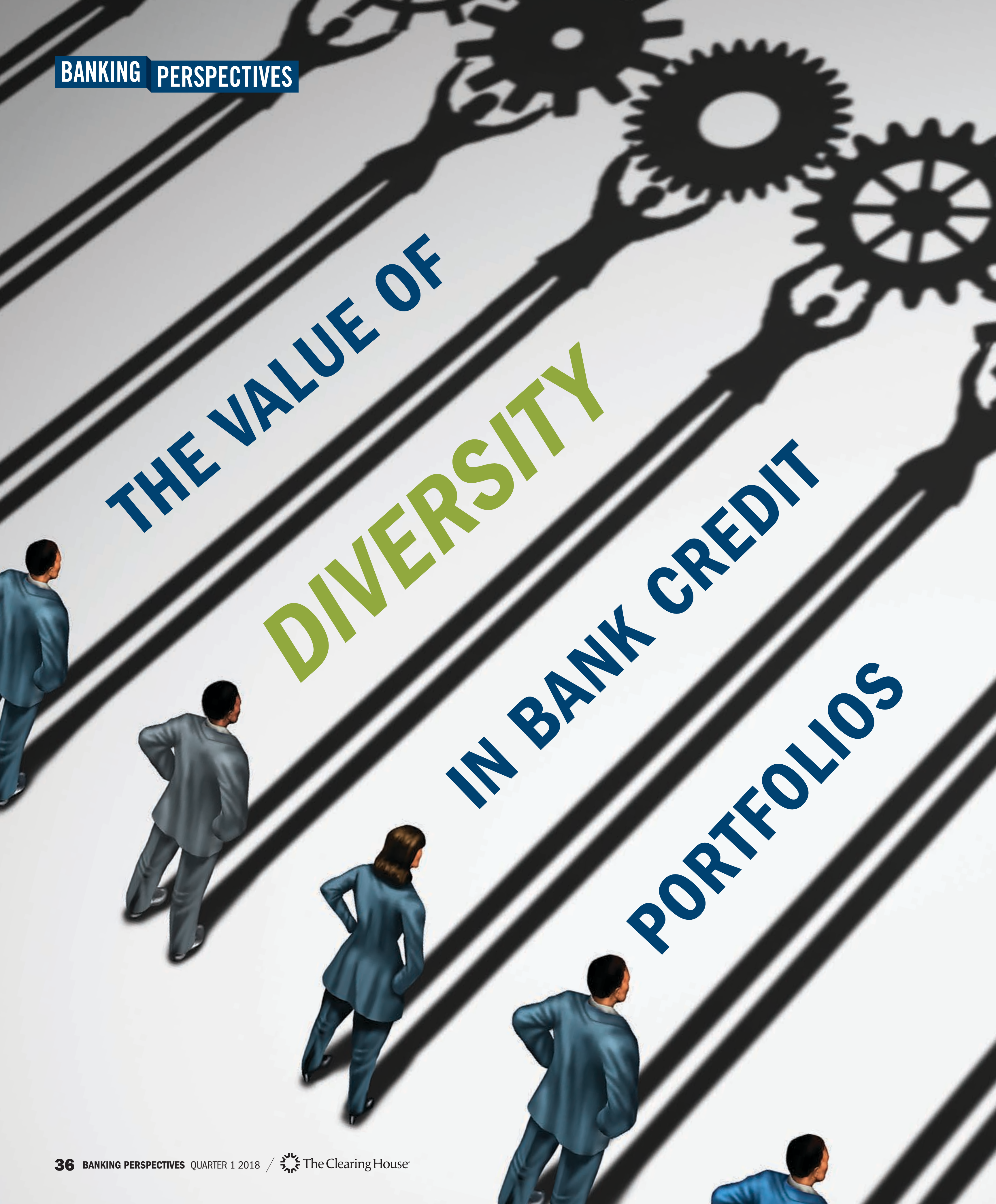

THE VALUE OF DIVERSITY IN BANK CREDIT PORTFOLIOS

DIVERSITY CAN BE A POSITIVE FORCE FOR A HEALTHY CREDIT MARKET AND A SYSTEMICALLY HEALTHY FINANCIAL SYSTEM.

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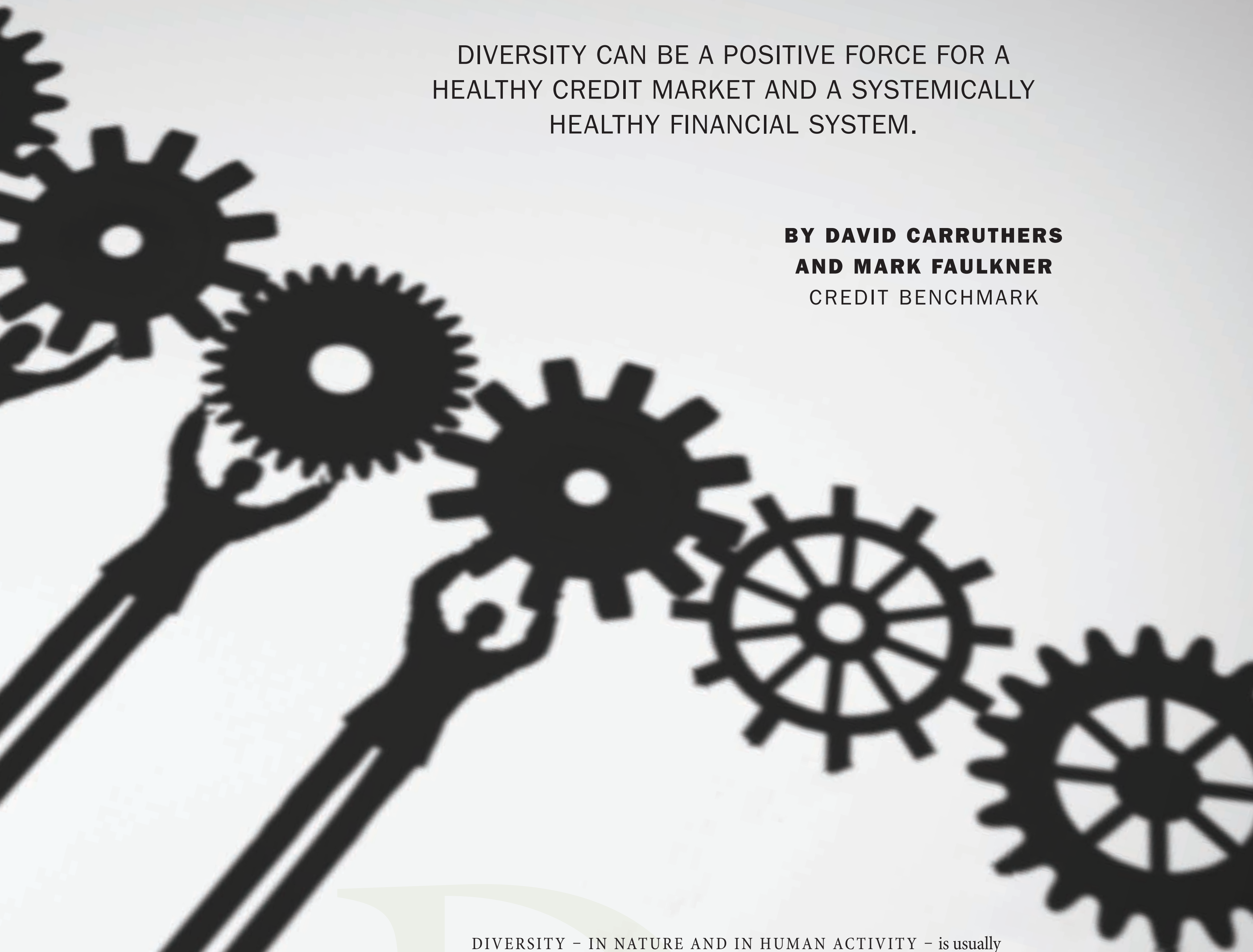
CREDIT BENCHMARK



DIVERSITY – IN NATURE AND IN HUMAN ACTIVITY – is usually seen as a force for good. This view has strong support among credit market participants, especially the banks that mobilize and deploy capital; they believe that there are economic and systemic benefits resulting from banks taking different views of risk. However, financial regulators are concerned about the role of this diversity in driving excess variability in risk-weighted assets. Regulators have argued for, and continue to impose, regulatory floors and ceilings to limit that variability; however, in some cases, these constraints could limit the scope for credit opinion diversity. Despite the differences in opinion, we find it encouraging that this important topic is now the subject of a constructive debate between the participants in the market and those who regulate it.

A broad and deep credit market is an essential element of a broad, deep, and robust economy, mobilizing idle capital and facilitating maturity transformation. But since the 2008–2009 crisis, credit markets have been subject to major and unprecedented distortions. Some of these have emerged from the markets themselves, but many have been imposed by central banks, politicians, and regulators.

Bank regulation is intended to prevent moral hazard and avoid undue risk-taking, but it inevitably acts as a standardizing factor. The challenge for regulators is to foster broader and deeper credit markets, while avoiding contagion across the banking system when an economic sector runs into credit problems. For a regulator, the ideal environment is one where different banks have different skill sets and make loans accordingly – encouraging diversification and limiting contagion. The task for the market and regulators alike is to successfully reach equilibrium between diversity and standardization and to identify when that point of balance needs to be moved. Bank-sourced data provides an effective way of tracking that balance.

This article uses bank-sourced consensus credit data to demonstrate changes in diversity over time and within different segments of the credit market. It will demonstrate that local and global diversity of credit opinions is measurable and suggests that this diversity can be a positive force for a healthy credit market and a systemically healthy financial system.

THE BANKING PERSPECTIVE

With imperfect information, financial systems gravitate toward fixed credit reference points to use as benchmarks. These are necessary in some form for planning and objective performance measurement. But the crisis of 2008–2009 revealed the risks when the system is anchored to a limited number of credit assessments.

Since then, the global banking industry has invested heavily in credit risk models to ensure that economic capital is aligned with its risk tolerance. The set of obligors captured in these assessments provides the building blocks of a large set of risk-diversified loan portfolios. However, paradoxically, many of these borrowers are outside the scope of traditional credit benchmarks: across a sample of the loan books of 20 global and major regional banks, more than 90% of the bank obligors are unrated by the major nationally recognized statistical rating organizations.[1]

THE REGULATORY PERSPECTIVE

According to The Clearing House Bank Conditions Index,[2] the resilience of the U.S. banking system is at a 20-year high across the dimensions of capital, liquidity, and risk aversion.

The largest banks now operate under the internal ratings-based (IRB) approach, known in the U.S. as the advanced approaches. These banks have mobilized their sophisticated (and diverse) credit assessments to ensure greater efficiency in risk-weighted asset (RWA) capital management than would be possible with standardized approaches. The Basel Committee on Banking Supervision (BCBS) restricts the scope for deploying these models for RWA purposes, with the implication that a "freedom to model" could be misused. But detailed analysis[3] suggests the opposite: large IRB and advanced-approach bank models are conservative and not a source of undue risk.

The BCBS's recent changes to the capital framework took longer than expected to be finalized, and one of the reasons was the considerable disagreement around the standards contained in the original proposals. These disagreements were not just between regulators and large banks; they were also between regulators themselves.

At one end of the spectrum, there is a regulatory view that all banks should operate on a standardized basis, an approach that would ensure that regulatory capital could be compared on a strictly like-for-like basis. A stylized version of this view can be characterized as: All banks have access to the same public information about XYZ Corporation, so they should all have the same assumptions about credit risk for that company.

At the other end of the spectrum, there is a view that the same public information can still lead to alternative views of creditworthiness through the exercise of judgment, different risk appetites, or in some cases through experience with the borrower (e.g., where some banks have private information, whether that is about the individual company or its sector or region). After all, bank lending best substitutes for, and is most necessary with, companies about which there is less-robust public information. Does a credit assessment represent a one-to-one relationship between current data and the single, correct credit view, or is it a one-to-many? For example, is Apple Inc. a relatively low-risk pile of billions of dollars of cash or a fashion-driven product company with all the risks that a change in the fickle world of global fashion might pose?

Although there are concrete steps that regulators can and do take to monitor systemic risk, this alternative view is also aimed at promoting diversity in loan books in order to discourage "herding" (the tendency for a common, but possibly erroneous, view to emerge due to banks pursuing the same sectors). This aim can be supported by a mature and diverse credit market while maintaining the existing capital management framework at the individual bank level. In this approach, regulators are observers of a well-diversified system while retaining the power to intervene if signs of herding emerge.

CREDIT PORTFOLIO MANAGEMENT AND THE VALUE OF DIVERSITY

Like any commercial business, a bank aims to maximize risk-adjusted returns. The theory is well known, but the practical implementation can be challenging and depends on the type of asset. One established approach used by the investment industry to link theory and practice is the work of Grinold and Kahn.[4] Their "Fundamental Law of Active Management" framework was developed to construct and manage investment portfolios against a chosen index benchmark. With some modifications, this can also be applied to credit portfolios.

The law is summarized by this simple formula:
Return per unit of risk = Skill x √ Breadth

Return per unit of risk, *e.g., information ratio, or average return versus benchmark index divided by the standard deviation of those returns.*

Skill *is the correlation between the expected and actual outcomes for individual assets*

Breadth *is the number of independent portfolio positions.*

> For a regulator, the **ideal environment is one where different banks have different skill sets** and make loans accordingly **— encouraging diversification and limiting contagion.**

Actual breadth is the number of independent constituents of the portfolio in a given time period.[5] If all assets move together by identical amounts, then they are not independent and the manager cannot outperform – relative return is only possible if there is some diversity in asset returns. Equally, if asset returns are very diverse, then the manager needs a high level of skill to select the concentrated subset that will outperform.

Diversity is key for differentiated returns as well as for risk management. But problems arise when the apparent diversity is not true diversity. In times of financial stress, correlations between similar types of assets tend to increase; diversity decreases when banks collectively abandon an entire sector that is in trouble, or more generally when there is a broad "flight to quality."

For credit portfolio management, each portfolio can be viewed as having an expected annual return (the exposure weighted average loan rates net of expected defaults), balanced against the risk of the portfolio that is driven by the covariance (correlation and volatility) of the borrower default risks in the portfolio. Ideally, the covariances should be zero (independent exposures and risks), but this can be difficult to measure due to the sparse nature of default data. Bank-sourced data provides monthly ex-ante views of default risk across a large obligor set, opening a new set of calibration possibilities for estimating default covariances.

The same framework can be applied to systemic banking risk. If all banks have similar loan portfolios, then systemic breadth is low. If the probability of default (PD) estimates are similar across loan books, then it is difficult for any one bank to outperform (or underperform) the others. The challenge for banks is that these similarities usually become apparent only after herding has happened.

In this context, diversity is a function of the number of banks that are actively assessing credit risk. The collective wisdom of the bank crowd in estimating PD values can be formalized in the "Diversity Prediction Theorem (DPT)":[6]

Crowd error = Average error – Diversity

Crowd error *is based on the differences between the average (i.e., group) PD prediction and the true PD value.*

Average error *is based on the individual bank prediction differences versus the true value.*

Diversity *is based on the differences between the individual bank predictions and the group prediction.*

A "wise crowd" will have a small crowd error. But if the average crowd estimate is significantly different from the true value, then the crowd error will be large, because the average error is much larger than the diversity. In other words, the diversity of the crowd is small because each bank is anchoring on a similar, erroneous PD value. If the crowd is made up of independent experts, then "anchoring" (the tendency for individuals to base their own estimates on those of others) is less likely and diversity is high.

The key unknown here is the true PD value. Historical data can help, but most systemic problems arise when the historical data is patchy or is not relevant in the current context. Examination of bank-sourced data over time can provide clues about the diversity of views within the banking system; it can also provide a rich set of comparative region and industry data, which can highlight where there are inconsistencies in the collective bank view.

BANK-CONTRIBUTED CONSENSUS CREDIT DATA SET

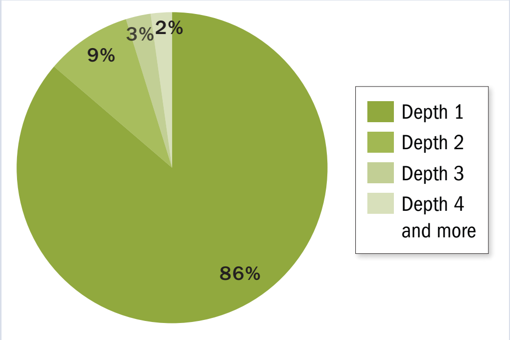
Credit Benchmark collects and publishes heavily anonymized credit estimates based on contributions from 20 banks which use the IRB/advanced approaches to manage and report regulatory capital.

This data set is collected monthly, with history currently available from May 2015. The data is published in the form of single obligor consensus credit estimates (a simple average of credit risk probabilities where there are three or more estimates from different banks), as well as in the form of aggregate indices and transition matrices. It covers sovereigns, corporates, financials, and funds.

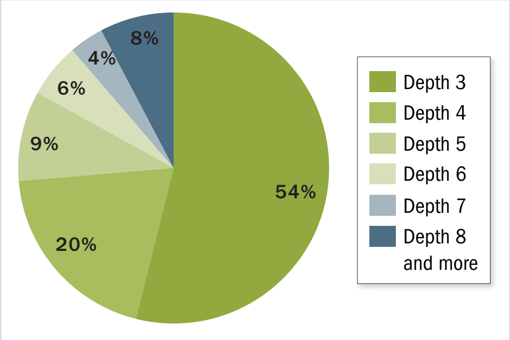
Figure 1 shows the contribution structure of bank-sourced credit data for a sample of U.S. and U.K. corporates.

FIGURE 1: CONTRIBUTION STRUCTURE OF BANK-SOURCED CREDIT DATA (U.S. AND U.K. CORPORATES)

All Mapped



All "Quorate" (i.e., 3 or more contributors)

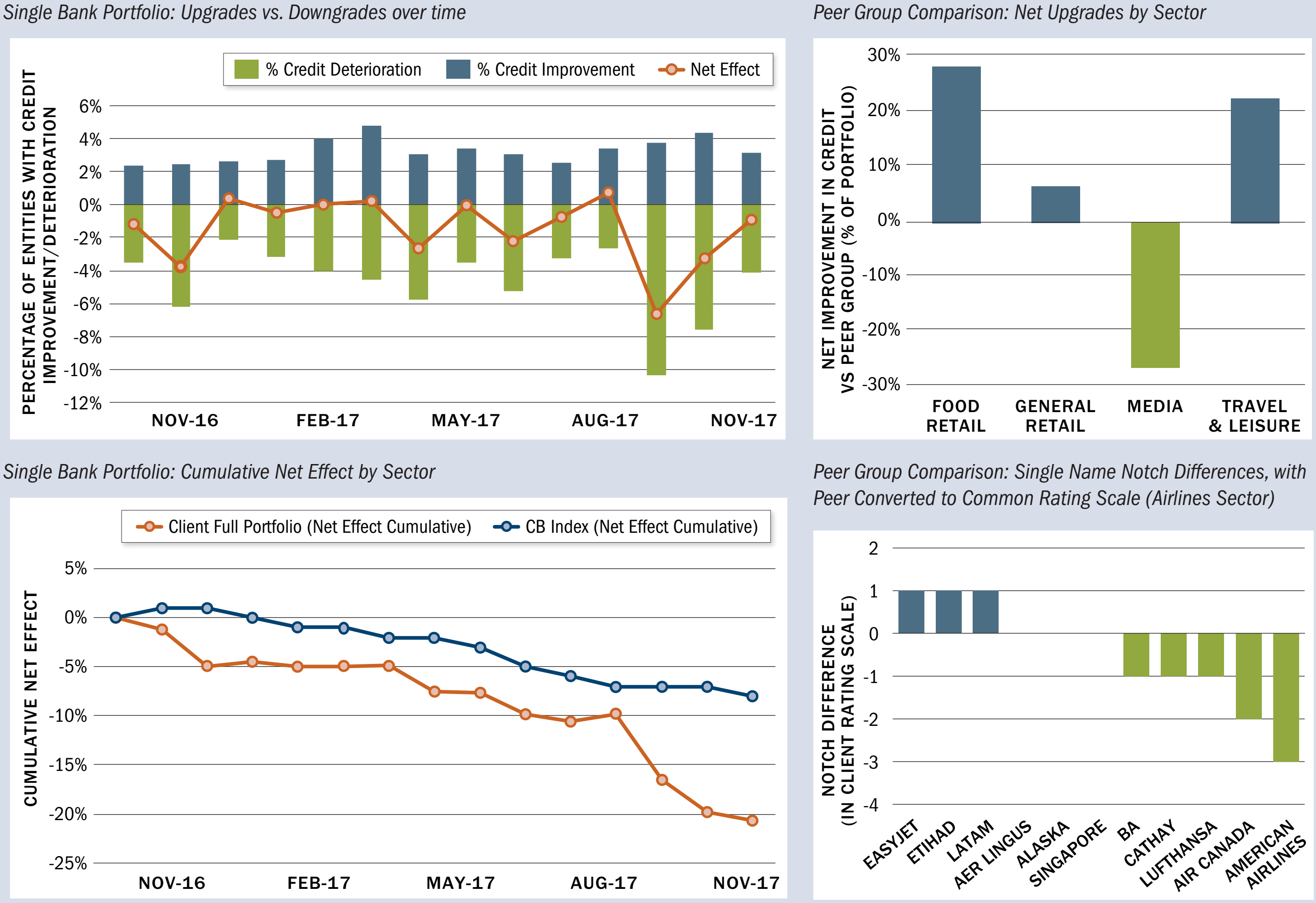


Source: Credit Benchmark

The chart on top shows that most (86%) borrowers in the current mapped data set are clients of only one of the large banks. This reveals a high level of diversity across banks at the individual obligor level. This data set can be used to derive credit trend indices and transition matrices, providing aggregate geographic and industry-level benchmarks.

The chart on the bottom shows the "quorate" subset of the mapped data set that can be anonymously published in single name form, because there are three or more contributing banks. Contributing banks use this data to provide like-for-like regional and sector benchmarks as well as for detailed obligor-level comparisons of individual credit risk estimates.

FIGURE 2: BENCHMARKING EXAMPLES



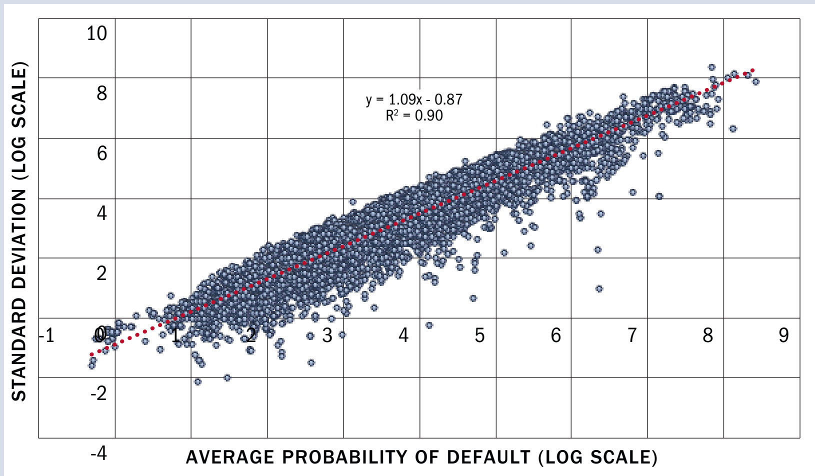
Source: Credit Benchmark

Figure 2 shows some examples of this benchmarking process in practice. This enables contributing banks to understand and assess their position relative to peers as it changes monthly.

These charts are part of a growing set of reports that are designed mainly by the contributing banks for internal use.

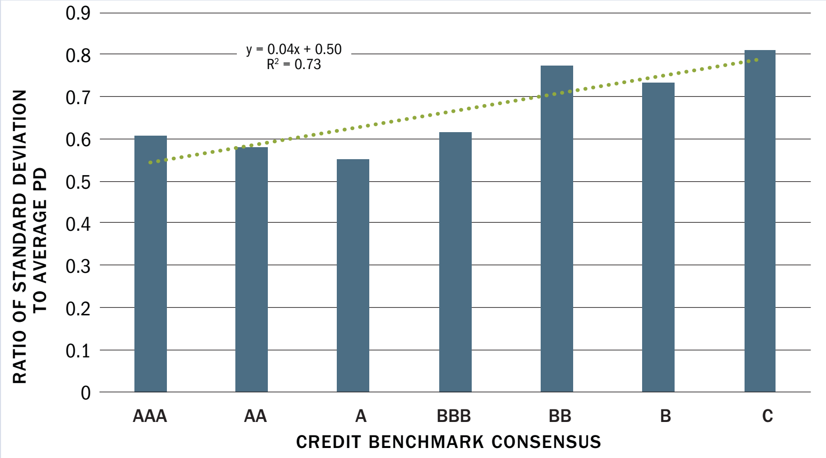
1. **DIVERSITY IN BANK CREDIT ESTIMATES – EVIDENCE FROM THE BANK-SOURCED DATA SET**
   Based on the Credit Benchmark obligor-level data, Figure 3 shows the logarithmic relationship between the (unweighted) average probability of default (X axis) and the standard deviation of bank estimates that make up the average (Y axis).

FIGURE 3: PD DISPERSAL (ALL QUORATE OBLIGORS, NOVEMBER 2017)



Source: Credit Benchmark

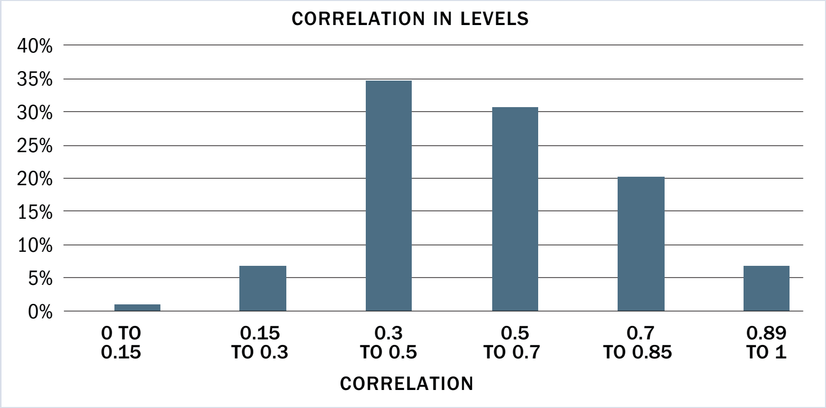
FIGURE 4: RELATIVE STANDARD DEVIATION BY CREDIT CATEGORY (ALL PUBLISHED OBLIGORS)



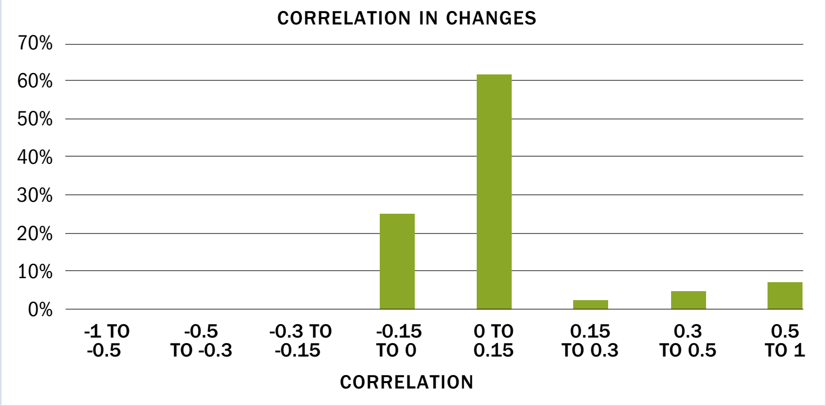
Source: Credit Benchmark

FIGURE 5: CORRELATIONS BETWEEN BANK PD ESTIMATES

Levels (November 2017)



Changes (January 2017 through November 2017)



The relationship is very strong and log-linear, although there are some noticeable individual outliers. This chart suggests that the standard deviation of the contributions – the "diversity" in DPT terms – is a positive function of the average PD level. If the average PD estimates are unbiased predictors of the true default frequency, then the crowd error will be low. This collection of bank experts will represent a "wise crowd."

Figure 4 shows the same data, grouped by credit category and normalized by PD to show the relative standard deviation.

This shows significantly higher uncertainty for non-investment-grade obligors – i.e., the diversity is higher.

A key concern with any contributed data set is the scope for feedback loops, mainly in the form of mean reversion. If every contributing bank has access to a report like that in Figure 2, there is scope for estimates to be revised to reduce outliers; over time, this could lead to reversion to the mean. This process is not a given, however; IRB and advanced-approaches banks use back-tested structural models for PD estimates; changes to these will affect an entire subgroup and will be fully audited. Ad hoc adjustments for single obligors are highly unlikely, and this type of data is as likely to be used to identify opportunities for contrarian positions from either a risk or return perspective.

To assess this, Figure 5 shows the correlations between individual bank PD estimates for fixed sets of obligors.

This shows a moderate to high correlation in PD levels but a low correlation in PD changes. In other words, banks tend to have similar views of the general level of credit risk for an obligor, but changes to those estimates are not synchronized.

Table 1 assesses mean reversion over time, for the period November 2016 to November 2017. This table uses various dispersion metrics, with the rationale that mean reversion across banks will appear in the form of lower dispersal on a like-for-like obligor basis.

TABLE 1: VARIOUS MEASURES OF MEAN REVERSION BASED ON CONTRIBUTIONS TO QUORATE PD AVERAGES

	STANDARD DEVIATION OF CONTRIBUTIONS	RELATIVE STANDARD DEVIATION OF CONTRIBUTIONS	MAXIMUM CONTRIBUTION - MINIMUM CONTRIBUTION	STANDARD DEVIATION OF LOGARITHM OF CONTRIBUTIONS	RELATIVE STANDARD DEVIATION OF LOGARITHM OF CONTRIBUTIONS	MAXIMUM CONTRIBUTION - MINIMUM CONTRIBUTION (LOGARITHMS)	AVERAGE ACROSS ALL MEASURES
Reversion (R)	52.1%	46.1%	46.2%	48.5%	45.2%	42.6%	46.8%
No Change	4.1%	4.1%	14.6%	4.1%	4.1%	14.5%	7.6%
Diversion (D)	43.8%	49.8%	39.2%	47.3%	50.7%	42.8%	45.6%

Source: Credit Benchmark; sample of 3,007 quorate obligors

This table shows that three of the metrics indicate a small majority for contributions that move closer together over time (reversion) and three of the metrics indicate a major that move further apart (diversion).

These results depend on the type of metric. For example, the linear distance between the maximum and minimum contribution values and the unadjusted standard deviation metrics are biased toward reversion. The relative standard deviation metrics and the logarithmic distance between the maximum and the minimum are biased toward diversion. Because PD values follow an approximately logarithmic distribution, these metrics may also reflect some adjustment for bias. Overall, the striking feature here is the dynamic nature of the data – very few of the observations show no change.

CONCLUSION

This article shows how the consensus data sets are being used by the banking industry to develop its own form of dynamic benchmarking at the obligor and credit portfolio levels. Bank-sourced data shows that credit opinions are updated frequently and diverge as often as they converge. The contributed data set also implies that bank views are especially diverse for low-quality obligors. Bank-sourced data also provides portfolio benchmarks for a broad range of sectors and individual companies, including those that are not covered by rating agencies. Within this set of benchmarks, banks can use their individual credit views as a business differentiator.

On a global basis, dynamic credit benchmarks can provide some of the key elements of a systemic risk monitoring infrastructure, and the use of bank-sourced credit data in this role ultimately can support a broader, deeper, and more robust global credit market. While diversity of credit opinions is thus alive and well within the leading global banks, likely with benefits for systemic risk, this diversity continues to face threats from well-intentioned regulation. There is clearly scope for a more open debate between regulators and the banking industry to agree the appropriate level of diversity at the local and global level. ■

Dynamic credit benchmarks can provide some of the key elements of a systemic risk monitoring infrastructure, and the use of bank-sourced credit data in this role can **support a broader, deeper, and more robust global credit market.**

ENDNOTES

1 Source: Credit Benchmark.

2 TCH Bank Conditions Index, Banking Perspective, Q3 2017, pp. 90-91.

3 https://www.creditbenchmark.com/research/impact-bcbs-proposals-irb-banks

4 Grinold, Richard, and Ronald Kahn. Active Portfolio Management. New York: McGraw-Hill, November 1999 (with reprints).

5 Note that skill also has a time dimension, so the annualized risk-return ratio may reflect the application of skill over multiple short time periods, as is typical of bank trading desks.

6 Hong, Lu, and Scott Page. "Interpreted and Generated Signals." Journal of Economic Theory, 144, no. 5 (September 2009): 2174-2196.