0.00%	0.11%	0.24%	1.18%	2.68%	1786	0.00%	0.09%	0.19%	0.99%	2.30%
2	1174	0.24%	0.36%	0.50%	2.81%	4.50%	1206	0.19%	0.29%	0.41%	2.41%	3.92%
3	931	0.50%	0.65%	0.81%	4.25%	6.13%	997	0.41%	0.53%	0.68%	3.69%	5.50%
4	677	0.81%	0.97%	1.14%	5.57%	7.62%	804	0.68%	0.83%	1.02%	5.04%	7.11%
5	555	1.14%	1.31%	1.50%	6.80%	9.01%	685	1.02%	1.20%	1.43%	6.44%	8.75%
6	487	1.50%	1.69%	1.91%	7.99%	10.40%	582	1.43%	1.65%	1.90%	7.89%	10.38%
7	457	1.91%	2.13%	2.37%	9.23%	11.77%	481	1.91%	2.15%	2.44%	9.29%	11.96%
8	389	2.37%	2.61%	2.88%	10.43%	13.09%	434	2.44%	2.73%	3.03%	10.71%	13.46%
9	347	2.88%	3.15%	3.45%	11.63%	14.42%	335	3.03%	3.33%	3.65%	11.99%	14.86%
10	371	3.45%	3.75%	4.09%	12.83%	15.74%	261	3.65%	3.98%	4.31%	13.26%	16.15%
11	289	4.10%	4.45%	4.83%	14.07%	17.09%	257	4.31%	4.63%	4.99%	14.38%	17.36%
12	262	4.84%	5.23%	5.62%	15.31%	18.35%	221	5.00%	5.36%	5.77%	15.50%	18.57%
13	256	5.63%	6.03%	6.48%	16.45%	19.56%	203	5.77%	6.19%	6.63%	16.66%	19.76%
14	217	6.48%	6.93%	7.45%	17.59%	20.76%	174	6.64%	7.09%	7.60%	17.78%	20.93%
15	224	7.46%	7.99%	8.62%	18.77%	22.02%	160	7.62%	8.11%	8.71%	18.90%	22.11%
16	198	8.63%	9.26%	10.00%	20.01%	23.28%	188	8.73%	9.33%	10.00%	20.07%	23.28%
17	199	10.03%	10.76%	11.54%	21.24%	24.44%	145	10.01%	10.68%	11.42%	21.18%	24.35%
18	180	11.56%	12.34%	13.24%	22.34%	25.49%	160	11.47%	12.21%	13.14%	22.26%	25.44%
19	163	13.25%	14.14%	15.12%	23.38%	26.42%	115	13.22%	14.10%	15.06%	23.36%	26.39%
20	129	15.13%	16.12%	17.21%	24.29%	27.21%	127	15.14%	16.05%	17.18%	24.27%	27.20%
21	140	17.31%	18.38%	19.59%	25.11%	27.86%	95	17.26%	18.42%	19.81%	25.12%	27.91%
22	96	19.65%	20.89%	22.29%	25.76%	28.32%	109	19.92%	21.39%	23.00%	25.87%	28.40%
23	113	22.40%	23.90%	25.56%	26.27%	28.57%	80	23.03%	24.64%	26.66%	26.35%	28.59%
24	90	25.69%	27.40%	29.53%	26.53%	28.50%	79	26.76%	28.77%	30.81%	26.55%	28.40%
25	94	29.72%	31.94%	34.24%	26.44%	27.98%	84	30.93%	33.05%	35.75%	26.36%	27.73%
26	83	34.29%	36.59%	39.84%	25.96%	26.89%	60	36.27%	38.82%	41.85%	25.60%	26.40%
27	75	40.03%	43.37%	47.99%	24.67%	24.60%	52	42.13%	45.22%	50.07%	24.22%	23.91%
28	74	48.75%	53.99%	60.54%	21.60%	19.91%	65	50.29%	55.27%	61.88%	21.17%	19.34%
29	38	61.35%	67.89%	75.11%	16.21%	13.24%	38	62.78%	69.90%	77.56%	15.33%	12.02%
30	17	76.42%	84.58%	94.51%	8.30%	3.07%	17	78.89%	86.73%	95.68%	7.19%	2.42%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel C-(ii): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1785	0.00%	0.12%	0.25%	1.21%	2.75%	1785	0.00%	0.12%	0.25%	1.21%	2.76%
2	1202	0.25%	0.38%	0.53%	2.89%	4.64%	1202	0.25%	0.38%	0.53%	2.90%	4.65%
3	978	0.53%	0.68%	0.86%	4.38%	6.39%	978	0.53%	0.68%	0.86%	4.39%	6.40%
4	757	0.86%	1.05%	1.25%	5.87%	8.09%	757	0.87%	1.05%	1.26%	5.88%	8.10%
5	603	1.26%	1.46%	1.69%	7.30%	9.67%	603	1.26%	1.47%	1.69%	7.31%	9.68%
6	480	1.69%	1.91%	2.16%	8.64%	11.15%	480	1.69%	1.92%	2.16%	8.65%	11.17%
7	452	2.16%	2.40%	2.68%	9.93%	12.59%	452	2.16%	2.41%	2.69%	9.94%	12.61%
8	372	2.68%	2.96%	3.27%	11.21%	14.02%	372	2.69%	2.96%	3.28%	11.23%	14.04%
9	395	3.28%	3.59%	3.93%	12.52%	15.44%	395	3.28%	3.60%	3.94%	12.54%	15.45%
10	299	3.94%	4.28%	4.65%	13.79%	16.78%	299	3.95%	4.29%	4.66%	13.81%	16.80%
11	251	4.66%	5.05%	5.42%	15.04%	18.05%	251	4.68%	5.06%	5.44%	15.06%	18.07%
12	254	5.43%	5.82%	6.25%	16.17%	19.25%	254	5.45%	5.83%	6.26%	16.18%	19.27%
13	221	6.26%	6.69%	7.19%	17.30%	20.45%	221	6.27%	6.70%	7.20%	17.31%	20.47%
14	203	7.19%	7.69%	8.22%	18.45%	21.61%	203	7.21%	7.70%	8.23%	18.46%	21.62%
15	174	8.23%	8.76%	9.35%	19.54%	22.71%	174	8.25%	8.78%	9.37%	19.56%	22.73%
16	160	9.38%	9.95%	10.65%	20.60%	23.79%	159	9.39%	9.97%	10.65%	20.61%	23.79%
17	184	10.67%	11.35%	12.09%	21.67%	24.81%	184	10.66%	11.35%	12.10%	21.68%	24.81%
18	145	12.10%	12.85%	13.68%	22.65%	25.73%	146	12.11%	12.86%	13.69%	22.66%	25.74%
19	156	13.70%	14.53%	15.49%	23.57%	26.58%	156	13.72%	14.54%	15.51%	23.58%	26.58%
20	111	15.51%	16.48%	17.55%	24.44%	27.32%	111	15.52%	16.49%	17.56%	24.45%	27.32%
21	138	17.59%	18.64%	19.87%	25.19%	27.92%	138	17.60%	18.65%	19.88%	25.19%	27.92%
22	96	19.93%	21.20%	22.64%	25.83%	28.37%	96	19.94%	21.20%	22.64%	25.83%	28.37%
23	113	22.75%	24.28%	25.97%	26.31%	28.58%	113	22.75%	24.28%	25.97%	26.31%	28.58%
24	90	26.11%	27.83%	29.98%	26.54%	28.47%	90	26.10%	27.83%	29.96%	26.54%	28.47%
25	94	30.18%	32.39%	34.68%	26.41%	27.91%	94	30.16%	32.37%	34.65%	26.41%	27.92%
26	83	34.73%	37.00%	40.19%	25.90%	26.81%	83	34.70%	36.96%	40.15%	25.90%	26.82%
27	75	40.37%	43.62%	48.09%	24.61%	24.57%	75	40.33%	43.58%	48.04%	24.62%	24.59%
28	74	48.82%	53.88%	60.23%	21.64%	20.03%	74	48.77%	53.84%	60.19%	21.66%	20.05%
29	39	61.02%	67.71%	76.06%	16.28%	12.77%	39	60.99%	67.69%	76.06%	16.29%	12.77%
30	16	77.04%	84.94%	94.57%	8.11%	3.04%	16	77.04%	84.95%	94.58%	8.11%	3.03%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel D-(i): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1708	0.00%	0.11%	0.24%	1.18%	2.68%	1813	0.00%	0.09%	0.19%	0.97%	2.25%
2	1159	0.24%	0.36%	0.50%	2.81%	4.51%	1214	0.19%	0.28%	0.40%	2.36%	3.86%
3	939	0.50%	0.65%	0.81%	4.25%	6.15%	1010	0.40%	0.52%	0.67%	3.64%	5.44%
4	691	0.81%	0.98%	1.15%	5.60%	7.68%	804	0.67%	0.82%	1.00%	4.99%	7.04%
5	567	1.15%	1.33%	1.53%	6.87%	9.11%	669	1.00%	1.19%	1.40%	6.37%	8.67%
6	490	1.53%	1.73%	1.94%	8.10%	10.51%	587	1.41%	1.63%	1.87%	7.81%	10.29%
7	445	1.95%	2.18%	2.42%	9.35%	11.89%	475	1.88%	2.12%	2.40%	9.21%	11.86%
8	391	2.41%	2.67%	2.94%	10.56%	13.24%	426	2.41%	2.69%	2.97%	10.61%	13.32%
9	340	2.93%	3.21%	3.50%	11.76%	14.53%	321	2.98%	3.26%	3.57%	11.86%	14.69%
10	346	3.50%	3.80%	4.13%	12.91%	15.81%	255	3.58%	3.89%	4.20%	13.09%	15.95%
11	281	4.13%	4.47%	4.85%	14.11%	17.12%	254	4.21%	4.52%	4.87%	14.19%	17.15%
12	257	4.85%	5.24%	5.62%	15.33%	18.36%	221	4.88%	5.23%	5.63%	15.31%	18.37%
13	254	5.63%	6.03%	6.46%	16.45%	19.54%	203	5.64%	6.04%	6.48%	16.47%	19.57%
14	211	6.47%	6.91%	7.43%	17.57%	20.75%	174	6.49%	6.94%	7.43%	17.60%	20.75%
15	227	7.44%	7.96%	8.59%	18.74%	21.99%	160	7.46%	7.94%	8.53%	18.72%	21.93%
16	203	8.61%	9.26%	10.01%	20.00%	23.28%	188	8.56%	9.15%	9.81%	19.90%	23.12%
17	199	10.04%	10.77%	11.56%	21.25%	24.45%	145	9.82%	10.48%	11.21%	21.03%	24.21%
18	180	11.57%	12.36%	13.25%	22.35%	25.50%	160	11.26%	12.00%	12.93%	22.12%	25.31%
19	163	13.26%	14.15%	15.13%	23.38%	26.42%	115	13.00%	13.88%	14.83%	23.24%	26.29%
20	129	15.14%	16.13%	17.22%	24.30%	27.21%	127	14.91%	15.81%	16.94%	24.17%	27.12%
21	140	17.32%	18.38%	19.60%	25.11%	27.86%	95	17.01%	18.17%	19.56%	25.04%	27.85%
22	96	19.65%	20.88%	22.29%	25.76%	28.32%	109	19.67%	21.13%	22.74%	25.82%	28.38%
23	113	22.39%	23.89%	25.54%	26.27%	28.57%	80	22.78%	24.38%	26.40%	26.32%	28.59%
24	90	25.68%	27.38%	29.49%	26.53%	28.50%	79	26.50%	28.51%	30.56%	26.55%	28.42%
25	94	29.69%	31.90%	34.19%	26.45%	27.99%	84	30.68%	32.81%	35.51%	26.38%	27.77%
26	83	34.23%	36.52%	39.76%	25.97%	26.91%	60	36.04%	38.60%	41.65%	25.64%	26.45%
27	75	39.95%	43.27%	47.86%	24.69%	24.64%	52	41.93%	45.03%	49.92%	24.27%	23.96%
28	74	48.62%	53.84%	60.36%	21.66%	19.98%	65	50.14%	55.16%	61.82%	21.21%	19.37%
29	39	61.16%	67.91%	76.22%	16.20%	12.69%	38	62.72%	69.89%	77.60%	15.33%	12.00%
30	16	77.19%	84.94%	94.45%	8.11%	3.10%	17	78.94%	86.80%	95.74%	7.16%	2.39%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel D-(ii): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	TTC2 default probability computation across different bins						TTC3 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1786	0.00%	0.11%	0.24%	1.19%	2.71%	1786	0.00%	0.11%	0.24%	1.19%	2.72%
2	1201	0.24%	0.37%	0.52%	2.85%	4.59%	1201	0.24%	0.37%	0.52%	2.86%	4.60%
3	978	0.52%	0.67%	0.85%	4.33%	6.33%	978	0.52%	0.67%	0.85%	4.34%	6.34%
4	757	0.85%	1.03%	1.24%	5.82%	8.03%	757	0.85%	1.04%	1.24%	5.83%	8.04%
5	603	1.24%	1.45%	1.67%	7.25%	9.61%	603	1.25%	1.45%	1.67%	7.26%	9.63%
6	480	1.67%	1.89%	2.14%	8.58%	11.10%	480	1.68%	1.90%	2.14%	8.60%	11.12%
7	452	2.14%	2.38%	2.66%	9.88%	12.54%	452	2.15%	2.39%	2.67%	9.90%	12.56%
8	372	2.66%	2.94%	3.25%	11.17%	13.98%	372	2.67%	2.94%	3.26%	11.19%	14.00%
9	395	3.26%	3.57%	3.92%	12.48%	15.40%	395	3.27%	3.58%	3.93%	12.50%	15.42%
10	299	3.92%	4.26%	4.63%	13.76%	16.75%	299	3.93%	4.28%	4.65%	13.78%	16.77%
11	251	4.65%	5.03%	5.41%	15.01%	18.03%	251	4.66%	5.04%	5.42%	15.03%	18.05%
12	254	5.42%	5.81%	6.24%	16.15%	19.24%	254	5.43%	5.82%	6.25%	16.17%	19.26%
13	221	6.25%	6.68%	7.18%	17.29%	20.45%	221	6.26%	6.70%	7.20%	17.31%	20.47%
14	203	7.19%	7.68%	8.21%	18.44%	21.61%	203	7.20%	7.70%	8.23%	18.46%	21.62%
15	174	8.23%	8.76%	9.36%	19.54%	22.72%	174	8.25%	8.78%	9.37%	19.56%	22.73%
16	159	9.38%	9.96%	10.64%	20.61%	23.79%	159	9.40%	9.98%	10.66%	20.62%	23.80%
17	184	10.66%	11.35%	12.10%	21.68%	24.81%	184	10.68%	11.37%	12.12%	21.69%	24.83%
18	146	12.11%	12.87%	13.71%	22.67%	25.74%	146	12.13%	12.89%	13.73%	22.68%	25.75%
19	156	13.73%	14.56%	15.53%	23.59%	26.59%	156	13.75%	14.58%	15.55%	23.60%	26.60%
20	111	15.55%	16.53%	17.60%	24.46%	27.33%	111	15.56%	16.54%	17.61%	24.47%	27.34%
21	138	17.64%	18.69%	19.93%	25.20%	27.93%	138	17.65%	18.70%	19.94%	25.21%	27.93%
22	96	19.99%	21.26%	22.71%	25.84%	28.37%	96	20.00%	21.27%	22.71%	25.84%	28.37%
23	113	22.82%	24.35%	26.04%	26.32%	28.58%	113	22.82%	24.35%	26.04%	26.32%	28.58%
24	90	26.17%	27.90%	30.04%	26.54%	28.46%	90	26.17%	27.89%	30.02%	26.54%	28.46%
25	93	30.24%	32.42%	34.68%	26.41%	27.91%	93	30.22%	32.39%	34.65%	26.41%	27.92%
26	84	34.72%	36.99%	40.18%	25.90%	26.81%	84	34.69%	36.95%	40.13%	25.90%	26.82%
27	75	40.36%	43.57%	47.98%	24.62%	24.60%	75	40.31%	43.52%	47.93%	24.63%	24.62%
28	74	48.71%	53.71%	59.99%	21.70%	20.14%	74	48.65%	53.65%	59.94%	21.72%	20.15%
29	39	60.77%	67.44%	75.78%	16.40%	12.91%	39	60.73%	67.41%	75.78%	16.41%	12.91%
30	16	76.77%	84.76%	94.52%	8.20%	3.07%	16	76.77%	84.77%	94.53%	8.20%	3.06%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel E-(i): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1729	0.00%	0.11%	0.24%	1.18%	2.68%	1820	0.00%	0.08%	0.18%	0.93%	2.19%
2	1151	0.24%	0.36%	0.51%	2.81%	4.52%	1213	0.18%	0.27%	0.39%	2.29%	3.77%
3	952	0.51%	0.65%	0.82%	4.26%	6.17%	1014	0.39%	0.50%	0.65%	3.55%	5.32%
4	687	0.81%	0.98%	1.16%	5.63%	7.72%	798	0.65%	0.79%	0.97%	4.88%	6.89%
5	578	1.16%	1.35%	1.54%	6.92%	9.18%	667	0.97%	1.15%	1.36%	6.23%	8.50%
6	489	1.54%	1.75%	1.97%	8.17%	10.59%	585	1.36%	1.58%	1.82%	7.65%	10.10%
7	438	1.98%	2.20%	2.44%	9.42%	11.97%	475	1.82%	2.06%	2.33%	9.04%	11.66%
8	373	2.44%	2.68%	2.95%	10.60%	13.27%	426	2.34%	2.61%	2.89%	10.43%	13.12%
9	335	2.95%	3.22%	3.51%	11.77%	14.55%	323	2.89%	3.17%	3.48%	11.68%	14.50%
10	344	3.51%	3.80%	4.13%	12.92%	15.82%	253	3.49%	3.79%	4.09%	12.91%	15.75%
11	281	4.14%	4.47%	4.85%	14.11%	17.12%	254	4.10%	4.41%	4.75%	14.00%	16.94%
12	257	4.86%	5.24%	5.63%	15.34%	18.37%	221	4.76%	5.10%	5.50%	15.12%	18.17%
13	254	5.64%	6.03%	6.47%	16.46%	19.55%	203	5.50%	5.90%	6.34%	16.28%	19.37%
14	211	6.48%	6.92%	7.44%	17.58%	20.76%	174	6.35%	6.79%	7.27%	17.42%	20.56%
15	227	7.45%	7.97%	8.60%	18.75%	22.00%	160	7.30%	7.78%	8.36%	18.55%	21.76%
16	203	8.62%	9.27%	10.03%	20.01%	23.29%	188	8.38%	8.97%	9.62%	19.74%	22.95%
17	199	10.05%	10.79%	11.57%	21.26%	24.46%	145	9.63%	10.29%	11.01%	20.88%	24.06%
18	180	11.58%	12.37%	13.26%	22.36%	25.50%	160	11.06%	11.79%	12.71%	21.98%	25.19%
19	163	13.27%	14.16%	15.14%	23.39%	26.43%	115	12.78%	13.65%	14.60%	23.12%	26.18%
20	129	15.15%	16.13%	17.22%	24.30%	27.22%	127	14.68%	15.57%	16.69%	24.06%	27.04%
21	140	17.32%	18.38%	19.59%	25.11%	27.86%	95	16.77%	17.92%	19.30%	24.96%	27.79%
22	96	19.65%	20.88%	22.27%	25.76%	28.32%	109	19.41%	20.87%	22.48%	25.76%	28.35%
23	113	22.38%	23.87%	25.52%	26.26%	28.57%	80	22.51%	24.11%	26.13%	26.29%	28.58%
24	90	25.65%	27.34%	29.45%	26.53%	28.50%	79	26.23%	28.24%	30.29%	26.55%	28.44%
25	94	29.64%	31.83%	34.11%	26.45%	28.00%	84	30.41%	32.54%	35.26%	26.40%	27.82%
26	83	34.16%	36.43%	39.65%	25.98%	26.94%	60	35.78%	38.35%	41.41%	25.68%	26.51%
27	75	39.84%	43.14%	47.71%	24.72%	24.69%	52	41.69%	44.81%	49.73%	24.32%	24.03%
28	74	48.46%	53.65%	60.14%	21.72%	20.07%	65	49.95%	55.00%	61.71%	21.26%	19.41%
29	39	60.95%	67.68%	75.99%	16.30%	12.81%	38	62.62%	69.84%	77.61%	15.35%	12.00%
30	16	76.96%	84.77%	94.37%	8.20%	3.15%	17	78.95%	86.83%	95.79%	7.14%	2.36%

Table 5: Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel E-(ii): Parameter permutations with ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%

Alternative #1 model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1757	0.00%	0.11%	0.23%	1.15%	2.62%	1757	0.00%	0.11%	0.23%	1.15%	2.63%
2	1169	0.23%	0.35%	0.49%	2.75%	4.44%	1169	0.23%	0.35%	0.50%	2.76%	4.45%
3	969	0.49%	0.64%	0.80%	4.19%	6.12%	969	0.50%	0.64%	0.81%	4.20%	6.13%
4	711	0.81%	0.97%	1.16%	5.59%	7.69%	711	0.81%	0.98%	1.16%	5.61%	7.71%
5	575	1.16%	1.34%	1.54%	6.90%	9.17%	575	1.16%	1.35%	1.55%	6.92%	9.19%
6	481	1.54%	1.75%	1.97%	8.16%	10.58%	481	1.55%	1.75%	1.97%	8.18%	10.60%
7	421	1.97%	2.19%	2.42%	9.38%	11.91%	421	1.97%	2.20%	2.43%	9.40%	11.94%
8	364	2.43%	2.66%	2.92%	10.54%	13.19%	364	2.43%	2.67%	2.92%	10.56%	13.21%
9	306	2.92%	3.17%	3.43%	11.68%	14.38%	306	2.93%	3.18%	3.44%	11.70%	14.40%
10	312	3.44%	3.69%	3.99%	12.72%	15.55%	312	3.45%	3.71%	4.00%	12.74%	15.57%
11	262	4.00%	4.30%	4.66%	13.83%	16.79%	262	4.01%	4.32%	4.67%	13.85%	16.82%
12	249	4.66%	5.03%	5.41%	15.01%	18.03%	249	4.68%	5.04%	5.43%	15.03%	18.05%
13	252	5.42%	5.80%	6.23%	16.14%	19.23%	252	5.43%	5.82%	6.25%	16.16%	19.25%
14	221	6.24%	6.67%	7.17%	17.28%	20.44%	221	6.26%	6.69%	7.19%	17.30%	20.46%
15	203	7.18%	7.68%	8.21%	18.44%	21.61%	203	7.20%	7.70%	8.23%	18.46%	21.63%
16	174	8.23%	8.77%	9.36%	19.55%	22.72%	174	8.25%	8.79%	9.38%	19.57%	22.74%
17	160	9.39%	9.97%	10.67%	20.62%	23.81%	160	9.41%	9.99%	10.69%	20.64%	23.83%
18	186	10.70%	11.39%	12.15%	21.70%	24.84%	186	10.72%	11.41%	12.17%	21.72%	24.86%
19	147	12.17%	12.93%	13.78%	22.71%	25.78%	147	12.19%	12.95%	13.80%	22.72%	25.79%
20	160	13.83%	14.67%	15.71%	23.64%	26.67%	160	13.86%	14.69%	15.73%	23.65%	26.67%
21	123	15.79%	16.83%	17.96%	24.58%	27.44%	123	15.81%	16.85%	17.98%	24.58%	27.45%
22	144	18.01%	19.17%	20.78%	25.34%	28.10%	144	18.03%	19.18%	20.79%	25.35%	28.10%
23	120	20.82%	22.44%	24.33%	26.06%	28.51%	120	20.83%	22.45%	24.33%	26.06%	28.51%
24	131	24.38%	26.31%	28.89%	26.48%	28.53%	131	24.39%	26.30%	28.88%	26.48%	28.53%
25	100	28.96%	31.55%	33.93%	26.47%	28.03%	100	28.95%	31.52%	33.89%	26.47%	28.03%
26	96	34.14%	36.49%	39.83%	25.97%	26.89%	96	34.11%	36.45%	39.78%	25.98%	26.91%
27	78	40.03%	43.37%	47.86%	24.67%	24.65%	78	39.98%	43.31%	47.79%	24.68%	24.67%
28	74	48.57%	53.50%	59.70%	21.77%	20.25%	74	48.50%	53.44%	59.65%	21.79%	20.27%
29	39	60.48%	67.11%	75.47%	16.54%	13.07%	39	60.43%	67.09%	75.47%	16.55%	13.07%
30	16	76.46%	84.55%	94.45%	8.31%	3.10%	16	76.46%	84.56%	94.47%	8.31%	3.10%

Table 6: Alternative #1 value-at-risk and conditional value-at-risk capital requirements

This table lists the asset-equivalent weighted-average value-at-risk and conditional value-at-risk bank capital requirements or equity capital ratios for the alternative permutations of TTC adjustments (TTC0, TTC1, TTC2, and TTC3) and systematic risk correlation values (from 40% to 60% in increments of 5%). Across the value-at-risk and conditional value-at-risk panels, the TTC1 adjustments consistently introduce non-trivial downward biases in the asset-equivalent weighted-average equity capital ratios relative to the TTC0 brute-force adjustments and the TTC2/TTC3 higher-order Taylor-series approximations. The more accurate TTC0, TTC2, and TTC3 asset-equivalent weighted-average value-at-risk and conditional value-at-risk bank equity capital ratios land in the intermediate range of 9% to 12% across the entire spectrum of systematic risk correlation values. The quantitative results that favor the recent proposal for substantially heighted bank capital requirements indicates first-order discrepancies between these alternative equity capital ratios and the newly introduced Basel equity capital ratio of 3% to 6% when the prudent econometrician raises the asset correlation value to 35% to account for default contagion in times of severe financial stress. The evidence resonates with the central thesis that the typical bank should hold a much larger capital cushion to absorb extreme losses in a financial downturn.

Alternative equity capital	φ =40%	φ =45%	φ =50%	φ =55%	φ =60%
Value-at-risk capital					
TTC0	9.77%	9.75%	9.74%	9.73%	9.72%
TTC1	8.97%	8.85%	8.73%	8.61%	8.50%
TTC2	9.72%	9.69%	9.66%	9.63%	9.61%
TTC3	9.73%	9.70%	9.67%	9.64%	9.62%
Conditional value-at-risk capital					
TTC0	11.92%	11.90%	11.92%	11.91%	11.90%
TTC1	11.11%	10.97%	10.83%	10.69%	10.56%
TTC2	11.92%	11.91%	11.87%	11.84%	11.77%
TTC3	11.92%	11.92%	11.88%	11.85%	11.78%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel A-(i): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	TTC0 default probability computation across different bins						TTC1 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1019	0.01%	0.15%	0.27%	1.47%	2.97%	1141	0.00%	0.13%	0.24%	1.30%	2.67%
2	1000	0.27%	0.40%	0.54%	3.02%	4.72%	1085	0.24%	0.34%	0.47%	2.72%	4.31%
3	853	0.54%	0.68%	0.84%	4.40%	6.29%	916	0.47%	0.60%	0.74%	4.02%	5.79%
4	774	0.84%	1.00%	1.16%	5.68%	7.73%	823	0.74%	0.88%	1.04%	5.21%	7.20%
5	637	1.17%	1.34%	1.52%	6.88%	9.09%	692	1.04%	1.21%	1.39%	6.45%	8.62%
6	541	1.52%	1.70%	1.91%	8.04%	10.41%	590	1.39%	1.58%	1.78%	7.66%	9.97%
7	520	1.91%	2.12%	2.35%	9.20%	11.72%	500	1.78%	1.98%	2.20%	8.82%	11.28%
8	458	2.35%	2.59%	2.84%	10.38%	13.01%	462	2.20%	2.42%	2.66%	9.97%	12.54%
9	446	2.85%	3.11%	3.39%	11.55%	14.30%	396	2.66%	2.90%	3.17%	11.08%	13.78%
10	369	3.40%	3.68%	4.00%	12.70%	15.56%	401	3.17%	3.45%	3.73%	12.24%	15.02%
11	395	4.00%	4.32%	4.66%	13.86%	16.79%	315	3.73%	4.02%	4.33%	13.33%	16.20%
12	309	4.66%	5.00%	5.37%	14.97%	17.96%	255	4.34%	4.65%	4.96%	14.41%	17.30%
13	253	5.37%	5.74%	6.09%	16.05%	19.04%	260	4.96%	5.27%	5.62%	15.37%	18.34%
14	259	6.10%	6.46%	6.86%	17.01%	20.06%	230	5.62%	5.97%	6.39%	16.37%	19.44%
15	231	6.87%	7.28%	7.75%	17.99%	21.11%	239	6.40%	6.83%	7.33%	17.47%	20.63%
16	236	7.77%	8.26%	8.82%	19.05%	22.21%	204	7.34%	7.84%	8.42%	18.62%	21.82%
17	208	8.83%	9.41%	10.06%	20.13%	23.32%	209	8.44%	9.03%	9.65%	19.80%	22.98%
18	199	10.08%	10.71%	11.37%	21.21%	24.32%	185	9.67%	10.30%	11.00%	20.88%	24.06%
19	180	11.38%	12.04%	12.77%	22.15%	25.22%	181	11.05%	11.79%	12.72%	21.98%	25.19%
20	164	12.79%	13.52%	14.33%	23.04%	26.06%	159	12.76%	13.72%	14.72%	23.15%	26.24%
21	131	14.34%	15.15%	16.12%	23.87%	26.83%	139	14.74%	15.74%	17.05%	24.14%	27.16%
22	159	16.15%	17.13%	18.43%	24.69%	27.58%	125	17.14%	18.50%	19.84%	25.15%	27.91%
23	125	18.47%	19.77%	21.27%	25.50%	28.18%	92	19.86%	21.19%	22.81%	25.83%	28.38%
24	131	21.31%	22.81%	24.82%	26.12%	28.54%	85	22.94%	24.63%	26.31%	26.35%	28.59%
25	100	24.88%	26.92%	28.83%	26.51%	28.54%	84	26.40%	28.03%	30.10%	26.54%	28.46%
26	99	29.00%	31.00%	33.94%	26.50%	28.03%	71	30.50%	32.93%	35.80%	26.37%	27.73%
27	79	34.09%	37.02%	41.48%	25.89%	26.49%	53	36.07%	38.99%	42.71%	25.57%	26.17%
28	73	41.61%	46.12%	52.49%	23.98%	23.06%	56	42.97%	46.89%	52.81%	23.78%	22.94%
29	38	53.43%	59.24%	68.01%	19.72%	16.62%	37	53.85%	60.02%	69.19%	19.43%	16.08%
30	14	69.88%	77.64%	88.75%	11.74%	6.21%	15	69.84%	79.04%	90.50%	11.06%	5.26%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel A-(ii): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1021	0.00%	0.15%	0.27%	1.44%	2.91%	1021	0.01%	0.15%	0.27%	1.44%	2.92%
2	999	0.27%	0.39%	0.53%	2.96%	4.64%	999	0.27%	0.39%	0.53%	2.97%	4.65%
3	852	0.53%	0.67%	0.82%	4.32%	6.18%	852	0.53%	0.67%	0.82%	4.33%	6.19%
4	774	0.82%	0.97%	1.14%	5.58%	7.61%	774	0.82%	0.97%	1.14%	5.59%	7.62%
5	637	1.14%	1.30%	1.48%	6.77%	8.96%	637	1.14%	1.31%	1.49%	6.78%	8.97%
6	544	1.49%	1.67%	1.87%	7.93%	10.28%	544	1.49%	1.67%	1.87%	7.94%	10.29%
7	522	1.87%	2.08%	2.31%	9.08%	11.59%	522	1.88%	2.08%	2.31%	9.10%	11.61%
8	459	2.31%	2.54%	2.80%	10.27%	12.91%	459	2.32%	2.55%	2.81%	10.28%	12.92%
9	447	2.80%	3.06%	3.34%	11.44%	14.19%	447	2.81%	3.07%	3.35%	11.46%	14.21%
10	371	3.35%	3.63%	3.95%	12.61%	15.47%	371	3.36%	3.64%	3.96%	12.62%	15.48%
11	394	3.95%	4.27%	4.61%	13.77%	16.70%	394	3.96%	4.28%	4.62%	13.79%	16.72%
12	303	4.61%	4.95%	5.31%	14.89%	17.87%	303	4.62%	4.96%	5.32%	14.90%	17.89%
13	253	5.32%	5.69%	6.05%	15.98%	18.97%	253	5.33%	5.70%	6.06%	15.99%	18.99%
14	260	6.05%	6.42%	6.83%	16.96%	20.01%	260	6.06%	6.43%	6.84%	16.97%	20.03%
15	230	6.83%	7.24%	7.73%	17.95%	21.08%	230	6.85%	7.25%	7.74%	17.97%	21.10%
16	238	7.75%	8.24%	8.82%	19.03%	22.21%	238	7.76%	8.25%	8.83%	19.04%	22.23%
17	204	8.82%	9.41%	10.05%	20.13%	23.32%	204	8.84%	9.42%	10.07%	20.14%	23.33%
18	199	10.08%	10.73%	11.39%	21.22%	24.34%	199	10.09%	10.74%	11.41%	21.23%	24.35%
19	180	11.40%	12.08%	12.83%	22.17%	25.26%	180	11.42%	12.09%	12.84%	22.18%	25.27%
20	164	12.84%	13.60%	14.42%	23.09%	26.10%	164	12.86%	13.61%	14.43%	23.09%	26.11%
21	131	14.43%	15.26%	16.26%	23.93%	26.88%	131	14.45%	15.28%	16.27%	23.93%	26.88%
22	159	16.29%	17.29%	18.63%	24.75%	27.63%	158	16.30%	17.29%	18.59%	24.75%	27.62%
23	125	18.67%	19.99%	21.53%	25.56%	28.22%	125	18.63%	19.97%	21.50%	25.55%	28.21%
24	131	21.57%	23.09%	25.14%	26.16%	28.56%	132	21.53%	23.08%	25.13%	26.16%	28.56%
25	100	25.19%	27.26%	29.18%	26.52%	28.52%	100	25.19%	27.25%	29.17%	26.52%	28.52%
26	99	29.35%	31.36%	34.29%	26.48%	27.97%	99	29.34%	31.34%	34.27%	26.48%	27.98%
27	79	34.44%	37.33%	41.72%	25.85%	26.43%	79	34.42%	37.31%	41.68%	25.85%	26.44%
28	73	41.84%	46.24%	52.45%	23.95%	23.07%	73	41.81%	46.21%	52.41%	23.96%	23.09%
29	38	53.36%	59.05%	67.69%	19.80%	16.77%	38	53.32%	59.01%	67.67%	19.81%	16.78%
30	14	69.55%	77.40%	88.71%	11.85%	6.23%	14	69.53%	77.40%	88.73%	11.85%	6.22%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel B-(i): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, <u>45%</u>, 50%, 55%, 60%}

Alternative #2 model	TTC0 default probability computation across different bins						TTC1 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1174	0.00%	0.12%	0.23%	1.22%	2.59%	1654	0.00%	0.12%	0.24%	1.26%	2.75%
2	1041	0.23%	0.34%	0.46%	2.66%	4.26%	1223	0.25%	0.37%	0.51%	2.85%	4.54%
3	845	0.46%	0.59%	0.74%	3.99%	5.79%	1019	0.51%	0.65%	0.82%	4.26%	6.18%
4	821	0.74%	0.88%	1.06%	5.24%	7.27%	761	0.82%	0.98%	1.16%	5.62%	7.72%
5	625	1.06%	1.23%	1.41%	6.53%	8.68%	623	1.16%	1.34%	1.54%	6.91%	9.17%
6	516	1.41%	1.59%	1.78%	7.69%	9.98%	514	1.54%	1.74%	1.95%	8.15%	10.54%
7	456	1.78%	1.97%	2.19%	8.80%	11.24%	462	1.96%	2.17%	2.41%	9.34%	11.87%
8	426	2.19%	2.41%	2.65%	9.94%	12.51%	378	2.41%	2.64%	2.91%	10.50%	13.18%
9	391	2.65%	2.88%	3.14%	11.05%	13.73%	419	2.91%	3.19%	3.50%	11.71%	14.52%
10	340	3.15%	3.41%	3.71%	12.16%	14.99%	319	3.50%	3.81%	4.16%	12.94%	15.88%
11	389	3.72%	4.02%	4.36%	13.33%	16.26%	296	4.17%	4.52%	4.88%	14.20%	17.17%
12	299	4.37%	4.71%	5.07%	14.51%	17.49%	266	4.88%	5.25%	5.68%	15.34%	18.44%
13	253	5.09%	5.46%	5.84%	15.66%	18.67%	255	5.69%	6.12%	6.60%	16.57%	19.72%
14	260	5.84%	6.22%	6.64%	16.70%	19.78%	212	6.62%	7.12%	7.65%	17.81%	20.99%
15	230	6.65%	7.08%	7.59%	17.77%	20.93%	181	7.67%	8.20%	8.80%	18.99%	22.19%
16	239	7.61%	8.13%	8.75%	18.92%	22.14%	189	8.82%	9.40%	10.02%	20.13%	23.29%
17	203	8.75%	9.37%	10.05%	20.10%	23.32%	148	10.03%	10.65%	11.34%	21.16%	24.30%
18	200	10.08%	10.77%	11.50%	21.25%	24.41%	160	11.38%	12.06%	12.91%	22.16%	25.30%
19	180	11.51%	12.23%	13.05%	22.27%	25.38%	115	12.97%	13.77%	14.63%	23.18%	26.20%
20	165	13.06%	13.88%	14.77%	23.24%	26.26%	127	14.70%	15.51%	16.52%	24.03%	26.97%
21	129	14.79%	15.68%	16.75%	24.11%	27.06%	95	16.59%	17.61%	18.85%	24.86%	27.68%
22	159	16.79%	17.88%	19.35%	24.95%	27.80%	109	18.95%	20.24%	21.66%	25.62%	28.24%
23	125	19.39%	20.84%	22.54%	25.76%	28.35%	80	21.69%	23.09%	24.86%	26.16%	28.54%
24	131	22.59%	24.28%	26.55%	26.31%	28.59%	79	24.95%	26.71%	28.50%	26.50%	28.55%
25	100	26.62%	28.93%	31.07%	26.55%	28.37%	84	28.61%	30.47%	32.84%	26.52%	28.18%
26	96	31.27%	33.43%	36.53%	26.33%	27.59%	71	33.30%	36.07%	39.33%	26.03%	27.01%
27	78	36.72%	39.90%	44.21%	25.41%	25.75%	53	39.64%	42.92%	47.09%	24.77%	24.89%
28	74	44.90%	49.75%	55.88%	22.96%	21.78%	56	47.38%	51.68%	58.09%	22.36%	20.91%
29	39	56.66%	63.24%	71.56%	18.16%	14.96%	36	59.19%	65.32%	73.72%	17.30%	13.92%
30	16	72.55%	81.02%	92.00%	10.09%	4.45%	16	74.76%	83.16%	93.48%	9.02%	3.64%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel B-(ii): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	TTC2 default probability computation across different bins						TTC3 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1181	0.00%	0.11%	0.22%	1.19%	2.54%	1181	0.00%	0.11%	0.22%	1.19%	2.54%
2	1039	0.22%	0.33%	0.45%	2.61%	4.18%	1039	0.22%	0.33%	0.45%	2.61%	4.18%
3	848	0.45%	0.58%	0.72%	3.91%	5.68%	848	0.45%	0.58%	0.72%	3.92%	5.69%
4	818	0.72%	0.86%	1.03%	5.15%	7.15%	818	0.72%	0.86%	1.03%	5.15%	7.16%
5	621	1.03%	1.20%	1.37%	6.41%	8.55%	621	1.03%	1.20%	1.38%	6.42%	8.56%
6	516	1.37%	1.55%	1.74%	7.57%	9.84%	516	1.38%	1.55%	1.74%	7.58%	9.85%
7	459	1.74%	1.92%	2.14%	8.67%	11.11%	458	1.74%	1.93%	2.14%	8.68%	11.12%
8	426	2.14%	2.36%	2.59%	9.81%	12.37%	426	2.15%	2.36%	2.60%	9.83%	12.38%
9	394	2.59%	2.83%	3.09%	10.93%	13.61%	394	2.60%	2.83%	3.09%	10.94%	13.61%
10	345	3.09%	3.36%	3.66%	12.06%	14.88%	337	3.10%	3.36%	3.66%	12.06%	14.87%
11	380	3.66%	3.97%	4.30%	13.23%	16.14%	387	3.66%	3.97%	4.31%	13.23%	16.15%
12	297	4.31%	4.64%	5.02%	14.40%	17.40%	298	4.31%	4.65%	5.01%	14.41%	17.40%
13	253	5.03%	5.40%	5.78%	15.56%	18.58%	253	5.03%	5.40%	5.78%	15.57%	18.59%
14	259	5.78%	6.16%	6.59%	16.62%	19.70%	260	5.79%	6.17%	6.60%	16.63%	19.72%
15	230	6.59%	7.03%	7.55%	17.70%	20.87%	230	6.61%	7.04%	7.56%	17.72%	20.89%
16	239	7.56%	8.09%	8.72%	18.88%	22.12%	239	7.58%	8.11%	8.73%	18.89%	22.13%
17	203	8.73%	9.35%	10.05%	20.08%	23.32%	203	8.74%	9.37%	10.07%	20.10%	23.33%
18	200	10.08%	10.79%	11.53%	21.26%	24.43%	200	10.09%	10.80%	11.54%	21.28%	24.44%
19	180	11.54%	12.28%	13.12%	22.30%	25.42%	180	11.56%	12.29%	13.13%	22.31%	25.43%
20	165	13.13%	13.97%	14.89%	23.29%	26.32%	165	13.14%	13.98%	14.90%	23.30%	26.32%
21	129	14.90%	15.83%	16.92%	24.17%	27.12%	129	14.92%	15.84%	16.93%	24.18%	27.12%
22	159	16.96%	18.08%	19.59%	25.01%	27.86%	159	16.97%	18.09%	19.59%	25.02%	27.86%
23	125	19.63%	21.12%	22.86%	25.81%	28.39%	125	19.64%	21.12%	22.86%	25.81%	28.39%
24	131	22.90%	24.62%	26.93%	26.35%	28.59%	131	22.90%	24.62%	26.92%	26.35%	28.59%
25	100	26.99%	29.32%	31.47%	26.54%	28.33%	100	26.99%	29.31%	31.46%	26.55%	28.34%
26	96	31.67%	33.82%	36.89%	26.29%	27.52%	96	31.66%	33.80%	36.87%	26.29%	27.53%
27	78	37.08%	40.19%	44.41%	25.35%	25.70%	78	37.05%	40.16%	44.37%	25.36%	25.71%
28	74	45.08%	49.78%	55.73%	22.95%	21.84%	74	45.04%	49.74%	55.69%	22.96%	21.86%
29	39	56.48%	62.94%	71.19%	18.28%	15.13%	39	56.44%	62.91%	71.18%	18.29%	15.14%
30	16	72.19%	80.81%	92.02%	10.19%	4.44%	16	72.19%	80.81%	92.04%	10.19%	4.43%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel C-(i): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	TTC0 default probability computation across different bins						TTC1 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1675	0.00%	0.11%	0.24%	1.18%	2.68%	1786	0.00%	0.09%	0.19%	0.99%	2.30%
2	1174	0.24%	0.36%	0.50%	2.81%	4.50%	1206	0.19%	0.29%	0.41%	2.41%	3.92%
3	931	0.50%	0.65%	0.81%	4.25%	6.13%	997	0.41%	0.53%	0.68%	3.69%	5.50%
4	677	0.81%	0.97%	1.14%	5.57%	7.62%	804	0.68%	0.83%	1.02%	5.04%	7.11%
5	555	1.14%	1.31%	1.50%	6.80%	9.01%	685	1.02%	1.20%	1.43%	6.44%	8.75%
6	487	1.50%	1.69%	1.91%	7.99%	10.40%	582	1.43%	1.65%	1.90%	7.89%	10.38%
7	457	1.91%	2.13%	2.37%	9.23%	11.77%	481	1.91%	2.15%	2.44%	9.29%	11.96%
8	389	2.37%	2.61%	2.88%	10.43%	13.09%	434	2.44%	2.73%	3.03%	10.71%	13.46%
9	347	2.88%	3.15%	3.45%	11.63%	14.42%	335	3.03%	3.33%	3.65%	11.99%	14.86%
10	371	3.45%	3.75%	4.09%	12.83%	15.74%	261	3.65%	3.98%	4.31%	13.26%	16.15%
11	289	4.10%	4.45%	4.83%	14.07%	17.09%	257	4.31%	4.63%	4.99%	14.38%	17.36%
12	262	4.84%	5.23%	5.62%	15.31%	18.35%	221	5.00%	5.36%	5.77%	15.50%	18.57%
13	256	5.63%	6.03%	6.48%	16.45%	19.56%	203	5.77%	6.19%	6.63%	16.66%	19.76%
14	217	6.48%	6.93%	7.45%	17.59%	20.76%	174	6.64%	7.09%	7.60%	17.78%	20.93%
15	224	7.46%	7.99%	8.62%	18.77%	22.02%	160	7.62%	8.11%	8.71%	18.90%	22.11%
16	198	8.63%	9.26%	10.00%	20.01%	23.28%	188	8.73%	9.33%	10.00%	20.07%	23.28%
17	199	10.03%	10.76%	11.54%	21.24%	24.44%	145	10.01%	10.68%	11.42%	21.18%	24.35%
18	180	11.56%	12.34%	13.24%	22.34%	25.49%	160	11.47%	12.21%	13.14%	22.26%	25.44%
19	163	13.25%	14.14%	15.12%	23.38%	26.42%	115	13.22%	14.10%	15.06%	23.36%	26.39%
20	129	15.13%	16.12%	17.21%	24.29%	27.21%	127	15.14%	16.05%	17.18%	24.27%	27.20%
21	140	17.31%	18.38%	19.59%	25.11%	27.86%	95	17.26%	18.42%	19.81%	25.12%	27.91%
22	96	19.65%	20.89%	22.29%	25.76%	28.32%	109	19.92%	21.39%	23.00%	25.87%	28.40%
23	113	22.40%	23.90%	25.56%	26.27%	28.57%	80	23.03%	24.64%	26.66%	26.35%	28.59%
24	90	25.69%	27.40%	29.53%	26.53%	28.50%	79	26.76%	28.77%	30.81%	26.55%	28.40%
25	94	29.72%	31.94%	34.24%	26.44%	27.98%	84	30.93%	33.05%	35.75%	26.36%	27.73%
26	83	34.29%	36.59%	39.84%	25.96%	26.89%	60	36.27%	38.82%	41.85%	25.60%	26.40%
27	75	40.03%	43.37%	47.99%	24.67%	24.60%	52	42.13%	45.22%	50.07%	24.22%	23.91%
28	74	48.75%	53.99%	60.54%	21.60%	19.91%	65	50.29%	55.27%	61.88%	21.17%	19.34%
29	38	61.35%	67.89%	75.11%	16.21%	13.24%	38	62.78%	69.90%	77.56%	15.33%	12.02%
30	17	76.42%	84.58%	94.51%	8.30%	3.07%	17	78.89%	86.73%	95.68%	7.19%	2.42%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel C-(ii): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	TTC2 default probability computation across different bins						TTC3 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1785	0.00%	0.12%	0.25%	1.21%	2.75%	1785	0.00%	0.12%	0.25%	1.21%	2.76%
2	1202	0.25%	0.38%	0.53%	2.89%	4.64%	1202	0.25%	0.38%	0.53%	2.90%	4.65%
3	978	0.53%	0.68%	0.86%	4.38%	6.39%	978	0.53%	0.68%	0.86%	4.39%	6.40%
4	757	0.86%	1.05%	1.25%	5.87%	8.09%	757	0.87%	1.05%	1.26%	5.88%	8.10%
5	603	1.26%	1.46%	1.69%	7.30%	9.67%	603	1.26%	1.47%	1.69%	7.31%	9.68%
6	480	1.69%	1.91%	2.16%	8.64%	11.15%	480	1.69%	1.92%	2.16%	8.65%	11.17%
7	452	2.16%	2.40%	2.68%	9.93%	12.59%	452	2.16%	2.41%	2.69%	9.94%	12.61%
8	372	2.68%	2.96%	3.27%	11.21%	14.02%	372	2.69%	2.96%	3.28%	11.23%	14.04%
9	395	3.28%	3.59%	3.93%	12.52%	15.44%	395	3.28%	3.60%	3.94%	12.54%	15.45%
10	299	3.94%	4.28%	4.65%	13.79%	16.78%	299	3.95%	4.29%	4.66%	13.81%	16.80%
11	251	4.66%	5.05%	5.42%	15.04%	18.05%	251	4.68%	5.06%	5.44%	15.06%	18.07%
12	254	5.43%	5.82%	6.25%	16.17%	19.25%	254	5.45%	5.83%	6.26%	16.18%	19.27%
13	221	6.26%	6.69%	7.19%	17.30%	20.45%	221	6.27%	6.70%	7.20%	17.31%	20.47%
14	203	7.19%	7.69%	8.22%	18.45%	21.61%	203	7.21%	7.70%	8.23%	18.46%	21.62%
15	174	8.23%	8.76%	9.35%	19.54%	22.71%	174	8.25%	8.78%	9.37%	19.56%	22.73%
16	160	9.38%	9.95%	10.65%	20.60%	23.79%	159	9.39%	9.97%	10.65%	20.61%	23.79%
17	184	10.67%	11.35%	12.09%	21.67%	24.81%	184	10.66%	11.35%	12.10%	21.68%	24.81%
18	145	12.10%	12.85%	13.68%	22.65%	25.73%	146	12.11%	12.86%	13.69%	22.66%	25.74%
19	156	13.70%	14.53%	15.49%	23.57%	26.58%	156	13.72%	14.54%	15.51%	23.58%	26.58%
20	111	15.51%	16.48%	17.55%	24.44%	27.32%	111	15.52%	16.49%	17.56%	24.45%	27.32%
21	138	17.59%	18.64%	19.87%	25.19%	27.92%	138	17.60%	18.65%	19.88%	25.19%	27.92%
22	96	19.93%	21.20%	22.64%	25.83%	28.37%	96	19.94%	21.20%	22.64%	25.83%	28.37%
23	113	22.75%	24.28%	25.97%	26.31%	28.58%	113	22.75%	24.28%	25.97%	26.31%	28.58%
24	90	26.11%	27.83%	29.98%	26.54%	28.47%	90	26.10%	27.83%	29.96%	26.54%	28.47%
25	94	30.18%	32.39%	34.68%	26.41%	27.91%	94	30.16%	32.37%	34.65%	26.41%	27.92%
26	83	34.73%	37.00%	40.19%	25.90%	26.81%	83	34.70%	36.96%	40.15%	25.90%	26.82%
27	75	40.37%	43.62%	48.09%	24.61%	24.57%	75	40.33%	43.58%	48.04%	24.62%	24.59%
28	74	48.82%	53.88%	60.23%	21.64%	20.03%	74	48.77%	53.84%	60.19%	21.66%	20.05%
29	39	61.02%	67.71%	76.06%	16.28%	12.77%	39	60.99%	67.69%	76.06%	16.29%	12.77%
30	16	77.04%	84.94%	94.57%	8.11%	3.04%	16	77.04%	84.95%	94.58%	8.11%	3.03%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel D-(i): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	TTC0 default probability computation across different bins						TTC1 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1841	0.00%	0.09%	0.19%	0.95%	2.31%	2226	0.00%	0.08%	0.19%	0.90%	2.26%
2	1178	0.19%	0.30%	0.43%	2.45%	4.02%	1359	0.19%	0.29%	0.42%	2.42%	3.98%
3	956	0.43%	0.55%	0.72%	3.81%	5.69%	922	0.42%	0.55%	0.70%	3.77%	5.58%
4	756	0.72%	0.88%	1.07%	5.24%	7.35%	692	0.70%	0.85%	1.02%	5.09%	7.10%
5	610	1.08%	1.27%	1.48%	6.66%	8.96%	561	1.02%	1.19%	1.38%	6.38%	8.58%
6	487	1.49%	1.70%	1.93%	8.03%	10.48%	487	1.38%	1.58%	1.79%	7.66%	10.00%
7	437	1.94%	2.17%	2.43%	9.33%	11.93%	382	1.79%	2.00%	2.25%	8.89%	11.42%
8	365	2.43%	2.70%	3.00%	10.63%	13.40%	396	2.25%	2.49%	2.76%	10.15%	12.81%
9	395	3.01%	3.32%	3.66%	11.97%	14.87%	299	2.76%	3.03%	3.34%	11.38%	14.17%
10	299	3.66%	4.01%	4.39%	13.30%	16.30%	260	3.35%	3.66%	3.97%	12.65%	15.52%
11	252	4.40%	4.78%	5.17%	14.61%	17.64%	249	3.98%	4.30%	4.65%	13.82%	16.78%
12	252	5.17%	5.56%	6.00%	15.80%	18.90%	219	4.66%	5.02%	5.44%	14.99%	18.07%
13	221	6.01%	6.45%	6.95%	16.99%	20.17%	203	5.45%	5.87%	6.33%	16.23%	19.37%
14	203	6.96%	7.47%	8.02%	18.21%	21.39%	171	6.34%	6.80%	7.32%	17.44%	20.61%
15	174	8.03%	8.58%	9.19%	19.37%	22.57%	160	7.34%	7.87%	8.50%	18.64%	21.90%
16	160	9.22%	9.82%	10.54%	20.49%	23.71%	189	8.52%	9.17%	9.89%	19.92%	23.18%
17	186	10.57%	11.28%	12.08%	21.63%	24.80%	144	9.91%	10.61%	11.40%	21.13%	24.34%
18	147	12.09%	12.89%	13.77%	22.68%	25.78%	160	11.46%	12.27%	13.29%	22.29%	25.52%
19	160	13.83%	14.70%	15.80%	23.66%	26.70%	115	13.37%	14.34%	15.40%	23.48%	26.54%
20	115	15.88%	16.90%	18.00%	24.60%	27.45%	127	15.49%	16.49%	17.75%	24.44%	27.38%
21	127	18.10%	19.12%	20.40%	25.33%	28.03%	95	17.83%	19.13%	20.69%	25.33%	28.08%
22	96	20.49%	21.80%	23.45%	25.95%	28.45%	109	20.81%	22.46%	24.28%	26.06%	28.51%
23	112	23.49%	25.13%	26.97%	26.39%	28.59%	80	24.31%	26.12%	28.40%	26.47%	28.55%
24	90	27.11%	29.01%	31.38%	26.55%	28.34%	79	28.52%	30.78%	33.09%	26.51%	28.14%
25	94	31.60%	34.06%	36.61%	26.27%	27.58%	84	33.23%	35.61%	38.64%	26.09%	27.16%
26	83	36.66%	39.20%	42.79%	25.53%	26.15%	60	39.23%	42.07%	45.45%	24.96%	25.39%
27	75	42.99%	46.64%	51.65%	23.84%	23.36%	52	45.75%	49.14%	54.43%	23.14%	22.34%
28	74	52.47%	58.04%	64.90%	20.17%	18.03%	65	54.66%	59.94%	66.83%	19.46%	17.16%
29	38	65.73%	72.31%	79.40%	14.24%	11.10%	38	67.74%	74.75%	82.07%	13.11%	9.73%
30	17	80.63%	87.94%	96.28%	6.56%	2.09%	17	83.28%	89.99%	97.17%	5.48%	1.59%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel D-(ii): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	TTC2 default probability computation across different bins						TTC3 default probability computation across different bins					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	1847	0.00%	0.08%	0.18%	0.93%	2.24%	1847	0.00%	0.08%	0.18%	0.93%	2.25%
2	1176	0.18%	0.29%	0.41%	2.38%	3.91%	1176	0.18%	0.29%	0.41%	2.38%	3.92%
3	952	0.41%	0.53%	0.69%	3.70%	5.54%	952	0.41%	0.53%	0.69%	3.71%	5.55%
4	756	0.69%	0.85%	1.03%	5.10%	7.18%	756	0.69%	0.85%	1.04%	5.11%	7.19%
5	610	1.04%	1.22%	1.43%	6.50%	8.77%	610	1.04%	1.23%	1.44%	6.51%	8.78%
6	487	1.43%	1.64%	1.87%	7.85%	10.28%	487	1.44%	1.65%	1.88%	7.87%	10.30%
7	437	1.87%	2.10%	2.36%	9.15%	11.73%	437	1.88%	2.11%	2.36%	9.17%	11.75%
8	365	2.36%	2.62%	2.92%	10.44%	13.20%	365	2.37%	2.63%	2.93%	10.46%	13.22%
9	395	2.93%	3.23%	3.57%	11.80%	14.69%	395	2.94%	3.24%	3.58%	11.82%	14.71%
10	299	3.57%	3.92%	4.30%	13.14%	16.13%	299	3.58%	3.93%	4.31%	13.16%	16.15%
11	252	4.31%	4.69%	5.08%	14.47%	17.50%	252	4.32%	4.70%	5.09%	14.49%	17.52%
12	252	5.08%	5.47%	5.91%	15.67%	18.78%	252	5.10%	5.49%	5.92%	15.69%	18.80%
13	221	5.92%	6.37%	6.88%	16.89%	20.08%	221	5.94%	6.38%	6.90%	16.91%	20.10%
14	203	6.89%	7.40%	7.96%	18.14%	21.34%	203	6.90%	7.42%	7.98%	18.15%	21.35%
15	174	7.98%	8.54%	9.17%	19.33%	22.54%	174	7.99%	8.56%	9.18%	19.34%	22.56%
16	160	9.19%	9.81%	10.55%	20.48%	23.72%	160	9.21%	9.83%	10.57%	20.50%	23.73%
17	186	10.58%	11.32%	12.14%	21.65%	24.83%	186	10.60%	11.33%	12.15%	21.67%	24.85%
18	147	12.15%	12.97%	13.89%	22.73%	25.84%	147	12.17%	12.99%	13.90%	22.74%	25.84%
19	160	13.95%	14.85%	15.98%	23.73%	26.77%	160	13.97%	14.87%	16.00%	23.74%	26.78%
20	115	16.07%	17.13%	18.27%	24.69%	27.53%	115	16.09%	17.14%	18.28%	24.69%	27.53%
21	127	18.37%	19.43%	20.75%	25.41%	28.09%	127	18.38%	19.44%	20.75%	25.41%	28.09%
22	96	20.84%	22.19%	23.88%	26.02%	28.48%	96	20.84%	22.19%	23.88%	26.02%	28.48%
23	112	23.92%	25.59%	27.46%	26.43%	28.58%	112	23.92%	25.59%	27.45%	26.43%	28.58%
24	90	27.61%	29.52%	31.90%	26.54%	28.29%	90	27.60%	29.51%	31.88%	26.54%	28.29%
25	93	32.12%	34.53%	37.03%	26.22%	27.49%	93	32.10%	34.50%	37.00%	26.22%	27.50%
26	84	37.08%	39.58%	43.09%	25.46%	26.07%	84	37.04%	39.54%	43.04%	25.47%	26.08%
27	75	43.29%	46.81%	51.61%	23.80%	23.37%	75	43.24%	46.75%	51.56%	23.82%	23.39%
28	74	52.40%	57.77%	64.45%	20.27%	18.22%	74	52.34%	57.73%	64.42%	20.29%	18.24%
29	38	65.27%	71.86%	79.06%	14.45%	11.27%	38	65.24%	71.85%	79.07%	14.45%	11.27%
30	17	80.33%	87.84%	96.35%	6.61%	2.05%	17	80.34%	87.85%	96.36%	6.61%	2.05%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel E-(i): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, <u>60%</u>}

Alternative #2 model	**TTC0 default probability computation across different bins**						**TTC1 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	2019	0.00%	0.06%	0.15%	0.76%	1.96%	2025	0.00%	0.04%	0.11%	0.58%	1.53%
2	1179	0.15%	0.24%	0.35%	2.10%	3.50%	1187	0.11%	0.17%	0.25%	1.63%	2.77%
3	873	0.35%	0.45%	0.59%	3.31%	4.98%	880	0.25%	0.33%	0.42%	2.61%	3.99%
4	700	0.59%	0.72%	0.88%	4.57%	6.49%	689	0.42%	0.52%	0.63%	3.63%	5.25%
5	579	0.88%	1.05%	1.23%	5.87%	8.01%	589	0.64%	0.75%	0.89%	4.71%	6.53%
6	475	1.23%	1.42%	1.63%	7.17%	9.48%	464	0.89%	1.03%	1.18%	5.80%	7.79%
7	423	1.63%	1.84%	2.07%	8.44%	10.90%	421	1.18%	1.33%	1.50%	6.88%	9.03%
8	338	2.07%	2.30%	2.55%	9.67%	12.25%	334	1.51%	1.67%	1.86%	7.95%	10.24%
9	313	2.55%	2.80%	3.05%	10.87%	13.52%	310	1.86%	2.05%	2.23%	9.00%	11.37%
10	269	3.06%	3.30%	3.60%	11.95%	14.74%	269	2.24%	2.42%	2.65%	9.97%	12.51%
11	232	3.60%	3.89%	4.23%	13.09%	16.02%	232	2.65%	2.88%	3.14%	11.03%	13.73%
12	234	4.24%	4.58%	4.95%	14.30%	17.29%	234	3.15%	3.41%	3.70%	12.17%	14.96%
13	234	4.96%	5.33%	5.75%	15.47%	18.54%	235	3.71%	4.00%	4.35%	13.30%	16.22%
14	196	5.76%	6.19%	6.68%	16.66%	19.83%	195	4.35%	4.69%	5.09%	14.48%	17.52%
15	196	6.70%	7.18%	7.74%	17.88%	21.10%	200	5.10%	5.51%	5.98%	15.73%	18.87%
16	166	7.75%	8.31%	8.92%	19.10%	22.31%	165	5.98%	6.45%	6.99%	17.00%	20.21%
17	160	8.95%	9.59%	10.35%	20.29%	23.56%	159	7.01%	7.54%	8.21%	18.29%	21.60%
18	188	10.38%	11.15%	12.01%	21.53%	24.75%	187	8.22%	8.89%	9.65%	19.66%	22.97%
19	145	12.02%	12.88%	13.82%	22.67%	25.80%	144	9.67%	10.42%	11.27%	20.98%	24.25%
20	160	13.88%	14.83%	16.02%	23.72%	26.79%	160	11.33%	12.20%	13.31%	22.25%	25.53%
21	115	16.11%	17.23%	18.43%	24.72%	27.57%	115	13.40%	14.45%	15.61%	23.54%	26.63%
22	127	18.53%	19.66%	21.07%	25.47%	28.15%	139	15.71%	16.95%	18.56%	24.62%	27.61%
23	96	21.16%	22.61%	24.43%	26.09%	28.52%	100	18.61%	20.25%	22.06%	25.62%	28.29%
24	112	24.47%	26.29%	28.32%	26.48%	28.56%	105	22.20%	24.03%	26.26%	26.28%	28.59%
25	90	28.48%	30.59%	33.20%	26.51%	28.13%	86	26.32%	28.54%	31.41%	26.55%	28.34%
26	97	33.45%	36.26%	39.19%	26.00%	27.04%	91	31.59%	34.50%	37.53%	26.22%	27.40%
27	87	39.37%	42.26%	46.18%	24.92%	25.17%	81	37.66%	40.74%	45.14%	25.24%	25.48%
28	75	46.61%	50.91%	57.06%	22.61%	21.32%	75	45.40%	49.95%	56.14%	22.90%	21.68%
29	78	57.51%	63.89%	73.13%	17.89%	14.21%	77	57.14%	64.10%	73.13%	17.81%	14.21%
30	44	73.73%	83.14%	97.56%	9.03%	1.38%	52	74.27%	83.98%	98.21%	8.60%	1.01%

Table 7: Alternative #2 TTC0, TTC1, TTC2, and TTC3 PD, VaR, and ConVaR algorithmic segmentation

We run the k-means clustering algorithm to establish the optimally chosen 30 default probability segments. This algorithmic segmentation accords with the spirit of the Basel Final Rule that the through-the-cycle default probability needs to be the bank's empirically based best estimate of the long-term average of one-year default rates for the risky asset exposures in the corresponding homogeneous risk segment. For the k-means clustering algorithm, we set the maximum number of iterations at 100 to ensure that the global convergence criterion is met. The k-means clustering algorithm optimizes the Calinski-Harabasz ratio of inter-group to intra-group variance. The optimal k-means algorithmic segmentation chooses the centroids for different default probability segments such that all of the centroids are sufficiently far apart from one another while each centroid attracts numerous default probability estimates with reasonably close proximity. This algorithmic segmentation allows us to gauge the baseline and alternative TTC bank capital requirements or equity capital ratios across the optimally chosen 30 default probability segments. For better clarity, we report the asset count, the minimum, average, and maximum default probabilities, as well as the value-at-risk and conditional value-at-risk bank capital requirements for each k-means segment.

Panel E-(ii): Parameter permutations with ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

Alternative #2 model	**TTC2 default probability computation across different bins**						**TTC3 default probability computation across different bins**					
K-means segment	Count	Minimum	Mean	Maximum	VaR	ConVaR	Count	Minimum	Mean	Maximum	VaR	ConVaR
1	2322	0.00%	0.07%	0.18%	0.85%	2.25%	2322	0.00%	0.07%	0.19%	0.86%	2.25%
2	1334	0.19%	0.30%	0.43%	2.44%	4.07%	1334	0.19%	0.30%	0.43%	2.44%	4.08%
3	888	0.43%	0.57%	0.73%	3.89%	5.77%	888	0.44%	0.57%	0.74%	3.90%	5.78%
4	662	0.74%	0.90%	1.09%	5.30%	7.40%	662	0.74%	0.90%	1.09%	5.32%	7.42%
5	535	1.09%	1.27%	1.49%	6.68%	8.96%	535	1.09%	1.28%	1.49%	6.69%	8.98%
6	449	1.49%	1.70%	1.93%	8.03%	10.46%	449	1.50%	1.71%	1.93%	8.04%	10.48%
7	367	1.93%	2.16%	2.42%	9.31%	11.90%	367	1.94%	2.17%	2.43%	9.33%	11.92%
8	333	2.42%	2.68%	2.93%	10.59%	13.23%	333	2.43%	2.69%	2.94%	10.61%	13.25%
9	277	2.94%	3.19%	3.48%	11.72%	14.50%	277	2.95%	3.20%	3.50%	11.74%	14.52%
10	233	3.49%	3.79%	4.13%	12.90%	15.82%	233	3.50%	3.80%	4.14%	12.92%	15.84%
11	234	4.14%	4.47%	4.85%	14.12%	17.11%	234	4.15%	4.49%	4.86%	14.14%	17.14%
12	234	4.85%	5.23%	5.65%	15.31%	18.39%	234	4.87%	5.24%	5.67%	15.33%	18.42%
13	196	5.66%	6.09%	6.59%	16.54%	19.71%	196	5.68%	6.11%	6.61%	16.56%	19.73%
14	196	6.61%	7.10%	7.67%	17.79%	21.02%	196	6.63%	7.12%	7.69%	17.81%	21.04%
15	166	7.68%	8.25%	8.88%	19.04%	22.28%	166	7.70%	8.27%	8.90%	19.06%	22.29%
16	160	8.91%	9.57%	10.36%	20.27%	23.56%	160	8.93%	9.59%	10.38%	20.29%	23.58%
17	188	10.39%	11.18%	12.07%	21.56%	24.79%	188	10.41%	11.21%	12.09%	21.57%	24.81%
18	145	12.08%	12.98%	13.95%	22.73%	25.87%	145	12.11%	13.00%	13.97%	22.74%	25.88%
19	160	14.02%	15.00%	16.24%	23.80%	26.87%	160	14.04%	15.02%	16.26%	23.81%	26.88%
20	115	16.34%	17.50%	18.75%	24.82%	27.66%	115	16.36%	17.52%	18.77%	24.83%	27.66%
21	127	18.86%	20.03%	21.49%	25.57%	28.21%	127	18.87%	20.04%	21.50%	25.57%	28.21%
22	96	21.59%	23.08%	24.95%	26.16%	28.55%	96	21.60%	23.08%	24.95%	26.16%	28.55%
23	112	25.00%	26.85%	28.91%	26.51%	28.53%	112	25.00%	26.84%	28.90%	26.51%	28.53%
24	90	29.08%	31.19%	33.80%	26.49%	28.05%	90	29.06%	31.17%	33.77%	26.49%	28.05%
25	93	34.04%	36.68%	39.42%	25.94%	26.99%	93	34.01%	36.65%	39.37%	25.95%	27.00%
26	84	39.46%	42.18%	45.98%	24.94%	25.23%	84	39.42%	42.13%	45.92%	24.95%	25.25%
27	75	46.19%	49.96%	55.09%	22.90%	22.09%	75	46.13%	49.90%	55.04%	22.91%	22.11%
28	74	55.93%	61.59%	68.55%	18.82%	16.37%	73	55.87%	61.45%	67.89%	18.87%	16.68%
29	38	69.39%	75.99%	83.00%	12.53%	9.25%	37	68.53%	75.41%	81.80%	12.80%	9.87%
30	17	84.18%	90.73%	97.63%	5.09%	1.34%	19	82.82%	89.92%	97.63%	5.52%	1.33%

Table 8: Alternative #2 value-at-risk and conditional value-at-risk capital requirements

This table lists the asset-equivalent weighted-average value-at-risk and conditional value-at-risk bank capital requirements or equity capital ratios for the alternative permutations of TTC adjustments (TTC0, TTC1, TTC2, and TTC3) and idiosyncratic risk correlation values (from 40% to 60% in increments of 5%). Across the value-at-risk and conditional value-at-risk panels, the TTC1 adjustments consistently introduce non-trivial downward biases in the asset-equivalent weighted-average equity capital ratios relative to the TTC0 brute-force adjustments and the TTC2/TTC3 higher-order Taylor-series approximations. The more accurate TTC0, TTC2, and TTC3 asset-equivalent weighted-average value-at-risk and conditional value-at-risk bank equity capital ratios land in the intermediate range of 8% to 13% across the wide spectrum of idiosyncratic risk correlation values. The quantitative results that favor the recent proposal for substantially heighted bank capital requirements indicates first-order discrepancies between these alternative equity capital ratios and the newly introduced Basel equity capital ratio of 3% to 6% when the prudent econometrician raises the asset correlation value to 35% to account for default contagion in times of severe financial stress. The evidence resonates with the central thesis that the typical bank should hold a much larger capital cushion to absorb extreme losses in a financial downturn.

Alternative equity capital	ξ=40%	ξ=45%	ξ=50%	ξ=55%	ξ=60%
Value-at-risk capital					
TTC0	10.78%	10.27%	9.74%	9.22%	8.68%
TTC1	9.77%	9.27%	8.73%	8.21%	7.66%
TTC2	10.71%	10.20%	9.66%	9.13%	8.59%
TTC3	10.72%	10.21%	9.67%	9.14%	8.60%
Conditional value-at-risk capital					
TTC0	13.08%	12.48%	11.92%	11.33%	10.61%
TTC1	11.98%	11.46%	10.83%	10.22%	9.39%
TTC2	13.00%	12.40%	11.87%	11.22%	10.62%
TTC3	13.01%	12.41%	11.88%	11.23%	10.64%

Figure 1: Systematic risk factor and its observable macroeconomic and sector-specific components

This chart shows the time-series plots of both the systematic risk factor and its observable and unobservable components over 1,000 annual cohorts. The systematic risk factor moves in tandem with the joint gyrations in the observable and unobservable components. The vast majority of the systematic, macroeconomic, and sector-specific risk factors land within the 95% confidence interval around zero. Only the first of these latter random variables, the observable part of systematic risk serves as one of the explanatory variables in the logit regression model of default likelihood. This observable variable is a linear combination of systematic macro fluctuations such as GDP growth, unemployment, house price variation, and so forth. The other explanatory variable is the observable component of idiosyncratic risk that represents a linear combination of asset-specific attributes such as FICO, loan-to-value, debt-to-income, and so forth. In brief, these observable variables help develop a reasonably accurate logistic default probability model for the subsequent value-at-risk and conditional value-at-risk equity capital analysis.

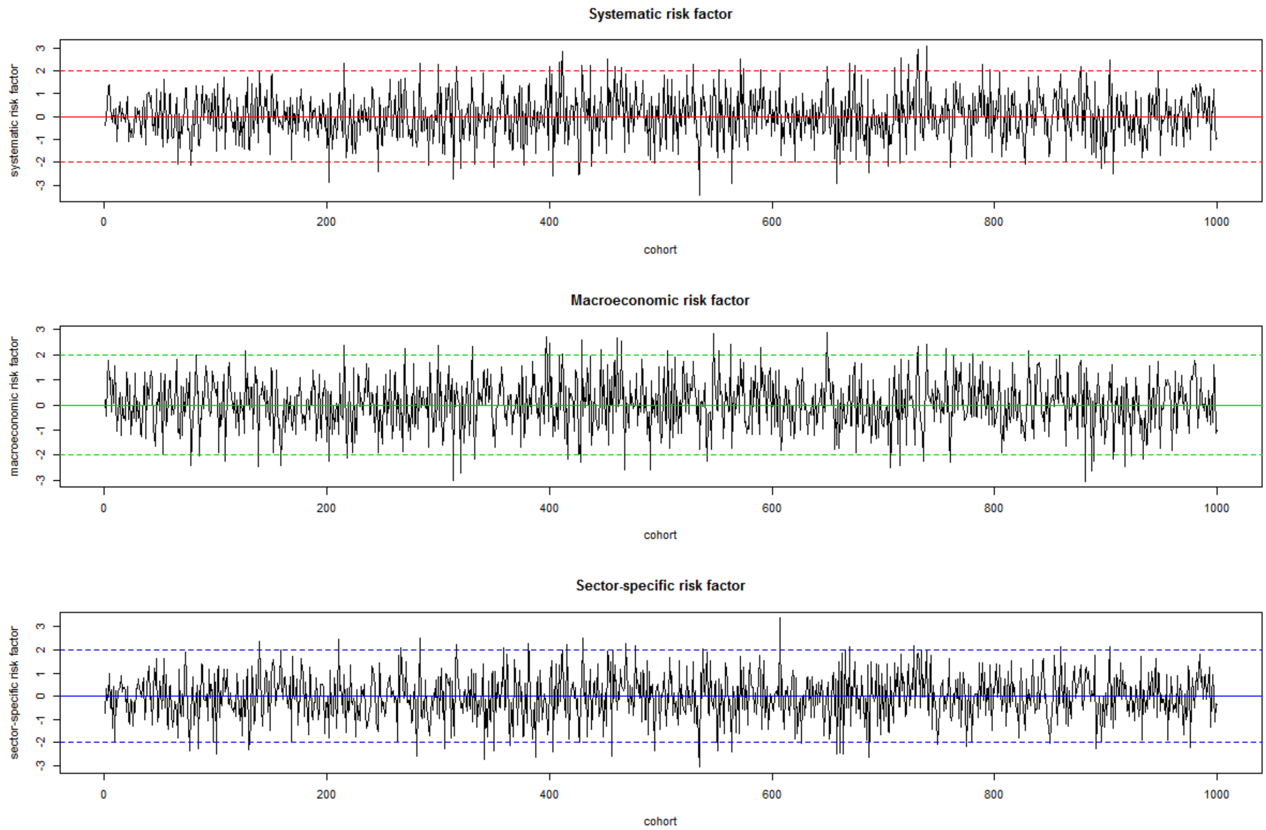


Figure 2: Stereoscopic visualization of default probability, confidence level, and value-at-risk equity capital

This chart provides the stereoscopic visualization of default probability (PD), confidence level (α), and value-at-risk equity capital (κ). The value-at-risk or conditional value-at-risk bank equity capital ratio is a highly non-linear quasi-concave function of default likelihood. At a given confidence level, the equity capital ratio first increases with PD up to some intermediate threshold and then decreases with PD. This watershed appears to be between 25% and 40%. This non-linear trend highlights an important part of the equity capital formula: the equity capital cushion covers only the large financial losses above and beyond the average loss, the latter of which simply equates PD times LGD. Therefore, the equity capital ratio first increases with PD as the marginal increase in financial risk exposure incurs large losses that in turn outweigh the average reserve for asset impairment. As PD increases, the likely loss severity declines up to some point at which the sum of additional losses is equal to the average loss provision. When PD rises above this watershed, the average loss provision more than fully offsets any marginal loss. In this latter case, the equity capital requirement decreases as the asset exposures exhibit much greater default likelihood in the highest PD segments. The conditional value-at-risk capital surface consistently embeds an overlay on top of the value-at-risk capital surface. The former exhibits a faster speed of capital deterioration than the latter in the right tail of the PD spectrum. Hence, the conditional value-at-risk equity capital requirement typically exceeds the value-at-risk equity capital requirement up to some PD threshold while the former declines more quickly than the latter beyond this PD threshold.

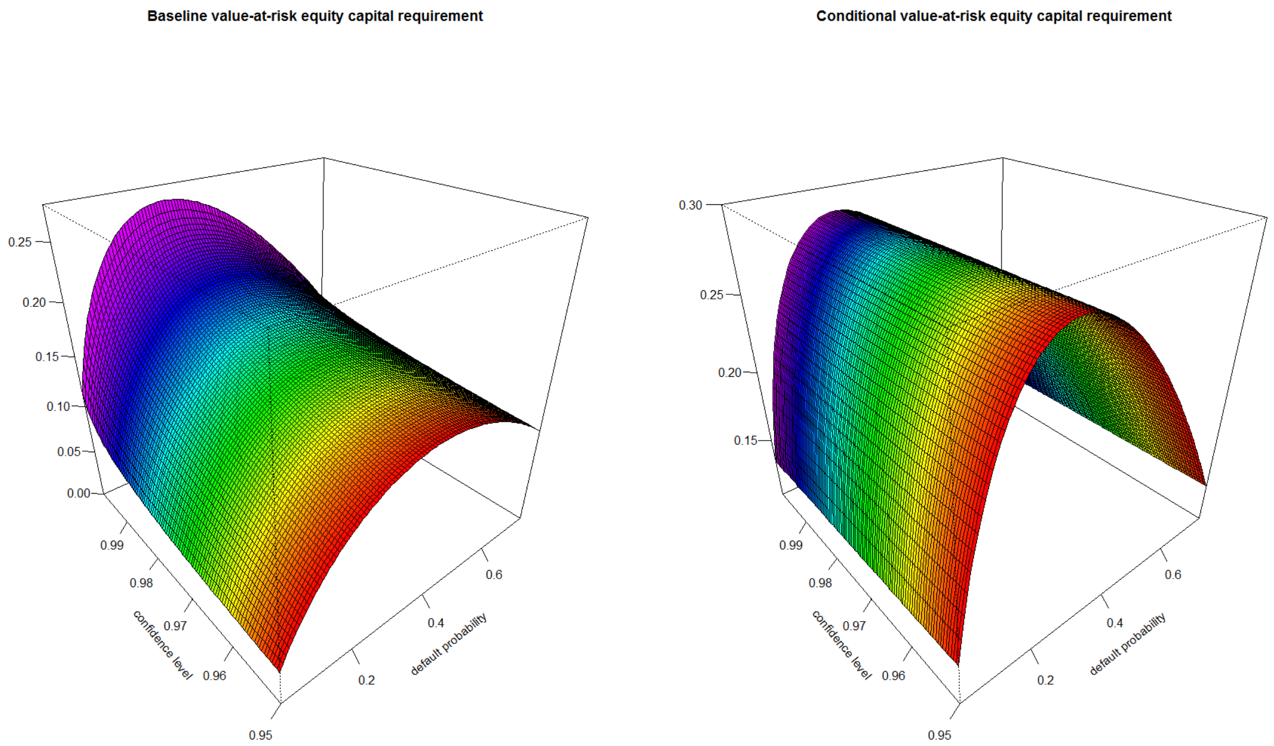


Figure 3: A time-series comparison of baseline TTC0, TTC1, TTC2, and TTC3 PDs

This chart encapsulates the point-in-time PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. Panels A to E show the information for the different asset correlation permutations ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%. Within each panel, the left-hand side displays the TTC0 PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. The long-term average TTC1 PD is less than the long-term average TTC0, TTC2, and TTC3 PDs by an order of magnitude. For instance, the baseline set of risk parameters {ρ, φ, ξ}={15%, 50%, 50%} yields the long-run average TTC0, TTC2, and TTC3 PDs near 5.30%, whereas, the long-run average TTC1 PD is no greater than 4.65%. Thus, the TTC1 method substantially underestimates the TTC0 PD and equity capital results that better accord with the spirit of the Basel TTC regulatory requirement. The right-hand side of each panel magnifies the fine neighborhood of the long-run average TTC0, TTC2, and TTC3 PDs. In particular, the long-run average TTC3 PD better approximates the long-run average TTC0 PD than the TTC2 counterpart. At any rate, the TTC2 and TTC3 PD approximations are both sufficiently close to the TTC0 origin. Our subsequent analysis suggests that these higher-order approximations are accurate enough for the equity capital differences to be reasonably minimal.

Panel A: Baseline TTC PD computation ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

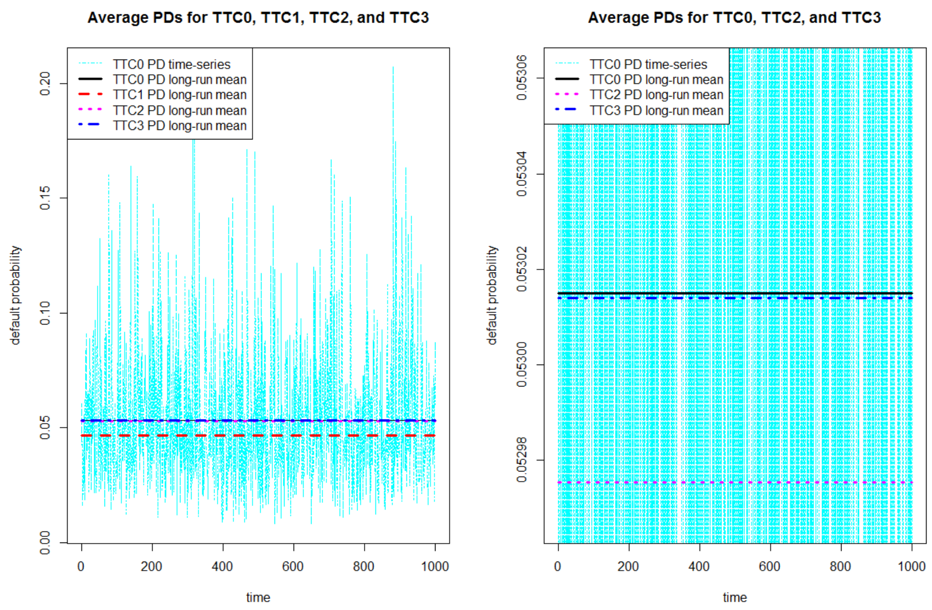
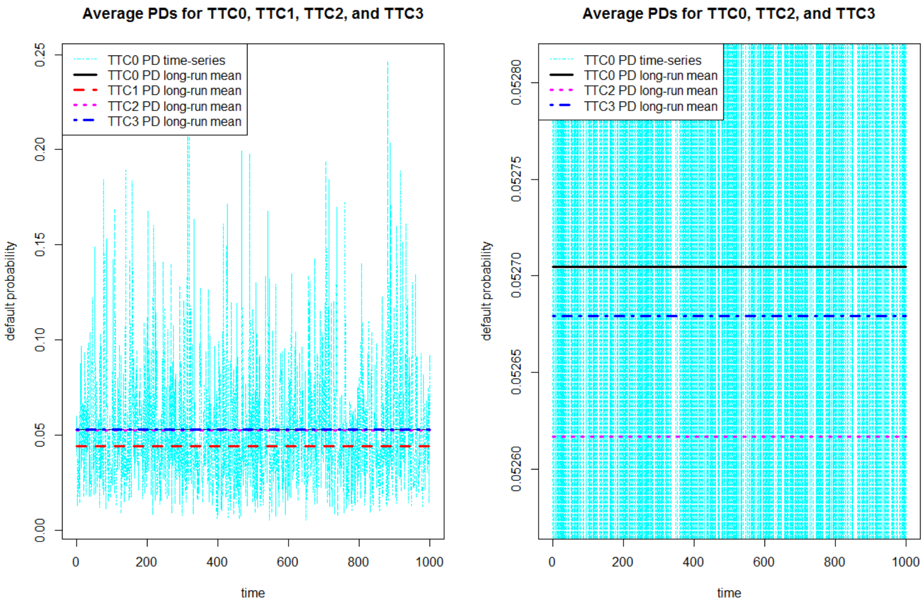


Figure 3: A time-series comparison of TTC0, TTC1, TTC2, and TTC3 PDs

Panel B: Baseline TTC PD computation ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%



Panel C: Baseline TTC PD computation ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

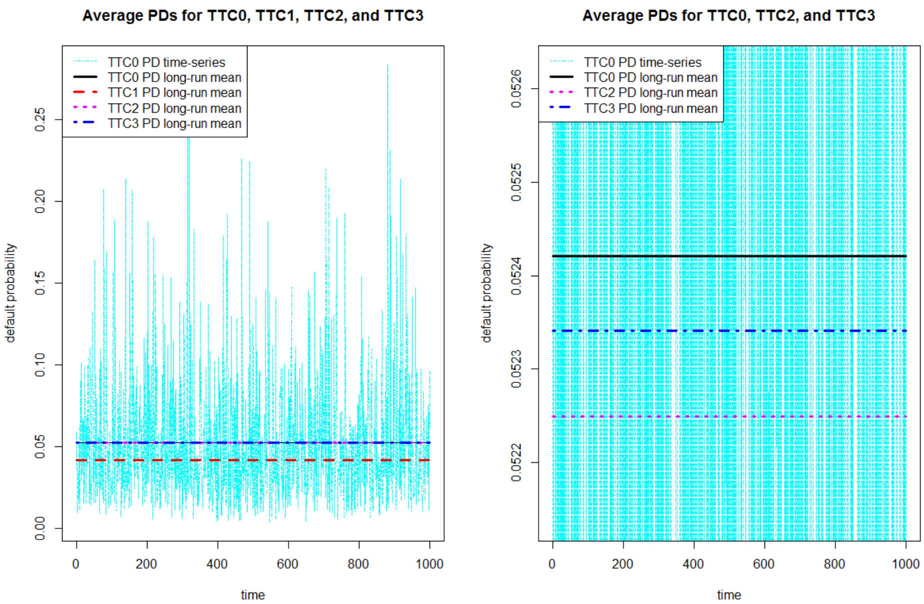
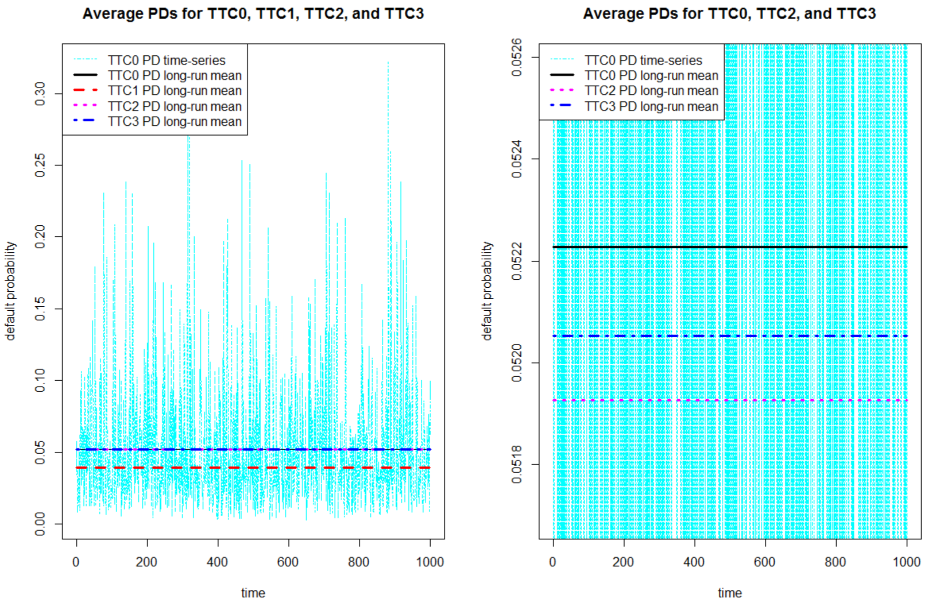


Figure 3: A time-series comparison of baseline TTC0, TTC1, TTC2, and TTC3 PDs

Panel D: Baseline TTC PD computation ρ={15%, 20%, 25%, <u>30%</u>, 35%}, φ=50%, and ξ=50%



Panel E: Baseline TTC PD computation ρ={15%, 20%, 25%, 30%, <u>35%</u>}, φ=50%, and ξ=50%

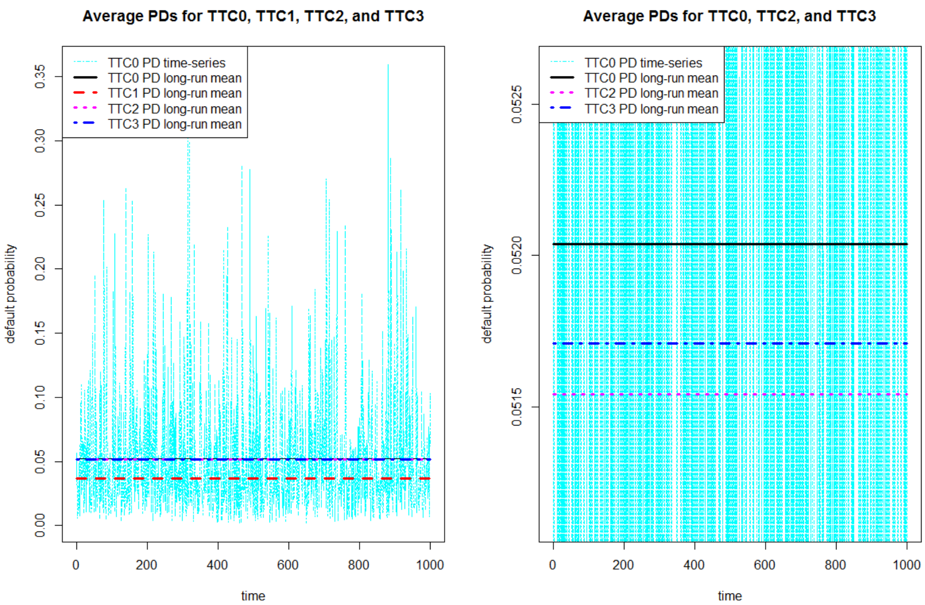


Figure 4-(a): Baseline TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ={15%, 20%, 25%, 30%, 35%}, φ=50%, and ξ=50%

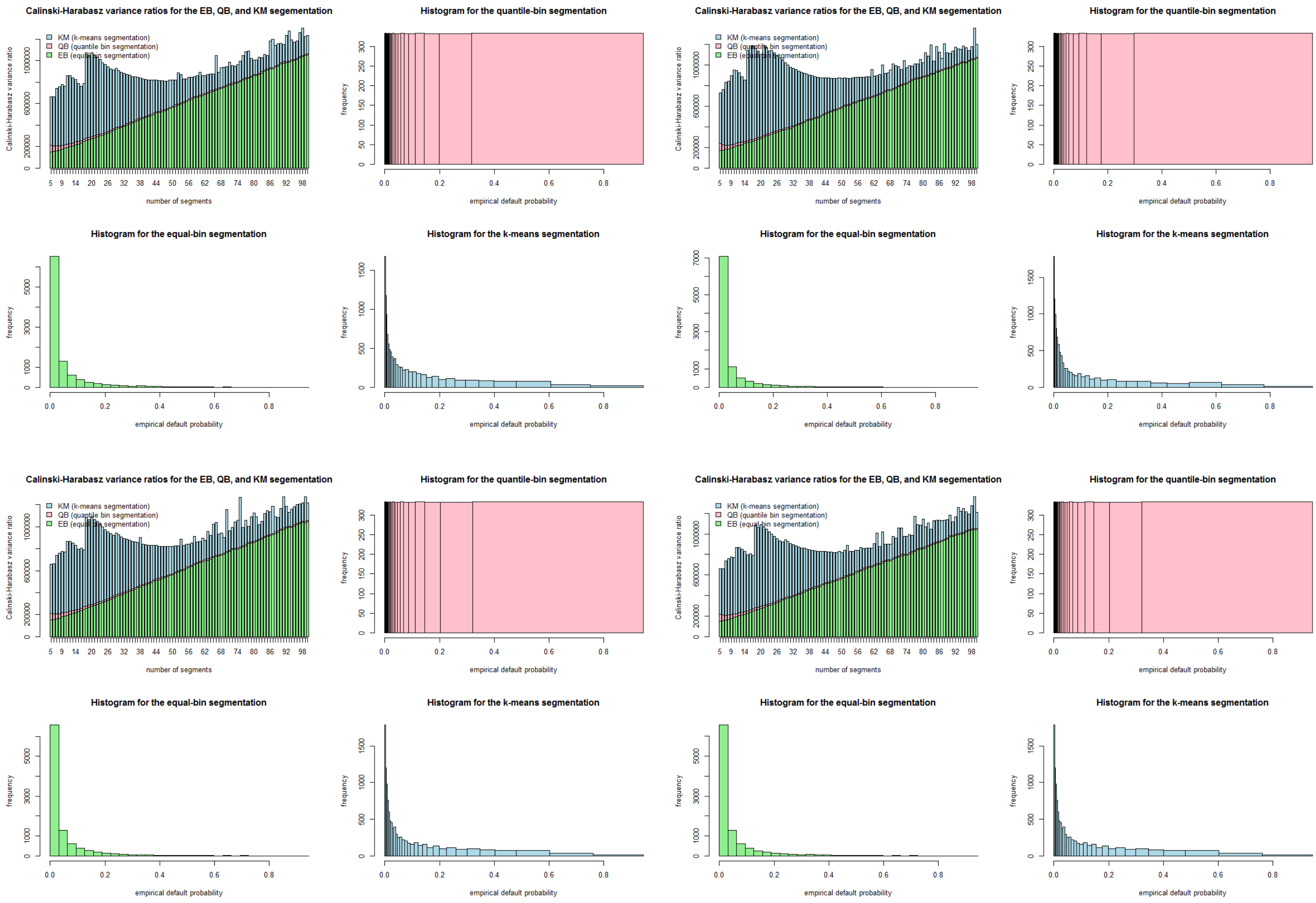


Figure 4-(b): Baseline TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ={15%, <u>20%</u>, 25%, 30%, 35%}, φ=50%, and ξ=50%

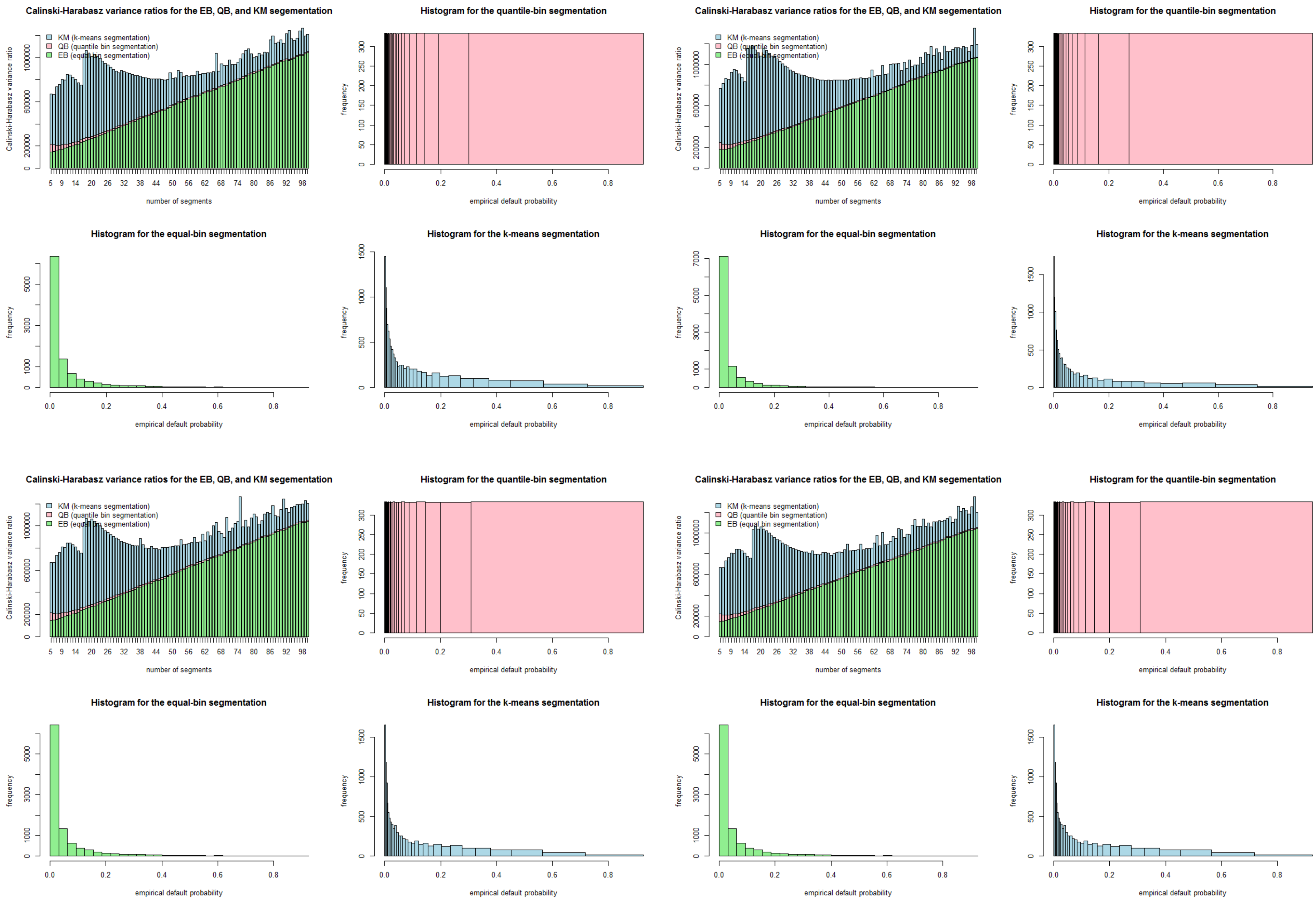


Figure 4-(c): Baseline TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ={15%, 20%, <u>25%</u>, 30%, 35%}, φ=50%, and ξ=50%

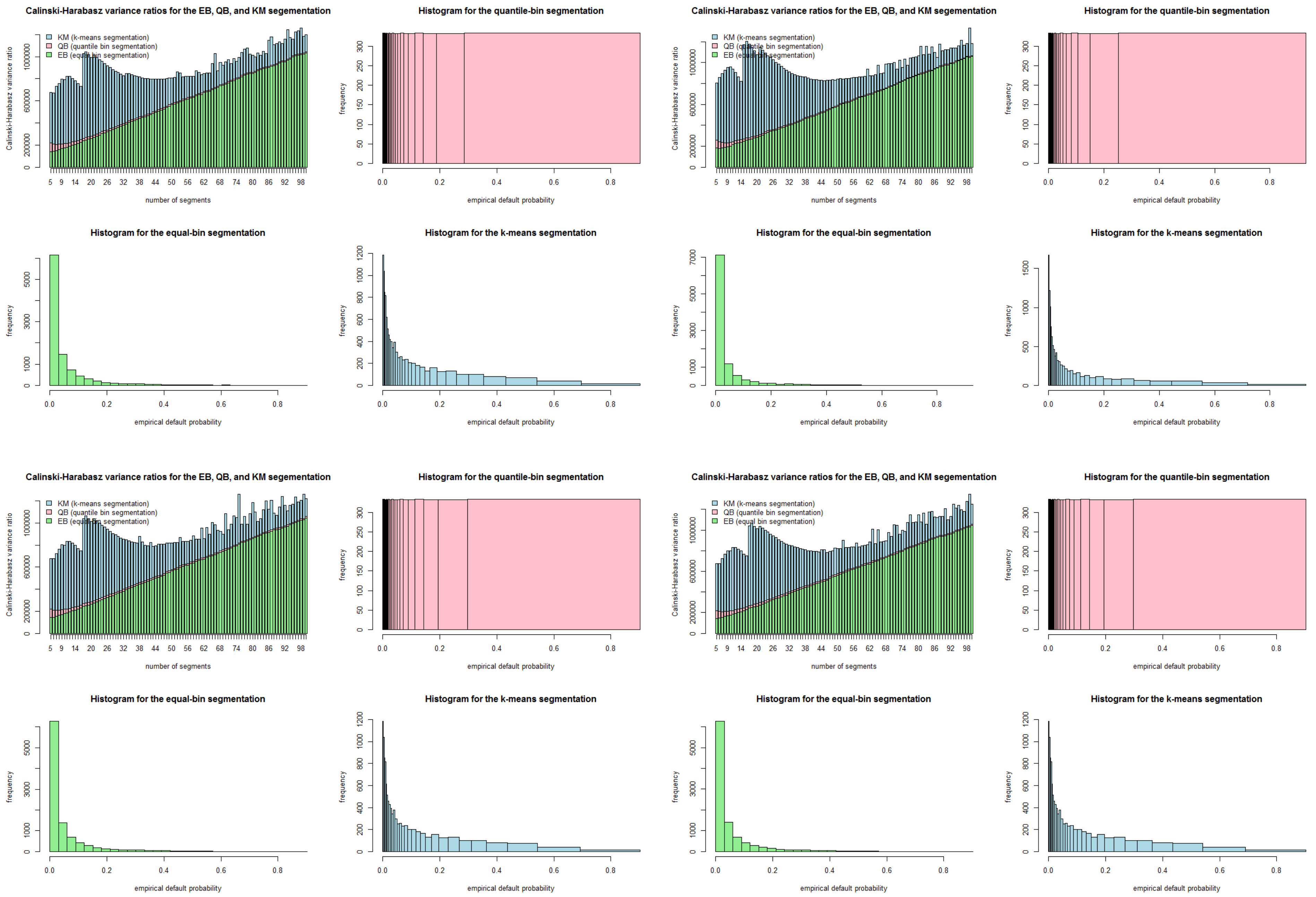


Figure 4-(d): Baseline TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ={15%, 20%, 25%, <u>30%</u>, 35%}, φ=50%, and ξ=50%

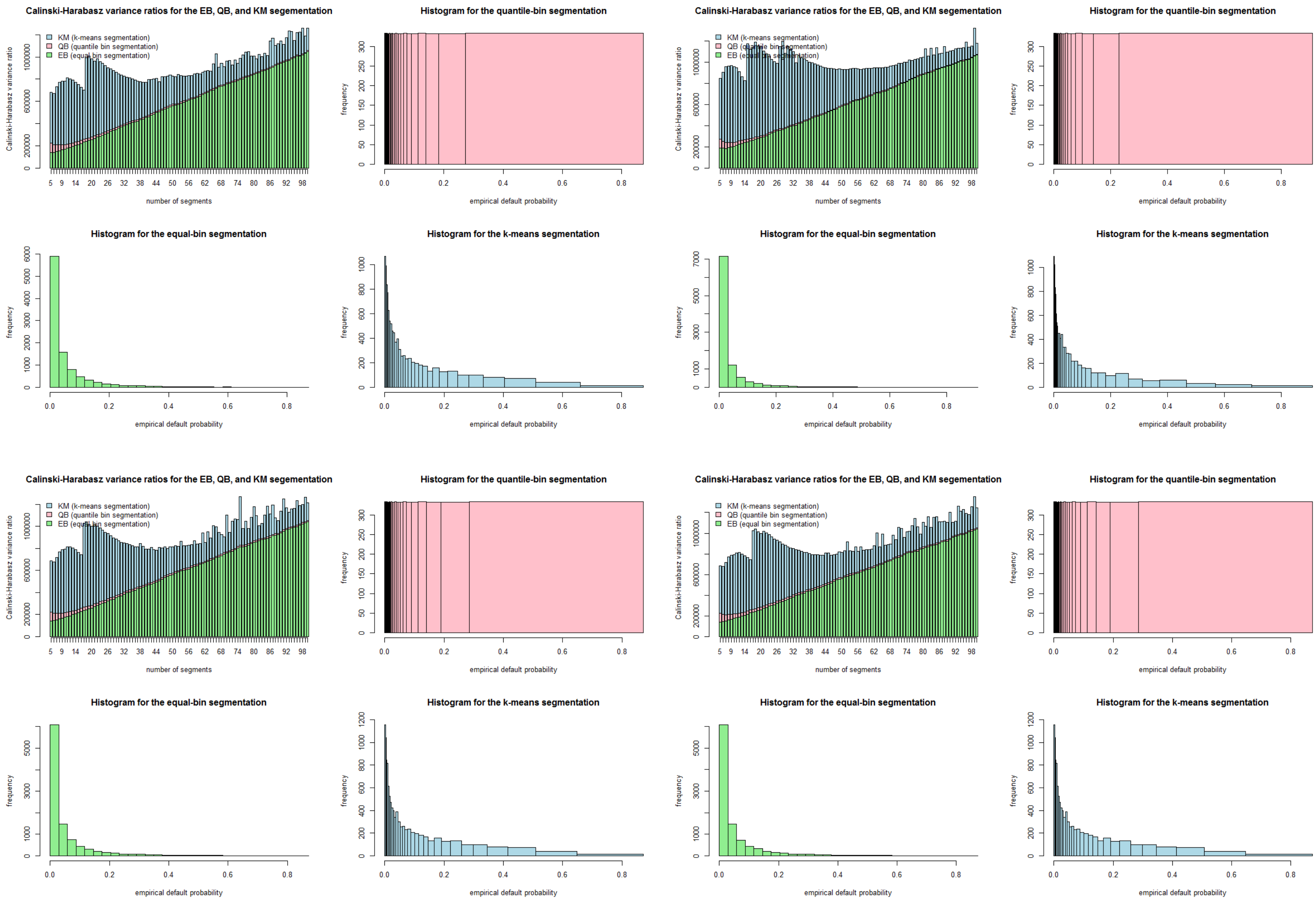


Figure 4-(e): Baseline TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ={15%, 20%, 25%, 30%, <u>35%</u>}, φ=50%, and ξ=50%

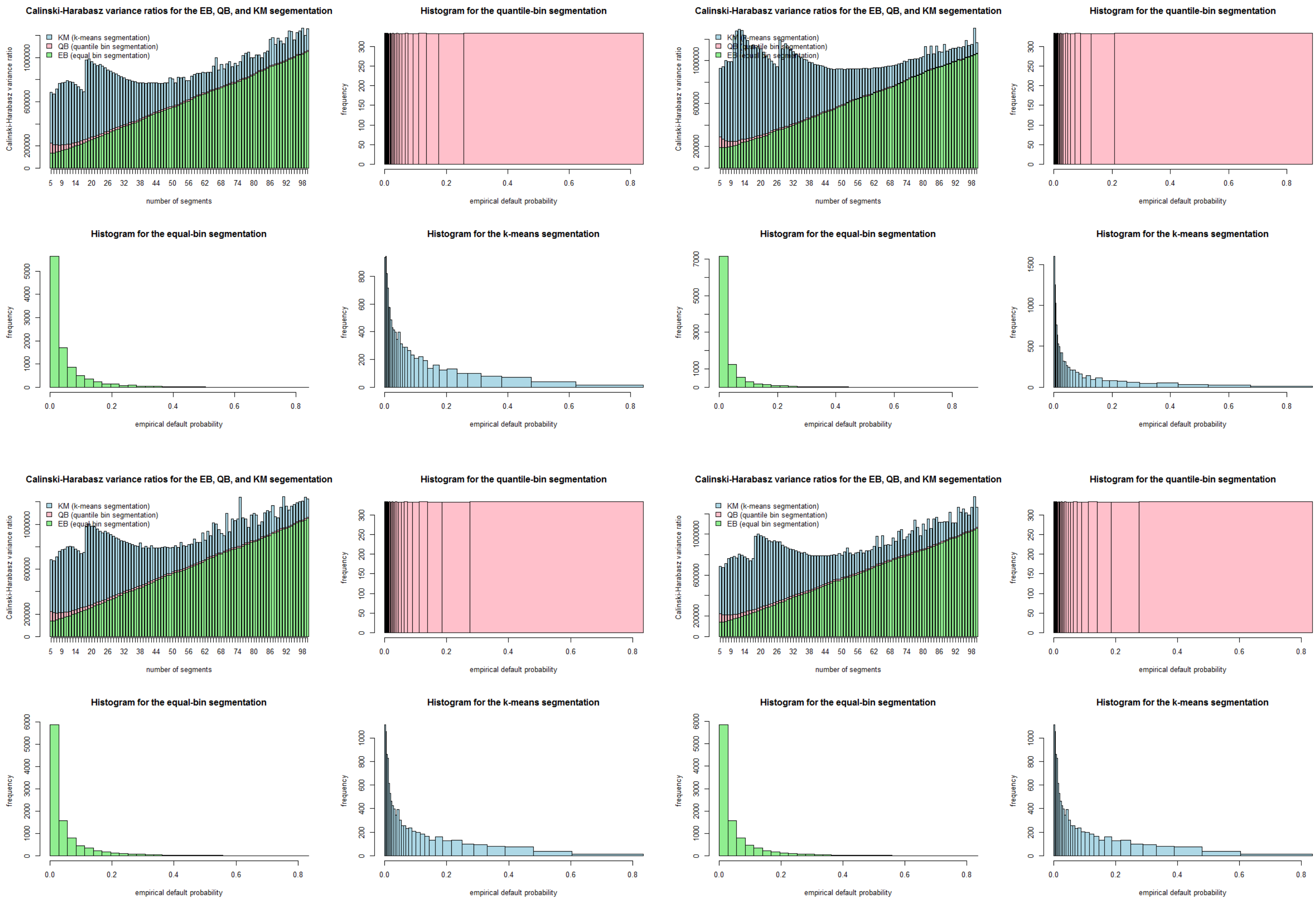


Figure 5: Baseline TTC0, TTC1, TTC2, and TTC3 value-at-risk equity capital

This chart shows the TTC0, TTC1, TTC2, and TTC3 value-at-risk equity capital ratios across the 30 k-means PD segments. At least three empirical results arise from this diagrammatical representation. First, the equity capital ratios exhibit a concave positive relation with PD across the first 20-25 segments. Beyond the watershed, the equity capital ratios quickly decline across the last 5 segments. A concave hump exists across the board, and higher asset correlation tends to lift the height of this hump. This phenomenon magnifies the cross-sectional variation in equity capital. Second, the TTC1 equity capital ratios underestimate the true TTC0 counterparts. This evidence is more pronounced for the special case of ρ=30%. Third, it is hard to identify any peculiar empirical relationship between PD and asset correlation. For an invariant equity capital ratio, higher asset correlation seems to correspond to the lower PD segments. However, this capital-invariance assumption does not hold in a dynamic equilibrium context. In effect, the value-at-risk equity capital ratios gyrate in response to changes in both asset correlation and PD segmentation. In this more realistic dynamic view, equity capital movements adjust in accordance with changes in both asset correlation and portfolio composition. The empirical relation between PD and asset correlation can be positive, negative, or ambiguous. This empirical relation depends upon how equity capital requirements dynamically react to the joint changes in asset correlation and PD segmentation.

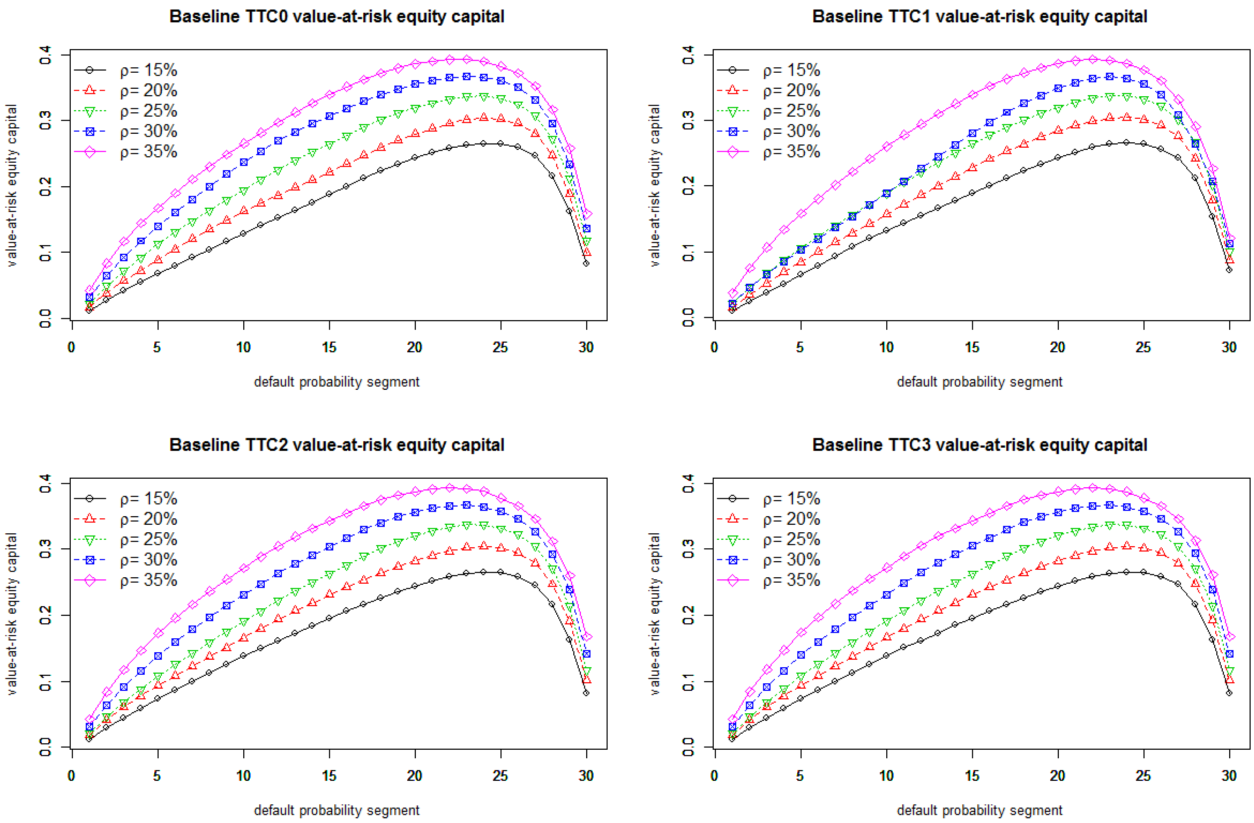


Figure 6: Baseline TTC0, TTC1, TTC2, and TTC3 conditional value-at-risk equity capital

This chart shows the TTC0, TTC1, TTC2, and TTC3 conditional value-at-risk capital ratios across the 30 k-means segments. At least three empirical results arise from this diagrammatical representation. First, the equity capital ratios exhibit a concave positive relation with PD across the first 20-25 segments. Beyond the watershed, the equity capital ratios quickly decline across the last 5 segments. A concave hump exists across the board, and higher asset correlation tends to lift the height of this hump. This phenomenon magnifies the cross-sectional variation in equity capital. Second, the TTC1 equity capital ratios underestimate the true TTC0 counterparts. This evidence is more pronounced for the special case of ρ=30%. Third, it is hard to identify any peculiar empirical relationship between PD and asset correlation. For an invariant equity capital ratio, higher asset correlation seems to correspond to the lower PD segments. Nevertheless, this capital-invariance assumption does not hold in a dynamic equilibrium context. The conditional value-at-risk capital ratios gyrate in response to changes in both asset correlation and PD segmentation. In this more realistic dynamic view, equity capital movements adjust in accordance with changes in both asset correlation and portfolio composition. The empirical relation between PD and asset correlation can be positive, negative, or ambiguous. This empirical relation depends upon how equity capital requirements dynamically react to the joint changes in asset correlation and PD segmentation.

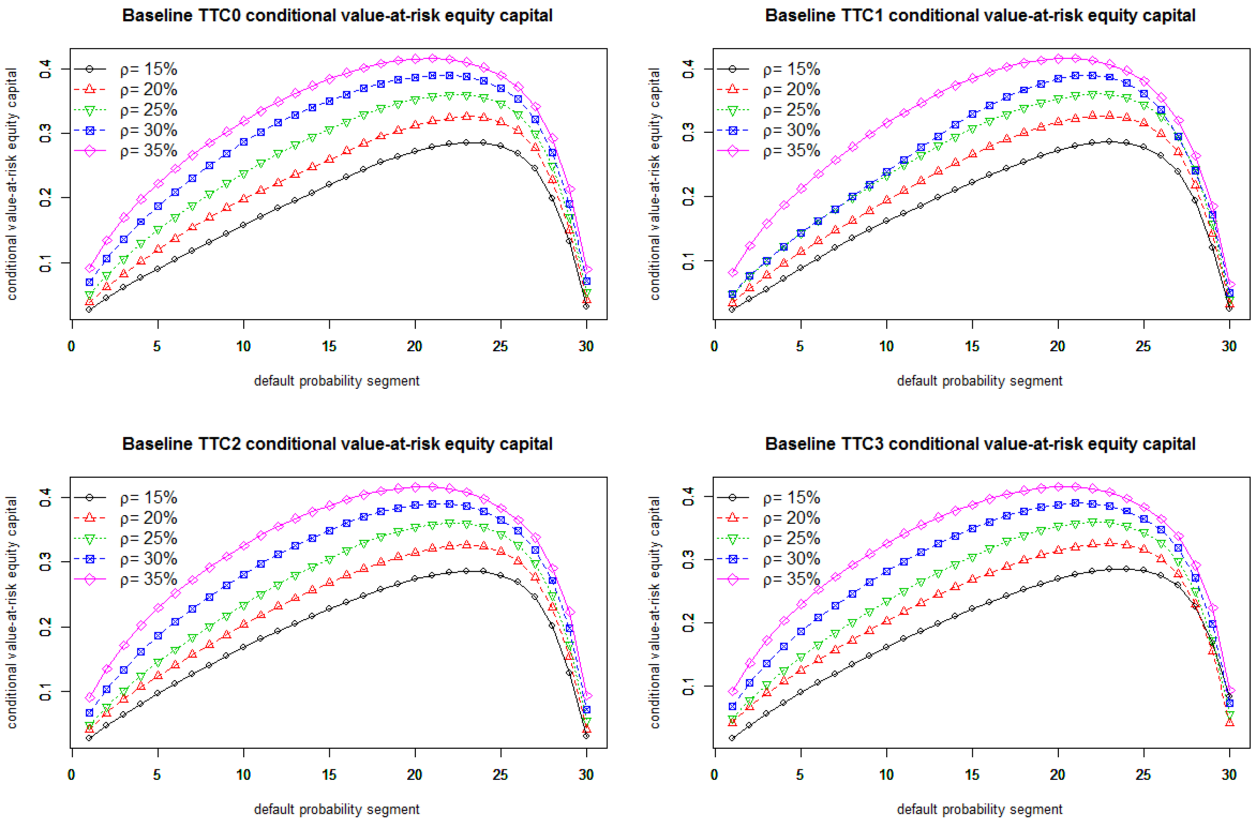


Figure 7: A time-series comparison of alternative TTC0, TTC1, TTC2, and TTC3 PDs

This chart plots the point-in-time PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. Panels A to E show this information for the alternative correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. Within each panel, the left-hand side plots the TTC0 PD time-series and the long-run average TTC0, TTC1, TTC2, and TTC3 PDs. The long-run mean TTC1 PD is lower than the long-term mean TTC0, TTC2, and TTC3 PDs by a full order of magnitude. For instance, the baseline set of risk parameters {ρ, φ, ξ}={15%, 50%, 50%} yields the long-run average TTC0, TTC2, and TTC3 PDs near 5.30%, whereas, the long-term average TTC1 PD is lower than 4.65%. Hence, the TTC1 approach substantially underestimates the TTC0 PD and equity capital results that better accord with the spirit of the Basel TTC regulatory requirement. The right-hand side of each panel magnifies the fine neighborhood of the long-term average TTC0, TTC2, and TTC3 PDs. The long-term average TTC3 PD sometimes slightly overestimates the long-term average TTC0 PD while the long-term average TTC2 PD underestimates the long-run average TTC0 PD. In effect, the long-run average TTC3 PD better approximates the long-run average TTC0 PD than the TTC2 counterpart. At any rate, the TTC2 and TTC3 PD approximations are both sufficiently close to the TTC0 origin. Our subsequent capital analysis suggests that these higher-order approximations are accurate enough for the equity capital differences to be reasonably minimal.

Panel A: Alternative #1 TTC PD computation ρ=15%, φ={<u>40%</u>, 45%, 50%, 55%, 60%}, and ξ=50%

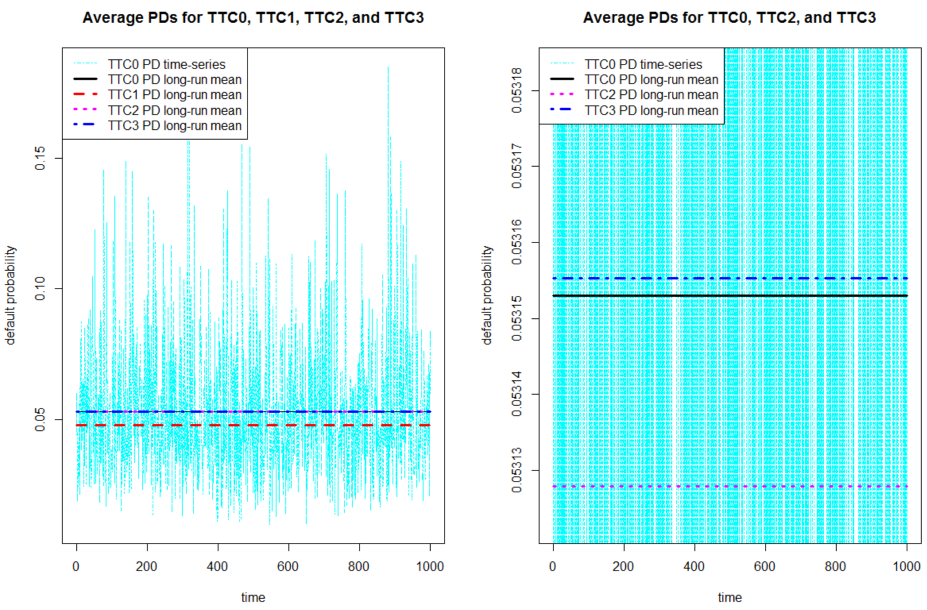
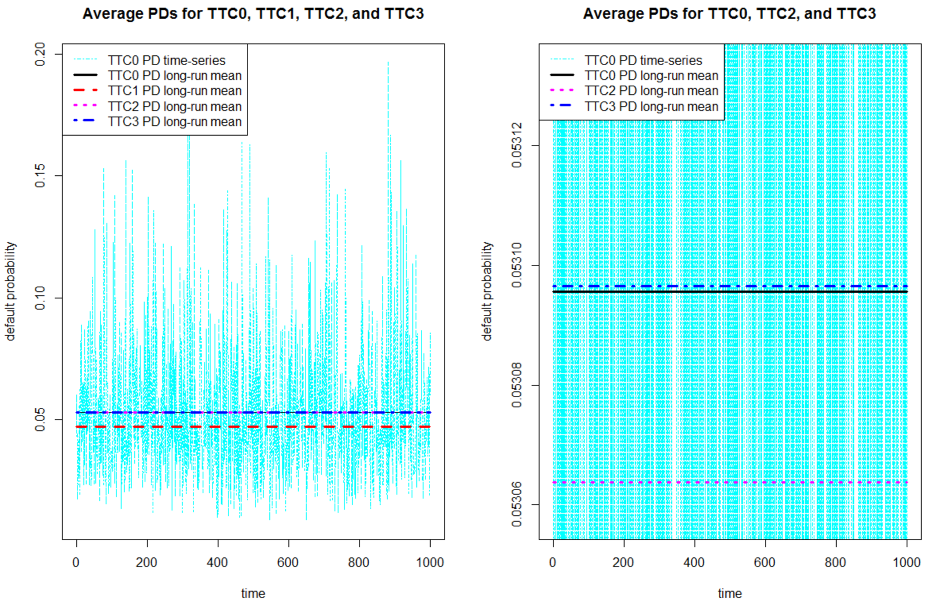


Figure 7: A time-series comparison of alternative TTC0, TTC1, TTC2, and TTC3 PDs

Panel B: Alternative #1 TTC PD computation ρ=15%, φ={40%, <u>45%</u>, 50%, 55%, 60%}, and ξ=50%



Panel C: Alternative #1 TTC PD computation ρ=15%, φ={40%, 45%, <u>50%</u>, 55%, 60%}, and ξ=50%

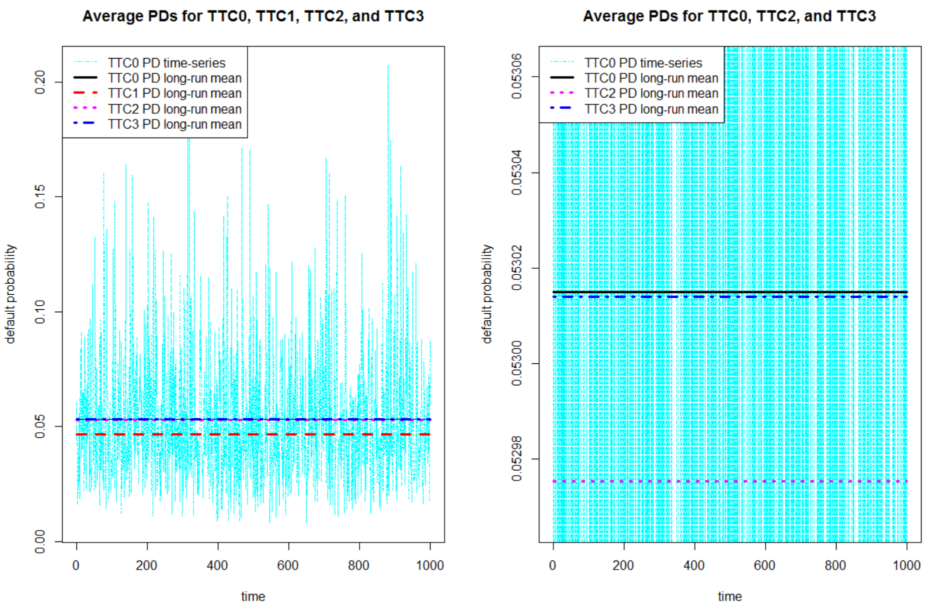
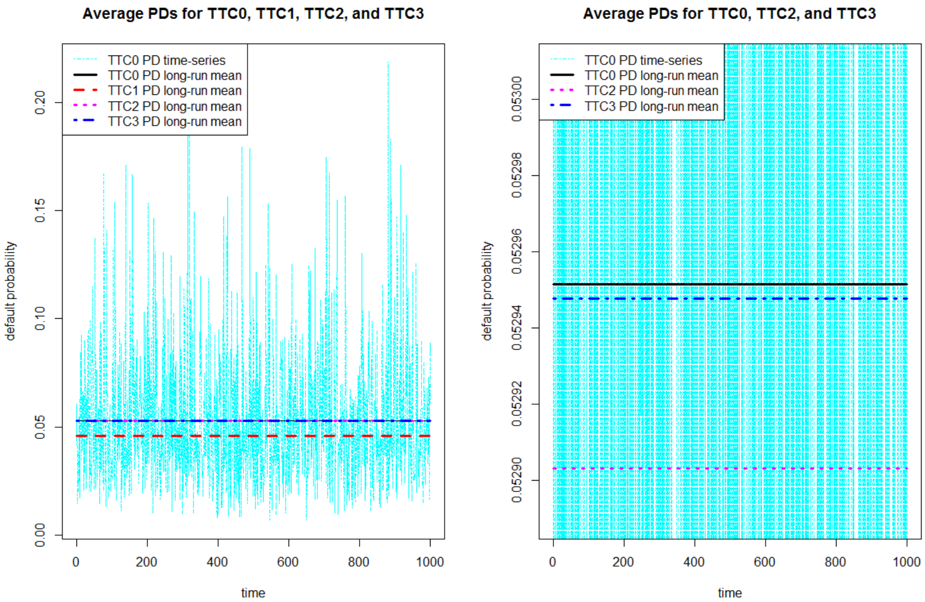


Figure 7: A time-series comparison of alternative TTC0, TTC1, TTC2, and TTC3 PDs

Panel D: Alternative #1 TTC PD computation ρ=15%, φ={40%, 45%, 50%, <u>55%</u>, 60%}, and ξ=50%



Panel E: Alternative #1 TTC PD computation ρ=15%, φ={40%, 45%, 50%, 55%, <u>60%</u>}, and ξ=50%

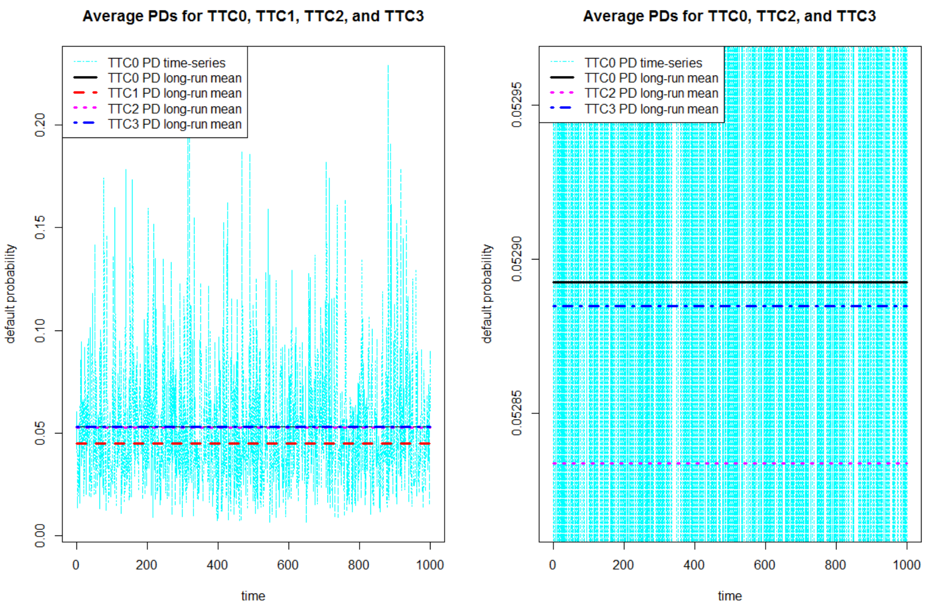
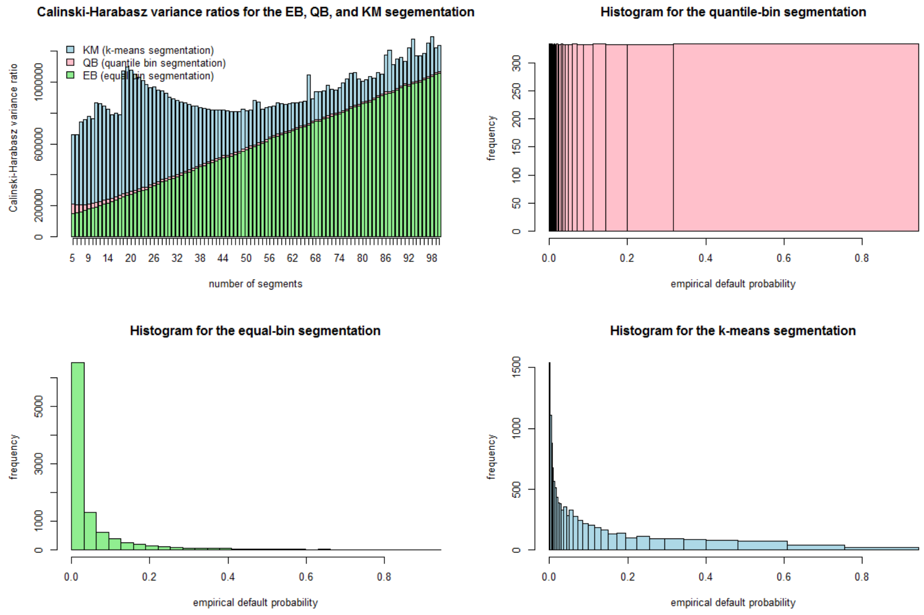
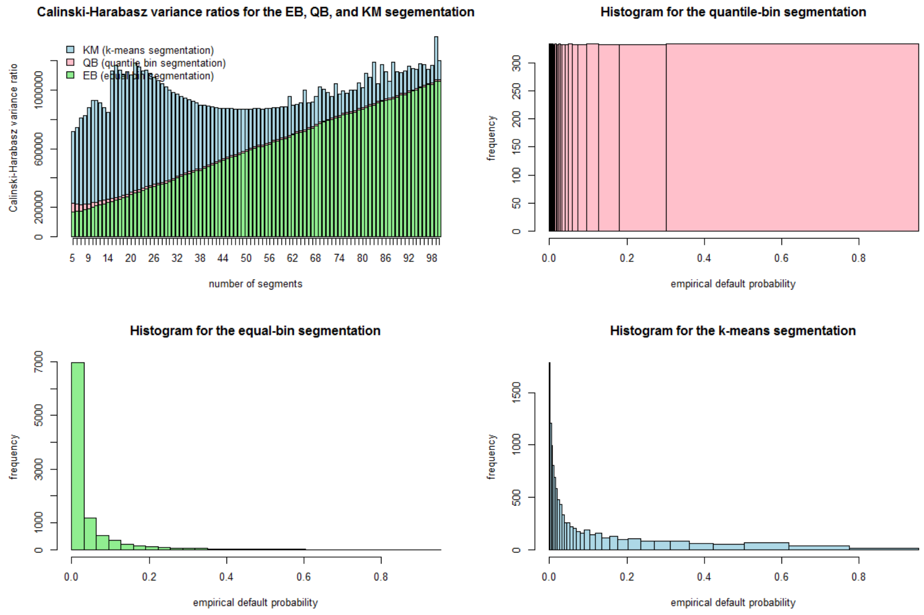
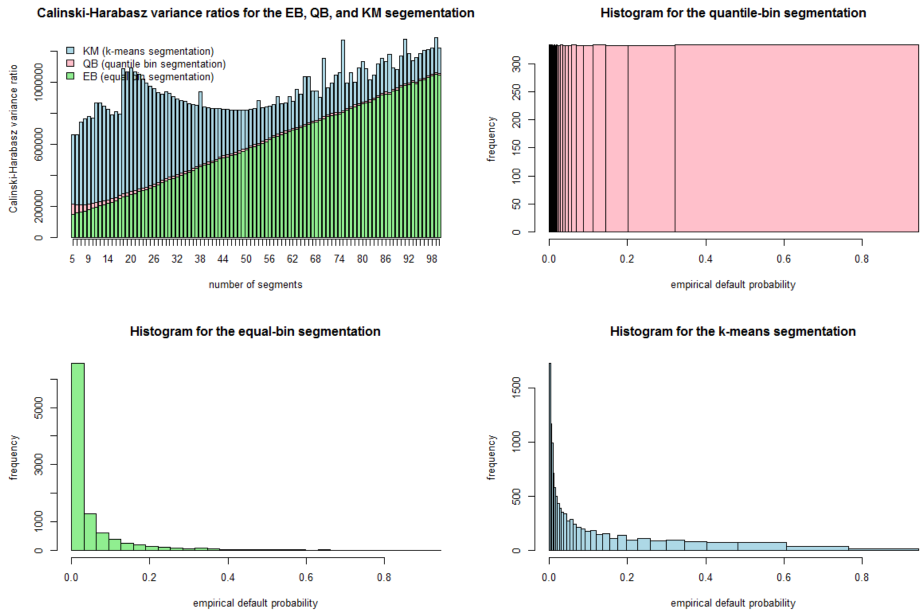


Figure 8-(a): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ={<u>40%</u>, 45%, 50%, 55%, 60%}, and ξ=50%







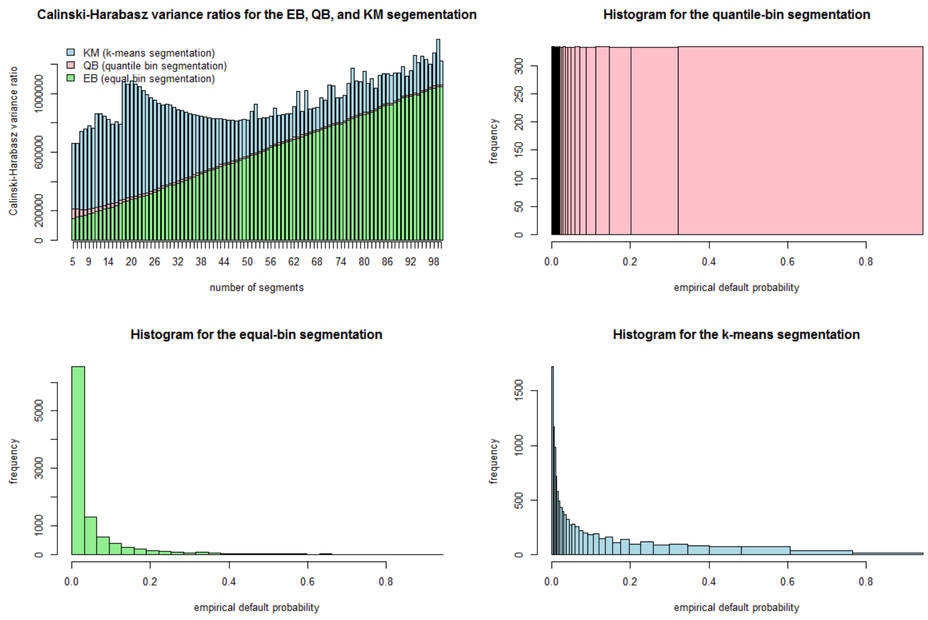


Figure 8-(b): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ={40%, <u>45%</u>, 50%, 55%, 60%}, and ξ=50%

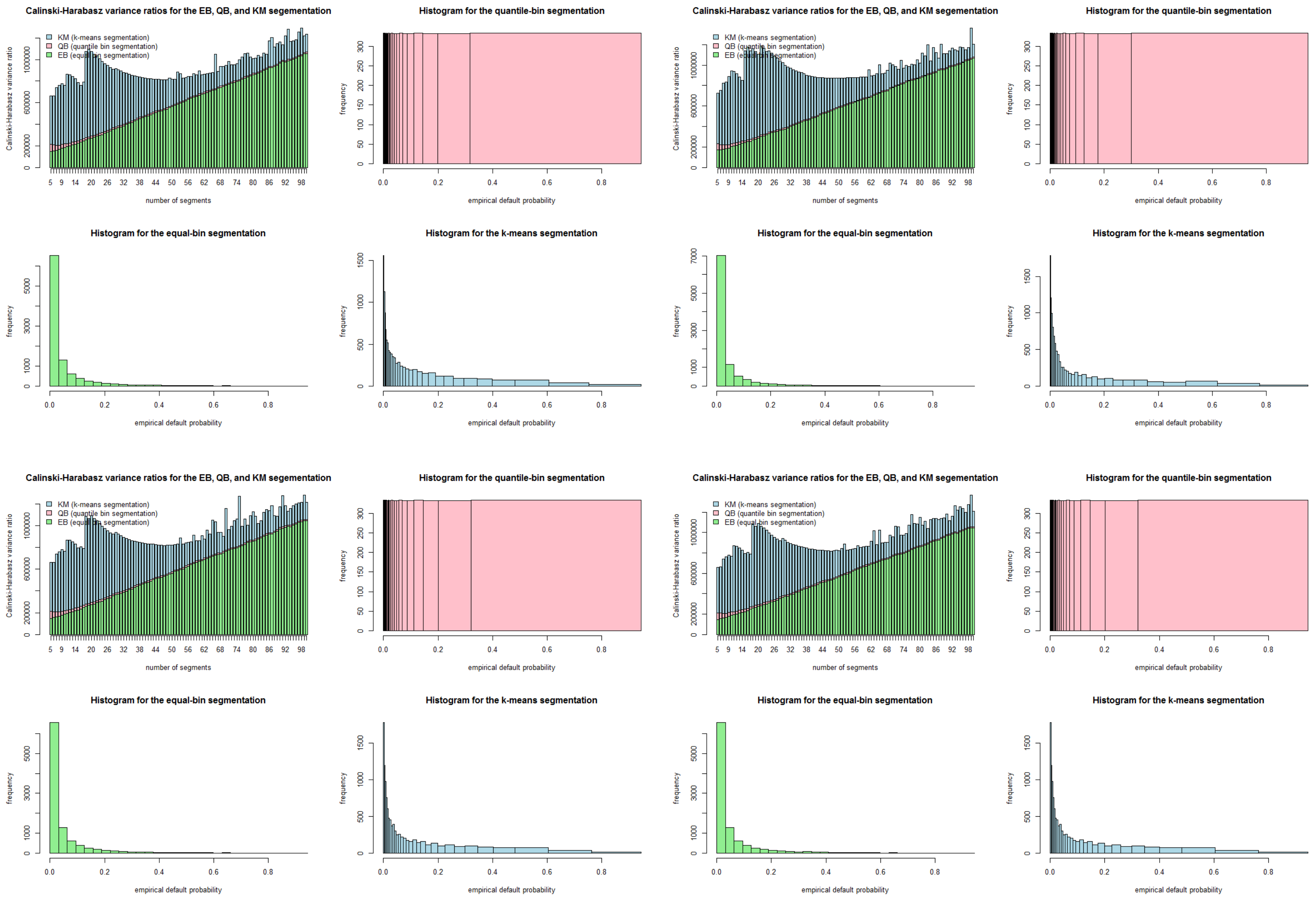


Figure 8-(c): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ={40%, 45%, <u>50%</u>, 55%, 60%}, and ξ=50%

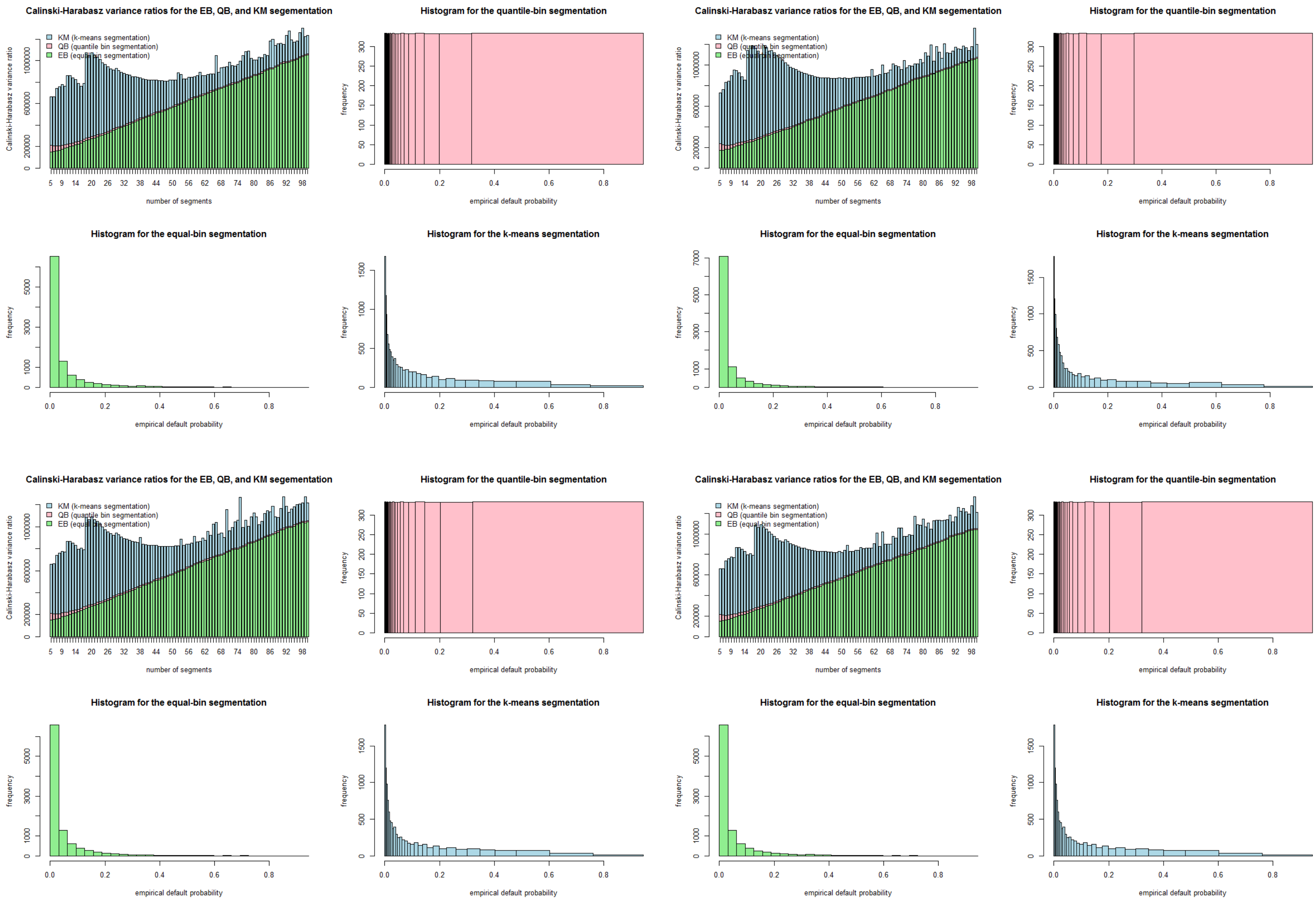


Figure 8-(d): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ={40%, 45%, 50%, <u>55%</u>, 60%}, and ξ=50%

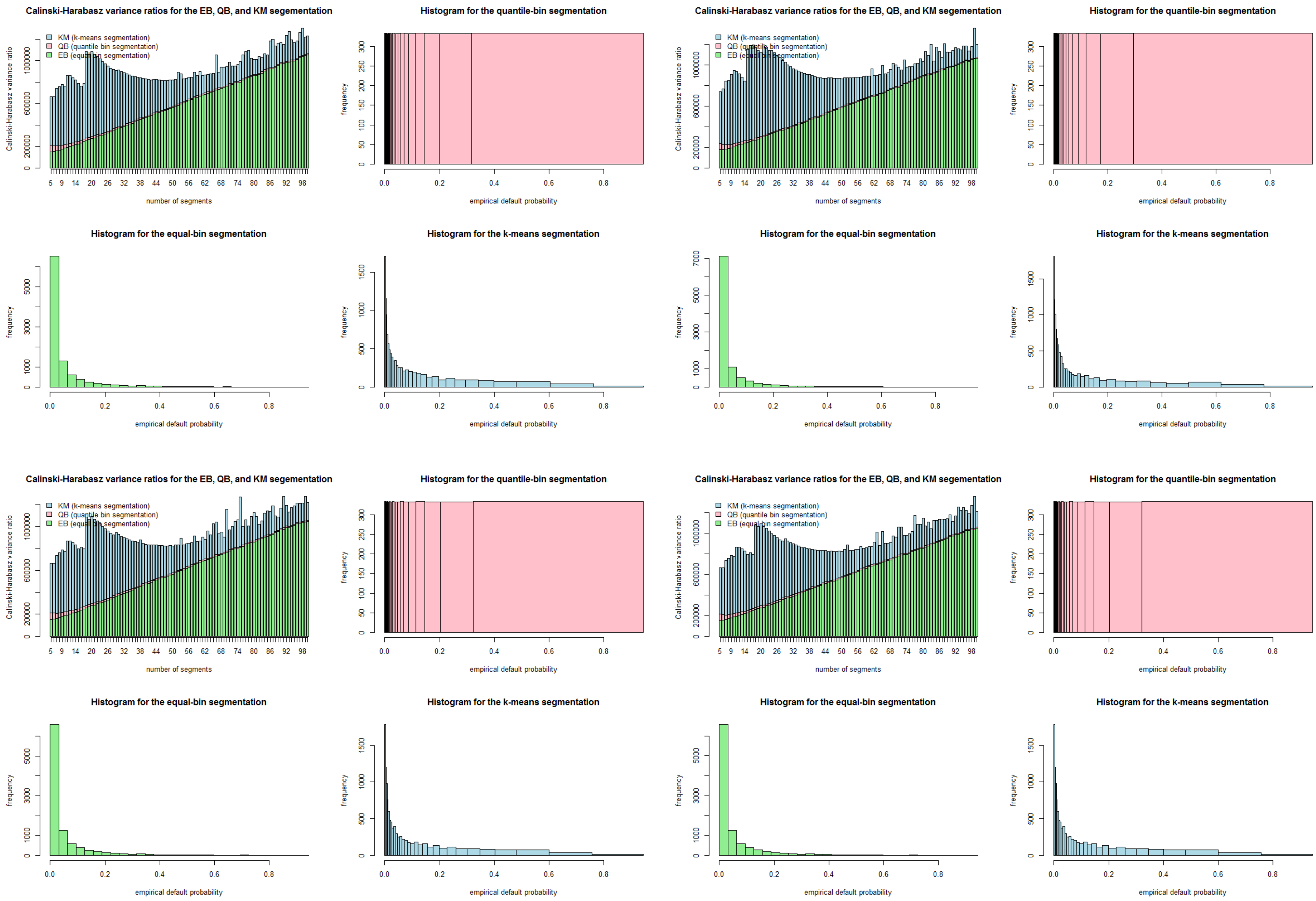


Figure 8-(e): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ={40%, 45%, 50%, 55%, <u>60%</u>}, and ξ=50%

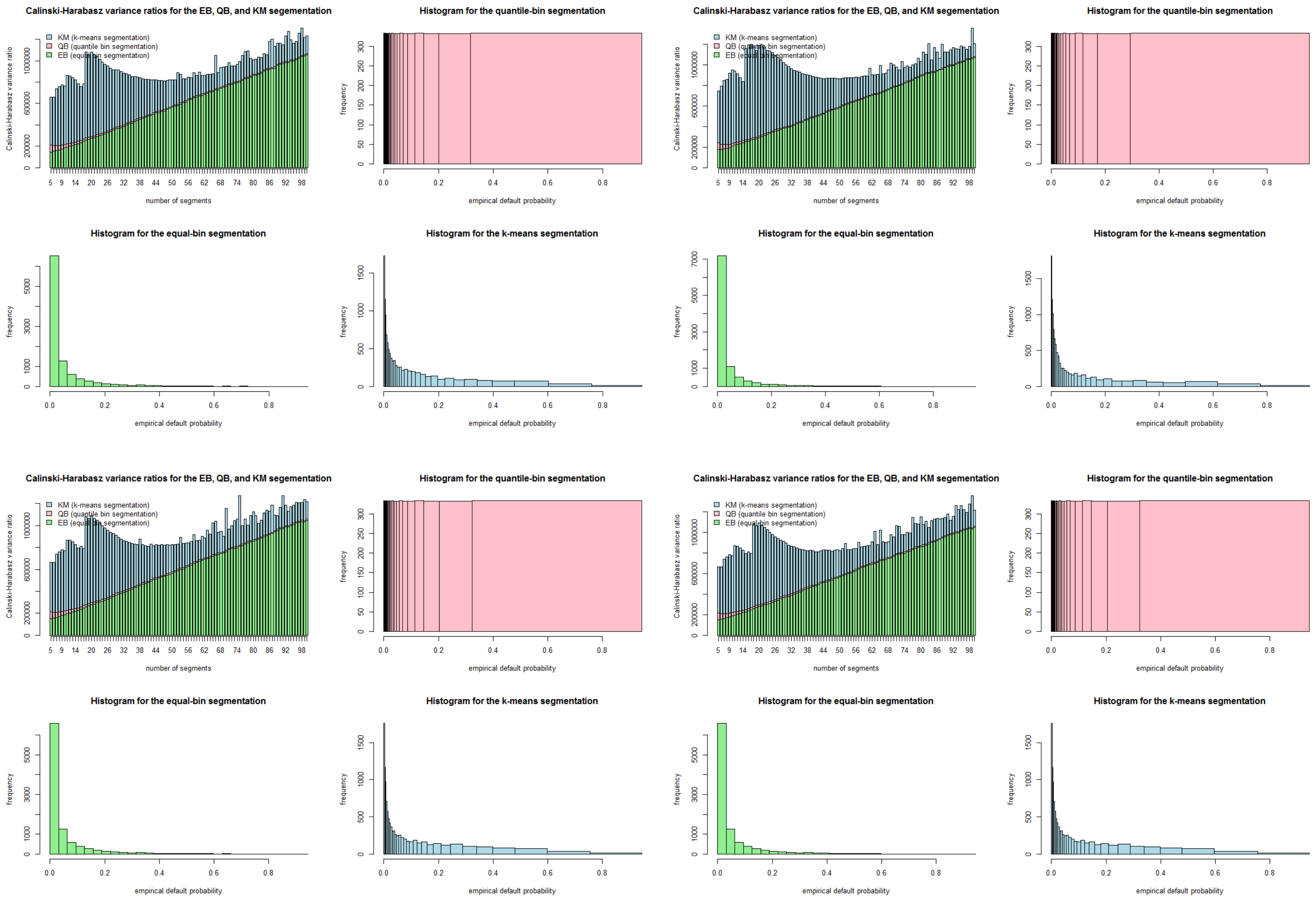


Figure 9: Alternative #1 TTC0, TTC1, TTC2, TTC3 value-at-risk equity capital

This chart displays the TTC0, TTC1, TTC2, and TTC3 value-at-risk equity capital ratios across the 30 k-means segments. The equity capital curve almost overlap although these curves reflect different systematic macro correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. This evidence is no surprise because our logistic default probability model is reasonably accurate with about 90% concordance percentages. Insofar as this model predicts binary default occurrence correctly most of the time, whether the observable systematic macro factor significantly correlates with the unobservable counterpart does not matter much. In summary, the value-at-risk equity capital ratios do not vary much in response to this alternative set of systematic risk correlation permutations.

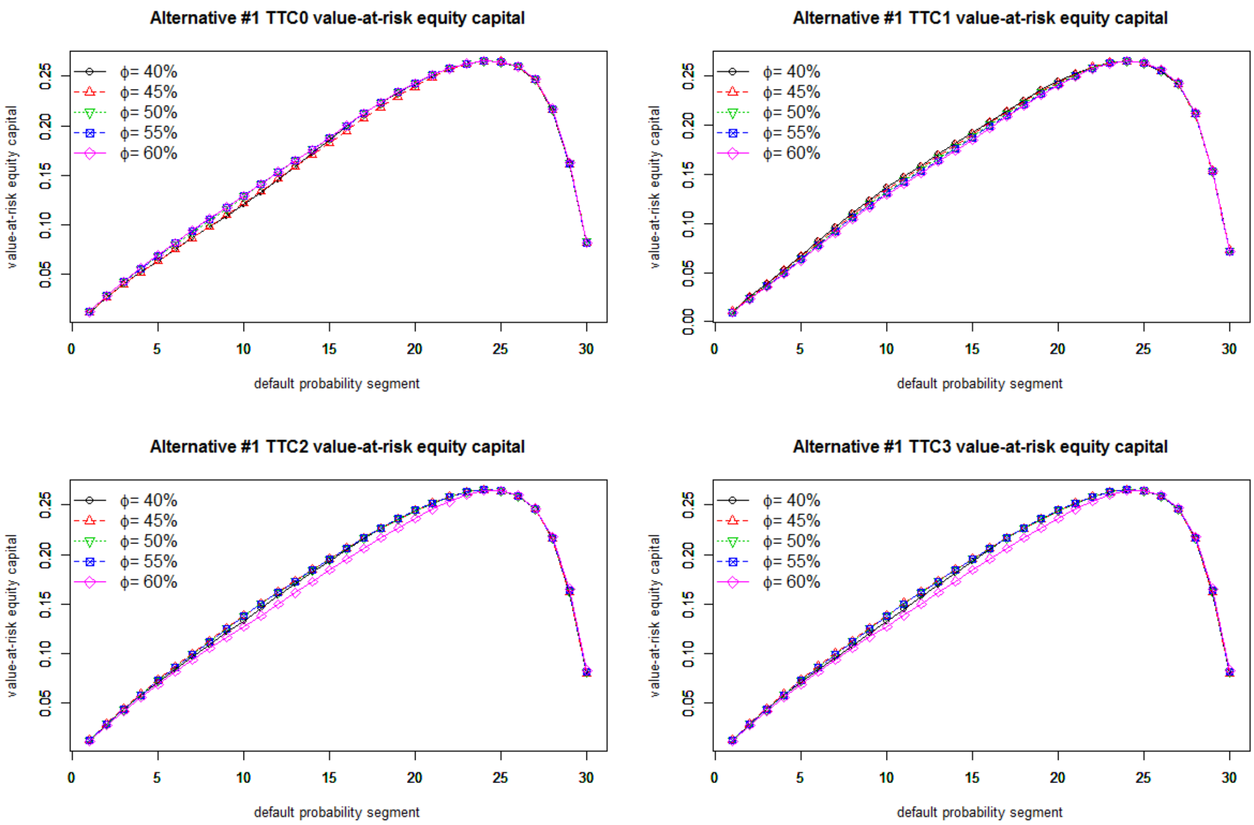


Figure 10: Alternative #1 TTC0, TTC1, TTC2, TTC3 conditional value-at-risk equity capital

This chart displays the TTC0, TTC1, TTC2, and TTC3 conditional value-at-risk equity capital ratios across the 30 k-means segments. The equity capital curve almost overlap although these curves reflect different systematic macro risk correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. This evidence is no surprise because our logit default probability model is reasonably accurate with about 90% concordance percentages. Insofar as this model predicts binary default occurrence correctly most of the time, whether the observable systematic macro risk factor significantly correlates with the unobservable counterpart does not matter much. The conditional value-at-risk equity capital ratios do not vary much in response to this alternative set of systematic macro correlation permutations.

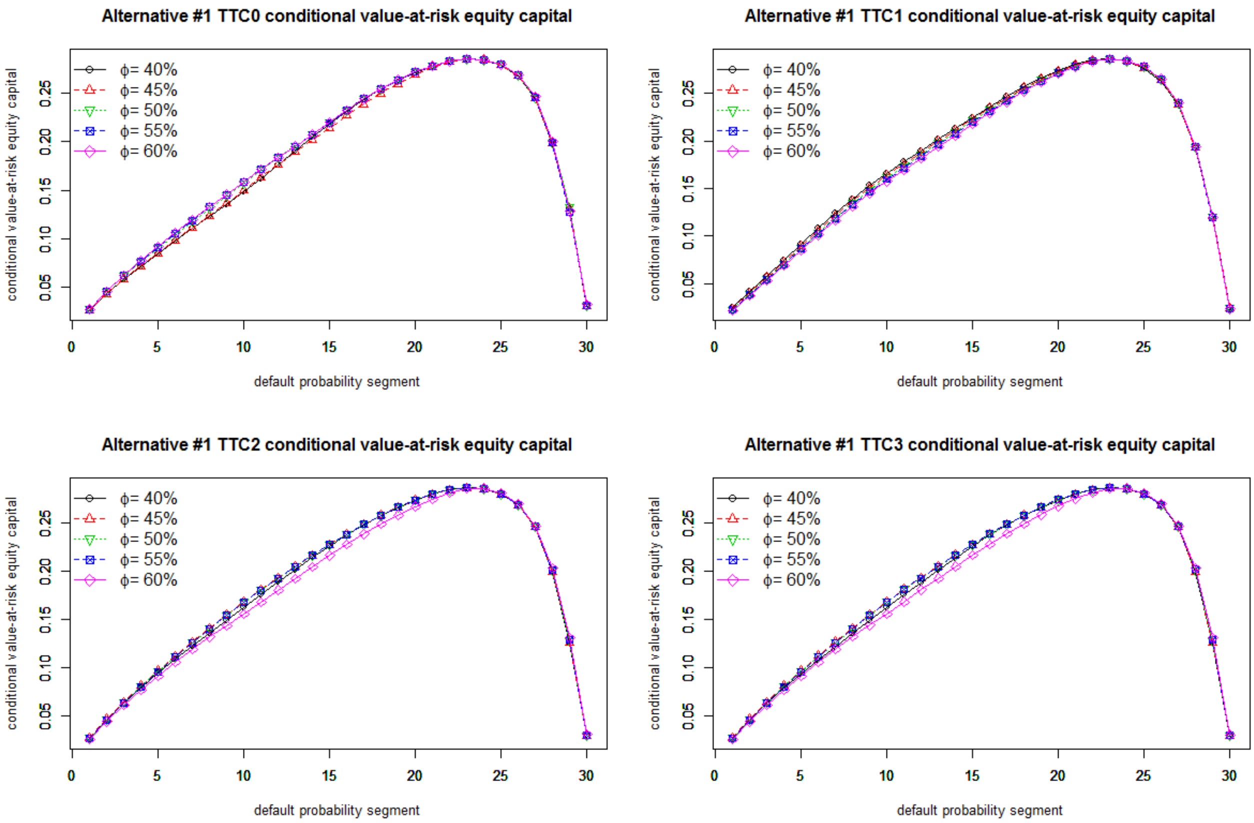


Figure 11: A time-series comparison of alternative TTC0, TTC1, TTC2, and TTC3 PDs

This chart plots the point-in-time PD time-series and the long-term average TTC0, TTC1, TTC2, and TTC3 PDs. Panels A to E show this information for the alternative correlation permutations ρ=15%, φ={40%, 45%, 50%, 55%, 60%}, and ξ=50%. Within each panel, the left-hand side plots the TTC0 PD time-series and the long-run average TTC0, TTC1, TTC2, and TTC3 PDs. The long-run mean TTC1 PD is lower than the long-term mean TTC0, TTC2, and TTC3 PDs by a full order of magnitude. For instance, the baseline set of risk parameters {ρ, φ, ξ}={15%, 50%, 50%} yields the long-term average TTC0, TTC2, and TTC3 PDs near 5.30%, whereas, the long-term average TTC1 PD is lower than 4.65%. Hence, the TTC1 approach substantially underestimates the TTC0 PD and equity capital results that better accord with the spirit of the Basel TTC regulatory requirement. The right-hand side of each panel magnifies the fine neighborhood of the long-term average TTC0, TTC2, and TTC3 PDs. The long-term average TTC3 PD sometimes slightly overestimates the long-term average TTC0 PD while the long-term average TTC2 PD underestimates the long-run average TTC0 PD. In effect, the long-run average TTC3 PD better approximates the long-run average TTC0 PD than the TTC2 counterpart. At any rate, the TTC2 and TTC3 PD approximations are both sufficiently close to the TTC0 origin. Our subsequent capital analysis suggests that these higher-order approximations are accurate enough for the equity capital differences to be reasonably minimal.

Panel A: Alternative #2 TTC PD computation ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

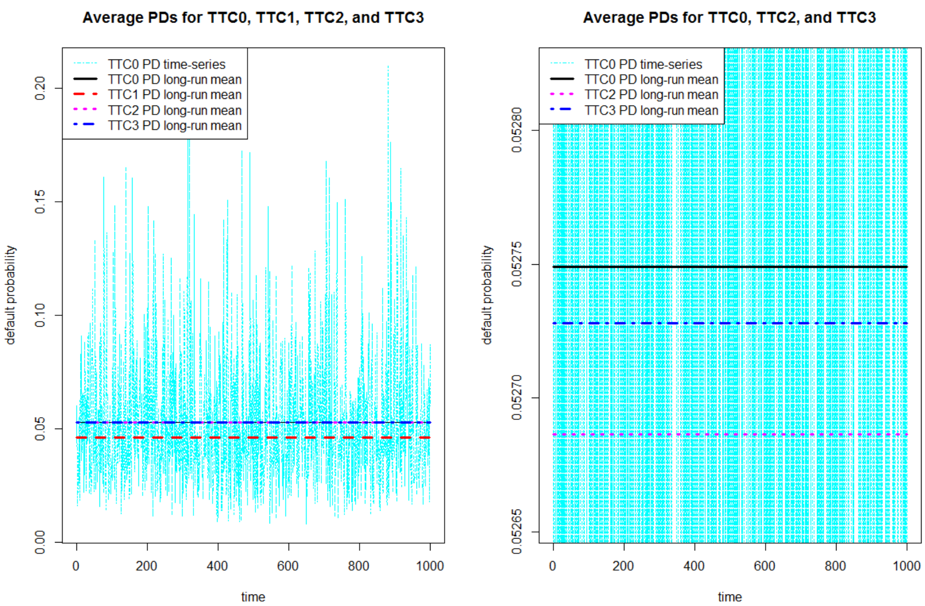
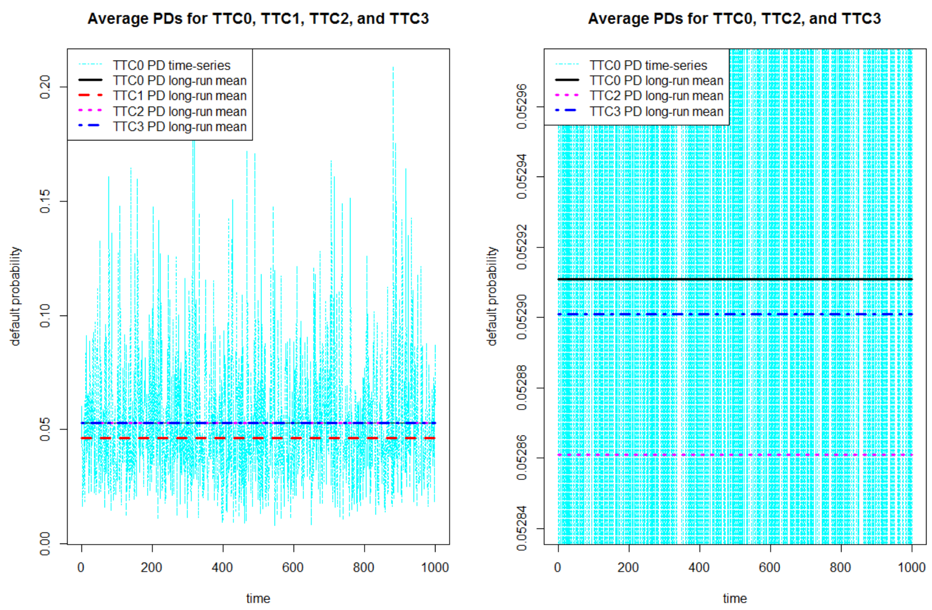


Figure 11: A time-series comparison of alternative TTC0, TTC1, TTC2, and TTC3 PDs

Panel B: Alternative #2 TTC PD computation ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}



Panel C: Alternative #2 TTC PD computation ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

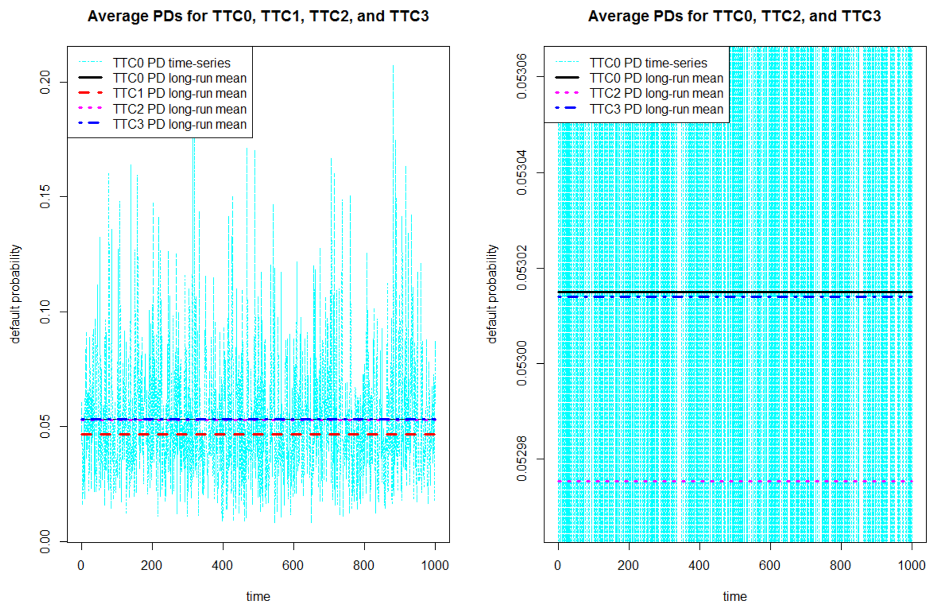
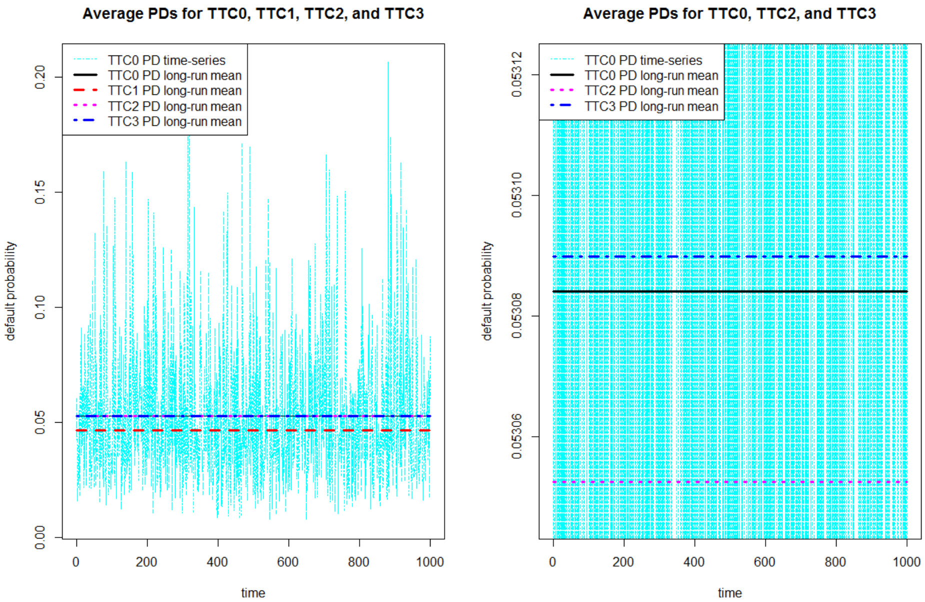


Figure 11: A time-series comparison of alternative TTC0, TTC1, TTC2, and TTC3 PDs

Panel D: Alternative #2 TTC PD computation ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}



Panel E: Alternative #2 TTC PD computation ρ=15%, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

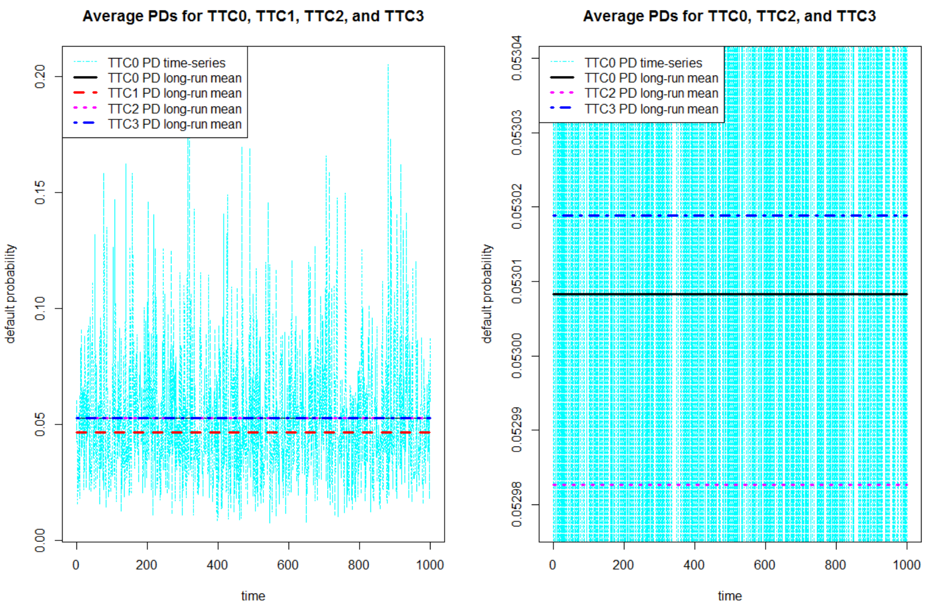


Figure 12-(a): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ=50%, and ξ={40%, 45%, 50%, 55%, 60%}

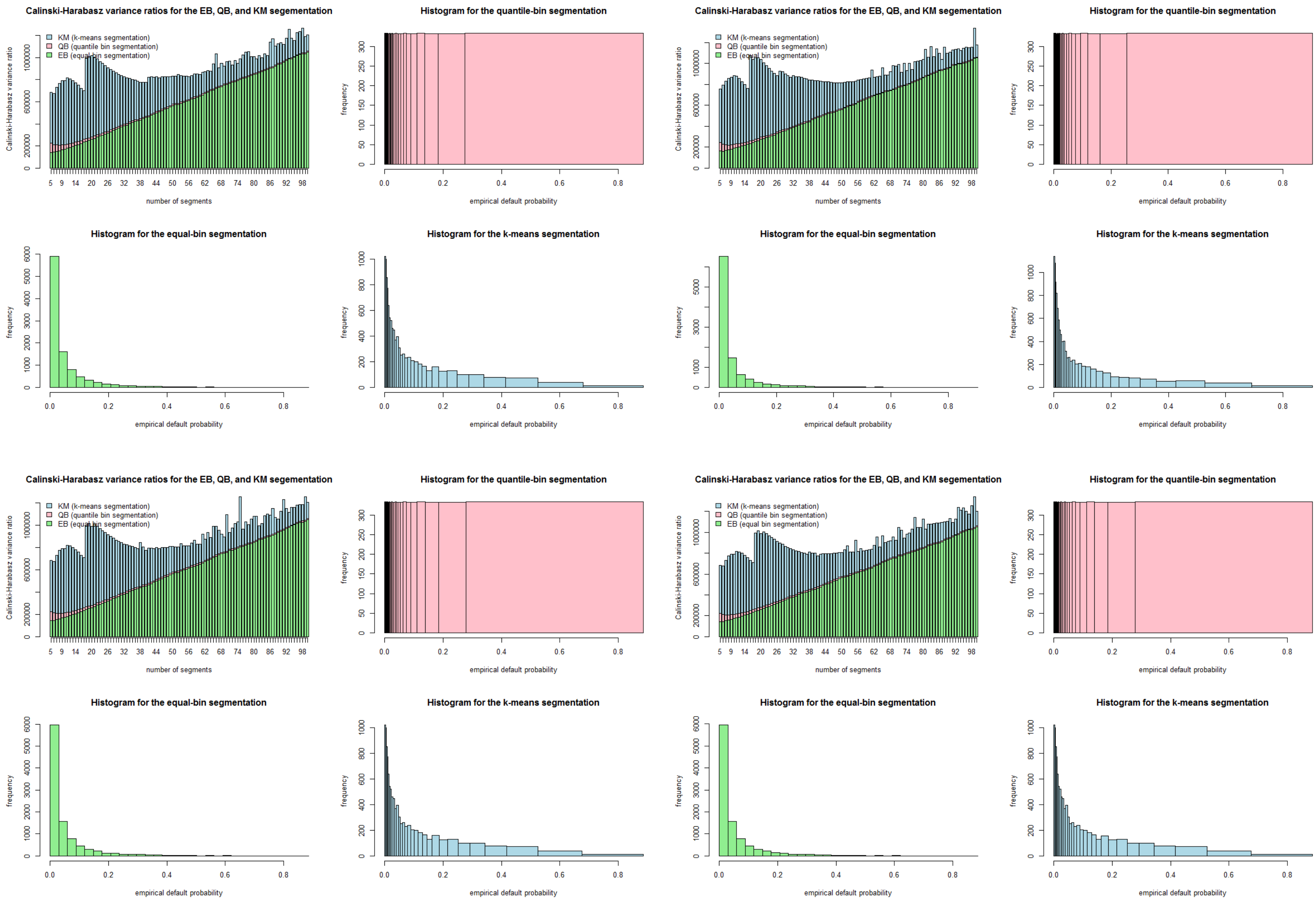


Figure 12-(b): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ=50%, and ξ={40%, <u>45%</u>, 50%, 55%, 60%}

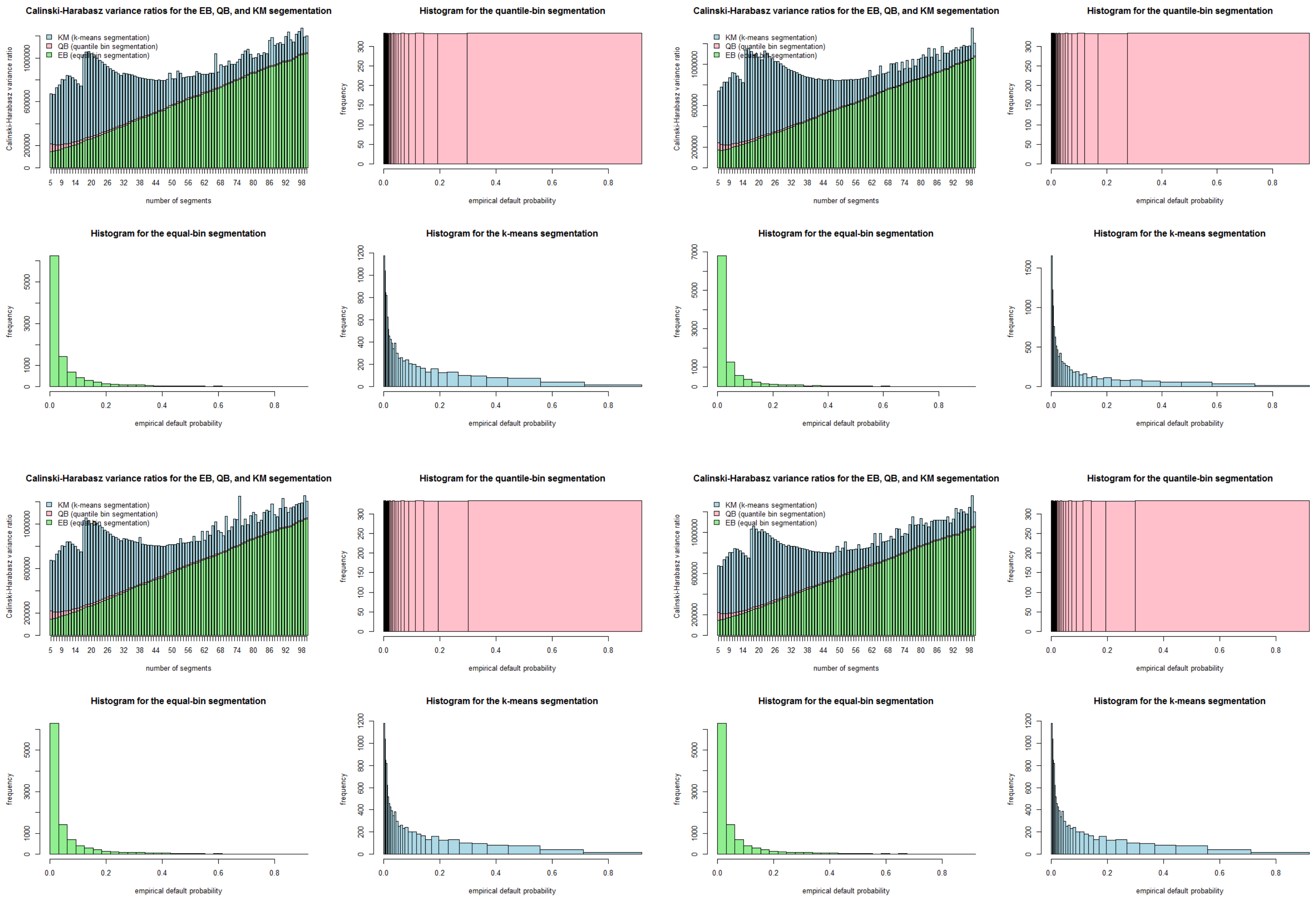


Figure 12-(c): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ=50%, and ξ={40%, 45%, <u>50%</u>, 55%, 60%}

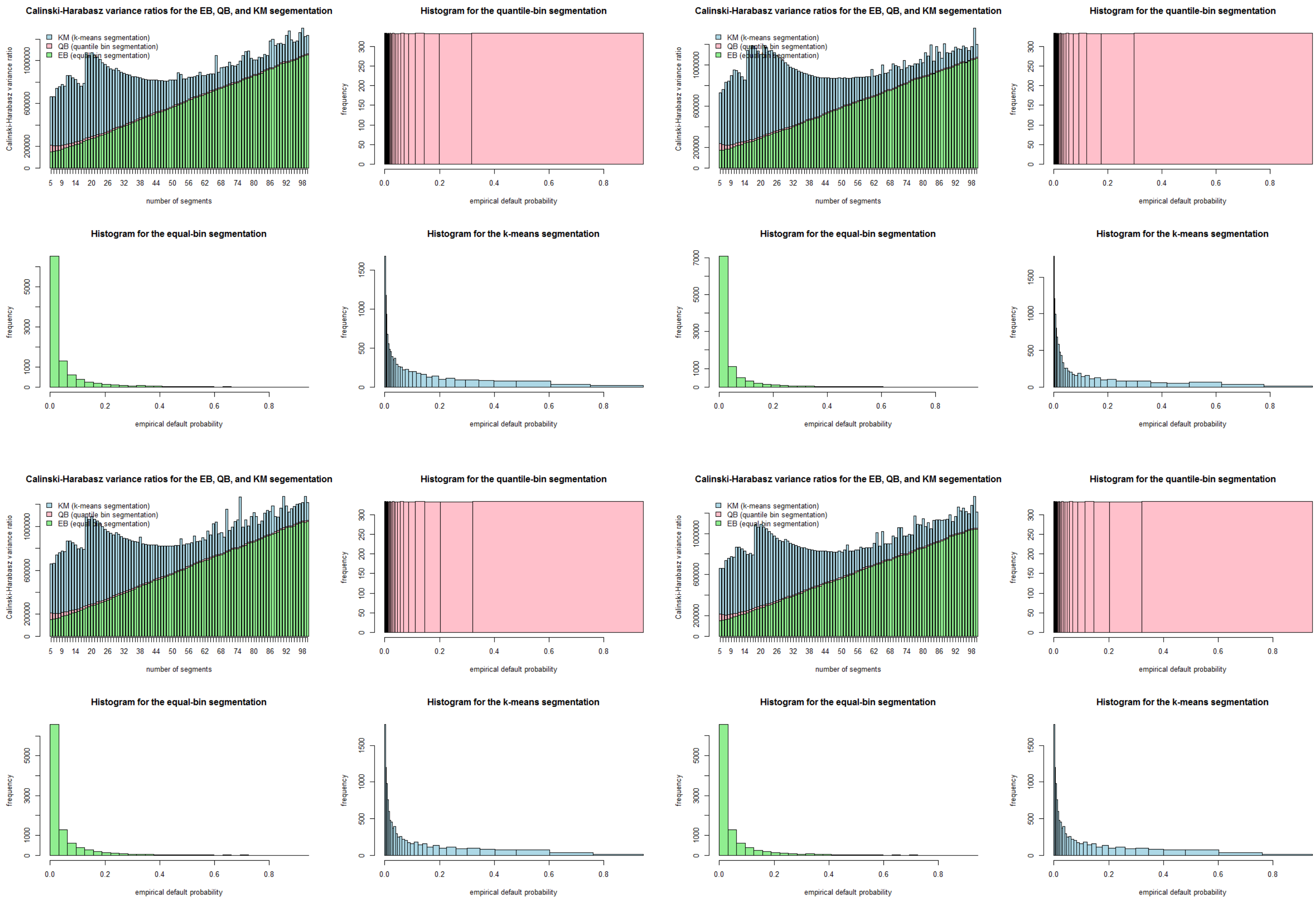


Figure 12-(d): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ=50%, and ξ={40%, 45%, 50%, <u>55%</u>, 60%}

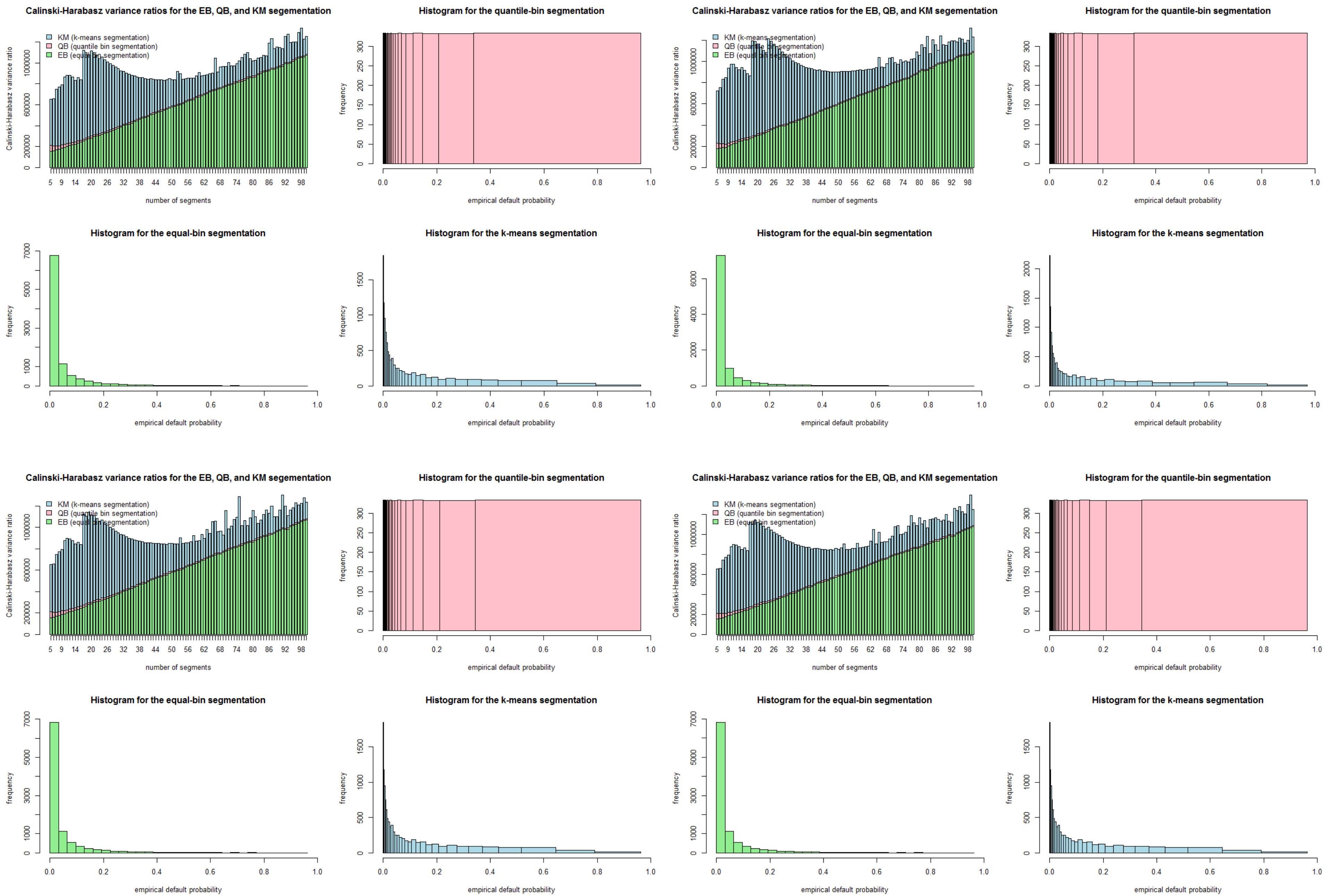


Figure 12-(e): Alternative #1 TTC0, TTC1, TTC2, and TTC3 PD histograms with ρ=15, φ=50%, and ξ={40%, 45%, 50%, 55%, <u>60%</u>}

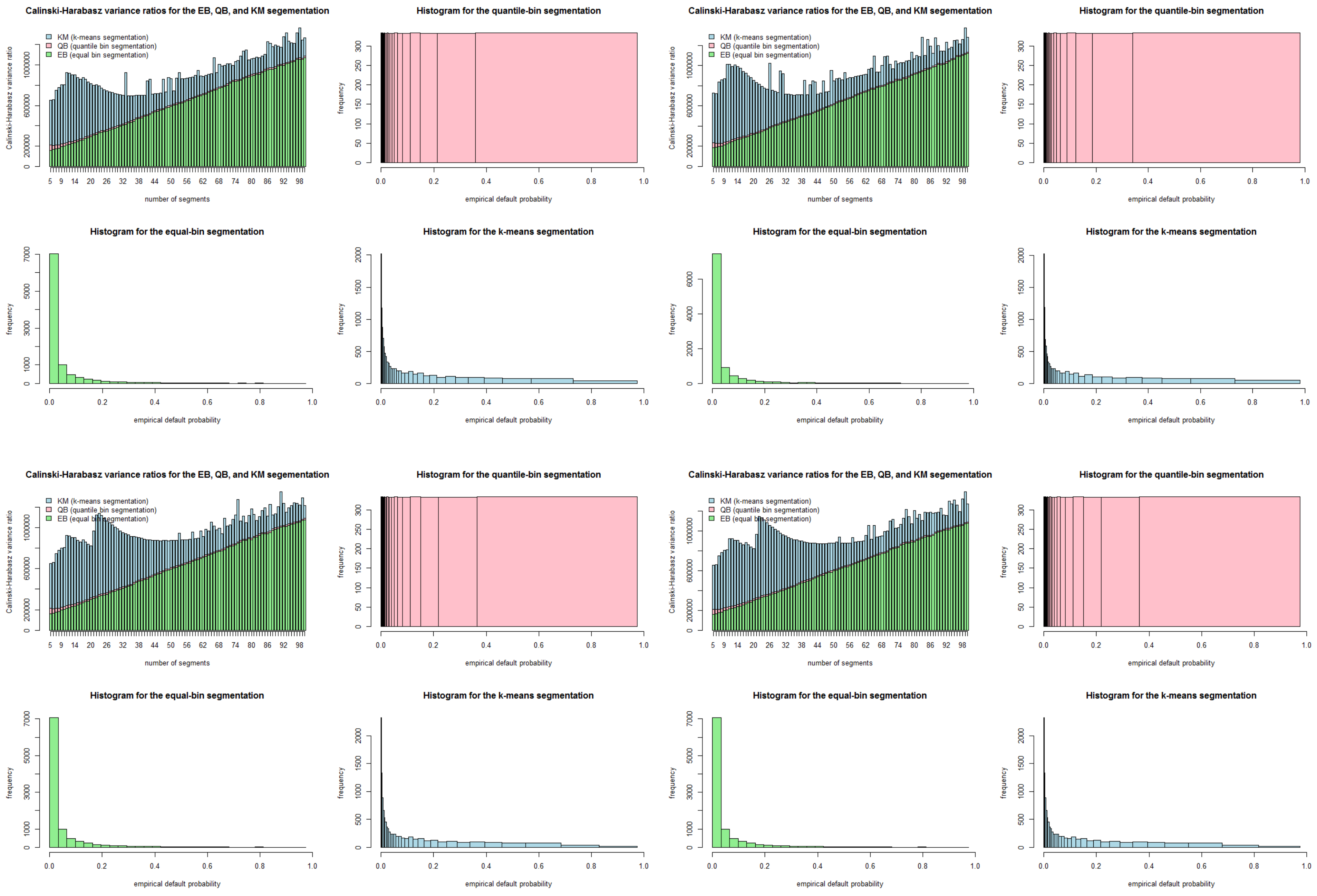


Figure 13: Alternative #2 TTC0, TTC1, TTC2, TTC3 value-at-risk equity capital

This chart shows the TTC0, TTC1, TTC2, and TTC3 value-at-risk equity capital ratios across the 30 k-means segments. When the idiosyncratic risk correlation value increases from 40% to 60% in increments of 5%, we observe a fair bit of credit migration from the higher PD segments to the lower PD segments. This increase in idiosyncratic risk correlation suggests that the econometrician faces less uncertainty around the idiosyncratic risk factor. This reduction in idiosyncratic uncertainty indicates lower model risk. A plausible economic interpretation indicates that this lower model risk translates into a tangible benefit in the form of equity capital relief. Hence, the bank requires a lower equity capital cushion when the logistic default probability model more accurately captures idiosyncratic risk through higher correlation between the observable and unobservable components of the idiosyncratic risk factor.

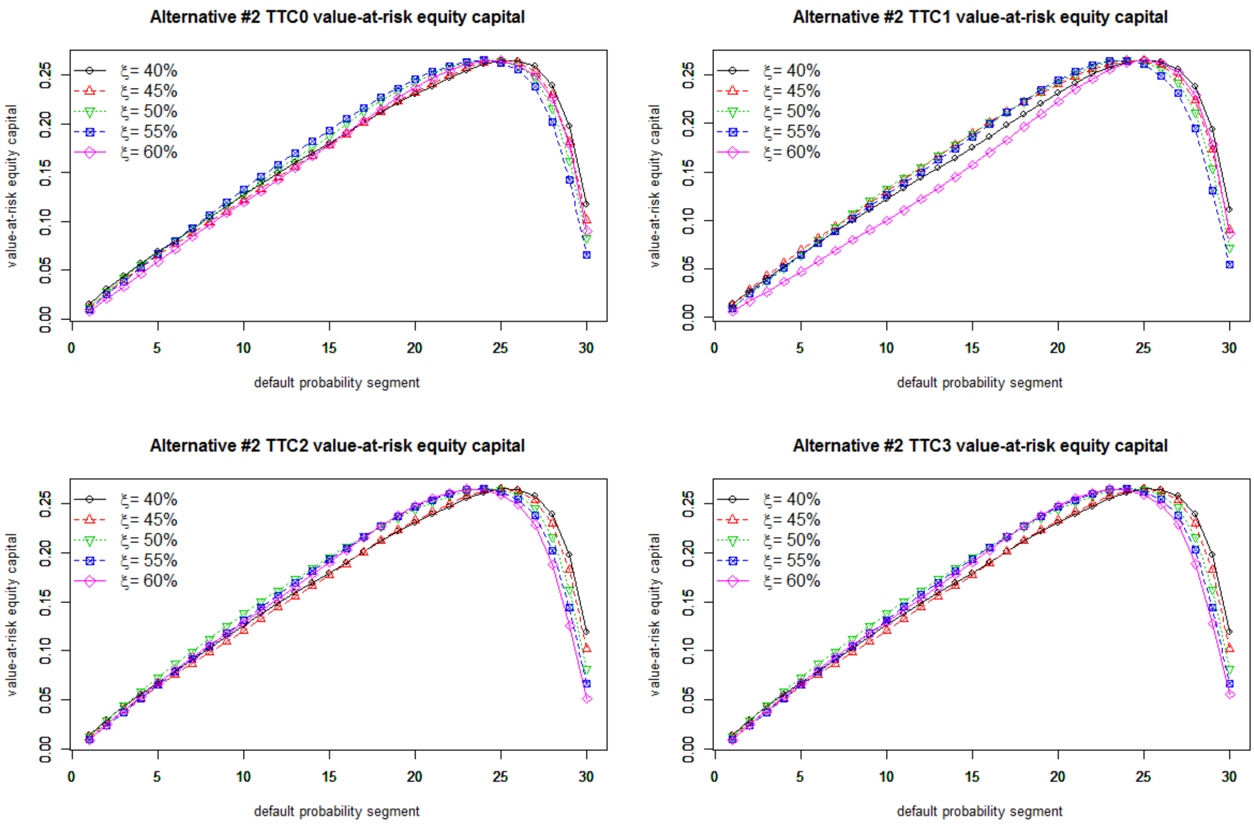


Figure 14: Alternative #2 TTC0, TTC1, TTC2, TTC3 conditional value-at-risk equity capital

This chart shows the TTC0, TTC1, TTC2, and TTC3 conditional value-at-risk capital ratios across the 30 PD segments. When the idiosyncratic risk correlation value increases from 40% to 60% in increments of 5%, we observe a fair bit of credit migration from the higher PD segments to the lower PD segments. This increase in idiosyncratic risk correlation suggests that the econometrician faces less uncertainty around the idiosyncratic risk factor. This reduction in idiosyncratic uncertainty indicates lower model risk. A plausible economic interpretation indicates that this lower model risk translates into a tangible benefit in the form of equity capital relief. Hence, the bank requires a lower equity capital cushion when the logistic default probability model more accurately captures idiosyncratic risk through higher correlation between the observable and unobservable components of the idiosyncratic risk factor.