

Moody's Analytics

RISK PERSPECTIVES

MANAGING DISRUPTION

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FROM THE EDITOR

Welcome to the ninth edition of *Moody's Analytics Risk Perspectives*[™], a publication created by risk professionals for risk professionals.

"It is not the strongest or the most intelligent who will survive but those who can best manage change," said Leon C. Megginson, a professor of management and marketing. The quote (often erroneously attributed to Charles Darwin) resonates as we work to separate the noise of economic, political, and regulatory uncertainty from the end goals of our work – better understanding and quantifying the risks we face. Keeping an eye on the proverbial prize can help separate the signal from the noise.

Our 2016 magazine editions focused on the challenges posed by the new accounting standards for allowance, IFRS 9 and CECL, and the resulting need for a new breed of expertise: risk management with a deep understanding of accounting and finance. In 2017, we are expanding on the themes of what is challenging the way we have always approached risk management in banking. Emerging technologies and new applications of existing technologies in banking have been grabbing headlines. Is the branch-banking relationship model dead? Does the speed of the credit approval process offered by the alternative lenders threaten the existence of small business lending products offered by banks? Does access to digital payment systems mean that millennials will not bank with traditional financial institutions?

"Disruptive technologies typically enable new markets to emerge," wrote Clayton M. Christensen in *The Innovator's Dilemma*. This view, which I share, suggests that disruption can lead to a larger pie. The question is how to manage this disruption, which is the theme of this edition. Our *Spotlight* section features articles on the criticality of effective onboarding processes in small business lending and applications of machine learning (a new application of an existing technology) to commercial loan credit risk assessment. We also feature an article on improving data preparation for modeling – a topic of passionate debate for credit modelers.

We have broadened the magazine to include an *Op-Ed* section, where we invite candid views from practitioners on emerging issues. Keith Berry and Cayetano Gea-Carrasco write on the impact of innovation on financial services, Dr. Anthony Hughes discusses the impact of ride-sharing services on auto production, and Dr. Deniz Tudor searches for better approaches to risk management as Dodd-Frank stress testing matures.

As always we welcome your comments and look forward to a conversation.



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RISK PERSPECTIVES

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BY THE NUMBERS

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R3 is a consortium of more than 70 of the world's biggest financial institutions working together to explore applications of blockchain technology in financial services.

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10%

The Financial CHOICE Act would effectively eliminate the Dodd-Frank burden on banks if they met a 10% leverage ratio.

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1930s

Automatic transmission, an early step toward self-driving vehicles, first entered the market in the 1930s.

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99%

Small businesses account for 99% of all firms in the US.

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5.58%

When making lending decisions, analyzing behavioral information in addition to financial information can help a lender avoid a loss of about 5.58% on a quarter of its portfolio.

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39%

We find that in 39% of instances, LGDs Granger-cause EDFs, while the reverse is true in 50% of cases.

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50%

Data quality investments can lead to a reduction of up to 50% in direct costs.

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10

One-year model accuracy ratios improve by up to 10 percentage points when models use both financial and behavioral data rather than only financial data.

**Machine Learning: Challenges, Lessons, and
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24hrs

Small and mid-sized enterprises can secure up to \$150,000 in under 24 hours via alternative lenders.

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90

In a calculation for lifetime expected credit losses for allowances, sample portfolios show credit earnings volatility of 90 basis points.

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1

Under the new CECL standard, firms must account for expected losses on day 1.


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1.5x

Volatility of CECL-based provision for sample banks' C&I portfolios is 1.5 times higher than that of incurred loss during the crisis period (2007 – 2010).

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OP-ED

OPEN INNOVATION IN A TIME OF TECHNOLOGY ACCELERATION

By Keith Berry and Cayetano Gea-Carrasco



Keith Berry
*Executive Director,
Emerging Business Unit*

Keith is the executive director responsible for Moody's Analytics Emerging Business Unit, based in New York. The Emerging Business Unit aims to identify, research, and develop new business opportunities for Moody's Analytics that are enabled by technology innovation.

Prior to his current role, Keith served as head of the credit assessment and origination business based in Hong Kong, head of professional services for the enterprise risk solutions division based in Paris, and head of software engineering for the enterprise risk solutions division based in San Francisco. He first joined Moody's Analytics in 2008.

Keith has an MBA from the Wharton School at the University of Pennsylvania and a bachelor's degree in engineering from the University of Durham.



Cayetano Gea-Carrasco
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Cayetano works with financial institutions to address their technology and enterprise risk management needs. Previously, he held leadership positions at various institutions and global banks. He is a regular speaker at international conferences and has published several articles in the areas of risk management, financial technology, and derivatives pricing. Cayetano holds a BSc. and an MSc. in telecommunication engineering, a master's in economics and finance, and an MSc. in financial mathematics, with distinction, from King's College London.

Today's technology is progressing increasingly quickly. The trend of improving computing power at decreasing costs has permeated the financial services industry, leading to notable capabilities including cloud computing, big data, and machine learning. In this article, we explore Moore's law and Joy's law, two governing principles in technology and innovation, and examine the role of new and emerging technologies in the rapidly evolving financial technology space.

We are living in a time of accelerating innovation. It's hard to believe that it was just 10 years ago that Apple introduced the iPhone. There are now estimated to be 3.9 billion smartphones in the world¹ and more than 2 million apps available in the Apple and Android app stores which enable your smartphone to be a high-end camera, get real-time news updates, track your fitness, trade stocks, deposit checks, and yes, make phone calls if you really need to.²

Technology is a key and well-documented driver of this acceleration. Technology acceleration is most clearly stated by Moore's law. First postulated by Intel cofounder Gordon Moore in 1965, Moore's law is the observation that the speed and power of microchips would double roughly every year (which he later updated to every two years) for only slightly more money with each new generation. The pattern predicted by Moore's law has generally held true for 50 years.

Moore's Law Applied to Financial Services

Moore's law provides an explanation for the fact that the processor in your iPhone today has more computing power than the Cray-2

supercomputer used by NASA in 1985. It's worth remembering that the Cray cost approximately \$16 million in 1985 and needed to be physically connected to the water main to provide cooling.³

Moore's law equally applies to storage. A gigabyte of storage capacity for the Cray-2 in 1985 would have cost \$105,000, but in 2016, a gigabyte of storage capacity on average cost less than 2 cents.⁴

This combination of exponentially decreasing cost of storage and exponentially increasing computing power are crucial drivers of three of the largest trends affecting the financial services industry right now: cloud computing, big data, and machine learning.

Cloud computing takes all of today's storage capacity and computing power and effectively makes it available as a utility. If I want to use a server with 64 processors and 256 gigabytes of memory, I can visit an online cloud provider, explore a few options, put in my credit card details, and have a server up and running in 10 minutes. The cost for all of that computing power is just \$3.45 per hour.⁵

1 Ericsson.com. "Latest mobile statistics: key figures." November 2016.

2 Statista. "Number of apps available in leading app stores." March 2017.

3 Walton. "As Moore's law turns 50, what does the future hold for the transistor?" Ars Technica, April 20, 2015.

4 Statistic Brain. "Average Cost of Hard Drive Storage." September 2, 2016.

5 Amazon Web Services, Inc. "Amazon EC2 Pricing." April 28, 2017.

Historically, software developers had to carefully manage storage costs by storing only the key data attributes required for a particular calculation. With exponentially decreasing storage costs, we now try to store every data attribute possible, because we may find in the future that it is predictive of something that we don't expect it to be predictive of today.

Big data refers to datasets that are too large or complex for traditional data processing methods to handle. Big data technologies allow us to store and analyze these huge and ever-growing datasets. These datasets, in turn, are the perfect training datasets for machine learning algorithms to spot patterns that we did not know existed. It is this combination of big data technologies and machine learning that allows Facebook to suggest the names of our friends who appear in a photo taken on our smartphone, or Spotify to provide us with new music recommendations.

We have customers using big data technologies to store all of their risk management data

in multiple ways across the financial services industry, such as in open source software, application program interfaces (APIs), consortiums, and partnerships.

The growth of big data has partially been driven by the processing and storage advances already mentioned, but it has equally been driven by Hadoop, one of the most successful open source projects of recent years. Hadoop is the software layer that allows us to store and process large quantities of data by distributing that data across multiple machines. Hadoop came into being after Google published a research paper in 2003 explaining how it managed the huge amounts of data needed for its search engine.⁶ The open source community set about implementing its own version of what Google described, ultimately creating Hadoop. Today, Hadoop continues to evolve and be developed by a team of volunteers from companies including Yahoo, Facebook, IBM, Microsoft, LinkedIn, Twitter, and many others.⁷

Cloud computing takes all of today's storage capacity and computing power and effectively makes it available as a utility.

alongside all of their customers' website usage logs, because it may reveal something interesting over time.

Joy's Law and Advancements in Fintech

Moore's law is one relatively well-known factor driving this period of accelerating innovation. A second, lesser-known factor is Joy's law.

Joy's law, attributed to Sun Microsystems cofounder Bill Joy, is the principle that "no matter who you are, most of the smartest people work for someone else." According to Joy, "It's better to create an ecology that gets all of the world's smartest people toiling in your garden for your goals. If you rely solely on your own employees, you'll never solve all your customers' needs."

We are seeing Joy's law manifest itself today

Of course, open source software is nothing new; the Linux operating system, first released in 1991, is the result of one of the earliest and most popular open source projects. However, in the last 10 years, we have seen an acceleration in the development of open source software in part through the establishment of GitHub. GitHub enables open source software developers to find each other's work and collaborate on new projects. In April 2017, GitHub reported it was hosting nearly 57 million projects and had almost 20 million users.⁸

In parallel, we have also seen a growth in large companies contributing software to the open source community. A prime example of this was when Microsoft open sourced the code for its .NET programming framework in 2014. Working with the open source community, .NET has now

6 Finley. "The Google Clones That Power NSA Surveillance." WIRED. December 12, 2013.

7 The Apache Software Foundation. "Who We Are: Apache Hadoop Project Members." April 27, 2017.

8 GitHub. "Celebrating nine years of GitHub with an anniversary sale." April 10, 2017.

been converted to run on both Linux and Mac operating systems in addition to Windows.

The financial services industry is starting to ramp up its contributions to open source with firms such as Goldman Sachs,⁹ Capital One,¹⁰ and Bloomberg¹¹ leading the way as active contributors to projects on GitHub.

APIs are the second major way we are seeing Joy's law manifesting itself today. APIs allow a piece of functionality to be exposed in a way that other users can access it. For example, I can get the latest weather forecast for my current location from a weather API, or the latest stock price for my company's stock from a stock price API. An API encapsulates a company's proprietary data and analytics, and the API provider can then govern how consumers use the API: Is it free or do they charge for use? Can the API be called a certain number of times per month at no charge? With access to the API, new products and services can be built.

We are currently seeing an explosion in APIs, with the ProgrammableWeb API directory listing more than 17,000 available APIs across multiple industries.¹² The financial services industry is seeing a similar increase in available APIs. This is being driven in part by the Second Payment Services Directive (PSD2) regulation in Europe, which includes provisions that banks need to enable account access by third parties by public APIs. However, it seems like every week another bank announces an API initiative.

At Moody's Analytics, we provide a lot of our products and services via APIs, whether it is to access a rating from our sister company, Moody's Investors Service, or to provide a probability of default calculation on a private firm. We plan to continue expanding the APIs that we provide.

We have recently observed a growing interest in industry consortiums working together to tackle new and evolving issues. The most successful of these initiatives is R3, the consortium of

more than 70 of the world's biggest financial institutions which have come together to explore how blockchain technology can be used in financial services. The consortium only came into being in September 2015 with nine founding members; however, it has since grown rapidly to its current level of membership. So far, the consortium has worked together to complete multiple proofs of concept and has created an open source distributed ledger platform called Corda which has been designed for the financial services world.

The final approach to Joy's law that we are observing is one of partnership, particularly partnerships between large, established industry players and innovative fintech startups. According to Financial Technology Partners, an investment bank with a fintech focus, financial technology companies raised \$36 billion in financing across more than 1,500 funding deals in 2016.¹³ As an example, Kabbage, an online provider of small business loans, has partnered with both Scotiabank and Santander UK to bring its fintech platform to the banks' customers.

Moody's Analytics is currently partnering with Seattle-based fintech company Finagraph to develop the MARQ™ portal and MARQ score, tools that enable banks to streamline the lending process by integrating data from customers' accounting systems directly into the banks' underwriting process. We are also partnering with San Francisco-based Spacequant to develop a new model in the commercial real estate space. We expect to continue developing these and other partnerships.

In summary, we believe that in an age of fast technology innovation governed by Moore's law, the only way to solve all of our customers' needs is to embrace Joy's law and develop an open ecosystem of partners and collaborators who can help us achieve that goal.

9 Goldman Sachs. "Open Source at Goldman Sachs." January 20, 2017.

10 Capital One DevExchange. "Open Source." April 12, 2017.

11 Tech at Bloomberg. "Open Source." 2017.

12 ProgrammableWeb. "Search the Largest API Directory on the Web." 2017.

13 Mesrobian, Elena. "Global FinTech Funding Reached \$36 Bn in 2016 With Payments Companies Securing 40% of Total Funds." Let's Talk Payments. January 2, 2017.

RECONSIDERING RISK MANAGEMENT, GOVERNANCE, AND STRESS TESTING

By Dr. Deniz Tudor

Because of the large role the financial sector played in the Great Recession, governing bodies have passed a wave of new regulations. The Dodd-Frank Act, signed into law in 2010, was the most significant of the reforms and introduced stress tests into banks' annual calendars. The banking industry has heavily criticized most of these new regulations, particularly Dodd-Frank, for being too costly, and economists and analysts have spoken against them for impeding growth in the supply of credit.¹ By contrast, supporters of Dodd-Frank claim that these regulations have made the financial system more stable and resilient. We believe that both positions have some merit. Some of the regulations in place today have improved practices in the financial system, while other regulations could benefit from simplification. In this article, we discuss areas such as capital stress testing where simplification of regulations and their execution could improve the flow of credit while protecting the financial system. Based on our experience with several client engagements, we recommend simplifying the capital stress testing process through improved governance, cost-benefit analysis, more realistic timelines, greater coordination between regulatory agencies, and increased regulator transparency.



Dr. Deniz Tudor
Director, Consumer Credit Analytics

Deniz is a director in the credit analytics group. She develops and stress tests credit models in various consulting projects. She has extensive experience in modeling residential, auto, and credit card loans. Deniz has a PhD from the University of California, San Diego and BA degrees in economics and business administration from Koç University in Turkey.

Introduction

The Great Recession was a wake-up call for banks and all other lenders to review their risk management practices and governance. Because of their size and impact on the economy, banks have gone through a major overhaul of processes and loss forecasting models that feed into capital formation decisions and have started depending more on specialization, expertise, and unbiased views.

In the wake of the recession and under-supervision by regulators, banks have adopted several best practices. For instance, they now consider the role of the macroeconomy more formally in their revenue and loss models and subsequently analyze the impact of the economy

on their forecasts. A natural extension of this was to integrate stress scenarios into forecasts as part of the Comprehensive Capital Analysis and Review (CCAR) stress testing process. This practice allowed banks to prepare for downside risks and adjust their capital plans based on future stress scenarios. Another welcome change was that banks began to prepare custom scenarios and include them in decision-making processes. These custom scenarios are intended to capture banks' own idiosyncratic risks, giving management quantitative insight into their key vulnerabilities.

Although there were long-awaited improvements in banks' risk management practices, new regulations have also brought

¹ Zandi, Mark and Jim Parrott. "Zandi: Credit constraints threaten housing recovery." *Washington Post*. January 24, 2014.

difficulties. To begin with, finalizing Dodd-Frank took much longer than planned. Delays – as well as uncertainty about the Federal Reserve's internal models and scenarios, interpretation of their feedback, and practical implementation issues – have affected the functionality and outlook of the financial sector. Dodd-Frank Act Stress Tests (DFAST) and CCAR examinations have taken on a life of their own and become a multi-billion-dollar industry. They are consuming resources, such as human capital and IT, which could otherwise be put toward improving

cause more harm than good, especially as many banks have already invested heavily in creating the framework to abide by the regulations. For example, the Financial CHOICE Act (Creating Hope and Opportunity for Investors, Consumers and Entrepreneurs), first proposed by the House Financial Services Committee, would effectively eliminate the Dodd-Frank burden on banks if they met a 10% leverage ratio.² This could encourage a risk management culture that is weak and vulnerable to revenue growth targets. Dodd-Frank allows the Fed to have a say on

Working toward the aims of Dodd-Frank – making the US financial system safer – is key to making regulations work for the economy. Following a process for the sake of having a process will not help avoid another Great Recession.

banks' bottom line or investing in innovation. On the regulators' side, lack of transparency and insight into the Fed's internal models, as well as confusion about the rules, have hurt the credibility of the regulations.

Why Now and How to Fix It

A new administration in the White House could provide opportunities for positive changes to regulation to encourage economic growth and discourage inefficient practices. In the rest of this article, we present our vision for improving the current stress testing framework and practices.

In terms of the future of Dodd-Frank, we can generalize proposals into four camps with varying degrees of potential economic impact:

1. Repeal Dodd-Frank in its entirety; allow banks to self-govern.
2. Repeal parts of Dodd-Frank.
3. Clarify and simplify the execution of Dodd-Frank.
4. Both 2 and 3.

Let's start with the first proposal. In our opinion, completely repealing Dodd-Frank, as proposed by many Republicans and the White House, would be the least viable option. Supporters of the repeal cite credit tightening as the main reason for the need for repeal; but a repeal could

dividends and share buybacks based on the capital plans it receives from banks, giving the central bank leverage. Without this leverage, the responsibility of corrective action would be largely delegated to the banks which, as we have seen in the past, can ignore sound practices for the sake of short-term profits.

The second proposal, involving the repeal of some parts of Dodd-Frank, is a more viable option. Many in the industry would welcome a repeal of the Volcker Rule, which prohibits banks from conducting certain investment activities with their own accounts. On the other hand, keeping capital and liquidity requirements would balance against potential risk-taking if the Volcker rule is repealed, since capital and liquidity shortages were the main reasons for bank failures during the Great Recession.

The third proposal would ease the enforcement of regulations, which makes the fourth proposal the best course of action in our opinion. This proposal responds to a question that has been long asked: What is the real problem, the regulations or their implementation? Our experience in working with several CCAR and DFAST banks leads us to conclude that it is the manner of implementing Dodd-Frank rules that has bred uncertainty and confusion. For instance, after submission, banks receive lists of matters

² Financial Services Committee. "Amendment in the Nature of a Substitute to H.R. 5983 Offered by Mr. Hensarling of Texas." September 12, 2016.

requiring attention (MRA) and matters requiring immediate attention (MRIA) that provide only vague guidance. These recommendations put banks on the defensive, eating up significant amounts of resources that banks could more efficiently use elsewhere.

Working toward the aims of Dodd-Frank – making the US financial system safer – is key to making regulations work for the economy. Following a process for the sake of having a process will not help avoid another Great Recession.

Capital Stress Testing

As part of CCAR and DFAST, which is a complementary exercise to CCAR, the Federal Reserve assesses whether banks with assets of \$10 billion or more have adequate capital to continue operations during adverse economic conditions. As part of this review, the Fed also assesses whether banks have robust, forward-looking, scenario-conditioned forecasts and whether underlying models account for unique risks of institutions. Forecasts from loss

for small and midsize banks with assets of \$50 billion or less.³ Likewise, large banks should be subject to stricter requirements given the greater risks they pose. Easing the regulatory burden on small banks would encourage more banks to open and increase competition, particularly important in the current environment of increasing interest rates. An increased number of small and midsize banks would also benefit small businesses, especially those that are finding it difficult to obtain loans through larger banks. Similarly, cost savings could be achieved by subjecting small portfolios to less scrutiny.

Regulator Transparency and Timelines

The Fed should be subject to the same transparency standards that the banks have to follow. Markets would also benefit from more flexible regulatory timelines.

Lack of Fed transparency regarding its models and regulatory scenarios has been a subject of criticism since DFAST began. Banks have requested more details on the assumptions behind the Fed's scenarios and methodologies

Releasing details of the Fed's model methodology can prevent wasted resources on guesswork and help banks understand the standards that they are judged against.

forecasting models ultimately decide whether institutions have sufficient capital to absorb losses.

The following sections give suggestions on how to fix the capital stress testing process.

Cost-Benefit Analysis

A thorough cost and benefit analysis should be conducted at institutions that are subject to regulations. This analysis should differentiate between the sizes of institutions and portfolios.

In a world where regulatory compliance is less stringent, one set of regulations would be sufficient for institutions of all sizes to simplify and avoid confusion, enable knowledge transfer, and deal with turnover more easily. However, given that compliance costs are non-trivial and risks to the economy in the event of failure vary by bank, requirements should be less stringent

for projecting revenue, losses, and regulatory capital ratios. Releasing details of the model methodology can level the playing field, prevent wasted resources on guesswork, and help banks understand the standards that they are judged against. The Fed fears that if these details are released, banks may try to game the system – that is, they might use the blind spots of the Fed's model to adjust portfolio characteristics and take risks in areas not well-captured by the model – but this concern could be handled by giving notice to an institution if such gaming is discovered. Alternatively, the Fed could continue to change its model from year to year to make it more difficult to game the system. Releasing the details of stress test scenarios could be beneficial, especially during times of uncertainty about the future and when the outlook is positive.⁴

³ The Fed has already been moving toward differentiating expectations from banks with different sizes and complexity.

⁴ In September 2016, Fed Governor Daniel Tarullo announced a series of reforms to the annual CCAR exercise, including changes designed to provide more transparency. For details, see: Tarullo, "Next Steps in the Evolution of Stress Testing," Yale University School of Management Leaders Forum, September 26, 2016.

More transparency could also help in the feedback the Fed gives to banks. For example, a common misunderstanding is that the Fed demands that banks develop their own internal models. However, regulators emphasize that banks may use external models as long as they thoroughly understand the models and take ownership of them. Leveraging third-party models may also help reduce costs, reduce turnaround time, offer more in-depth documentation, and, hence, increase transparency into data cleaning and model methodology. Some of these models can also be used for multiple purposes, which is increasingly a goal for banks these days.

Conflicts Between Regulatory Agencies

Banks should comply with a simple set of rules and regulations rather than addressing conflicting guidance from different agencies.

This is of particular concern for midsized banks, as there is much confusion about how much scrutiny they will be subject to from different regulatory agencies when it comes to data and model methodology. Midsized banks face challenges in regard to data, timelines, and human resources which make it hard and costly for them to deal with increased scrutiny and inconsistent guidance. All banks, and especially midsized ones, would benefit if rules and implementation guidance were consistent across regulatory agencies such as the Fed, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC). These inconsistencies in guidance may affect modeling methodologies or data treatments as well as scenarios.

Governance

Banks should regard risk management and stress testing models as part of day-to-day business and integrate them into existing processes. Regulators should encourage this.

With no incentives to look beyond the letter of the regulation, banks can engage in "checking the box" behavior, simply reacting to feedback and following regulations blindly. Instead, institutions should be incentivized to focus on proactive risk management by consciously thinking about the purpose of models, outcomes, and uses. Forecast accuracy, which would lead to enhanced credit formation, should be preferred

to the conservative approach of overestimating losses.

Another best practice involves improved collaboration within a bank, which can reduce costs by allowing for the development and use of a single set of models for many purposes. In banks where the channels of communication are open for modelers and line-of-business teams, processes are more efficient and knowledge transfer happens easily. This should be the ideal for risk modelers as they aim to produce meaningful models that can be used by many departments of the bank, including line-of-business teams. To this end, all parties involved should also understand the purpose of the models, as well as the constraints in model development which can stem from concerns about data, economic factors, econometrics, and time and resource limitations.

Finally, building too many models is not only costly but also difficult to manage effectively. A proliferation of models may provide a variety of results, which can cause lines of business to be wary of contradictory model outputs. Thus, banks need a clearly articulated process for dealing with mixed signals. Ideally, the same set of models should be used for stress testing, portfolio management, strategic planning and forecasting, and setting risk appetites. Risk models should be fully integrated across all business lines and should be actively used in decision-making instead of simply checking the box for regulators.⁵

Conclusion

Dodd-Frank has moved risk management from an afterthought to a main consideration in banks, a change in mindset that helps keep the financial system sound. However, complexity and lack of clarity in the regulations have created inefficiencies. Simplification of regulations should unleash economic growth, reduce costs, minimize uncertainty, and help banks prioritize and focus resources to more beneficial endeavors such as business growth. Simplification would also encourage growth in the number of banks. Finally, some deregulation is warranted, but it is important not to go too far. Reducing regulations too much could lead to a return to old methods in which risk management was merely an afterthought.

⁵ Gea-Carrasco, Cayetano. "Leveraging Stress Testing for Performance Management." GARP 16th Annual Risk Management Convention. February 24, 2015.

Do you have the capabilities to estimate credit impairment for CECL?

The new CECL standard will change the way firms measure credit losses. Early preparation is key. Moody's Analytics can help you develop the capabilities you need for successful CECL implementation. From data and models to credit impairment software, we can help you establish a holistic approach as you transition to CECL.

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MOODY'S
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THE EFFECT OF RIDE-SHARING ON THE AUTO INDUSTRY

By Dr. Anthony Hughes



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Ride-share technology, facilitated by universal smartphone penetration, has decimated the taxi industry; meanwhile, coincidentally, carmakers have enjoyed record sales. In this article, we consider some possible longer-term ramifications of ride-sharing for the broader auto industry. Rather than declining sales volumes, as many pessimists have predicted, the biggest threat seems instead to be increased vehicle homogenization. This holds the potential to radically affect the profitability of new vehicle manufacturing and the viability of the used car industry in general.

Many in the auto industry are concerned about the impact of ride-sharing. Opinions related to the issue typically fall into one of two camps. First, there are the "technology optimists" who imagine ride-sharing companies with fleets of self-driving cars dominating the highways next year. Others point to various regulatory and technological issues that are likely to slow progress toward this brave new world.

The objective of this article is to analyze the impact of ride-share services like Uber and Lyft on the private transportation market. For dealers, financiers, and manufacturers, the volume of car sales is a critical determinant of financial success. Assuming a constant mark-up in either the new or used car market, industry profits will be dictated by the number and dollar volume of retail sales ultimately made to consumers or ride-sharing companies and contractors. Forces that erode industry pricing power are also a critical concern. We will explore both issues.

Since ride-sharing has only existed for a short time, it is probably too early to empirically identify any structural break that may have occurred as a result of the new technology. For this reason, we will adopt a more theoretical approach, and a simplified economic model will be sketched out. We will then relax some of the assumptions in our framework and consider the effect on volume and pricing.

For simplicity, assume there is only a primary (new vehicle) market for cars. In other words, vehicles are purchased new and then "driven into the ground" by their homogeneous owners. Assume further that the number of private journeys undertaken by society is fixed and that taking one journey in a homogeneous private vehicle causes one unit of physical depreciation. Assume all cars are driverless.

If a consumer simply chooses to substitute a journey taken in his or her own car for one taken in a ride-share, the total amount of vehicle depreciation suffered by society will be unaffected.

Now, let's say that one ride-share vehicle replaces 10 cars that were previously privately owned and spent 90% of their potential driving time garaged. Under our assumptions, the total number of depreciation units is unchanged, but the units are now concentrated in one-tenth as many vehicles as observed under the status quo. If the vehicles in question have a fixed lifetime, consistent with the assumption of vehicle homogeneity, the ride-share cars will depreciate to scrap value 10 times faster than equivalent privately owned vehicles.

In terms of the effect on the car market, though there are one-tenth as many cars in service, they will be refreshed by their owners 10 times as often, implying that new vehicle sales volumes will be unaffected by the introduction

of ride-sharing. Since the demand for vehicle depreciation units is the same under both scenarios, and since vehicles are assumed homogeneous with a fixed supply curve, prices of vehicles should likewise be unaffected. Having fewer cars on the road does not necessarily imply that there will be fewer car sales.

This very simple framework gives us a starting point for some more interesting analysis. We will consider the impact of ride-share on the markets for new versus used cars. Most of the analysis will assume that ride-sharing will grow to dominate the market for private modes of transportation, though this outcome is far from certain. The effect of driverless vehicle technology will also be considered, though much of the analysis will assume a driverless future.

Effect on the New Car Industry

Many commentators focus on the notion that ride-sharing will lead to a reduced number of cars in use and immediately jump to the conclusion that ride-sharing will negatively impact vehicle manufacturers. As the description of our baseline model points out, however, perhaps they need not worry.

First, let's consider the impact of relaxing the assumption of vehicle homogeneity; we will instead assume that technological advances in car design are continually being made. One implication of this new assumption is that vehicles will not only suffer from physical depreciation but will also face obsolescence. In this situation, a car that has yet to reach its terminal number of depreciation units may be scrapped simply because more technologically advanced cars are available for consumers to drive (or, indeed, to ride in).

Manufacturers benefit from the inevitable obsolescence of the vehicles they produce. If vehicle technology did not advance, manufacturers would move more units by offering unreliable vehicles with a short lifespan. Carmakers engage in research and development specifically to entice owners to trade up to newer, safer, more reliable models with more creature comforts. Buyers expecting to own their vehicles for many years will be willing to pay a premium for cars that precisely match their anticipated needs.

The fact that non-ride-share cars are owned for longer in our model means that obsolescence is a bigger issue for them. If all cars on the road were

ride-shares – driven heavily in service of their customers – far fewer vehicles would be replaced due to obsolescence prior to the exhaustion of the vehicles' physical life. This means that for a given number of passenger miles traveled, there will be fewer vehicle sales, relative to the status quo, as a result of the introduction of ride-sharing.

Ride-share owners will demand reliable vehicles but will be largely indifferent to features that will not stand the test of time or that would not be valued by the bulk of their clientele. Ride-shares, like traditional taxis, should be clean and safe, but other features will be largely irrelevant; when was the last time you waved off a cab because it happened to be a 2003 Ford Taurus? Manufacturers currently have little interest in building only bulletproof, homogeneous cars (like taxis) that owners drive until salvage and never want to trade. Commoditization, simply put, would be an existential threat for the car industry as we know it today.

Companies like Uber and Lyft, though, have a strong interest in securing access to such vehicles. Our bold prediction is that if ride-sharing companies become truly huge, they will seek to buy vehicle manufacturers and shift research and development efforts firmly in the direction of cost reduction and reliability.

The next assumption to relax in our model is the fixed number of passenger miles. In reality, ride-sharing services are able to draw people away from public transportation and into private automobiles. I know from personal experience that if I am in downtown Manhattan with my wife and two kids, looking to get to Central Park, it's cheaper and more convenient to book a ride-share than to catch the subway. I am certain that similar comparisons are being made across the city, country, and world.

For illustrative purposes, let's assume that prior to the introduction of ride-sharing, half of all journeys were made by private vehicles and half were made using public transportation. As the new industry grows, some journeys via either of these two methods will transfer to this new service. Assuming riders are indifferent between the three options, each will grab one-third of all journeys once the market for ride-sharing fully matures. Note that because both private vehicles and ride-shares use passenger cars, we now have two-thirds of all journeys occurring in such vehicles.

It's hard to guess the exact way the industry will evolve. The existence of ride-sharing may prompt people to ditch their cars, providing a boost for both public transit and private ride-shares. I suspect, though, that ride-share companies compete more directly with buses and trains (not to mention traditional taxis). It is reasonable, however, to infer that Uber-style services will increase the total proportion of all journeys taken while seated in something resembling a car.

In addition to this line of thinking, there is the potential that ride-sharing will increase the total number of journeys undertaken. It's easy to imagine people within our society for whom taxis are too expensive, buses too dirty and crowded, and private vehicles too costly to maintain. If services like Lyft – cheaper than a taxi while retaining the comfort of a private vehicle – can induce infrequent consumers of transportation to expand their usage, there is no reason the total market for transportation services cannot expand.

In conclusion, therefore, insofar as the new car industry is in the business of selling homogeneous units of vehicle depreciation, it should do just fine as ride-sharing services diffuse into our daily lives. I would be surprised, though, if the industry viewed itself in this light. Because ride-share passengers will under-value any investment made by vehicle owners in bells and whistles (like sport suspension or entertainment option packages), cars will be far more homogeneous in a world dominated by ride-sharing.

If this happens, the industry will be unrecognizable. In new car markets, manufacturers will have a greatly diminished scope to reap monopoly profits by offering differentiated products to niche purchasers. It makes more sense to imagine a world where companies like Toyota and Uber (dare I suggest the name Tuber?) become a single entity.

Used Cars

We now introduce a secondary used vehicle market to our base model; we are, by necessity, also dropping a number of our assumptions of homogeneity. The used car industry exists, after all, mainly because of heterogeneity among consumers and vehicles.

To elaborate, some people have a preference for, and capacity to purchase, new cars, though

they only remain new for an infinitesimally short period of time. Others are either content or forced by financial circumstance to only consider used vehicles. Consumers also have shifting preferences – a coupe may be a great choice for a college student but completely impractical for a young family. It therefore makes sense for vehicles to be passed between a variety of owners before they are eventually scrapped. The used car industry thrives by acting as a go-between – implicitly matching sellers with buyers – for an appropriate fee.

Let's consider for a moment the fate of one car in particular. I recently met a full-time Uber driver in Dallas who had 140,000 miles clocked on his 2014 Kia Sorento. The vehicle was in great condition and very well-maintained. If the car's owner continues to drive at the current rate for another five years, the car will then have been driven more than half a million miles. While an eight-year-old Sorento with 80,000 miles will most likely find a new owner, a similar vintage vehicle that has driven a distance equal to a round-trip journey to the moon may not be able to find a buyer.

A logical conclusion to this analysis is that if ride-sharing eventually dominates the market for private transportation, cars will, on average, pass through far fewer owners during their usable lifespans. Indeed, in such a world, I see no plausible situation where a drivable car would be sold to another party. The net result is a lower volume of used vehicle transactions and thus a significantly smaller used vehicle industry overall.

The fact that ride-share vehicles are likely to be more homogeneous also impacts the used car industry. At present, Uber differentiates somewhat by size (UberXL) and quality (UberBLACK) but is generally ambivalent between cars with the same basic configuration. When choosing Uber, the coupe-owning college student will typically not forgo the five-mile ride to campus because a Nissan Pathfinder arrives. The young family may need something broadly resembling a Pathfinder – so the professional ride-share driver (or whoever owns the driverless Pathfinder) will simply avoid buying the coupe in the first place.

In the short run, ride-share drivers will give a tremendous boost to the used car industry. A lightly used two-year-old certified pre-owned (CPO) vehicle, traded due to obsolescence or

changing consumer taste, would be a great option for someone looking to drive ride-shares for a living. With 100% ride-share penetration, however, CPO will come to have a new meaning: ClaPped Out!

Self-Driving Cars

Let's assume for a moment that self-driving cars are introduced into a world where ride-sharing does not and cannot exist. Would we expect any disruption to the auto industry? Bear in mind that self-driving technologies have been gradually introduced to cars over the past century or more. Automatic transmission, for example, is a self-driving technology that first entered the market in the 1930s. Instead of depressing the clutch and changing gears, the car

prime culprit should the auto industry fall into decline.

Conclusion

My 11-year-old son recently told me he was concerned by the introduction of self-driving cars. He's not worried about HAL refusing to open the pod bay doors; he just wants to learn how to drive the old-fashioned way. I told him to relax. As Bill Gates says, we tend to overestimate the change that will occur in the next two years and underestimate the change that will occur in the next 10. I suspect that my boy will learn to drive, and hopefully enjoy it as much as I do, and that ride-shares and driverless technology will make life better for him and his contemporaries in their 20s and beyond.

If self-driving cars become widely available, and "driving" habits do not change, they will have precisely zero impact on the passenger vehicle industry.

magically does the job for you. Other examples are cruise control, on-board computers, back-up cameras, GPS, and parking assist features, all of which have diffused into the car industry without creating an existential threat. Any labor-saving device could be viewed as an incremental shift in the direction of self-driving cars. It's just that these days, the technologies are freeing the "driver" from taking any action besides choosing the destination.

If self-driving cars become widely available, and "driving" habits do not change, they will have precisely zero impact on the passenger vehicle industry. Self-driving cars will still depreciate, need repairs, be status symbols, and be upgraded every so often by owners as new features are introduced. However, depreciation rates may decline somewhat, especially if cars can be programmed to take themselves in for an oil change at 2 am on the third Wednesday of each quarter.

Ride-sharing holds a much greater potential to disrupt the auto industry. If driverless technology accelerates the diffusion of ride-sharing, which seems likely, many will point to autonomous cars as the downfall of the erstwhile auto industry. In our view, though, while driverless technology will definitely ravish the labor market – all driving-related jobs are at risk from the technology – ride-shares will be the

After all, some people (myself included) enjoy driving and will continue to demand old-style cars even after self-driving technology is perfected. Even the keenest driver will, however, appreciate a cheap ride-share after having a few too many glasses of wine or when avoiding paying for parking at the airport. Cars with manual gearboxes and steering wheels will be privately owned even in the steady state. The utility of ride-shares using autonomous vehicles, however, should be obvious and will undoubtedly capture a slice of the transportation market during the next decade.

If this slice is substantial, car production will shift toward more homogeneous vehicles that meet the needs of the highest proportion of riders at the lowest total cost. While enthusiasts will continue to buy Mazda Miatas, Jeeps, and BMW M3s, the standard ride-share will more closely resemble the autonomous form of a Kia Sorento or Dodge Caravan.

It is this commoditization that constitutes the biggest threat to the auto industry. At present, carmakers seek to produce niche products in order to attract loyal, repeat customers. If vehicles are used by customers in half-hour chunks, there is no room for loyalty.

Carmakers will instead be providing a vital commodity and will likely be regulated accordingly.





SPOTLIGHT

WHEN GOOD DATA HAPPEN TO GOOD PEOPLE: BOOSTING PRODUCTIVITY WITH HIGH-QUALITY DATA

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With ever-increasing requirements for a higher quantity and quality of analytical output, the need to boost productivity in risk management has become more acute. In pursuing these productivity gains, we have observed that investments in data quality can offer dramatic improvements and typically pay for themselves. In this article, we aim to enable readers to make pragmatic upgrades by showing the mechanisms through which data quality and productivity interact, drawing on a useful analogy to lean manufacturing principles. From this discussion, we are able to define data quality as it pertains to risk analytics. We provide a quantitative and qualitative discussion of the benefits that can be realized with better data quality. Finally, we conclude with case studies that provide real examples of data quality in practice.

Introduction

Post-crisis regulations such as the Dodd-Frank Act have dramatically increased the consequences to financial institutions of unsound risk analytics. The analytical complexity and massive downside risks of unacceptable regulatory submissions lead firms to maintain large headcounts of high-cost analytical employees who transform data into projections of their institutions' financial performance. In our experience, this "get it right at any cost" situation results in material inefficiency, waste, and delay.

While there are many sources of waste, we frequently observe data quality to be a root cause. Dealing with some "garbage in" when there is no room for even a little "garbage out" is expensive. Bank risk managers and stress testing teams felt this acutely in the 2017 Comprehensive Capital Analysis and Review (CCAR) stress tests, when the Federal Reserve released a data error and revised it a week later.

The incident prompted rework, compressed schedules, and created uncertainty.

Obviously, increasing data quality improves the productivity of these analytical risk management processes. What may not be obvious is how best to invest in data quality and what return on investment may be possible. Even defining data quality in the context of risk analytics is not straightforward.

In this article, we quantify the impact of data quality improvements on analytical productivity. We describe the key mechanisms of waste caused by data that we have observed in our work and provide examples of how to address them. These mechanisms lead to a functional definition of data quality. We conclude with several examples of the impact of improving data quality on efficiency in analytical tasks.

What's the Bottom Line?

Investing in data quality can provide a range of substantial cost savings. In research¹ and in

¹ Hansen, Mark David. "Zero Defect Data: Tackling the Corporate Data Quality Problem." Massachusetts Institute of Technology. January 1991.

our own experience, data quality investments consistently lead to a 30% to 50% reduction in direct costs – expenses such as payroll that are necessary for the actual production of analytical results and supporting documentation.

Improved data quality can also provide substantial indirect gains, cutting the costs that arise from quality problems and uncertainty.

Although quantification of indirect costs remains elusive, we find two broad sources of such costs: model development time and confidence levels.

Model development time: Accurate data is a necessary – though not sufficient – condition for constructing a predictive model. If historical performance data for a loan portfolio are incorrect, a model developed on such a dataset will fail to capture the true underlying relationships between performance and economic factors. Noisy data will either provide weak signals at best or spurious correlations at worst.

From our experience developing a wide variety of econometric forecasting models, we find that poor data quality is the main reason for increasing the cycle time for model development. Having analytical modelers spend time addressing fundamental data issues during the model development process is wasteful for two reasons. First, being downstream consumers of data, modelers will waste time locating and communicating with the appropriate data experts within the organization. Second, the data corrections that modelers ultimately develop for their specific projects will not be captured at the source. The latter issue is particularly costly, as it implies that an institution may end up paying to address a single data error multiple times.

Confidence: High data quality creates confidence. It reduces noise, which in turn reduces model uncertainty. More broadly, model users who have low confidence in reported data are inclined to add an “uncertainty premium” to model results.

In the specific case of loss forecasting and allowance calculation, bad data may lead managers to assume conservative estimates ultimately leading to higher-than-necessary

capital allocation. In this case, the cost of poor data quality directly translates into higher-than-required capital buffers and loss allowance provisions. While this may be prudent, overly conservative projections can price lenders out of the market, disappointing shareholders and ceding opportunities to more nimble competitors.

The indirect benefits of confidence may go beyond the business users of models. High-quality data are necessary to gain the confidence of model validators, senior managers, regulators, auditors, and other interested parties. Even if a model is well-constructed and estimated using state-of-the-art techniques, data anomalies can distract and call into question the integrity of model results – adding to compliance and other costs.

Quality is Productivity is Quality

The inseparable relationship between quality and productivity has been known in the manufacturing world for years,^{2,3} and research on the topic of data quality has made effective use of the analogy.⁴ Experience with serving our risk management clients and our own internal data processes has shown that the analogy also applies to quantitative analytical work. We have found, time and again, that there is a virtuous cycle between increasing quality and increasing productivity. Better-quality data boost analytical productivity by reducing wasted effort, idle resources, process bloat, and the number of required judgment calls. Likewise, higher productivity increases quality by automating error-prone tasks, reducing haste, and leaving time to evaluate results.

We have identified four major buckets of waste: rework, questioning, process deviations, and peak load.

Rework: The most obvious source of waste is having to discard a result and do the same task again. The serial nature of analytical processes makes rework issues especially costly when upstream steps are error-prone and weak error detection results in late identification of problems. Such situations may require even more of the process to be repeated.

2 Shewhart, Walter A. *Economic Control of Quality of Manufactured Product*. New York: McGraw-Hill, 1931.

3 Deming, W. Edwards. *Out of the Crisis*. Cambridge, Mass.: MIT Press, 1986.

4 See Ref 1.

Questioning: Evaluating anomalous results incurs additional costs, both in time spent and in the quality of the resources applied. Questioning an analytical result usually entails several higher-end tasks including troubleshooting, trade-off analysis, and ultimately making judgment calls. Judgment calls frequently require escalation of an issue to a person with the authority to make a decision. Improved data quality should reduce questioning time by reducing the frequency of anomalous results, caused by actual errors or poor models, and facilitating the troubleshooting process.

Process deviations: Unacceptable input data, such as model drivers with values outside required bounds, may not be addressable by rework and could require a change to the process itself. Changes must be developed, documented, and often validated. Furthermore, process deviations increase the probability of repeated errors, should the amended analytical step be repeated.

Peak load: All of the above reasons may delay the completion of upstream tasks, leaving less time for downstream tasks. When the available time for downstream tasks gets compressed, the organization may be forced to apply more resources to meet deadlines. This creates a spike in the demand for analytical capacity, which may require carrying excess staff or contracting for temporary help. When upstream tasks are completed efficiently, there is a decreased probability of downstream tasks being compressed.

The experience of the 2017 CCAR stress tests has elements of all four of these types of waste. The data quality concern was that the Federal Reserve issued incorrect data for BBB bond yields in its supervisory scenarios. A week later, it issued corrected scenario data. The rework this caused is obvious: Analysts set to work upon the initial release of data and were required to repeat some or all of this work in response to the revised data. Additional questioning occurred, with institutions seeking to determine what this change meant for them and how best to proceed. Analytical results received further questioning after recalculations to evaluate the impact of the revised guidance. The

unanticipated correction in scenario guidance certainly created process deviations, since doubtless few, if any, institutions anticipated this occurrence. Finally, the rework and additional week of delay in receiving definitive figures from the Federal Reserve compressed schedules and created higher peak loads.

Defining Data Quality

Identifying the channels where data problems can impair productivity enables us to propose functional requirements for data quality in risk analytics. High-quality data should be (1) verifiably correct, (2) fit for use, and (3) documented. These are thematically similar to data requirements in regulatory guidance,⁵ but in this section we tailor their meaning and add specifics in terms of how they relate to the productivity of risk analytics processes.

Verifiably correct: Numerical correctness is clearly the minimum threshold for data quality. Running an analysis using incorrect data will likely incur rework or process deviation waste. However, the ability to independently verify numerical correctness further increases the quality of the data. This is especially important when using third-party data such as economic or market risk variables. The ability to independently verify data accelerates troubleshooting and avoids communication iterations with vendors or internal parties that would add delay and downstream peak load issues. Verifiability can come in several forms, such as backlinks to primary sources, quality declarations, unique identifiers, and accessible quality logs.

Fit for use: For data to produce sound analytical results, they must accurately quantify the concept they intend to measure. Modelers should consider both the definition of the data and their objective properties, such as time series length, frequency, timeliness, and consistency. Data that are too aggregated or nonspecific may provide weak or wrong fits, such as if national data on house prices were used when one could use state-, metro-, or ZIP code-level data. Using true high-frequency data should almost always be superior to interpolating lower-frequency data. Dealing with outliers or definitional breaks reduces degrees of freedom in model estimation.

⁵ See Basel Committee on Banking Supervision, "Principles for effective risk data aggregation and risk reporting," BCBS 239, January 2013; and Office of the Comptroller of the Currency, "Supervisory Guidance on Model Risk Management," OCC 2011-12, April 4, 2011.

Data that are fit for use should produce better-functioning models with more trusted results. This not only speeds up model development, but also reduces the expected questioning time and probability of process deviations.

Documented: Documentation is essential to the interpretation of data. To do their job effectively, modelers and analysts need to know specifics on how the data are defined and constructed: Exactly which loans are included in this sample? Where estimation is used, one should know the uncertainty associated with the estimate: Is the volatility in this time series due to volatility in real life or uncertainty in estimation? Anomalous data points should be notated and explained: Does this temporary spike in charge-offs represent a policy change, an unexplained but actual rise, or erroneous data? This knowledge gives modelers the tools to decide proper treatment of the data when creating models and increases the confidence in their choices. Questioning time for analysts and validation teams should be reduced when tracing the sources of model results.

Quality in Practice

Several guiding principles underlie the data quality initiatives we have implemented in our analytical processes:

- » Prioritize upstream data inputs, especially in model development.
- » Implement high-throughput quality checks to verify the thousands of variables being forecast.
- » Maximize use of objective pass/fail tests with low rates of false positives.
- » Log judiciously and store intermediate results.
- » Press data vendors to improve their delivered data quality.
- » Catalog data centrally and insure all users have access to the latest catalog.

The following case studies illustrate the application of these principles in real situations.

Case 1: Consumer Credit Loss Modeling

A large regional bank needed to create expected credit loss models for its auto loan portfolio to complete a regulatory submission for the Federal Reserve's annual CCAR and Dodd-Frank Act stress testing programs. Two broad data quality issues – cataloging and consistency – impacted the cost, quality, and timing of the models that

were produced for this project.

A member of the IT department provided the project managers with a data dictionary and a high-level summary of the bank's historical data. At first blush, the information indicated that the bank had monthly, historical performance data available from 2003 to 2015 for more than 3 million auto loan and lease originations. The data included a number of commonly used borrower and loan characteristics that were captured at the time the accounts were originated.

Based on this wealth of information, the data were sufficient to build a robust competing risk model of performance at the loan level. We interviewed the model's intended users, who identified a set of desirable features and variables they wanted the model to consider – such as the debt-to-income ratio of borrowers – when predicting default probabilities.

After defining the scope and success criteria for the models, the first task was for bank staff to inspect the bank's system of records and construct a loan-level dataset containing monthly performance observations for all of the loans in its historical portfolio.

The data quality issue of cataloging was immediately apparent at this stage of the project, as the modeling team discovered the bank's loan data were stored on a variety of disparate systems – the result of years of mergers and acquisitions. Not only was the provided data dictionary incomplete and outdated, but it also failed to indicate that variables were defined and labeled inconsistently across multiple databases.

This second data quality issue, inconsistency of data across time, resulted in significant direct and indirect costs to the bank. The modeling project was halted for four months while the bank commandeered resources to merge and normalize the data. Five full-time, highly skilled database programmers were deployed for this effort at a direct cost in excess of \$250,000. In addition, the bank incurred indirect costs such as loss of revenue and competitiveness due to delaying other scheduled activities and projects. The loss of modeling and business team time was highly disruptive, and the competing business priorities created a tumultuous work environment.

The compressed timeline that resulted translated into a direct cost, as the bank had to

hire contractors to expedite model development and validation. Despite the additional expense, the quality of the models ultimately suffered;

reducing both the size and duration of this peak load while improving quality, with the goal of materially increasing analytical output

High data quality is fundamental to sound risk management and analytical productivity.

portions of the model development process that are typically sequential, such as experimentation and revision, had to be done in tandem to save time. The revised timeline did not allow for the full battery of tests that had been originally planned, necessitating some compromises on business user requests.

Lack of confidence in the data introduced real costs as well. Senior leadership grew nervous with the delays and developed a contingency plan in the event that data cleaning and model development were not completed in time. This effort increased the overall cost of the project by about a third and produced models that were both inferior and unusable for other applications. In the end, the main modeling effort was completed in time and the contingency plan was not needed – but not before the additional expense was incurred.

An observer may have attributed delays in the project to the modeling team's efforts, as the only tangible project deliverable – model documentation – was delayed relative to the projected delivery date. However, looking at the project through a wider lens – as the bank did in a subsequent debrief – it was clear that the root cause of the delay was traceable to poor data quality.

Case 2: Macroeconomic Scenarios

Each month, Moody's Analytics produces macroeconomic forecasts and alternative economic scenarios for 58 countries. The process involves about 45 economists, many of whom are senior, and usually takes three weeks per month. Data for the process come from more than 100 sources around the world.

The high complexity and large resource requirement of this forecast process create monthly peak loads which impose bounds on analytical throughput and scheduling. Consequently, we strategically invested in

and shortening process time. To that end, we redesigned the forecasting process with an emphasis on implementing the concepts previously discussed. Several key investments were made, notably in a new infrastructure for updating historical data, a new initial forecast system, standardized forecast quality-check programs, and mistake-proofing the forecast editing process.

The central features of the new historical data infrastructure are improved archiving, logging, transparency, and high-throughput quality checks. The system takes as inputs a mapping spreadsheet with definitions, equations, and metadata and produces the complete dataset needed for the forecast. The system also runs a barrage of quality tests on all data and results. Along the way, it archives the mapping information, raw data, processed data, and the output of all quality checks run. Archiving intermediate results improves our ability to diagnose problems quickly and explain unexpected results. Furthermore, we log each calculation to accelerate troubleshooting. This not only makes the actual update process go faster, but also facilitates answering questions that may come from analysts downstream.

The quality checks run by the historical data infrastructure efficiently surface potential problems and focus attention on what is important. These checks include:

- » Data with large or deep revisions relative to the previous month's forecast run
- » Metadata changes
- » Discontinued data
- » Highly lagged data
- » Sparse data

Next, the initial forecasting system merges the new historical data, model equations, and

carried-over forecast assumptions to produce an initial forecast. If it fails to produce the intended results, forecasters need to perform a substantial

there is reported history. The same protection of numerical values also extends to shared assumption data that flow into all models in use.

Our support program redesign implemented *poka-yoke*, or “inadvertent error prevention,” to protect data quality.

amount of cleanup work downstream. We substantially improved the initial forecasting system by the addition of integrity checks, which verify that intended steps did, in fact, occur as intended. These checks verify the following:

- » Every variable in the model has updated history.
- » All intended exogenous overrides are applied to the forecast.
- » Exogenous add-factor variables created by re-endogenizing variables produce exactly the desired result.

Additionally, we archive a copy of the initial forecasting package – data, equations, add-factors, and quality findings – to facilitate troubleshooting and trace the causes of specific results downstream.

After that, we enhanced the process by which economists impart judgment into the forecast by adding universal quality checks and redesigning support programs to prevent forecasters from taking actions that would impair quality.

The universal quality checks inspect for objectively implausible results such as values going negative that should not, long-run seasonality in a forecast of a deseasonalized variable, and unprecedented growth being forecast in the first period of forecast. The support programs display these quality findings prominently each time an economist runs the model.

The support program redesign implemented *poka-yoke*, or “inadvertent error prevention,”⁶ in several ways. If an economist attempts to edit the forecast of a variable that he or she should not edit, the solve program halts and displays an appropriate message. The program also firewalls actual historical figures from editing and overrules any attempted edits where

Overhauling the process with a focus on data quality achieved telling results. Economists reported their time before and after the operational redesign and showed a 30% reduction in direct time spent forecasting.

Quality improved measurably: Delivery schedules moved forward by several days, and forecast restatements went from common to rare. More than one economist remarked that the improvement in upstream data quality reduced cleanup time and let them spend more time adding value to the forecast.

Conclusion

Data quality is fundamental to sound risk management and analytical productivity. As our case studies have illustrated, problems with data quality can trickle through and affect every subsequent analysis, model, and decision made by an institution. These problems incur substantial direct and indirect costs. Conversely, high data quality creates a virtuous cycle of productivity and quality, reducing labor costs, accelerating schedules, and bolstering confidence in analytical output.

Despite the common refrain from every business executive that information is central to his or her ability to make proper decisions, data quality often doesn't get the attention – or the funding – that revenue-generating initiatives do. However, our experience and research show that the benefits of investing in data quality are widespread and pay for themselves quickly.

The indirect costs of not investing in data quality are significantly higher than the direct costs of implementing quality programs. The costs of data assurance are low relative to the benefits. Before dismissing data quality initiatives as expensive, businesses need to consider their return on investment through the lens of cost avoidance.

6 Shingo, Shigeo. *Zero Quality Control: Source Inspection and the Poka-Yoke System*. Portland, Ore.: Productivity Press, 1986.

MACHINE LEARNING: CHALLENGES, LESSONS, AND OPPORTUNITIES IN CREDIT RISK MODELING

By Dinesh Bacham and Dr. Janet Yinqing Zhao



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Janet joined the research team of Moody's Analytics in 2008. She leads RiskCalc model development and small business modeling efforts. Janet works closely with clients to facilitate better understanding and applications of RiskCalc models. She also pushes forward on research initiatives such as exposure-at-default modeling, accounting quality measurement, and machine learning in credit risk modeling. She has published in academic and professional journals. Janet has a PhD in finance from City University of Hong Kong and a PhD in accounting from Carnegie Mellon University.

Thanks to rapid increases in data availability and computing power, machine learning now plays a vital role in both technology and business. Machine learning contributes significantly to credit risk modeling applications. Using two large datasets, we analyze the performance of a set of machine learning methods in assessing credit risk of small and medium-sized borrowers, with Moody's Analytics RiskCalc model serving as the benchmark model. We find the machine learning models deliver similar accuracy ratios as the RiskCalc model. However, they are more of a "black box" than the RiskCalc model, and the results produced by machine learning methods are sometimes difficult to interpret. Machine learning methods provide a better fit for the nonlinear relationships between the explanatory variables and default risk. We also find that using a broader set of variables to predict defaults greatly improves the accuracy ratio, regardless of the models used.

Introduction

Machine learning is a method of teaching computers to parse data, learn from it, and then make a determination or prediction regarding new data. Rather than hand-coding a specific set of instructions to accomplish a particular task, the machine is "trained" using large amounts of data and algorithms to learn how to perform the task. Machine learning overlaps with its lower-profile sister field, statistical learning. Both attempt to find and learn from patterns and trends within large datasets to make predictions. The machine learning field has a long tradition of development, but recent improvements in data storage and computing power have made them ubiquitous across many different fields and applications, many of which are very commonplace. Apple's Siri, Facebook feeds, and Netflix movie recommendations all rely upon some form of machine learning. One of the earliest uses of machine learning was within credit risk modeling, whose goal is to use financial data to predict default risk.

When a business applies for a loan, the lender

must evaluate whether the business can reliably repay the loan principal and interest. Lenders commonly use measures of profitability and leverage to assess credit risk. A profitable firm generates enough cash to cover interest expense and principal due. However, a more-leveraged firm has less equity available to weather economic shocks. Given two loan applicants – one with high profitability and high leverage, and the other with low profitability and low leverage – which firm has lower credit risk? The complexity of answering this question multiplies when banks incorporate the many other dimensions they examine during credit risk assessment. These additional dimensions typically include other financial information such as liquidity ratio, or behavioral information such as loan/trade credit payment behavior. Summarizing all of these various dimensions into one score is challenging, but machine learning techniques help achieve this goal.

The common objective behind machine learning and traditional statistical learning tools is to learn from data. Both approaches aim to

investigate the underlying relationships by using a training dataset. Typically, statistical learning methods assume formal relationships between variables in the form of mathematical equations, while machine learning methods can learn from data without requiring any rules-based programming. As a result of this flexibility, machine learning methods can better fit the patterns in data. Figure 1 illustrates this point.

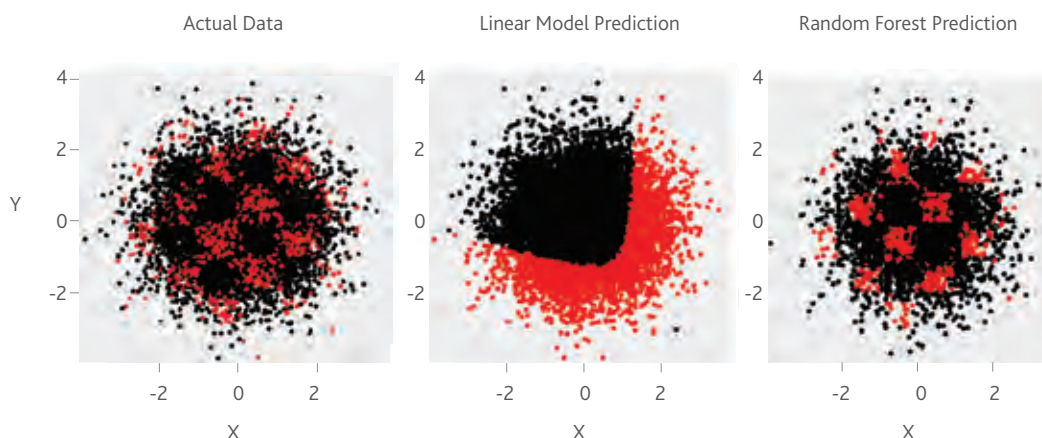
Machine Learning Approaches

Now let's look at three different machine learning algorithms: artificial neural networks, random forest, and boosting.

Artificial Neural Networks

An artificial neural network (ANN) is a mathematical simulation of a biological neural network. Its simple form is shown in Figure 2. In this example, there are three input values and

Figure 1 Statistical model vs. machine learning



Source: Moody's Analytics

In this simulated example, the first chart shows the actual distribution of data points with respect to X and Y, while the points in red are classified as defaults. One can relate this to a geographical map, where the X axis is longitude, and the Y axis is latitude. The areas in red represent high-risk demographics, where we see a higher default rate. As expected, a linear

two output values. Different transformations link the input values to a hidden layer, and the hidden layer to the output values. We use a back-propagation algorithm to train the ANNs on the underlying data. ANNs can easily handle the non-linear and interactive effects of the explanatory variables due to the presence of many hidden layers and neurons.

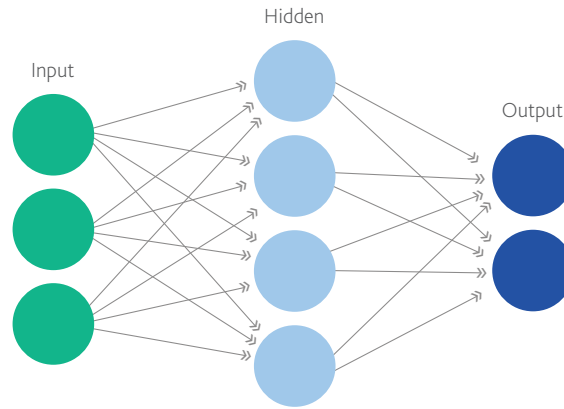
A machine learning model, unconstrained by some of the assumptions of classic statistical models, can yield much better insights that a human analyst could not infer from the data.

statistical model cannot fit this complex non-linear and non-monotonic behavior. The random forest model, a widely used machine learning method, is flexible enough to identify the hot spots because it is not limited to predicting linear or continuous relationships. A machine learning model, unconstrained by some of the assumptions of classic statistical models, can yield much better insights that a human analyst could not infer from the data. At times, the prediction contrasts starkly with traditional models.

Random Forest

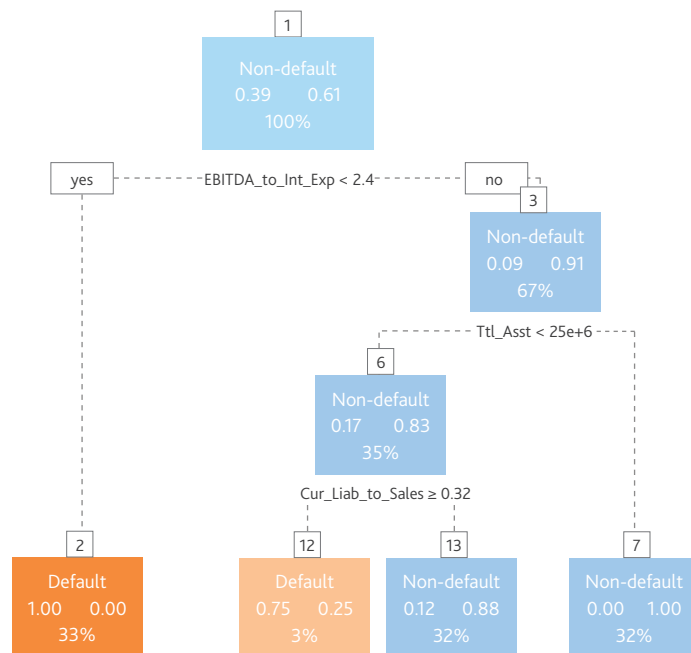
Random forests combine decision tree predictors, such that each tree depends on the values of a random vector sampled independently, and with the same distribution. A decision tree is the most basic unit of the random forest. In a decision tree, an input is entered at the top and, as it traverses down the tree, the data is bucketed into smaller and smaller subsets. In the example shown in Figure 3, the tree determines probability of default based on three variables: firm size; the ratio of earnings before interest,

Figure 2 Artificial neural network



Source: Moody's Analytics

Figure 3 Random forest



Source: Moody's Analytics

tax, depreciation, and amortization (EBITDA) to interest expense; and the ratio of current liabilities to sales. Box 1 contains the initial dataset in which 39% of the firms are defaulters and 61% are non-defaulters. Firms with EBITDA-to-interest expense ratios less than 2.4 go into Box 2. Box 2, accounting for 33% of the data, is 100% composed of defaulters. Its orange color indicates higher default risk, whereas the blue color indicates lower default risk. The random forest approach combines the predictions of many trees, and the final decision is based on the average of the output of the underlying independent decision trees. In this exercise, we

use the bootstrap aggregation of several trees as an advancement to a simple tree-based model.¹

Boosting

Boosting is similar to random forest, but the underlying decision trees are weighted based on their performance. Consider the parable of the blind men and the elephant, in which the men are asked to touch different parts of the elephant and then construct a full picture. The blind men are sent in six different batches. The first group is led to randomly selected spots, and each person's (partial) description is evaluated on how well it matches the actual description. This group

¹ Breiman, Leo. "Random Forests." *Machine Learning*, volume 45, issue 1. October 2001.

Figure 4 Data information

Variable	Financials Only	Financials + Behavioral
Time period	1990 – 2014	1999 – 2014
Number of firms	240,000+	101,000+
Number of defaults	16,000+	5,700+
Number of observations	1,100,000+	1,100,000+

Source: Moody's Analytics

Figure 5 Input variable descriptions for the PD models

Variable	Description
Firm information	Firm characteristics such as sector and geography
Financial ratios	Set of financial statement ratios constructed from the balance sheet and income statement items; the same set of input ratios used for the RiskCalc US 4.0 model are utilized here
» Balance sheet	
» Income statement	
Credit usage	Utilization on the line of credit available to the borrower
Loan payment behavior	Loan-level past due information of the borrowers over time
Loan type	Type of the loan: revolving line or term loan

Source: Moody's Analytics

happens to give an accurate description of only the trunk, while description of the rest of the body is inaccurate. The incomplete sections are noted, and when the second batch of blind men is led into the room, they are steered to these parts. This process is repeated for the remaining batches. Finally, the descriptions are combined additively by weighting them according to their accuracy and, in this case, the size of the body parts as well. This final description – the combination – describes the elephant quite well.

In boosting, each decision tree is similar to a group of blind men, and the description of the elephant is synonymous to the prediction problem being solved. If a tree misclassifies defaulters as non-defaulters or vice versa, the subsequent trees will put more weight on the misclassified observations. This idea of giving misclassified areas additional weight (or direction while sending in a new group) is the difference between random forests and boosting.

Moody's Analytics RiskCalc Model

The RiskCalc model produces expected default probabilities for private firms by estimating the impact of a set of risk drivers. It utilizes a generalized additive model (GAM) framework, in which non-linear transformations of each risk driver are assigned weights and combined into a single score. A link function then maps the

combined score to a probability of default.

The RiskCalc model delivers robust performance in predicting private firm defaults. But how does it compare to other machine learning techniques? We use the three popular machine learning methods to develop new models using the RiskCalc sample as a training set. We seek to answer the following questions: Do the machine learning models outperform the RiskCalc model's GAM framework in default prediction? What are the challenges we face when using the machine learning methods for credit risk modeling? Which model is most robust? Which model is easiest to use? And what can we learn from the alternative models?

Results

Data Description

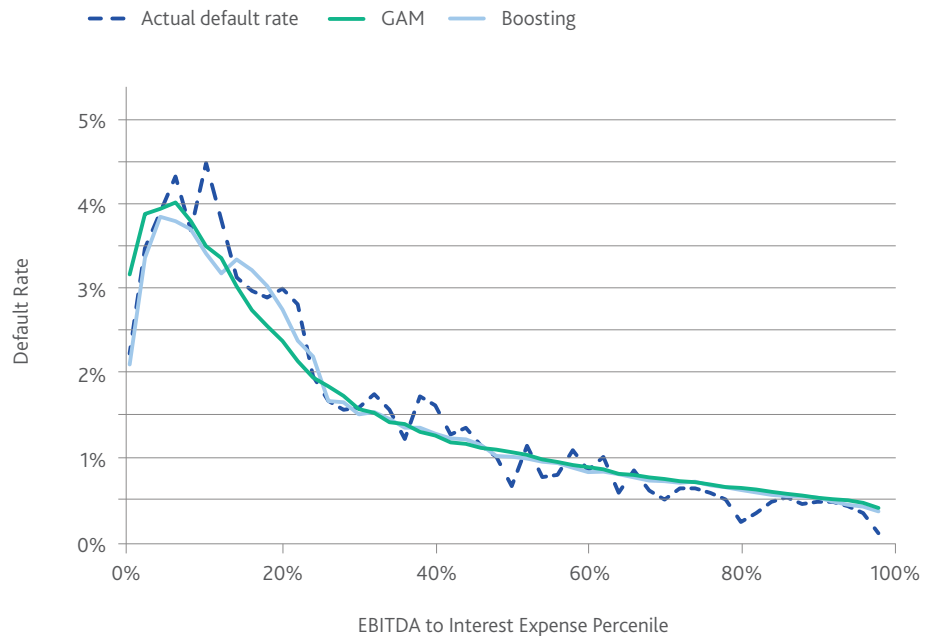
To analyze the performance of these three approaches, we consider two different datasets. The first dataset comes from the Moody's Analytics Credit Research Database (CRD) which is also the validation sample for the RiskCalc US 4.0 corporate model. It utilizes only firm information and financial ratios. The second dataset adds behavioral information, which includes credit line usage, loan payment behavior, and other loan type data. This information comes from the loan accounting system (LAS), collected as part of the CRD. We

Figure 6 Model performance

Method	1-Year Model Accuracy Ratio	
	Financial Information Only	Financials + Behavioral
RiskCalc (GAM model)	55.9%	65.8%
Random forest	58.9%	66.5%
Boosting	59.1%	67.5%
Neural network	56.6%	66.4%

Source: Moody's Analytics

Figure 7 Comparing machine learning and GAM PD levels for different values of EBITDA to interest expense



Source: Moody's Analytics

want to test for additional default prediction power using the machine learning techniques and the GAM approach with both datasets. Figure 4 shows the summary of the two datasets.

Model Performance

For both datasets, we use the GAM model's rank ordering ability as the benchmark. We measure rank ordering ability using the accuracy ratio (AR) statistic. Figure 5 shows the set of explanatory variables.

Cross-Validation

Because machine learning offers a high level of modeling freedom, it tends to overfit the data. A model overfits when it performs well on the training data but does not perform well on the evaluation data. A standard way to find out-of-sample prediction error is to use k-fold cross-validation (CV). In a k-fold CV, the dataset is divided into k subsets. One of the k subsets is used as the test set, and the other k-1 subsets are combined to form a training set. This process

is repeated k times. If the accuracy ratio, a measure of model performance, is high for the training sample relative to the test sample, it indicates overfitting. In this case, we impose more constraints on the model and repeat cross-validation until the results are satisfactory. In this example, we use a fivefold cross validation. Figure 6 reports the average AR across the five trials.

We observe that machine learning models outperform the GAM model by 2 to 3 percentage points for both datasets. The accuracy ratio improves by 8 to 10 percentage points when we add loan behavioral information, regardless of the modeling approach. Credit line usage and loan payment information complement financial ratios and significantly enhance the models' ability to predict defaults.

Where Machine Learning Excels

Machine learning methods are particularly powerful in capturing non-linear relationships.

Figure 8 Overfitting of machine learning algorithms

Ratio/PD	Case 1	Case 2
EBITDA to interest expense	4X	40X
Return on assets (ROA)	-17%	212%
Cash to assets	1%	10.5%
Debt to debt plus equity	77%	89%
Retained earnings to current liability	-6X	357X
Total assets	\$500,000	\$5,800,000
Boosting PD	0.2% (A3)	13.7% (Caa/C)
GAM PD	8.9% (Caa/C)	0.54% (Baa3)
Status	No default	No default

Source: Moody's Analytics

Let's take a closer look at the EBITDA-to-interest-expense ratio. Intuitively, this ratio has a non-linear relationship with default risk. In Figure 7, we divide the ratio into 50 percentiles and calculate the average values of predicted probability of default (PD) and the actual default rate. We plot this with the ratio percentiles on the x-axis and the default rate (in %) on y-axis. The default rate decreases as the ratio of EBITDA to interest expense increases. However, on the left-hand side, there is an inflection point where the EBITDA becomes negative. When EBITDA is negative, as the interest expense decreases making the ratio more negative, the default risk should decrease. From the graph, we observe that the machine learning method of boosting provides a more accurate prediction of the actual default rate than the GAM model, especially on the left-hand side. We observe this similar behavior from the plots of other ratios, as well. Hence, we observe modest prediction improvement for machine learning methods.

Overfitting Problem

Despite the use of cross-validation to minimize overfitting, machine learning models may still produce results that are difficult to interpret and defend. Figure 8 shows two cases in which the PD determined by the boosting method differs significantly from the PD determined by the GAM approach.

In case 1, a company with a negative return on assets (ROA), a low cash-to-assets ratio, and a high debt-to-debt-plus-equity ratio is classified as safe, with an implied rating of A3. Intuitively, this firm's PD should reflect a higher level of risk, as predicted by GAM. Similarly in case 2, a firm with high EBITDA to interest expense, high ROA, and high retained earnings is categorized as

Caa/C using the boosting method. In both cases, the complex nature of the underlying algorithm makes it difficult to explain the boosting method's non-intuitive PD. The RiskCalc model's results, based on the GAM model, are much more intuitive and easier to explain.

Summary

This exercise analyzes the performance of three machine learning methods using the RiskCalc software's GAM model as a benchmark. The machine learning approaches deliver comparable accuracy ratios as the GAM model. Compared to the RiskCalc model, these alternative approaches are better equipped to capture the non-linear relationships common to credit risk. At the same time, the predictions made by the approaches are sometimes difficult to explain due to their complex "black box" nature. These machine learning models are also sensitive to outliers, resulting in an overfitting of the data and counterintuitive predictions. Additionally, and perhaps more interestingly, we find that expanding the dataset to include loan behavioral variables improves predictive power by over 10 percentage points for all modeling methods.

While the approaches we study all have their merits and have comparable accuracy levels, we believe that to improve default prediction accuracy and to expand the field of credit risk modeling in general, efforts should focus on the data dimension. Besides financial statement and loan payment behavioral data, additional information such as transactional data, social media data, geographical information, and other data can potentially add a tremendous amount of insight. We must gather more varied, non-conventional data to further refine and improve our approaches to assessing risk.



Moody's Analytics

Risk and Finance Practitioner Conference 2017

Our annual Risk and Finance Practitioner Conference brings together industry experts and leading risk and finance practitioners from across the globe.

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MoodyAnalytics.com/RFPC17

Interview with Keith Berry

EXECUTIVE DIRECTOR, MOODY'S ANALYTICS EMERGING BUSINESS UNIT

In its 12th year, we have renamed the conference to be the Risk and Finance Practitioner Conference. Why?

Our flagship conference is closely tied to the concerns of our clients. With economic trends and banking regulations reshaping the industry, our clients' challenges are shifting. Risk management is no longer an isolated function. Risk, treasury, and finance functions are increasingly connected. For example, the requirement to stress test banks' entire balance sheet forces a combination of scenario-conditioned credit risk analysis and strategic business planning. Similarly, the new accounting rules for credit losses are forcing traditional risk analysis to play a direct role in financial reporting. As a result, business mentalities are adjusting. Firms are beginning to recognize the importance of an enterprise-wide risk culture and adopt more holistic views of risk measurement. These industry changes suggested to us the need to update the focus of our conference. We chose the new name to reflect the growing importance of the convergence of risk and finance and a creation of essentially a new discipline.

The theme of this year's conference is "The Rise of Risktech." What market trends led to this theme selection?

We are observing increasing adoption of emerging technologies in finance. These advancements are bringing fintech into back- and middle-office processes, enabling more proactive risk management and faster lending decisions with greater accuracy. We expect this surge of risk technology, or risktech, to disrupt the industry. First, the dropping cost of data storage is enabling firms to adopt big data strategies. This, in turn, creates an opportunity to leverage technologies like machine learning and artificial intelligence for risk management and banking analytics. The side effect of these trends is a change in job requirements. Full separation of technology departments from analytical functions is no longer possible. Banks need more people throughout their firms with the skills to manage and interpret the data. And while firms have started using risktech and have begun to adopt these strategies, we see many more opportunities for the industry to optimize. We will use this year's conference to explore these topics.

What impacts are we seeing on our banking clients?

Banks are not typically early adopters of technology trends. However, the current state of the industry is forcing them to rethink their processes to remain competitive. They have to adapt to today's secular low-rate environment and keep up with alternative lenders that threaten to draw customers away by making faster decisions. We are seeing an unprecedented appetite for cloud solutions across bank sizes and complexity levels – something that was difficult to conceive of just three or four years ago. Adoption of tools developed and popularized by technology firms allows banks to cut processing time and minimize risk exposure. Velocity and efficiency: these ideas are fundamental to the rise of risktech. Banks are finding that the technology can connect front- and back-office information to enable less manual and more analytics-driven credit origination processes. This leads to cost savings, improved efficiencies, and a better bottom line. We plan to delve into these promising technologies, their applications in risk management, and the efficiencies they offer at this year's Risk and Finance Practitioner Conference.

BATTLE FOR SMALL BUSINESS CAPITAL ACCESS: TRADITIONAL VS. ALTERNATIVE LENDERS

By Michael Schwartz



Michael Schwartz
*Director, Small Business
Lending Advisor*

At Moody's Analytics, Michael designs and develops small business lending and credit decisioning solutions for financial institutions. Prior to joining Moody's Analytics, Michael served as customer success director for fintech start-up Fundera, a marketplace created to pair small business owners with banks and alternative lenders. Michael also spent more than six years with PNC Bank, starting with the commercial underwriting group and then transitioning to the business bank segment, focusing on SBA commercial lending. Michael has a BS in finance with an economics minor from the University of Pittsburgh.

Small businesses are the root of the US economy, driving over 60% of new job creation and accounting for over 50% of all US sales.¹ However, a negative impact on this sector – traditional banks being slow to bridge the capital access gaps resulting from the Great Recession – continues to stunt growth.

Historically, established banks were the backbone small businesses relied upon to access the capital necessary for growth. With the advent of fintech and the emergence of online lending less than a decade ago, innovators disrupted traditional lending models by offering those in need alternative options to easily secure financing. The demand for capital remains high, and with the economy trending positively, both traditional and alternative lenders must revisit strategies to maximize their market share. Fintech players have leveraged investor capital and are at a pivotal moment where they must prove their sustainability. Banks, on the other hand, are embracing the changing environment and are looking to prioritize a segment that has been overlooked in the last decade. By evaluating and acting upon current industry trends, traditional lenders will themselves succeed by taking advantage of the opportunity

to provide funding to businesses of all sizes.

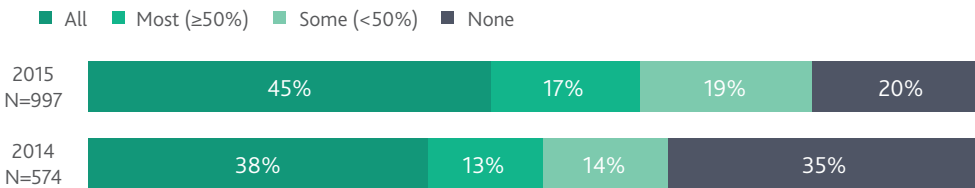
Missed Opportunities

Just over 15 years ago, little-known startup Netflix was offered up for sale to movie rental mainstay Blockbuster, which opted to pass.² The concept of acquiring a subscription network for movie rentals, offering at-home delivery, may have seemed far-fetched. Why alter a flourishing system in which customers would willingly head out to their local branch to pick up the same copy?

Venerable photography company Kodak finally saw the digital age coming and tried to get ahead in organizing for the change.³ However, poor execution at a time when innovators were picking up traction resulted in Kodak falling behind and, eventually, becoming obsolete.

Whether they never saw the change coming, or because innovators leapt too far ahead, history

Figure 1 Total financing approved, limited to states surveyed in both years (% of applicants)



Source: Federal Reserve

1 US Small Business Administration. "Small Business Trends." 2017.
2 Chong, Celena. "Blockbuster's CEO once passed up a chance to buy Netflix for only \$50 million." *Business Insider*. July 17, 2015.
3 Jones, Milo and Philippe Silberzahn. "Do You Have A Digital Strategy? Kodak Had One Too." *Forbes*. May 30, 2016.

shows that time and time again industry leaders fail because of their inability to see or adapt to the change that is sprinting their way.

Watching the booming fintech alternative lending space gain more and more momentum, it is safe to assume the banking industry is poised for similar change. And, without the application of strategic measures to reestablish the commercial lending industry as a whole, it is likely that leading financial technology firms will surpass the incumbents' ability to fully serve their clients.

How Do Banks Start Serving Small and Medium-Sized Enterprises Again?

There are almost 30 million small businesses in the US, which make up over 99% of all firms in the country. As the primary source of job creation, these businesses play a pivotal role in the economy. According to the US Small Business Administration Office of Advocacy, small businesses accounted for over 60% of net new jobs since 1993.⁴

Post-2008, capital access available to these small businesses diminished for a number of reasons. Many banks did not survive the economic downturn, and those that did took a variety of measures to prevent any potential recurrence. Credit standards were fine-tuned, with even the most solvent companies struggling to secure capital for both survival and growth. Banks had to contend with increased regulatory oversight, which resulted in higher operational costs and significantly reduced margins. This perfect storm affected funding for small

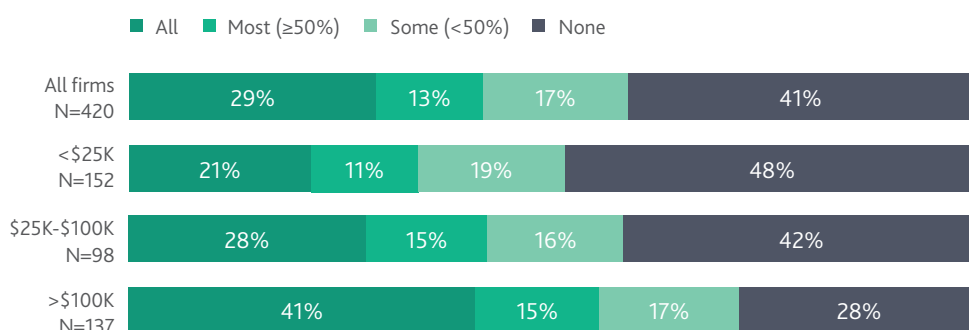
businesses, and only recently has the tide begun to turn for this critical segment of our economy.

As the economy has been steadily getting back on track, small and medium-sized enterprises (SMEs) are today able to secure financing more freely, but there is still much room for improvement. According to the "2015 Small Business Credit Survey: Report on Employer Firms" produced by several Federal Reserve Banks, 55% of businesses surveyed in 2015 were declined or received less than the requested capital amount.⁵ Although roughly one in two small business owners could not secure the requested amount of capital, this was actually an improvement from 62% in 2014. Figure 1 shows the full breakdown.

In addition, the Federal Reserve Banks' "2015 Small Business Credit Survey: Report on Nonemployer Firms" revealed that 71% of those surveyed were declined or received less than their requested amount, as shown in Figure 2.⁶ Microbusinesses (non-employer and employer firms with under \$100,000 in annual revenue) appear to show the greatest unmet need for capital.

The biggest underlying problem is that traditional banks employ the same workflow processes and staffing resources toward analyzing applications regardless of loan size, making the pursuit of small business lending a high-maintenance and less profitable endeavor. In a 2013 New York Fed Small Business Credit Survey, more than 50% of SMEs reported applying for a loan or line of credit of less than

Figure 2 Total financing approved, limited to states surveyed in both years (% of applicants)



Source: Federal Reserve

4 Small Business Administration Office of Advocacy. "Frequently Asked Questions." March 2014.

5 Federal Reserve Banks of New York, Atlanta, Boston, Cleveland, Philadelphia, Richmond, & St. Louis. "2015 Small Business Credit Survey: Report on Employer Firms." March 2016.

6 Federal Reserve Banks of New York, Atlanta, Boston, Cleveland, Philadelphia, Richmond, & St. Louis. "2015 Small Business Credit Survey: Report on Nonemployer Firms." December 2016.

\$100,000.⁷ This statistic accentuates the fact that the capital access gap remains unfulfilled, even though the potential profit in servicing these smaller loans is substantial – if progressive process improvements are implemented.

The Biggest Opportunity Could Be Found on Main Street

Knowing what small businesses mean for our economy, as well as the potential lending market that banks are barely tapping into, how do banks start more meaningfully serving this segment

that experience capital access restrictions are the sole proprietors and local “Main Street” operations. These firms should not be ignored, as they generate countless jobs and are the backbones of many cities and towns across the nation.

Banks need to understand that when they are servicing an SME, they are working with a customer that often has a more immediate, and smaller, capital need. This is in comparison to “larger” businesses that may command

The biggest underlying problem is that traditional banks employ the same workflow processes and staffing resources toward analyzing any application, regardless of loan size, making the pursuit of small business lending a high-maintenance and less profitable endeavor.

again? An important step in approaching this marketplace is to consider the definition of the SMEs in question.

The Small Business Administration (SBA) Office of Advocacy defines a small business as an independent business having fewer than 500 employees.⁸ There is more to the equation, however. According to a Harvard Business Review study conducted by former SBA Administrator Karen Mills, four main types of small businesses exist, and if all categorized business types are treated the same, a disparity in the ability to serve them effectively ensues.⁹

It is apparent that of the roughly 30 million small businesses, fewer than 5% will come anywhere near the “high growth” threshold. In other words, the majority of small businesses

more substantial funding requirements. As the commercial lending landscape evolves, leveraging and augmenting multiple sources of information can result in more expansive credit models that impact a number of variables, including the time needed to generate a decision. With proper credit risk measures applied, the effort level to underwrite a small business loan can be streamlined, and pursuing these loans can become more efficient and desirable.

Learn from the Successful Innovators

Where banks let down small businesses, alternative lending – a key component of the fintech industry – stepped in to fill the void. That perfect storm led to a tremendous opportunity for new entrants looking to bridge the capital access gap and provide uncomplicated funding

Figure 3 The four main types of small businesses

Type of Firm	Number of Firms*	Description
Non-employee businesses	23 million	Sole proprietorships
Main Street	4 million	Local businesses serving consumers and other local businesses
Suppliers	1 million	Suppliers to other businesses in the traded sector
High-growth	200,000	Fast-growing, innovation-driven businesses

*Note that an estimated 500,000 small businesses are non-suppliers in the traded sector and do not fall into any of the above categories.

Source: Harvard Business Review

7 Federal Reserve Bank of New York. “Fall 2013 Small Business Credit Survey.” September 2013.

8 US Small Business Administration Office of Advocacy. “Frequently Asked Questions.” June 2016.

9 Mills, Karen. “The 4 Types of Small Businesses, and Why Each One Matters.” *Harvard Business Review*. April 30, 2015.

where it was needed most.

This industry that barely existed a few years ago has been rapidly expanding. Fintech startups have excelled by making computerized process improvements to the application and credit analysis workflow, and minimizing overhead by automating as many steps as possible. In 2015, Morgan Stanley forecast that these alternative lenders would reach \$47 billion, or 16% of total SME loan issuance in the US, by 2020.¹⁰ Similar findings have been shared by Business Insider Intelligence, which further measured the impact

that can be tactically integrated into existing systems and processes is the key to competing with the fintech players.

Many incumbents have been slow to act, potentially waiting to see how new entrants would fare once the credit environment began to shift. Others took the opportunistic approach and found ways to partner with innovators early. Major players such as OnDeck and Fundation have established partnerships with JPMorgan Chase Bank, Regions Bank, and Citizens Bank. These collaborations have allowed the

For banks to remain relevant, they must expand product lines to include innovative solutions that cater to clients.

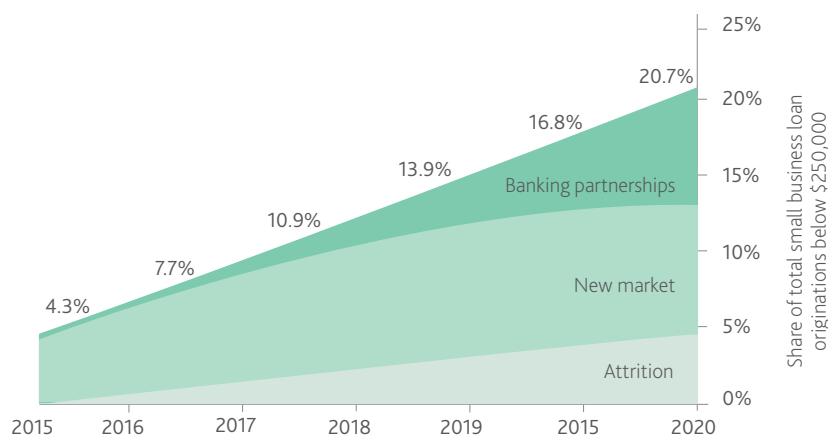
to the small business lending market as it relates to loan originations below \$250,000 (see Figure 4).¹¹ The 2015 Fed Small Business Credit Surveys reported that 20% of employer firms and 28% of non-employer firms applied to an online lender. Looking ahead, the primary catalyst for growth in the sector will be credit expansion, yet both Morgan Stanley and Business Insider expect there to be a noticeable market share shift from traditional banks to fintech players.

How Banks Can Learn From Alternative Lending's Success

With constant improvements in technology and banks' competition growing faster and smarter, traditional banks need to adapt and take advantage of today's tools. Finding solutions

traditional banks to access the technological innovations proven successful by the startups. By expanding the horizons of growth potential while retaining valued depository relationships and allowing for various cross-sell opportunities, the banks can improve upon their innate advantages. It's important to remember that banks retain the trust factor that is inherent in maintaining a high level of customer service, which is difficult for innovators to replicate. Banking services also go beyond just lending, and SMEs may welcome the opportunity to work with familiar institutions that can fulfill the broad range of their financial needs. Identifying the right partner is crucial, but outsourcing the ability to satisfy existing and prospective customers is imperative as the space

Figure 4 Forecast alternative SME lending, US market share



Source: Business Insider

¹⁰ Srethapramote, Smittipon, et al. "Global Marketplace Lending: Disruptive Innovation in Financials." Morgan Stanley blue paper. May 19, 2015.

¹¹ Bakker, Evan. "Small Business Alternative Lending: Alternative roads to capital will add billions to the small business lending market." *Business Insider*. April 29, 2016.

continues to evolve.

For banks to remain relevant, they must expand product lines to include innovative solutions that cater to clients. CIT Bank acquired Direct Capital, an SME commercial leasing firm, in 2014. Direct Capital soon expanded its suite to meet customer needs, offering a three- to 18-month working capital loan product that mirrors those of fintech players such as OnDeck and CAN Capital. By providing six months of recent bank statements, a driver's license photo, and a voided check, an SME can secure up to \$150,000 in under 24 hours. The terms are simple to understand: a fixed daily payback structure and full cost of capital disclosed up front, with no undefined fees. This product can compete with many of the "alternative lenders" that are offering similar loans, often with unfavorable terms. This is just one example of evolving a product suite to meet SME demand while supporting healthy growth and customer retention.

As the economy strengthens, there is great lending opportunity, with many avenues for SMEs and banks to consider. Those that have already engaged in partnerships with new entrants are ahead of the curve – but there are costs involved with these collaborations, and there are ways banks can accomplish similar goals in-house. In a 2016 working paper, Karen Mills and Brayden McCarthy identify four broad strategies for incumbents to consider:¹²

1. **Strategic partnership strategy:** Mills and McCarthy note that by pursuing strategic partnerships, banks are able to offer their SME product lines to existing and prospective clients through an online credit marketplace. This opportunity to leverage innovative products can be incorporated into an existing SME product suite.
2. **Arms-length partnership strategy:** This risky dual strategy calls for banks to buy loans originated by alternative lenders, while also establishing a referral partner for marginal or non-creditworthy applicants when a bank declines an application. Customer satisfaction is imperative for repeat business; finding the right partner to refer a declined

existing or prospective client to can preserve the trust factor that banks continue to maintain. Purchasing SME loans originated on alternative platforms can broaden existing loan portfolios without applying costly resources.

3. **Long-tail incubation strategy:** In an effort to hedge the risk of disruption, banks can take the approach of investing in and incubating new or existing fintech players. This strategy has unknown variables and may require a greater capital investment; however, there is an opportunity to diversify the banks' balance sheets while expanding future earnings potential. Research and development efforts require continuous attention, so leveraging excess capital and/or resources to enhance existing processes and offerings, while retaining full control, may be considered a safer option.
4. **Build or buy:** The final strategy Mills and McCarthy put forth is to develop new technology and/or product lines to compete with new entrants, or to purchase existing players offering competitive solutions. Banks have survived through good and bad times by adapting to changing environments. The fintech threats are present, but there is still time for banks to build solutions by applying tactical strategies that have worked in the past.

Staying Ahead to Remain Relevant

Traditional lenders now have the opportunity to embrace the changes Blockbuster and Kodak did not. Banks need to not only preserve their current market share, but also seize the opportunity to expand their lending base and improve their involvement with the important SME segment. Automated underwriting, expanded acquisition channels, and new credit products are becoming the new standard in SME lending. Banks should consider leveraging existing relationships by expanding access to capital in a practical way, enabling convenience, and applying progressive risk management practices. The time to internalize the fintech movement's innovations and plan for a more successful future is now.

¹² Mills, Karen and Brayden McCarthy. "The State of Small Business Lending: Innovation and Technology and the Implications for Regulation." Harvard Business School working paper. 2016.

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The background is a dark, abstract image featuring out-of-focus light sources. On the left, there are vertical streaks of bright white light. Scattered across the lower half and right side are numerous red, circular bokeh lights. The overall color palette is dominated by deep blues, reds, and whites.

PRINCIPLES AND PRACTICES

COMBINING INFORMATION TO BETTER ASSESS THE CREDIT RISK OF SMALL FIRMS AND MEDIUM-SIZED ENTERPRISES

By Dr. Douglas W. Dwyer



Dr. Douglas W. Dwyer
*Managing Director,
Research*

Douglas heads the Moody's Analytics single obligor research group. This group produces credit risk metrics of small businesses, medium-sized enterprises, large corporations, financial institutions, and sovereigns worldwide. The group's models are used by banks, asset managers, insurance companies, accounting firms, and corporations to measure name-specific credit risk for a wide variety of purposes. We measure credit risk using information drawn from financial statements, regulatory filings, security prices, derivative contracts, and behavioral and payment information. Previously, Doug was a principal at William M. Mercer, Inc. He has a PhD from Columbia University and a BA from Oberlin College, both in economics.

Lenders are increasingly tasked with making good lending decisions quickly. Such decisions require the ability to combine different types of information. Lenders typically rely on purely financial information to assess the credit risk of medium-sized enterprises. For small businesses, however, they consider more behavioral factors such as usage of credit lines, history of late payments, and the age of a relationship. Going forward, lenders will be able to access current financial information as well as behavioral information for both small firms and medium-sized enterprises. In order to quickly act on such information, firms will need to be able to combine such information into a unified risk assessment. In this article, we discuss the issues associated with acquiring such information and transforming it into a business decision. We also present a unified modeling approach for combining the information into a credit risk assessment for both small firms and medium-sized enterprises.

Introduction

A good origination process allows a lender to make loans faster, increase market share, and lower operational costs. A good risk model lowers charge-offs and provisions – especially during business downturns. To remain competitive, lenders to small firms and medium-sized enterprises will need to have both.

A lender can evaluate the risk of a borrower based on the borrower's behavior. Does the entity have a history of late payments? How long has it been a borrower? Does it have lines of credit? If so, is it maxing out these lines? If

borrower's assets exceed its liabilities? Is revenue sufficient to meet non-discretionary obligations? Is its financial performance stable over time? Is it improving? We think of answers to these questions as **financial information**.

If a lender uses the first type of information alone, then it will understate the risk of borrowers with positive behavioral information and poor financials.

Likewise, if a lender uses only the second type of information, it will understate the risk of borrowers with poor behavioral information but good financials.

A lender that assesses both behavioral information and financial information is able to make better decisions than a lender that does not.

you visit the enterprise, is it what it claims to be? We think of answers to such questions as **behavioral information**.

Additionally, the lender can analyze the borrower's finances. Does the value of the

A lender that assesses both types of information will be able to make better decisions than a lender that does not. This requires information collection as well as a model that can combine both types of information into a summary risk

measure, as shown in Figure 1. In this article, we explore modeling options.

Where to draw the line between a small firm and a medium-sized enterprise is subject to robust debate. For this article, we will look at two slices of our Credit Research Database (CRD). The first slice, the small firm sample, is made up of firms with less than \$1 million in assets. The medium-sized enterprise sample comprises firms with \$10 million to \$50 million in assets. We will show that one unified model framework that combines both financial and behavioral information can accurately predict the default rate in both samples.

Conventional Approach

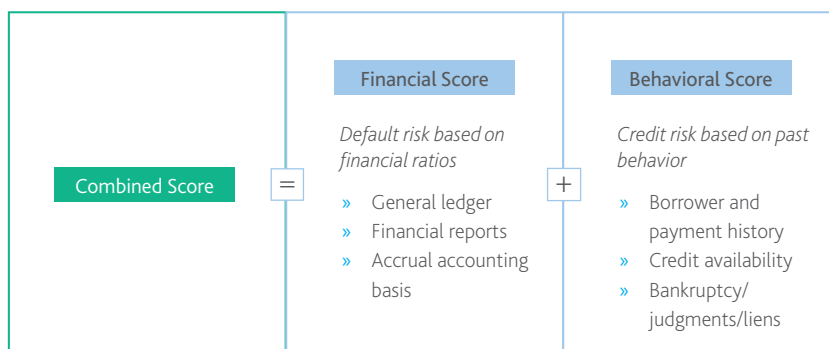
The conventional approach holds that financial information is more important for medium-sized enterprises than for small businesses. Small businesses often do not have audited financial statements and may use cash accounting. Consequently, lenders are uncertain of the reliability of such information. Further, the financials of the owner and the businesses are likely comingled to a certain degree. In this segment, banks rely more on tax returns, collateral information, personal and business

pro-forma financial statements. Banks also look at financial information of the guarantee (if any), and information on customers and suppliers. Business credit reports are used to validate information collected directly from the borrower.

Information technology will improve the accuracy and transparency of small businesses' finances. Businesses are increasingly using online software to maintain their general ledger, which documents every transaction of a firm. Having the general ledger online allows a computer to produce an on-the-fly financial statement that can then be used to evaluate the risk of a borrower. A lender can require a borrower to generate a financial statement via software that accesses the borrower's general ledger. As these financials can be based on accrual accounting, they may avoid the distortions that cash accounting creates in the statements of many small businesses.

Due to improving IT systems, the risk assessment process of small businesses will be able to include techniques that have traditionally been applied to medium-sized enterprises. Omitting this information can result in underestimated loss rates.

Figure 1 Combining different types of information



Source: Moody's Analytics

credit reports, borrowing activity, and credit utilization than on financial statement information.

Firms that are large enough to be considered medium-sized enterprises will typically use accrual accounting and have audited financial statements. In this segment, banks use quantitative models to assess default risk based on financial statements. The assessment is supported by an analysis of business plans and

Implications of Ignoring Information

We illustrate the implications of ignoring information using a pair of 2x2 diagrams. One can sort each borrower into one of the four quadrants according to the combination of their financial score and their behavioral score. The top right quadrant reflects poor financial and behavioral scores, while the lower left reflects good behavioral and financial scores. Firms with bad financial scores but good behavioral go into

the upper left quadrant, and firms with good financials but bad behavioral fall into the lower right quadrant. We choose the quadrants so that half the sample is classified as having good financials and the other as having bad financials, and likewise for behavioral. Consequently, each cell has about 25% of the sample.¹ Of course, one would expect default rates to be highest in the upper right-hand corner and lowest in the lower left-hand corner. The lower right and upper left corners would be in between.

As we have actual data, we can measure the default rates of each quadrant and color code them in proportion to the default rates. To do so, we need both a behavioral score and a financial score.

Our financial score is based on the RiskCalc model and uses financial statement information; the specific line items are available in a bank's FR Y-14Q reporting form. The financial score summarizes all financial information into one number representing the default risk of the firm. We utilize the RiskCalc CCA v4.0 credit measure for this purpose and focus on the small firm sample.

Our behavioral score is based on loan accounting system data; comparable information can be found in a bank's FR Y-14Q. With a bank's loan accounting system, we can track how long a business has been a borrower from a bank, whether it has a history of making timely payments, and whether it is fully utilizing its lines of credit. We have built a model that measures the business's credit risk given this information. Using these scores, we assign small businesses to each quadrant. More details on the data used for this article are in the appendix to this article.

Figure 2 shows two such grids. In both grids, the triangle on the upper left of each cell represents the actual default rate. In the upper right-hand cell of both grids, the actual default rate is 5.24%, which is color-coded, accordingly, in dark red. In the lower left-hand corner of each grid, the actual default rate is 0.43%, which is color-coded, accordingly, in a light pink to indicate low

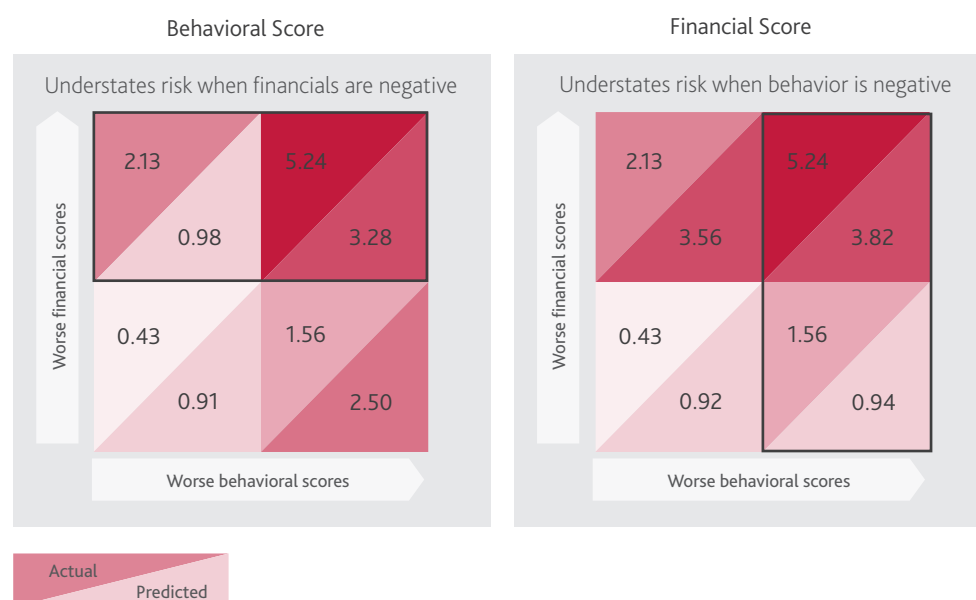
risk. The triangle in the lower right of each cell represents the predicted default rate according to the model.

In the first grid, the predicted values are based on the behavioral score alone; in the second, they are based on the financial score alone. In the lower right-hand cell of each grid, the actual default rate is 1.56% indicated in the upper left corner of the cell. The lower right-hand triangle of each cell represents the predicted default rate based on the model. The first grid utilizes behavioral information alone and therefore overestimates the risk of this quadrant (2.50%). The colors of the cell indicate this as the lower right triangle is a darker red than the upper left triangle in the cell. The second grid utilizes financial information alone and therefore underestimates the risk of this cell (0.94%). The colors of the cell indicate this as the upper left triangle is a darker red than the lower right triangle in this cell.

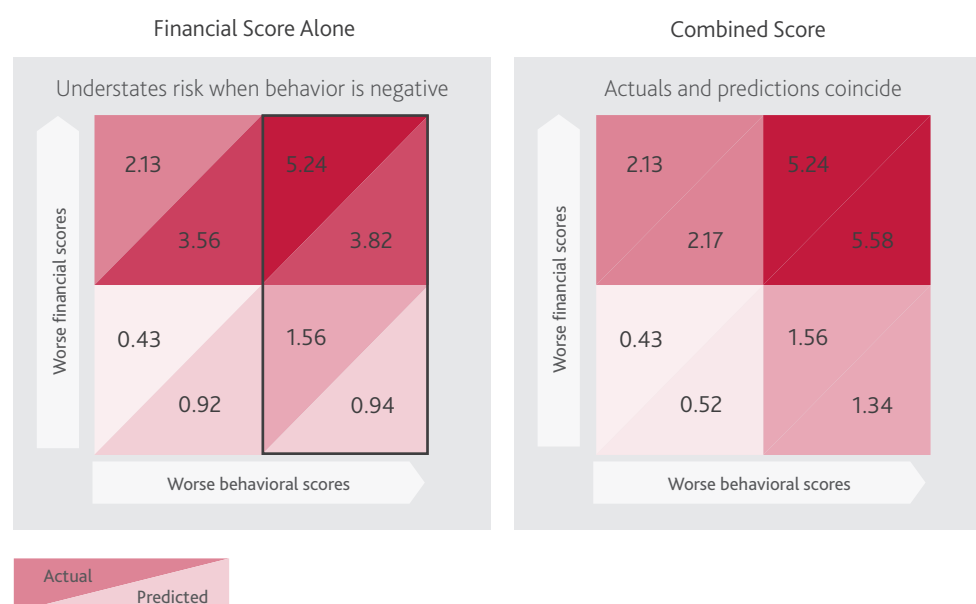
The first grid of this figure illustrates that if one relies on behavioral information alone, one overstates the risk of firms with good financials: In the lower row, the actual versus predicted was 0.43% versus 0.91%, and 1.56% versus 2.50%. Further, one understates the risk of firms with poor financials. In the upper row, the actual versus predicted was 2.98% versus 0.98% and 5.24% versus 3.28%. The second grid of this figure illustrates that if one relies on financial information alone, one overstates the risk of firms with good behavioral: In the right-hand column, the actual versus predicted was 0.43% versus 0.92% and 2.13% versus 3.56%. Further, one understates the risk of firms with poor behavioral: In the right-hand column, the actual versus predicted was 1.56% versus 0.94% and 5.24% versus 3.82%.

Figure 3 contrasts the implications of using both types of information to strictly relying on financial information. Note that utilizing both types of information results in a predicted default rate that coincides closely with the actual, as indicated by very similar colors of the triangles within each cell. Where risk is highest

¹ Strictly speaking, good behavioral scores are associated with good financial scores, which implies that the cells where the signals from behavioral information and financial information agree are better populated than when the signals disagree. Further, in the small firm sample, 53% of firms have the median or better behavioral score due to the discrete nature of the independent variables in the behavioral model. The breakdown of the small firm sample is as follows: 25% for bad financials and good behavioral, 25% for bad financials and bad behavioral, 29% for good financials and good behavioral, and 21% for good financials and bad behavioral. The corresponding numbers for the medium-sized enterprise sample are 23%, 27%, 27%, and 23%.

Figure 2 Implications of using behavioral scores or financial scores in isolation for small firms

Source: Moody's Analytics

Figure 3 Combined score accurately predicts the default rate in all four quadrants for small firms

Source: Moody's Analytics

(in the upper right quadrant), the combined model predicts 5.58% while financials alone predict 3.82% and behavioral scores predict 3.28%. If a lender relied on a single model, it would make the loan with partial information, perhaps charging these borrowers 4% above the funding costs. If the lender had the full

information, however, it would likely turn down the potential borrower. By turning down such loans, a lender avoids a 5.58% loss rate on approximately 25% of its portfolio. Therefore, the net benefit of these rejections to the lender would be approximately 0.40% on the portfolio as a whole.²

² We compute this saving as the difference between the expected default rate (5.58%) and the yield in excess of the funding costs (4%) and then multiply by ¼ to reflect that approximately one-quarter of the portfolio would be in this quadrant. This calculation does make a number of assumptions including that both the risk and the return are homogeneous within the quadrant and that LGD is 100%. The true cost benefit calculation of rejecting these potential borrowers is more involved, but the results are indicative of a substantial savings from using a combined model.

Overstating the risk of firms that are safe has its own costs as well. For the firms with both good financial and behavioral scores, their risk is overstated by a factor of two. This elevated estimate of risk may lead the lender to ask for more collateral or more yield than is required. Further, lenders may perform more due diligence than is required, which slows down the origination process. Consequently, they may lose business to another lender who is able to process the deal faster and offer more attractive terms.

So far, we have looked at the implications of combining behavioral information and financials for small firms. We will now look at the implications of combining these information types for both small firms and medium-sized enterprises.

Dynamic Weights

Behavioral information is useful for understanding the credit risk of a small business, but is it as useful for medium-sized enterprises? Conventional wisdom would say no – for medium-sized enterprises, the financial statement information is much better, so credit assessments can rely more on the financial statements. One can address the question empirically by constructing a model that measures the relative importance of financial information and behavioral information by firm size.

Using our sample of firms with up to \$50 million in assets, one can estimate a model in which the relative importance of financial factors increases with the size of the firm using the equation that follows. The basic idea is to let the weight on financial statement information be a linear function of the size of the firm (measured by log of assets):

$$pd(B,F) = G(\gamma_0 + \gamma_1(w_{Size}F + (1-w_{Size})B))$$

Where

- » B is the behavioral score
- » F is the financial score
- » $pd(B,F)$ is the probability of default for the given behavioral and financial scores
- » γ_0 and γ_1 are parameters to be estimated that determine the level and the variability of the PD, respectively
- » w_{Size} is the weight on the financial factors, determined by:

$$w_{Size} = \alpha_0 + \alpha_1 \log(\text{Size})$$

- » Size is measured as the log of total assets and α_0 and α_1 are parameters to be estimated
- » G is a link function that transforms the combined score into a probability of default; in this article, we use a probit function

If the behavioral information is more important for smaller firms, we should see a positive coefficient on α_1 . Figure 4 shows that the weight on the financial statement information increases with firm size. For a medium-sized enterprise with \$50 million in assets, the weight on financial information comes out to 65%. This weight is consistent with conventional wisdom, in that many scorecards that we see used in practice use a weight in this range for the financial index. For a small firm with total assets of \$200,000, the weight comes to about 51%. Consistent with conventional wisdom, the weight on financials is lower for small firms than for medium-sized enterprises. What is perhaps surprising is that the weight on financials is about 51% for the smallest firms. Many credit analysts would have expected it to be lower.

Comparing a Dynamic Weight to a Fixed Weight

What are the implications of using a dynamic weight on financials? Using a dynamic weight makes the model more complicated; is the added complexity worth the bother? When does the added complexity make a difference?

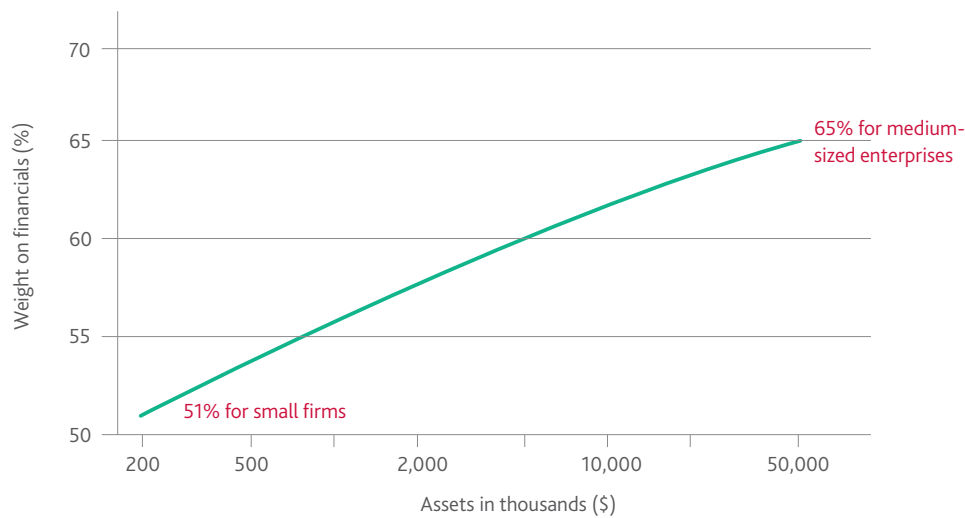
In building a model, one of the challenging questions is how complicated to make it. As models become more complex, they tend to be more difficult to use and support. Further, the factors driving the model's risk assessment typically become less transparent. Nevertheless, the complexity likely improves the fit of the model. If so, when and by how much? If a much better model always produces a probability of default (PD) that is within 20% of the PD produced by the simpler model (e.g., a PD that increases from 2.0% to 2.4%), it will be difficult to convince a practitioner that the much better model is, in fact, much better. Alternatively, if the much better model typically produces a PD very similar to the simple model's but produces contrasting results under specific circumstances that appeal to intuition, then the practitioner could be convinced that the much better model is, in fact, much better.

We address this question with two 2x2 grids and include three numbers inside each cell of each grid, as shown in Figure 5. Small firms are represented in the first grid, and medium-sized enterprises are in the second. The behavioral factors are again on the horizontal axis, and the financial scores are on the vertical axis. The upper left triangle of each cell contains the actual default rate. The right-hand triangle in each cell is the predicted default rate based on

the fixed-weight model, which is the simple model. And the bottom triangle in each cell is the predicted default rate based on the dynamic weight model, the complex model. Once again, each triangle is color-coded to match the intensity of the cell's numbers.

Note that the color of the bottom triangle largely coincides with the color of the upper left triangle in all eight cells. This indicates that the complex model's predictions are in

Figure 4 The weight on a financial score increases with firm size



Source: Moody's Analytics

Figure 5 Dynamic weight more accurately predicts defaults in all four quadrants for small firms and medium-sized enterprises



Source: Moody's Analytics

line with the realized default rates. For the right-hand triangles, the color differential is largest in the lower right quadrant for both small firms and medium-sized enterprises. This quadrant is where the financials are good but the behavioral factors are bad. For small firms in this quadrant, the simple model understates the risk (1.10% predicted versus 1.56% realized), and for medium-sized enterprises, the model overstates the risk (0.55% versus 0.31%). This finding is intuitive: By using the same weight on small firms as for medium-sized enterprises, one overstates the importance of financial statements for small firms and therefore overstates the risk in this quadrant; likewise, one understates the importance of financial statements for medium-sized firms.

Such differences are not huge, representing about a notch in ratings (e.g., Baa3 versus Ba1). They are large enough, however, to justify the added complexity of the model. In a sense, this approach is simpler than the conventional approach. The conventional approach uses different models for medium-sized enterprises and small businesses and requires a somewhat arbitrary cutoff for which borrower fits into which segment. With this approach, a modeler can use one scorecard for both small businesses and medium-sized firms, with a weight on the financials that gradually increases with firm size.

Conclusion

In this article, we have demonstrated the implications of combining financial and behavioral information in the credit assessments of both small businesses and medium-sized enterprises. Both types of information are important for both types of borrowers, with behavioral information being somewhat more important for small firms than for larger ones. For medium-sized enterprises, one should place a two-thirds weight on financial statement information and a one-third weight on behavioral factors. For small firms, one should weight financial and behavioral information equally. This finding may surprise some, as small businesses' financial statement information may not even be collected as part of the credit assessment process.

Going forward, successful lenders will likely start using automated approaches to collect both financial statement information and behavioral information for small firms for two reasons. First, one will increasingly be able to automatically collect such data. Second, collecting and using both types of information allows the lender to make better decisions. In this article, we have shown how to complete one step required for this transformation of the credit risk management process: how to combine both types of information into a better assessment of credit risk.

Appendix

For this article, we estimated the combined model on the North American CRD sample that includes more than 1.1 million quarterly observations from more than 100,000 firms with more than 5,000 defaults. The data begins in 1990 and runs through 2014. In this sample, we are able to get both firm-level financial statement information as well as information on credit line usage, payment status on current balances, and history of late payments. Finally, we are able to link this borrower information to data on whether the firm defaulted within the next year.

The financial score is based on the RiskCalc Expected Default Frequency (EDF) credit measure. The behavioral score is based on a model that uses credit line usage, payment status on current balance, and borrower history to predict default. For the figures in this article, we first focused on a sample of small firms with less than \$1 million in total assets. There were 250,000 observations from 30,000 unique firms with 2,000 default events.

For the figures in this article that contrast small firms to medium-sized enterprises, we used the small firm sample as described above and a medium-sized enterprise sample. The medium-sized sample includes firms with between \$10 million and \$50 million in total assets. This sample included 200,000 observations, 19,000 unique firms, and 700 defaults.

In order to combine the outputs of the RiskCalc EDF model with the behavioral model, we transformed both the RiskCalc EDF credit measure and the behavioral model PD. The specific transformation that we used was the inverse of a standard cumulative normal distribution. Such a transformation makes the distribution of financial scores and behavioral scores more bell-shaped and less skewed relative to the untransformed RiskCalc EDF credit measure or untransformed behavioral model PD.

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Ranked 22nd in the
Overall Top 100
Rankings



Best Credit Risk
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– RiskCalc

MODELING STRESSED LGDS FOR MACROECONOMIC SCENARIOS

By Dr. Samuel W. Malone and Dr. Martin A. Wurm



Dr. Samuel W. Malone
Director of Research

Sam leads the quantitative research team within the CreditEdge™ research group. In this role, he develops novel risk and forecasting solutions for financial institutions while providing thought leadership on related trends in global financial markets. He is author of the book *Macrofinancial Risk Analysis*, published in the Wiley Finance series with foreword by Nobel Laureate Robert Merton, as well as the author of more than 20 peer-reviewed articles in academic journals. He has BS degrees in mathematics and economics from Duke University, where he graduated summa cum laude, and a doctorate in economics from the University of Oxford.



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New accounting standards, which place increased emphasis on the ability of banks to calculate current expected credit losses, also make clear the importance of using models that appropriately link probabilities of default (PDs) and losses given default (LGDs) to macroeconomic drivers. At the same time, calculating conditional expected credit losses under Fed-supervised stress tests requires stressed PDs and LGDs as inputs. While validated stressed PD models are already on offer, efforts to properly model LGDs as a function of macroeconomic drivers are still in their infancy. In this article, we develop and validate a model for stressed LGDs aimed at meeting this need. Empirically, we find that LGDs sometimes lead PDs by several months during crisis periods. At the sector level, our stressed LGDs provide reasonably accurate forecasts out-of-sample for most sectors and exhibit attractive qualities under the Fed's baseline, adverse, and severely adverse Comprehensive Capital Analysis and Review (CCAR) scenarios for all 13 sectors studied.

Introduction

Recent regulatory trends have forced banks to develop new probability of default (PD), loss given default (LGD), and exposure at default (EAD) models. Such developments are driven by the expansion of regulatory stress testing, as well as novel current expected credit loss (CECL) and international financial reporting (IFRS 9) standards. The literature on PDs is ample, and practitioners typically have access to both internal modeling approaches as well as industry-wide estimates; however, LGDs and EADs lack similar treatment. The Bank for International Settlements, for instance, has long remarked upon the fact that banks have more difficulties in establishing estimates of their own LGDs vis-à-vis PDs.¹

As a step toward closing this gap, we first

develop metrics of stressed LGDs for North America. Our LGDs are calculated at the industry level from Moody's Analytics CreditEdge™ database and are similar in nature to existing point-in-time (PIT), stressed EDF measures based on the same source.² Such information provides practitioners with an important baseline for the establishment of firm-level estimates. We further demonstrate that historical sector LGDs Granger-cause average EDFs for several industries in Moody's Analytics CreditEdge data. This finding is important because it suggests that the early warning value of well-calibrated PIT LGD measures may have been somewhat underestimated by risk and investment practitioners. Second, we discuss the interpretation of our stressed LGD model for the financial sector. Finally, we show that the out-

¹ See Allen and Saunders, 2003; and Basel Committee on Banking Supervision, 2005.

² See Ferry, Hughes, and Ding, 2012a and 2012b.

of-sample accuracy and behavior under stress scenarios of our sector LGD models are generally quite good.

Before proceeding, a caveat is in order. The work underlying this article relies on calibrated sector LGDs from the Moody's Analytics fair value spread (FVS) model, rather than realized LGD data at the issuer level. There are good reasons for this: Calibrated sector LGDs are consistent by design with both bond spread data and issuer-level Expected Default Frequency (EDF) data. By extension, they are consistent with the stressed EDFs already used in stress testing work. Further, well-behaved sector-level LGD data – as opposed to more granular data – facilitates the initial development of econometric models in which LGDs respond in an intuitive and appropriate way to macroeconomic drivers under stress. These advantages notwithstanding, a first-best stressed LGD model must ultimately take into account issuer-level, realized LGD data, rather than calibrated sector LGDs alone.

Fortunately, realized LGDs by issuer and

limited here to the approximately 12,000 firms in the US and Canada. Average sector LGDs for senior and subordinate debt are already available for 13 TPM industry sectors⁴ at the monthly frequency, with data beginning in December 2005. To obtain corresponding metrics of sector EDFs, we take the equally-weighted average across the individual firm EDFs within a given sector in each month.

For ease of exposition, we will primarily display graphical results for the banking and services sectors only, with notes on other sectors in the text. Figure 1 charts the history for the senior and subordinate sector LGDs and these sector EDFs for the available sample period. Several patterns stand out clearly for these and other sectors. First, senior LGDs are generally lower and less volatile than their subordinate counterparts. Second, LGDs – more so than EDFs – co-vary differently with the state of the economy across sectors. LGDs in some sectors, such as the telecommunication sector (TPM sector 10), are broadly countercyclical; LGDs for other sectors, such as banks (TPM sector 1),

In practice, the positive correlation between PDs and LGDs for financial institutions works to increase the variance of their time-varying expected credit losses. This results in increased model risk.

instrument seniority level can be constructed using Moody's Analytics Default and Recovery Database (DRD), and such data will directly inform our forthcoming research on stressed realized LGD models.³ In that context, the present article primarily offers a proof-of-concept: It is possible to produce reliable, validated estimates of LGD for a wide variety of North American issuers under conditions of macroeconomic stress. We believe this finding alone is a positive development from a regulatory compliance and risk management perspective.

Sector LGDs and Sector EDFs

For our stressed LGD model, we employ the expansive CreditEdge dataset. Our analysis is

appear more cyclical, with higher LGDs occurring during the period defining the Great Recession.

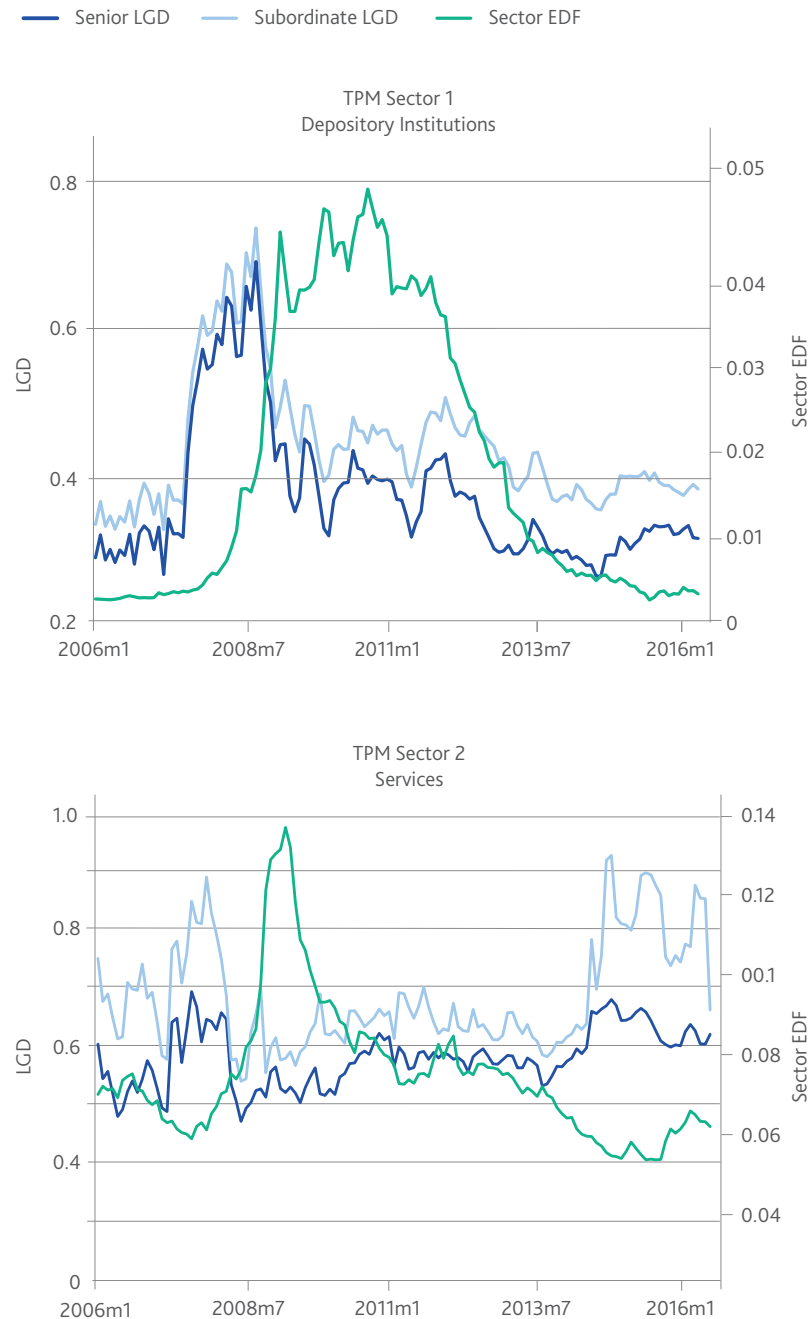
LGDs in the raw materials and mining sector (TPM sector 9), in contrast, do not appear cyclical at all. Rather, the sector LGD appears to be in almost secular decline from 2006 to 2014, after which subordinate LGDs shoot up in response to the 2014 plunge in energy prices.

In contrast to the case of LGDs, virtually all sectors experienced an increase in their average EDF levels in the aftermath of the global financial crisis, with slight variations in timing and degree, followed by a subsequent period of relative calm. The most noticeable exceptions to this rule are the raw materials and the mining and energy sectors, which both saw an

³ See Malone and Wurm, forthcoming.

⁴ TPM industry sectors refer to the sector categories encoded in the CreditEdge sector LGD database.

Figure 1 Sector LGDs and EDFs for the banking and services sectors



Source: Moody's Analytics

increase in EDFs after 2014. Consequently, the contemporaneous relationship between EDFs and LGDs varies in subtle ways across industries. Figure 2 summarizes the Pearson correlation coefficients, by sector, between the three pairs of variables drawn from the set of senior sector LGDs, subordinate sector LGDs, and sector EDFs. Across sectors, correlation coefficients between senior and subordinate LGDs are positive and typically quite high, as expected. The main stylized fact of note that emerges from Figure 2, rather, is that “financial services sectors

are special.” In particular, whereas LGD-EDF correlations are almost uniformly negative for non-financial sectors, the correlations for financial sectors (1, 7, and 13) are positive.

The reason for this finding likely originates in the forces of valuation and interdependence at work amongst financial institutions. The PDs of financial institutions depend on the value of their collateral, which is linked to their LGDs, and the value of their collateral often depends upon the PDs of the counterparties that owe them claims; therefore, financial institutions' PDs and LGDs

Figure 2 Pearson correlation coefficients: LGDs and EDFs

TPM Sector	Senior LGD, Subordinate LGD	Senior LGD, Sector EDF	Subordinate LGD, Sector EDF
1. Depository institutions	0.97	0.21	0.24
2. Services	0.78	-0.52	-0.49
3. Aeronautics	0.89	-0.74	-0.71
4. Computers/electronics	0.72	-0.05	-0.21
5. Healthcare/pharmaceuticals	0.84	-0.47	-0.62
6. Energy/utilities	0.69	-0.12	-0.28
7. Nonbank finance	0.92	0.72	0.68
8. Consumer goods	0.52	-0.73	-0.57
9. Raw materials/mining	0.83	-0.46	-0.16
10. Transportation	0.44	0.27	-0.31
11. Industrial machinery	0.76	-0.11	-0.29
12. Telecommunication	0.96	-0.85	-0.84
13. Public financial services	0.88	0.41	0.45

Source: Moody's Analytics

are endogenous. This is one reason for which the cross-ownership of liabilities across financial institutions can make them more vulnerable to contagion.⁵

In practice, the positive correlation between PDs and LGDs for financial institutions works to increase the variance of their time-varying

attention to both LGD and PD modeling as well as the natural dependence between these two activities.

As a first step to thinking about how to model sector LGDs, therefore, we examine whether they exhibit lead-lag relationships with EDFs. Specifically, we test for the presence of Granger

In 39% of instances, LGDs Granger-cause EDFs, while the reverse is true in 50% of cases.

expected credit losses. This results in increased model risk. It may also cause more cyclical reserve requirements under new IFRS 9 and CECL standards if banks do not pay careful

causality between senior and subordinate LGDs for each sector, respectively, with the corresponding sector EDF. These results are presented in Figure 3.⁶

⁵ For details about the underlying mechanisms at work, see Gray and Malone (2008).

⁶ The null hypothesis of the Wald test for Granger causality is that the coefficients on the p-lags of a variable of interest in a vector autoregressive equation are jointly zero, that is to say, that they do not Granger-cause the left-hand-side variable. Thus, a low p-value suggests the presence of Granger causality. We choose the lag length of each vector autoregression (VAR) by picking the lag preferred by the majority of these four criteria: the final prediction error (FPE), Akaike information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan-Quinn information criterion (HQIC). Where the criteria are split, we base our preference on the AIC. The presented results are not very sensitive to the reliance of one criterion over another.

Figure 3 Granger causality tests: EDFs and LGDs

TPM Sector	Equation	Excluded	Wald Test p-value	Excluded Granger-Causes Dependent?
1. Depository institutions	Senior LGD	Sector EDF	0.11	No
	Sector EDF	Senior LGD	0.00	Yes
	Subordinate LGD	Sector EDF	0.31	No
	Sector EDF	Subordinate LGD	0.00	Yes
2. Services	Senior LGD	Sector EDF	0.05	Yes
	Sector EDF	Senior LGD	0.81	No
	Subordinate LGD	Sector EDF	0.35	No
	Sector EDF	Subordinate LGD	0.66	No
3. Aeronautics	Senior LGD	Sector EDF	0.01	Yes
	Sector EDF	Senior LGD	0.29	No
	Subordinate LGD	Sector EDF	0.16	No
	Sector EDF	Subordinate LGD	0.08	Yes
4. Computers/electronics	Senior LGD	Sector EDF	0.00	Yes
	Sector EDF	Senior LGD	0.54	No
	Subordinate LGD	Sector EDF	0.12	No
	Sector EDF	Subordinate LGD	0.16	No
5. Healthcare/ pharmaceuticals	Senior LGD	Sector EDF	0.48	No
	Sector EDF	Senior LGD	0.06	Yes
	Subordinate LGD	Sector EDF	0.07	Yes
	Sector EDF	Subordinate LGD	0.66	No
6. Energy/utilities	Senior LGD	Sector EDF	0.26	No
	Sector EDF	Senior LGD	0.43	No
	Subordinate LGD	Sector EDF	0.79	No
	Sector EDF	Subordinate LGD	0.68	No
7. Nonbank finance	Senior LGD	Sector EDF	0.05	Yes
	Sector EDF	Senior LGD	0.10	Yes
	Subordinate LGD	Sector EDF	0.01	Yes
	Sector EDF	Subordinate LGD	0.37	No
8. Consumer goods	Senior LGD	Sector EDF	0.06	Yes
	Sector EDF	Senior LGD	0.02	Yes
	Subordinate LGD	Sector EDF	0.02	Yes
	Sector EDF	Subordinate LGD	0.02	Yes

Source: Moody's Analytics

Figure 3 (Cont'd) Granger causality tests: EDFs and LGDs

TPM Sector	Equation	Excluded	Wald Test p-value	Excluded Granger-Causes Dependent?
9. Raw materials/mining	Senior LGD	Sector EDF	0.23	No
	Sector EDF	Senior LGD	0.21	No
	Subordinate LGD	Sector EDF	0.57	No
	Sector EDF	Subordinate LGD	0.56	No
10. Transportation	Senior LGD	Sector EDF	0.14	No
	Sector EDF	Senior LGD	0.50	No
	Subordinate LGD	Sector EDF	0.61	No
	Sector EDF	Subordinate LGD	0.02	Yes
11. Industrial equipment/ machinery	Senior LGD	Sector EDF	0.01	Yes
	Sector EDF	Senior LGD	0.66	No
	Subordinate LGD	Sector EDF	0.87	No
	Sector EDF	Subordinate LGD	0.15	No
12. Telecommunication	Senior LGD	Sector EDF	0.00	Yes
	Sector EDF	Senior LGD	0.01	Yes
	Subordinate LGD	Sector EDF	0.00	Yes
	Sector EDF	Subordinate LGD	0.00	Yes
13. Public financial services	Senior LGD	Sector EDF	0.08	Yes
	Sector EDF	Senior LGD	0.11	No
	Subordinate LGD	Sector EDF	0.05	Yes
	Sector EDF	Subordinate LGD	0.48	No

Source: Moody's Analytics

From Figure 3, we find that in 39% of instances, LGDs Granger-cause EDFs, while the reverse is true in 50% of cases. Sector EDFs tend to Granger-cause senior LGDs more reliably (in 62% of cases), whereas they hold less predictive power for subordinate EDFs (39% of sectors).

Notably, in the case of depository institutions (sector 1) we find that both senior and

the stage with the need to produce realistic scenario forecasts for the dependent variable under stress.

As a benchmark estimation approach, we employ a principal component regression⁸ (PCR) using as explanatory variables Moody's Analytics stressed EDF forecasts as well as other drivers obtained from Moody's Analytics macro model.

The objective of a stress forecast is to replicate the behavior of a variable under particular macroeconomic assumptions.

subordinate sector LGD measures Granger-cause the sector EDF, whereas the reverse is not true. While banks' PDs may help forecast growth,⁷ it turns out that the early spike in banks' LGDs provided an even better early warning indicator during the crisis. The measured spike in bank LGDs prior to the crisis is consistent with a deterioration in the value of their real estate-linked collateral.

Stressed Sector EDFs and LGDs

Let's proceed to model-building. To obtain good conditional stressed LGD forecasts, one needs to identify a set of suitable macroeconomic drivers. "Realism" in this context does not refer only to "forecast accuracy," although that is also obviously desirable. The objective of a stress forecast is rather to replicate the behavior of a variable under particular macroeconomic assumptions. For instance, if senior LGDs in transportation tend to drop in an economic downturn, a good scenario forecast needs to approximate the direction and magnitude of such behavior given a shock of similar severity. This is different from the approach of standard time-series forecasting methodologies, such as vector-autoregressive models, where the objective is to minimize the forecast error of any given series based on observed history. In stress testing applications, certain in-sample properties such as goodness of fit or serial correlation share

Sector EDFs are natural inputs to sector LGD models based on conceptual considerations and, at least for some sectors, based on the presence of observed nonzero historical correlations. The CreditEdge software already contains estimates on stressed firm EDFs based on both the Fed's regulatory Comprehensive Capital Analysis and Review (CCAR) scenarios, as well as some of Moody's Analytics own macroeconomic scenarios.⁹ To establish stressed sector EDF forecasts, we simply compute the equally-weighted average of firm-level scenario forecasts at every point of the forecast horizon across all firms in a sector.¹⁰

The varying strength in correlation between the variables in Figure 2 implies that some sector EDFs are insufficient on their own to adequately predict sector LGDs. We therefore extend the pool of potential drivers to include variables from the Fed's CCAR scenarios and Moody's Analytics own macro model forecast. For our full set of variables, we obtain the first five principal component scores, which we use as forecast drivers. The full set of variables is listed in Figure 4 and corresponds roughly to a similar list in Poi (2016).

The choice of the PCR modeling approach is based on two considerations. First, the limited sample size prevents us from including more than only a handful of macro drivers before

7 See Hughes and Malone, 2015.

8 We alternatively considered a generalized linear model with a logit link, since LGDs are censored between 0 and 1. Based on in-sample fit, however, we prefer simple least squares.

9 For methodological details see Ferry, Hughes, and Ding, 2012.

10 Since jump-offs can occur between the sector EDFs in history and their scenario forecasts, we splice each series to smooth them.

Figure 4 Drivers

Concept	Transform	Source
Industry-specific sector EDF	Level	Moody's Analytics forecast
Consumer price index (CPI): urban consumer – all items, index 1982-84=100, seasonally adjusted (SA)	% change	US Bureau of Labor Statistics (BLS); Moody's Analytics forecast
Employment: total nonagricultural, millions, SA	% change	BLS; Moody's Analytics forecast
Gross domestic product, change in billions, 2009 USD, seasonally adjusted annual rate (SAAR)	% change	US Bureau of Economic Analysis (BEA); Moody's Analytics forecast
New home sales: single-family houses, millions, SAAR	% change	US Census Bureau (BOC); Moody's Analytics forecast
Existing home sales: single-family, millions, SAAR	% change	National Association of Realtors (NAR); Moody's Analytics forecast
Existing single-family home price: median, thousands USD, SA	% change	NAR; Moody's Analytics forecast
Retail sales: retail sales and food services, billions USD, SAAR	% change	BOC; Moody's Analytics forecast
S&P 500 composite: price index – average, index 1941-43=10, not seasonally adjusted (NSA)	% change	Standard & Poor's (S&P); Moody's Analytics forecast
Income: personal – total, change in 2009 USD, SAAR	% change	BEA; Moody's Analytics forecast
Income: per capita disposable income, change in 2009 USD, SAAR	% change	BEA; Moody's Analytics forecast
Futures price: Brent Crude oil one-month forward, USD per billion, NSA	% change	European Central Bank (ECB); Moody's Analytics forecast
New vehicle sales: cars and light trucks, millions of units, SAAR	% change	BEA; Moody's Analytics forecast
Household survey: unemployment rate, %, SA	level	BLS; Moody's Analytics forecast
Interest rates: Moody's bond yield – Aaa corporate – bonds with maturities 20 years and above, % per annum (p.a.), NSA	level	Moody's Investors Service; Moody's Analytics forecast
Interest rates: Moody's bond yield – Aa corporate – bonds with maturities 20 years and above, % p.a., NSA	level	Moody's Investors Service; Moody's Analytics forecast
Interest rates: Moody's bond yield – A corporate – bonds with maturities 20 years and above, % p.a., NSA	level	Moody's Investors Service; Moody's Analytics forecast
Interest rates: Moody's bond yield – Baa corporate – bonds with maturities 20 years and above, % p.a., NSA	level	Moody's Investors Service; Moody's Analytics forecast
Interest rates: CDs secondary market – one-month, % p.a., NSA	level	US Board of Governors of the Federal Reserve System (FRB); Moody's Analytics forecast
Interest rates: CDs secondary market – three-month, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: CDs secondary market – six-month, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: federal funds rate, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: three-month Treasury bills, secondary market, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: six-month Treasury bills, secondary market, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: one-year constant maturity securities, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: two-year constant maturity securities, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: three-year constant maturity securities, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: five-year constant maturity securities, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: seven-year constant maturity securities, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: 10-year constant maturity securities, % p.a., NSA	level	FRB; Moody's Analytics forecast
Interest rates: 30-year constant maturity securities, % p.a., NSA	level	FRB; Moody's Analytics forecast
LIBOR rates: one-month US dollar deposits, % p.a., NSA	level	ICE Benchmark Administration Limited (IBA); Moody's Analytics forecast
LIBOR rates: three-month US dollar deposits, % p.a., NSA	level	IBA; Moody's Analytics forecast
LIBOR rates: six-month US dollar deposits, % p.a., NSA	level	IBA; Moody's Analytics forecast
LIBOR rates: 12-month US dollar deposits, % p.a., NSA	level	IBA; Moody's Analytics forecast
Interest rates: bank prime rate, % p.a., NSA	level	FRB; Moody's Analytics forecast

Source: Moody's Analytics

Figure 5a Principal component factor loadings – banking sector

Concept	Component				
	1	2	3	4	5
Industry-specific sector EDF	-0.09	-0.22	0.26	0.00	0.22
CPI: urban consumer – all items	0.10	0.08	0.35	-0.20	-0.53
Employment: total nonagricultural	-0.03	0.30	0.00	-0.21	-0.13
Gross domestic product	-0.01	0.31	0.17	-0.05	0.07
New home sales: single-family houses	-0.09	0.22	-0.09	0.33	-0.12
Existing home sales: single-family	-0.13	0.04	-0.06	0.38	0.02
Existing single-family home price: median	-0.07	0.28	-0.05	0.24	-0.02
Retail sales: retail sales and food services	-0.02	0.28	0.33	-0.03	-0.02
S&P 500 composite: price index – average	-0.04	0.21	0.33	0.24	0.21
Income: personal – total	0.00	0.26	0.02	-0.43	0.28
Income: per capita disposable income	0.00	0.19	-0.09	-0.47	0.37
Futures price: Brent Crude oil one-month forward (free on board (fob))	0.06	0.03	0.49	-0.06	-0.34
New vehicle sales: cars and light trucks	-0.10	0.21	0.28	0.11	0.26
Household survey: unemployment rate	-0.13	-0.19	0.24	0.10	0.17
Interest rates: Moody's bond yield – Aaa corporate – bonds with maturities 20 years and above	0.14	-0.23	0.18	-0.05	0.09
Interest rates: Moody's bond yield – Aa corporate – bonds with maturities 20 years and above	0.14	-0.24	0.13	-0.08	0.06
Interest rates: Moody's bond yield – A corporate – bonds with maturities 20 years and above	0.14	-0.26	0.11	-0.10	0.02
Interest rates: Moody's bond yield – Baa corporate – bonds with maturities 20 years and above	0.13	-0.27	-0.02	-0.08	-0.04
Interest rates: CDs secondary market – one-month	0.22	0.08	-0.05	0.02	-0.06
Interest rates: CDs secondary market – three-month	0.22	0.07	-0.06	0.01	-0.07
Interest rates: CDs secondary market – six-month	0.22	0.06	-0.08	0.01	-0.08
Interest rates: federal funds rate	0.22	0.09	-0.01	0.04	0.00
Interest rates: three-month Treasury bills – secondary market	0.21	0.09	-0.03	0.07	0.04
Interest rates: six-month Treasury bills – secondary market	0.22	0.09	-0.04	0.06	0.03
Interest rates: one-year constant maturity securities	0.22	0.08	-0.04	0.06	0.04
Interest rates: two-year constant maturity securities	0.22	0.06	-0.04	0.08	0.08
Interest rates: three-year constant maturity securities	0.22	0.05	-0.03	0.09	0.11
Interest rates: five-year constant maturity securities	0.22	0.02	0.01	0.10	0.14
Interest rates: seven-year constant maturity securities	0.21	-0.02	0.07	0.11	0.19
Interest rates: 10-year constant maturity securities	0.21	-0.05	0.13	0.10	0.17
Interest rates: 30-year constant maturity securities	0.18	-0.07	0.24	0.14	0.16
LIBOR rates: one-month US dollar deposits	0.22	0.06	-0.02	0.00	-0.04
LIBOR rates: three-month US dollar deposits	0.22	0.02	-0.05	0.02	-0.03
LIBOR rates: six-month US dollar deposits	0.22	0.04	-0.04	-0.02	-0.06
LIBOR rates: 12-month US dollar deposits	0.22	0.03	-0.06	-0.01	-0.06
Interest rates: bank prime rate	0.22	0.08	-0.02	0.03	0.00

Source: Moody's Analytics

Figure 5b Linear regression result

TPM - Sector 1 - Depository Institutions	Subordinate	Senior
Scores for component 1	-0.006**	-0.004
	(0.000)	(0.000)
Scores for component 2	0.007**	0.011***
	(0.000)	(0.000)
Scores for component 3	-0.027***	-0.026***
	(0.000)	(0.000)
Scores for component 4	0.000	0.002
	(0.000)	(0.000)
Scores for component 5	0.036***	0.036***
	(0.000)	(0.000)
Constant	0.444***	0.368***
	(0.010)	(0.010)
Adjusted R ²	0.69	0.65
Root-mean-square error (RMSE)	0.06	0.06
N	113	113
Sample period is 2015m12 - 2016m4. Numbers in parentheses are robust standard errors.		

*** denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level.

Source: Moody's Analytics

running into multicollinearity problems. Principal component analysis (PCA) allows us to largely overcome this issue. Second, while the original 28 variables used in the last CCAR cycle yield plausible results for certain sectors (such as transportation), they do not generate enough stress for others (such as depository institutions). The specific purpose of PCA is to select a small set of variables whose variation explains the maximal amount of the variation present in the full set of macroeconomic drivers. Given our goal of modeling sector LGDs, we construct a dataset of macroeconomic drivers, such as GDP, along with measures of housing and labor market performance, equity market performance, and various interest rates.¹¹

With principal component estimates in hand, we next regress each sector's senior LGD against the principal components, and use forecasts under the regulatory scenarios to obtain estimates for

stressed senior LGDs. The factor loadings for the PCA for sector 1 (depository institutions) are displayed in Figure 5a.¹² Basic cutoff criteria such as the Kaiser criterion suggest using five principal components to capture the joint variation of our set of drivers. The explained variation for the banking sector is about 92%. Figure 5b reports the results of regressing the component scores on the senior sector LGD.

From Figure 5a, we see that component 1 is essentially an interest rate level factor, component 2 is (approximately) a GDP growth and employment macro factor, component 3 is a market and oil price factor, component 4 is a housing activity-to-disposable income factor, and component 5 is a real disposable income growth factor. Components 2, 3, and 5 also give nontrivial weight to the sector EDF for depository institutions.

¹¹ Notice that some macroeconomic variables, such as GDP, are only available at a quarterly frequency. These variables are interpolated in Moody's Analytics macro forecast, using a cubic spline.

¹² Since the sector EDFs vary from industry to industry, the factor loadings are not exactly identical in across sectors. They are, however, otherwise similar. These results are not reported.

Figure 6 In-sample fit

	R ²		RMSE		Mean Absolute Error (MAE)	
	Senior	Subordinate	Senior	Subordinate	Senior	Subordinate
Sector 1	0.70	0.67	0.06	0.06	0.05	0.05
Sector 2	0.41	0.40	0.05	0.09	0.03	0.07
Sector 3	0.45	0.42	0.07	0.11	0.05	0.08
Sector 4	0.58	0.42	0.04	0.08	0.03	0.06
Sector 5	0.79	0.59	0.05	0.08	0.04	0.06
Sector 6	0.59	0.58	0.05	0.07	0.04	0.05
Sector 7	0.66	0.61	0.04	0.05	0.03	0.04
Sector 8	0.58	0.47	0.03	0.06	0.02	0.05
Sector 9	0.55	0.46	0.04	0.08	0.03	0.06
Sector 10	0.36	0.17	0.04	0.07	0.03	0.05
Sector 11	0.70	0.47	0.04	0.08	0.03	0.06
Sector 12	0.81	0.80	0.06	0.06	0.05	0.05
Sector 13	0.50	0.58	0.04	0.04	0.03	0.03

Source: Moody's Analytics

In Figure 5b, components 2, 3, and 5 are also the most consistently statistically significant drivers of both senior and subordinate sector LGDs. The coefficient for component 1 is statistically significant at the 5% level in the subordinate sector LGD model, but not in the model for the senior LGD. Based on adjusted R-squared figures of 69% and 65% for the subordinate and senior LGD models, respectively, we can surmise that the five principal components describe the fluctuations in the depository institution sector LGDs reasonably well.

Summary statistics for the in-sample performance of the five-component PCR for each sector are reported in Figure 6. R-squared values for the senior LGD models range from 36% to 81%, indicating significant variability in the explanatory power of the five components across sectors. Also, the explanatory power of the five components for senior LGDs is somewhat better than for subordinate LGDs.

We now examine the out-of-sample performance of our models. For this purpose, we

estimate the model coefficients using data from January 2006 to August 2013, and then forecast LGDs based on the realized values of model drivers (hence components) from September 2013 until early 2016, when our sample ends. The graphical forecast results are shown in Figure 7 for the case of the banking and services sectors for both senior and subordinate LGDs. Overall, the model performs quite well for some sectors (and parts of the capital structure) and less well for others.

Figure 8 reports root-mean-square errors (RMSEs) and mean absolute errors (MAEs) for the out-of-sample exercise. There is clearly scope for additional research to improve the performance of the models for some sectors, such as sector 3 (aeronautics). However, for financial sectors, the models perform well out-of-sample, with RMSEs in the range of 2% to 4%.

We now turn to the performance of our models under the Federal Reserve's stress test scenarios. In Figure 9, we report sector LGD forecasts under

Figure 7 Out-of-sample results for the banking and services sectors



Source: Moody's Analytics

Figure 8 Out-of-sample fit

	RMSE		MAE	
	Senior	Subordinate	Senior	Subordinate
Sector 1	0.04	0.03	0.05	0.05
Sector 2	0.03	0.12	0.05	0.18
Sector 3	0.09	0.17	0.14	0.27
Sector 4	0.04	0.13	0.06	0.19
Sector 5	0.02	0.10	0.03	0.15
Sector 6	0.07	0.06	0.11	0.08
Sector 7	0.02	0.04	0.02	0.07
Sector 8	0.03	0.08	0.04	0.11
Sector 9	0.02	0.10	0.04	0.14
Sector 10	0.04	0.07	0.07	0.10
Sector 11	0.01	0.10	0.02	0.14
Sector 12	0.04	0.05	0.06	0.07
Sector 13	0.04	0.02	0.06	0.02

Source: Moody's Analytics

the baseline, adverse, and severely adverse scenarios provided by the Fed in early 2016. The results are encouraging, and the stressed LGDs appear to exhibit very plausible patterns under each of the different scenarios. Both the direction of the shocked LGDs as well as their magnitudes under the severely adverse scenario in particular are consistent with the paths followed by LGDs during the worst part of the Great Recession.

Conclusion

The stressed LGD methodology whose results we have summarized in this article provide a practical solution for banks and other financial

institutions that require public firm LGD estimates for risk management and compliance purposes. This approach complements private firm LGD estimates available through outlets such as Moody's Analytics RiskCalc software. Going forward, we expect that further improvements in LGD modeling will help drive efforts to measure current expected credit losses more accurately. In particular, firm-specific accounting information might be matched with past records of realized losses given default in order to differentiate LGD estimates across firms within a given sector and geography.

Figure 9 LGD forecasts under the Fed's 2016 baseline, adverse, and severely adverse scenarios

Source: Moody's Analytics

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A close-up photograph of industrial machinery. The image shows several metallic components, including a large gear with teeth visible in the bottom left corner. Two prominent metal plates with oval-shaped, polished metal fasteners or sensors are visible, running diagonally across the frame. The lighting is warm and focused, highlighting the textures and metallic surfaces of the machinery.

REGULATORY REVIEW

PREDICTING EARNINGS: CECL'S IMPLICATIONS FOR ALLOWANCE FORECASTS

By Joy Hart and Anna Labowicz



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Joy has more than 10 years of financial services experience in a variety of areas. As a product management director, she currently focuses on development of portfolio risk management tools including the RiskFrontier™ software. Joy has a BS in aerospace engineering from Massachusetts Institute of Technology and an MBA from NYU Stern.



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The new CECL and IFRS 9 accounting standards will require financial institutions to adjust loss allowances based on forward-looking expectations and calculate lifetime losses. In this article, we demonstrate the effect of the new allowance framework by quantifying allowances and credit earnings volatility for a sample portfolio. Our case study finds that along with a shift in the level of allowance, portfolio dynamics and concentrations play an increasingly important role in understanding and communicating expected performance and earnings.

A financial institution's allowance for loan and lease losses (ALLL) is an important estimate with significant impacts on an organization's overall earnings and capital. While this reserve calculation has always had the potential to be quite complex, the new accounting procedures brought by the current expected credit loss model (CECL) and International Financial Reporting Standard 9 (IFRS 9) change the important elements of the process. With these new regimes, allowances must be updated on every reporting date to reflect more than current credit conditions; credit quality will need to be measured from a forward-looking perspective which, by definition, will vary through time. The resulting overall portfolio loss allowance, and thus earnings, can exhibit substantial volatility.

The industry has already had a taste of the potential impacts of using expected cash flows for allowances with acquisitions of distressed loans and purchase loan accounting. This fair value accounting on acquired loans exhibited incredible volatility when compared to other assets. In CECL and IFRS 9, this forward-looking approach applies to the entire institution, and the expected patterns will be much more sensitive to the economic cycles, portfolio composition, and calculation assumptions.

This shift in predictability of losses and earnings will demand significant time from senior management not only to explain differences

period over period, but also to accurately and confidently communicate expected patterns given anticipated strategy choices and market conditions.

Determining Credit Earnings

There are two main decision types which drive the ability to accurately forecast allowances and overall earnings:

1. Framework and methodology choices – data granularity, a reasonable and supportable look-back period, scenario narrative, and a wide array of smaller elements
2. Business and strategy choices – loan structure, type, industry, and geographic distribution, as well as potential for clustered defaults and downgrades (concentration)

Clearly, there are methodology choices that impact overall results; however, it is also clear that the economic dynamics of the portfolio and its composition have an important effect on outcomes.

The predictability of losses is mostly driven by the economic relationships in the portfolio, which are best described by concentration effects (e.g., name, sector, product, and geography). Some of the dynamics are quite intuitive; for example, an institution heavily invested in California real estate would have losses closely related to statewide housing prices as well as important commercial sectors in

California. However, more diversified institutions will find a systematic approach helpful in fully understanding, anticipating, and communicating outcomes over time.

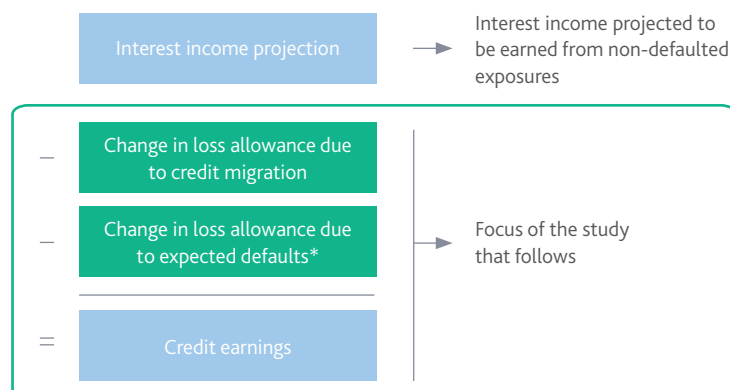
We find that a systematic approach using a simulation to determine credit earnings volatility provides a useful measure to help senior management anticipate what parts of the

basic formula for calculating credit earnings.

Case Study: Lifetime Expected Credit Loss

In the following study, we isolate the impact of shifting from a simple one-year expected credit loss (ECL) to the lifetime ECL allowance framework required by CECL for a sample global corporate loan portfolio created by Moody's Analytics. While the true economics

Figure 1 Credit earnings generated by a portfolio from time t_0 to t_1



*The expected recovery amount is implicitly included in change in loss allowance due to expected defaults. In other words, we assume an imminent default does not incur 100% but rather $100\% \times \text{LGD}$ loss allowance.

Source: Moody's Analytics

Figure 2 Portfolio characteristics: Top five countries and industries represented

Country	Percentage	Industry	Percentage
US/Caribbean	36.48%	Entertainment and leisure	7.13%
Japan	13.54%	Food and beverage	4.57%
United Kingdom	11.71%	Machinery and equipment	4.39%
France	10.52%	Business products wholesale	3.98%
Germany	9.67%	Utilities and electric	3.78%

Source: Moody's Analytics

portfolio, management actions, and scenarios most impact predictability. This measure encapsulates the credit risk in earnings for the entire institution, as well as the contribution by portfolio segment, sector geography, etc.

Armed with an understanding of the dynamics within the portfolio, management can take actions to reduce portfolio credit earnings volatility and better communicate the anticipated volatility, given a market outlook or set of strategic choices. Figure 1 provides the

and performance of the portfolio remain the same, the study isolates the impact on the attractiveness of particular portfolio segments given a shift in calculation horizon. Figure 2 shows the top countries and industries represented in the sample portfolio.

The portfolio was analyzed twice with the same starting default probabilities and an analysis horizon of one year. As a straightforward example of the potential dynamics of increasing the ECL to lifetime, allowances were calculated

Figure 3 Analysis results at the portfolio level

Run	1	2
Expected credit losses for allowances	12 month	Lifetime
Total commitment	\$99,485,000,000	\$99,485,000,000
Loss allowance at analysis date	\$567,173,735	\$1,689,309,883
Expected loss allowance at horizon	\$546,748,873	\$1,226,551,122
Expected change in loss allowance	\$(20,424,862)	\$(462,758,761)
Credit earnings volatility	0.8024%	0.8854%

Source: Moody's Analytics

using one-year ECL in the first run, and lifetime ECL in the second run. Using a correlation-based model, we simulated the credit earnings at horizon to determine the expected credit earnings value and volatility over the next year. We also calculated a new measure known as the credit earnings sharpe ratio, which provides a way to quantify profitability with consideration given to the new allowance requirements. Our quantitative measure ranks both segments and instruments by assessing their marginal contributions to credit earnings volatility or the credit earnings sharpe ratio.

Results from the two runs match intuitive expectations that the overall portfolio allowance level and volatility will increase when applying a lifetime loss metric. Further, we see intuitive patterns where particular loan characteristics are more or less attractive when considering longer loss horizons. For example, for the entire portfolio of approximately 6,000 instruments, the weighted average time to maturity was approximately 3.5 years. The 1,000 top-ranked instruments based on 12-month expected loss allowances have a longer average time to maturity, while the top-ranked instruments under lifetime allowances have a significantly shorter average time to maturity. This broad pattern supports the expectation that the new accounting standards will incentivize institutions to favor shorter-term instruments.

Forward-looking credit considerations impact allowances under the new standards, so we are not surprised to find that many of the highest contributors to volatility of credit earnings are exposures that have some of the highest default probabilities. However, when comparing the two runs, there were several areas in the portfolio

where assets ranked poorly based on credit earnings volatility – despite the fact that they had smaller default probabilities in the 12-month analysis.

The analysis becomes much more insightful once we look more deeply into segment dynamics and individual instrument impacts. Portfolio diversification plays a much larger role when looking at longer periods of time, which encourages institutions to consider the relative benefit of an instrument or segment and look more closely at overall portfolio composition.

The relative benefits of certain sectors clearly change based on the required allowance horizon. We see in this analysis that the top-ranked exposures when using 12-month ECL for allowances are different than the top-ranked exposures when considering lifetime allowances. In Figure 4, we see the patterns within the portfolio. It is important to remember that the economics of the portfolio are the same in both runs, so our simulation correctly reflects that many of the best performers under 12-month allowances are the same under lifetime allowances. At the same time, there are clear cases where sectors are ranked significantly differently.

In our study, it becomes clear that interactions of various segments within the overall portfolio can play an important role in outcomes. For example, we see that the Swiss machinery and equipment segment is very attractive when looking over a single-year period; however, when we consider the full life of the loan, that segment becomes significantly less attractive due to the expected volatility of allowances in this category. Conversely, all of the real estate categories broadly increase in relative

Figure 4 Top 20 projections for lifetime allowances by credit earnings sharpe ratio

Country	Industry	Rank – Lifetime	Credit Earnings Sharpe Ratio – Lifetime	Rank – 12-Month	Credit Earnings Sharpe Ratio – 12-Month
Japan	Real estate	1	420.65	4	391.29
US/Caribbean	Construction	2	387.19	2	1,755.33
Germany	Publishing	3	316.42	3	392.03
Australia	Real estate	4	292.68	6	297.94
France	Food and beverage	5	286.76	8	290.07
Switzerland	Machinery and equipment	6	286.50	1	1,757.27
Switzerland	Lumber and forestry	7	255.74	14	256.41
US/Caribbean	Paper	8	253.13	18	249.90
US/Caribbean	Electronic equipment	9	241.46	10	269.69
Japan	Food and beverage	10	232.69	5	298.59
United Kingdom	Mining	11	227.10	30	226.73
US/Caribbean	Investment management	12	221.76	35	217.77
US/Caribbean	Oil, gas, and coal exploration/production	13	215.91	32	219.78
Japan	Retail/wholesale	14	215.67	33	219.54
Germany	Food and beverage	15	209.80	36	213.22
United Kingdom	Entertainment and leisure	16	206.74	39	206.37
Australia	Chemicals	17	206.51	40	206.15
US/Caribbean	Oil refining	18	203.63	42	201.73
US/Caribbean	Business products wholesale	19	202.36	38	209.74
US/Caribbean	Publishing	20	200.40	50	196.21

Source: Moody's Analytics

attractiveness when we evaluate our portfolio with a lifetime perspective.

We find that there is value in quantifying the risk and profitability of not only the portfolio as a whole, but also the interaction of individual elements within. Segment-level insights provide a quantitative basis for understanding dynamics, as well as hard numbers for reference when communicating strategy, expectations, and policy shifts to internal and external stakeholders. In our example, the analysis indicates a clear justification for increased investments in real estate in a lifetime allowance environment and decreasing focus (or shorter durations) in some industrial categories.

It is also worth noting that the above analysis is based on a benign credit environment. The impact of using a forward-looking default

probability will have a significant impact in the negative part of the credit cycle. There will be even greater costs and uncertainty for organizations holding risky instruments, as a simple change in default probabilities alone will cause significant volatility in earnings.

As CECL rolls out across financial institutions in the US, and IFRS 9 takes effect for much of the world, managers must adopt new ways to manage risk, compare instruments, and communicate expected outcomes and dynamics. As we have shown in this simple study, these considerations must be worked into business as usual for institutions and should be addressed at origination and in strategy to ensure organizations are following strategic and lucrative business practices given a new set of dynamics introduced by CECL.

ACCOUNTING FOR PURCHASED CREDIT DETERIORATED FINANCIAL ASSETS: CURRENT AND FUTURE GAAP

By Masha Muzyka, CPA



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The current expected credit loss (CECL) model is expected to fix the delayed recognition of credit losses and provide a uniform approach for reserving against credit losses on all financial assets measured at amortized cost. However, CECL introduces new complexities. In this article, we explore existing and future accounting and operational challenges faced by institutions acquiring financial assets with credit deterioration.

The Financial Accounting Standards Board (FASB) has historically recognized that collectability of contractual amounts is a crucial piece of financial information for investors to consider when making lending decisions. Current Generally Accepted Accounting Principles (GAAP) set by the FASB address impairment accounting by creditors by consistently incorporating concepts related to contractually required payments receivable, initial investment, and cash flows expected to be collected (see Accounting Standard Codification (ASC) Topic 310 – Receivables). Introduced in December 2003, purchased credit impaired (PCI) accounting requires entities to implement a complex accounting treatment of income and impairment recognition for PCI assets¹ where expectation of collectability is reflected in both purchase price and future expectations of cash flows, while contractual cash flows are ignored. Since adoption, entities struggled with operational challenges, income volatility, and comparability of PCI versus originated assets accounting.

The current expected credit loss (CECL) model, taking effect in 2020 for public business entities that are SEC filers, attempts to align measurement of credit losses for all financial assets held at amortized cost and specifically

calls out potential improvements to the accounting for PCI assets. CECL changes the scope by introducing the concept of purchased credit deteriorated (PCD) financial assets and makes the computation of the allowance for credit losses for PCDs, as well as recognition of interest income, more comparable with the originated assets.

In this article, we will focus on changes in the accounting for loans² with evidence of deterioration of credit quality since origination. We will also explore potential complexities which remain despite the attempt to align the accounting for purchased and originated assets.

Definitions and Scope

To understand how CECL changes the accounting for purchased loans, it is important to start with definitions. According to the current GAAP, PCI loans are loans that:

1. Are acquired by the completion of a transfer.
2. Exhibit evidence of credit quality deterioration since origination.
3. Meet a probability threshold, which indicates that upon acquisition, it is probable the investor will be unable to collect all contractually required payments receivable.

Accurately defining which acquired assets should

¹ See FASB, "Statement of Position 03-3: Accounting for Certain Loans and Debt Securities Acquired in a Transfer," and FASB, "ASC 310-30, Receivables – Loans and Debt Securities Acquired With Deteriorated Credit Quality."

² CECL changes the accounting for other PCD assets, including debt securities, which are not in scope for this article.

be considered PCI presents an operational challenge, given the often inadequate amount of data available to the acquirer at the time of acquisition. While being conservative, entities end up scoping in assets that, over their remaining life, significantly outperform the expectation and for which all contractually required cash flows are subsequently collected. Once an asset is designated as a PCI, it remains a PCI regardless of its performance (unless it is modified as a troubled debt restructuring). Most core banking systems are not set up to handle special accounting based on expected cash flows, causing financial institutions to implement systems and processes on top of what is used for the originated book.

CECL, which completely supersedes current accounting for PCI financial assets, continues to require different treatment at initial recognition for purchased loans with evidence of credit quality deterioration, and defines PCD assets as:

1. "Acquired individual financial assets (or acquired groups of financial assets with similar risk characteristics) that,
2. As of the date of acquisition, have experienced a more-than-insignificant deterioration in credit quality since origination, as determined by an acquirer's assessment."

Compared to the current GAAP, CECL changes the scope by adding the more-than-insignificant criterion and removing the probability threshold. Identifying PCD assets will most likely continue to present an operational challenge when defining more-than-insignificant deterioration. The FASB suggests considering multiple qualitative factors,³ and the abilities to systematically consume large amounts of data points, apply data rules, and appropriately tag the acquired assets are key in accurate PCD designation.

How does PCD designation affect the financials at acquisition and beyond? To demonstrate, Figure 1 summarizes the basis of accounting for the acquired loans under current and future GAAP and reviews changes to day 1 and day 2 accounting requirements.

Changes to Day 1 Accounting

On day 1 (at acquisition or origination), CECL requires firms to measure the credit losses for newly recognized financial assets. The allowance for credit losses is recorded to present the net amount expected to be collected on the balance sheet. For non-PCD assets, credit loss expense is recorded on the income statement to establish the allowance; the difference between the purchase price and loan receivable is amortized over the remaining life of the loan.

For PCD assets, there is no income statement impact on day 1: The initial allowance for credit losses is added to the purchase price and is considered to be part of the PCD loan amortized cost basis. The loan-level non-credit-related discount is derived from the difference between the receivable and amortized cost, and amortized over the remaining life of the PCD asset. Note that GAAP presents an interesting misalignment between PCDs and all other financial assets carried at amortized cost: origination or acquisition of non-PCD assets that are less risky than PCD by definition results in a recording of a lifetime loss through the income statement while acquisition of PCDs impacts the balance sheet only.

A circularity concern arises when including allowance for credit losses in the PCD's amortized cost, where allowance may not be measured until amortized cost is known. (Similarly, when the discounted cash flow approach is used, effective interest rate determination gives rise to a circularity issue where such a rate cannot be determined until the discounted rate is determined.) To avoid this, the FASB provided additional guidance for amortized cost basis and effective interest rate calculation. When the discounted cash flow methodology is used, the expected credit losses (ECLs) are discounted at the rate that equates future expected cash flows with the purchase price. When other methodologies are used to calculate ECL, the allowance is based on the unpaid principal balance of the loan.

Under the current GAAP, it is not appropriate to record a loss allowance at acquisition, and the acquired loan is recorded at its purchase price.

3 See ASC Topic 326, paragraphs 326-20-55-58 and 326-20-55-4.

Figure 1 Comparison of current and future GAAP for PCD assets

	GAAP Reference	Loan Type	Increase in Expected Cash Flows	Decrease in Expected Cash Flows	Interest Income Recognition
Present GAAP	ASC 310-20, Receivables – Nonrefundable Fees and Other Costs	Acquired loan where an investor expects to collect all contractual cash flows due	Reduce the allowance amount; no impact to the effective interest rate	Increase the allowance amount; no impact to the effective interest rate; at acquisition, book at fair value/ purchase price; no day 1 allowance	Based on contractual cash flows; effective interest rate is the contractual adjusted for deferred premiums and discounts existing at acquisition
	ASC 310-30, Receivables – Loans and Debt Securities Acquired with Deteriorated Credit Quality	Acquired loan where it is probable at acquisition that an investor will be unable to collect all contractual cash flows due	Reduce or reverse in full the allowance amount first; increase the effective interest rate	Increase the allowance amount; use the current effective interest rate to discount expected cash flows and calculate the impairment amount; at acquisition, book at fair value/ purchase price	Based on the expected cash flows; recalculate the accretable yield amount as the excess over revised expected cash flows and the loan's recorded investment
Future GAAP	ASC 326, Financial Instruments – Credit Losses	Acquired loan that at acquisition experienced a more-than-insignificant deterioration in credit quality since origination	Reduce the allowance amount; no impact to the effective interest rate	Increase the allowance amount; at acquisition, recognize credit-related discount as an allowance against the loan's amortized cost balance	Based on contractual cash flows; accrete to income only the non-credit-related discount existing at origination
		Acquired loan that at acquisition did not experience a more-than-insignificant deterioration in credit quality since origination	Reduce the allowance amount; no impact to the effective interest rate	Increase the allowance amount; at acquisition, recognize the lifetime expected loss through allowance and income statement	Based on contractual cash flows; accrete to income the full difference between contractual cash flow and purchase price

Source: FASB

For loans acquired in a business combination, the initial recognition of those loans is based on the present value of amounts expected to be received. Allowance for credit losses for the PCI loans reflects only those losses that are incurred by the investor after acquisition. The difference between gross expected cash flows and contractual cash flows over the life of the loan represents a nonaccretable difference, which is disclosed at acquisition in the financial statement footnotes but not on the balance sheet. The difference between PCI loan purchase price and gross expected cash flows is accreted to income over the life of the loan using effective interest rate (accretable yield amount).

Let's use a simple example to demonstrate the differences in day 1 and day 2 accounting for PCD and PCI. Assume that an entity acquired a fixed-rate loan for \$60 with a coupon monthly rate of 3%, par balance of \$100, and a five-month remaining contractual life with no expectation of prepayment. The contractual amortization schedule is presented in Figure 2.

Under PCI accounting (current GAAP), an entity will make the following day 1 entry to record the loan purchase at its fair value, with DR

representing a debit amount and CR representing credit:

DR loan	100.00
CR cash	60.00
CR contra loan (mark)	40.00

(Loan is recorded at its purchase price. Day 1 amortized cost equals \$60.)

Unlike the current standard, CECL does not require a discounted cash flow methodology for PCD assets. However, to compare PCI and PCD accounting, we will use the discounted cash flow methodology to calculate ECL. To determine the allowance for credit losses on day 1 for the PCD loan using this methodology, ECLs are discounted at the rate that equates net present value of the future expected cash flows with the purchase price. We will assume the cash flow stream shown in Figure 3 over the life of the asset, taking into consideration past events, current conditions, and reasonable and supportable forward-looking information.

To record the day 1 allowance for credit losses for this PCD loan, we need to calculate the discount rate that equates the expected cash flows with the purchase price of the asset. This

Figure 2 Contractual amortization schedule for a sample loan

Period	Payment	Remaining Principal	Stated Interest	Cash (Out) Inflow	Carrying Value
				(\$100.00)	
1	(\$21.84)	\$18.84	\$3.00	\$21.84	\$81.16
2	(\$21.84)	\$19.40	\$2.43	\$21.84	\$61.76
3	(\$21.84)	\$19.98	\$1.85	\$21.84	\$41.78
4	(\$21.84)	\$20.58	\$1.25	\$21.84	\$21.20
5	(\$21.84)	\$21.20	\$0.64	\$21.84	\$0.00
Total	(\$109.20)	\$100.00	\$9.17	\$109.20	

Source: Moody's Analytics

Figure 3 Sample cash flow stream

Period	Contractual Cash Flow	Expected Cash Flow	Expected Gross Loss
1	\$21.84	\$10.00	\$11.84
2	\$21.84	\$20.00	\$1.84
3	\$21.84	\$20.00	\$1.84
4	\$21.84	\$10.00	\$11.84
5	\$21.84	\$10.00	\$11.84
Total	\$109.20	\$70.00	\$39.20

Source: Moody's Analytics

required discount rate is 5.63%. Allowance for the credit losses equals the net present value of the expected cash flows lost discounted by 5.63%, that is \$32.92. To determine the initial amortized cost for the PCD asset, an entity has to add the allowance amount to the purchase price. The remaining difference between the loan receivable and PCD loan amortized cost is the non-credit-related discount that has to be tracked for amortization purposes from day 1.

DR loan	100.00
CR cash	60.00
CR allowance	32.92
CR non-credit discount	7.10

(Day 1 PCD amortized cost = purchased price + day 1 allowance for credit losses = \$92.92)

As demonstrated, PCD accounting will continue to present an operational challenge for entities

due to the requirement to calculate, track, and amortize loan-level non-credit-related discounts.

Changes to Day 2 Accounting

After acquisition, recognition of income and expected losses under current and future GAAP also differs.

CECL PCD accounting for interest income recognition is consistent with non-PCD acquired or originated loan accounting, except for the treatment of the day 1 purchase discount. The day 1 discount attributable to credit losses is not amortized into income, which is achieved by adding it to the day 1 amortized cost. Interest income for PCD loans is recognized similar to originated assets based on contractual cash flows where the non-credit-related discount is amortized over the remaining life of the loan. Note that the discount rate used to calculate day 1 allowance under the discounted cash

Figure 4 Amortization schedule for a PCD loan

Period	Payment	Remaining Principal	Stated Interest	Interest Income	Amortization	Unamortized Discount	Cash (Out) Inflow	Carrying Value
		\$100.00					(\$92.92)	\$92.92
1	(\$21.84)	\$81.16	\$3.00	\$5.23	\$2.23	\$4.85	\$21.84	\$76.31
2	(\$21.84)	\$61.76	\$2.43	\$4.30	\$1.86	\$2.99	\$21.84	\$58.77
3	(\$21.84)	\$41.78	\$1.85	\$3.31	\$1.46	\$1.54	\$21.84	\$40.24
4	(\$21.84)	\$21.20	\$1.25	\$2.27	\$1.01	\$0.53	\$21.84	\$20.67
5	(\$21.84)	\$0.00	\$0.64	\$1.16	\$0.53	\$0.00	\$21.84	\$0.00
Total	(\$109.20)		\$9.17	\$16.27	\$7.09		\$109.20	

Source: Moody's Analytics

flow methodology is the same as the effective interest rate⁴ that would be used to recognize interest income on the PCD loan.⁵

Using our example, the amortization schedule for the PCD loan is shown in Figure 4, and the period 1 interest income recognition journal entry is as follows:

DR non-credit discount	2.23
DR accrued interest receivable	3.00
CR interest income	5.23

(Amortization of non-credit-related discount and accrued interest receivable are recorded based on the day 1 amortized cost of \$92.92.)

PCI accounting for interest income recognition is complex and based on the expected cash flow changes over time. It requires effective interest rate recalculations as the cash flow expectations improve over time. A Statement of Position released by the FASB states:

"If, upon subsequent evaluation... based on current information and events, it is probable that there is a significant increase in cash flows previously expected to be collected or if actual cash flows are significantly greater than cash flows

previously expected, the investor should:

1. Reduce any remaining valuation (or allowance for loan losses) for the loan established after its acquisition for the increase in the present value of cash flows expected to be collected, and
2. Recalculate the amount of accretable yield for the loan as the excess of the revised cash flows expected to be collected over the sum of (a) the initial investment less (b) cash collected less (c) write-downs plus (d) amount of yield accreted to date."

The FASB also instructs, "The investor should adjust the amount of accretable yield by reclassification from nonaccretable difference." The resulting yield is used as the effective interest rate in any subsequent application, including the calculation of the future impairment amount. The amount of accretion is tied to the future expectations of cash flows, while contractual cash flows are ignored. PCI accounting, applied to performing assets that were, perhaps erroneously, designated as PCIs at acquisition, often results in unusually high effective yields as well as unreasonable impairment amounts when a decrease in

4 As defined in ASC Topic 326, effective interest rate is "the rate of return implicit in the financial asset, that is, the contractual interest rate adjusted for any net deferred fees or costs, premium, or discount existing at the origination or acquisition of the financial asset."

5 PCI accounting allows loans to be aggregated into a pool if they are not accounted for as debt securities, are acquired in the same fiscal quarter, and have common risk characteristics. The pooled loans can then use a composite interest rate and expectation of cash flows expected to be collected for that pool. Once a pool is assembled, its integrity is maintained for purposes of applying the recognition, measurement, and disclosure provisions of PCI accounting. CECL does not provide for the PCD pool accounting (due to individual allocation of the non-credit-related discount) but allows for the maintenance of existing pools upon the transition from PCI to PCD. Pool accounting is outside the scope of this article, which focuses on individually accounted PCI and PCD loans.

Figure 5 Day 1 accretion schedule for a PCI loan

Period	Expected Payments	Interest Income	Principal Reduction (Payment - Interest)	Ending Balance
				\$60.00
1	\$10.00	\$3.40	\$6.60	\$53.40
2	\$20.00	\$3.00	\$17.00	\$36.40
3	\$20.00	\$2.00	\$18.00	\$18.40
4	\$10.00	\$1.10	\$8.90	\$9.50
5	\$10.00	\$0.50	\$9.50	\$0.00
Total	\$70.00	\$10.00	\$60.00	

Source: Moody's Analytics

expected cash flows triggers discounting with such yields.

For simplicity, we will assume that the expected cash flows for the PCI loan are the same as

standard allows recognition of interest income, to the extent that the net investment in the financial asset would increase to an amount greater than the payoff amount.

An investor has to estimate credit losses over the contractual term of the financial asset, consider even a remote probability of a loss, and incorporate information on past events, current conditions, and reasonable and supportable forecasts.

for PCD in our example. The day 1 accretion schedule is shown in Figure 5, and the period 1 interest income recognition journal entry is as follows:

DR contra loan (mark)	3.40
CR interest income	3.40

(Recognition of interest income for the PCI loan is based on the expected cash flows. Contractual interest income is not booked for accounting purposes.)

Neither standard considers it appropriate to record into income amounts that are not expected to be collected at acquisition. While current GAAP establishes a nonaccretable difference for PCI assets outside of financial statements, CECL includes a credit-related discount into amortized cost for PCDs. Neither

The FASB decided that purchased assets and originated assets should follow the same accounting model approach to the extent possible. Consequently, other than applying a "gross-up approach" for the PCD assets (i.e., including day 1 allowance in the amortized cost basis), estimation of the expected credit losses for PCD assets follows the same methodology as originated assets under CECL. Allowance method is not prescribed (i.e., discounted cash flow approach is not required for PCD loans⁶). An investor has to estimate credit losses over the contractual term of the financial asset, consider even a remote probability of a loss, and incorporate information on past events, current conditions, and reasonable and supportable forecasts. Furthermore, the loss estimate should be based on point-in-time measures, reflecting the entity's current environment and the

6 There are certain additional requirements when discounted cash flow methodologies are used to calculate the discount rate, as well as a different basis for calculation when other methods are utilized. See ASC Topic 326, paragraphs 326-20-30-13 and 326-20-30-14.

Figure 6 Amortization under PCI, based on excess cash flow (ECF)

Period	Expected Payments	Interest Income	Principal Reduction (Payment - Interest)	Ending Balance
				\$60.00
1	\$7.00	\$3.40	\$3.60	\$56.40
2	\$20.00	\$3.20	\$16.80	\$36.60
3	\$20.00	\$2.10	\$17.90	\$18.60
4	\$10.00	\$1.00	\$9.00	\$9.70
5	\$10.00	\$0.50	\$9.50	\$0.00
Total	\$67.00	\$10.20	\$56.80	

Source: Moody's Analytics

instrument's "position" in the economic cycle rather than average-based, through-the-cycle measures.

Current GAAP states that an investor should continue to estimate cash flows expected to be collected over the life of the PCI loan. A PCI loan is considered impaired "if, upon subsequent evaluation based on current information and events, it is probable that the investor is unable to collect all cash flows expected at acquisition plus additional cash flows expected to be collected arising from changes in estimate after acquisition."

That is, if a PCI asset is not impaired, then no additional reserve is booked or an existing allowance is reversed. Entities are required to use discounted cash flow methodology to estimate expected credit losses on the PCI loans. The impairment amount is calculated by comparing the loan's recorded investment with the net present value of remaining expected cash flows discounted at the effective interest rate. The loan's recorded investment is defined as the sum of the loan's fair value on day 1 adjusted for accumulated accretion, plus payments and charge-offs to date. The day 2 PCI allowance is booked through income statement provision for credit losses.

Based on these outlined requirements, it is clear that the loss estimate would change for the same loan even if the same loss estimate methodology (e.g., discounted cash flow approach) is used. Removal of the probability

threshold/requirement for impairment and incorporation of forward-looking information are primary reasons for the expected difference.

Let's continue using our example and assume that in the first period, instead of receiving \$10.00 of expected cash flows, we received only \$7.00. Let's also assume that our future cash flow expectation or contractual life does not change.

Under PCI accounting, the loan will be impaired as actual cash flows were below expected. The impairment will be calculated by discounting the remaining expected cash flows using the existing effective interest rate of 5.63%. We compare this net present value of \$53.40 to the recorded investment of \$56.40 (day 1 carrying amount of \$60.00 plus accretion of \$3.40 minus payment of \$7.00), resulting in a \$3.00 allowance amount. See the updated accretion schedule for this PCI loan in Figure 6. Note that the accretion income is booked based on the carrying value of \$53.40 (recorded investment net of allowance amount) going forward.

DR provision expense 3.00

CR allowance for credit losses 3.00

(Income statement impact is recorded to reflect PCI loan impairment.)

DR contra loan (mark) 3.20

CR interest income 3.20

(Interest income is recorded for the PCI loan for period 2.)

Figure 7 PCD loan's amortization schedule recalculated based on a new required contractual payment

Period	Payment	Remaining Principal	Stated Interest	Interest Income	Amortization	Unamortized Discount	Cash (Out) Inflow	Carrying Value
		100					(92.92)	92.92
1	(\$7.00)	\$96.00	\$3.00	\$4.34	\$1.34	\$5.74	\$7.00	\$90.26
2	(\$25.83)	\$73.05	\$2.88	\$5.08	\$2.20	\$3.54	\$25.83	\$69.51
3	(\$25.83)	\$49.42	\$2.19	\$3.91	\$1.72	\$1.82	\$25.83	\$47.60
4	(\$25.83)	\$25.07	\$1.48	\$2.68	\$1.20	\$0.62	\$25.83	\$24.45
5	(\$25.83)	(\$0.00)	\$0.75	\$1.38	\$0.62	\$0.00	\$25.83	(\$0.00)
Total	(\$110.32)		\$10.30	\$17.39	\$7.08		\$110.32	

Source: Moody's Analytics

For the PCD loan under CECL, day 2 allowance calculations are consistent with the CECL discounted cash flow methodology as follows. Net present value of the expected cash flows (\$53.40) is compared to the amortized cost of \$90.26 as of the second reporting period; see Figure 7, where this PCD loan's amortization schedule is recalculated based on a new required contractual payment. The day 2 allowance equals \$36.86. The amortized cost amount already includes the day 1 allowance of \$32.92 due to the gross-up approach. Thus, an additional provision expense of \$3.94 is booked for the difference between day 2 and day 1 allowance amounts.

DR provision expense	3.94
CR allowance for credit losses	3.94

(Record additional allowance through income statement on the PCD loan.)

DR non-credit discount	2.20
DR accrued interest receivable	2.88
CR interest income	5.08

(Interest income is recorded for period 2 based on the same effective interest rate but increased monthly payment.)

Note that due to the receipt of the less-than-

expected payment, too much income was recognized for the first period, and the discount amortization is adjusted from \$2.23 down to \$1.34. Consequently, a catch-up journal entry is recorded to adjust the remaining unamortized balance of the non-credit-related discount against interest income:

DR interest income	0.89
CR non-credit discount	0.89

Conclusion

As entities transition to CECL,⁷ we expect that certain PCD accounting operational difficulties will continue to exist due to allocation and amortization of the non-credit-related discount at the individual asset level. CECL closely aligns credit loss measurement methodologies across originated and purchased portfolios and provides for consistent income recognition models based on contractual cash flows. However, the introduction of the lifetime loss estimate, including the incorporation of forward-looking information, demands significant improvements in entities' data collection, accessibility, and retention capabilities, as well as more granular and potentially more sophisticated loss measurement methodologies and analytics and reporting.

⁷ Upon CECL adoption, entities will not be required to retrospectively reassess whether their existing PCI assets meet the definition of PCD. Rather, they will adjust the amortized cost basis of the PCI assets to reflect the addition of the allowance and begin accreting into income the non-credit-related discount after the adjustment to the amortized cost basis using the interest method based on the effective interest rate.

WHAT DO HALF A MILLION LOANS SAY ABOUT THE IMPACT OF CECL ON LOAN LOSS ALLOWANCE?

By Dr. Yanping Pan, Dr. Yashan Wang, and Dr. Hao Wu



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The Financial Accounting Standards Board (FASB) issued Accounting Standards Update (ASU) 2016-13 (the current expected credit loss (CECL) model) in June 2016 to replace the existing incurred loss model. One of the main reasons for issuing the ASU was that the incurred loss model resulted in banks delaying credit loss recognition and setting loss allowances that were “too little, too late” during economic downturns. Most stakeholders believe that CECL will have a significant impact on allowance and provision, earnings, and capital. This article examines CECL's potential impacts from an empirical perspective. Using historical data (500,000 commercial and industrial (C&I) loans from 15 US banks), we calculate and compare loan- and portfolio-level loss allowances under the incurred loss model and CECL. We find that CECL generally helps alleviate the “too little, too late” problem seen during the financial crisis. However, we observe significant variations in allowances across banks and over time. Loss allowances under CECL are not always higher than those under the incurred loss methodology. The impact of CECL on allowance depends on portfolio characteristics such as loan maturity, economic cycle, and banks' lending policies and allowance practices. In addition, we find that CECL generally leads to higher volatilities in loss allowance.

The “Too Little, Too Late” Problem

The 2008 global financial crisis amplified the need to improve existing financial reporting standards. Specifically, the incurred loss model under US Generally Accepted Accounting Principles (GAAP) for impairment calculation and reporting was criticized by regulators¹ and various market participants for delaying credit loss recognition and setting loss allowances that were “too little, too late” during economic downturns. Under the incurred loss model, banks recognize impairment for financial instruments when credit losses are determined to be “probable and reasonably estimable,” as of the

reporting date. Currently, GAAP restricts the ability for banks to record expected credit losses that do not yet meet the “probable” threshold. It has been observed that banks generally determine the loss allowance amount to be set aside based on historical loss experiences, which were low in the years leading up to the financial crisis.

To address the “too little, too late” issue of the existing model, in June 2016, the FASB issued the long-awaited financial accounting standards update ASU 2016-13: “Financial Instruments – Credit Losses: Measurement of Credit Losses on Financial Instruments.” Commonly known as

¹ As an example, see US Government Accountability Office, 2013.

the current expected credit loss (CECL) model, it requires institutions to estimate the expected credit loss over the life of financial instruments, based on historical information, current conditions, and reasonable forecasts, and to set aside lifetime expected credit losses as the loss allowance.

Many stakeholders expect CECL's impact to be substantive; however, assessments are scarce and typically based on surveys conducted among a small group of banks or studies of synthetic portfolios constructed as of a specific analysis date. This article seeks to shed some light on CECL's impact from an empirical perspective.

internal rating, and/or probability of default (PD). In addition, we use Moody's Analytics RiskCalc software, an industry-leading default risk assessment solution for private firms, to generate both the through-the-cycle (TTC) and point-in-time (PIT) forward-looking Expected Default Frequency (EDF) measures for each observation within the loan accounting system database. In total, we have 393,479 unique term loans and 181,933 facility draws from 151,468 borrowers, constituting a total of approximately 3.64 million observations. The mean and median times to maturity across all observations are 2.13 years and 1.58 years, respectively.



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The goal of the incurred loss model is to estimate those loan losses incurred in the portfolio but not yet identified and charged off.

Using historical loan data from 15 US banks, we calculate loan- and portfolio-level loss allowances under the incurred loss model and the CECL model at a quarterly frequency from 2003 to 2015. We can then assess how loss allowances would have differed during this 12-year period if CECL had been implemented in 2003.

Data: Moody's Analytics CRD

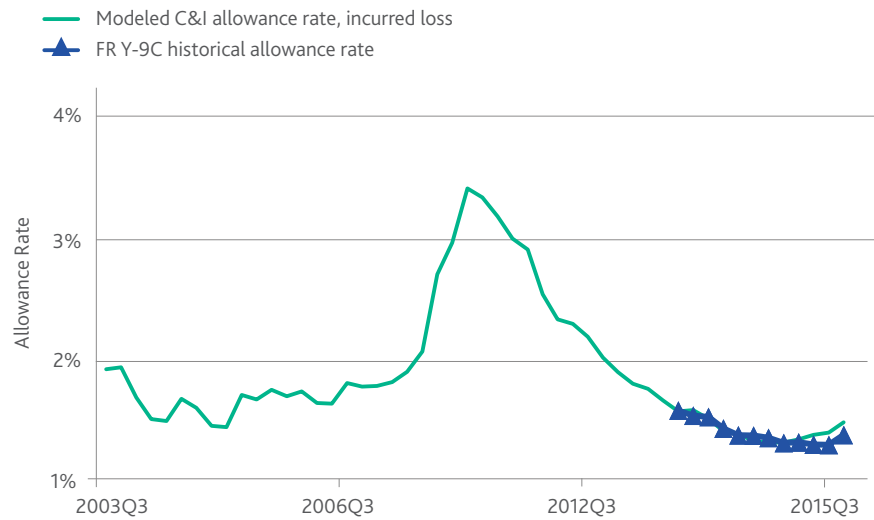
The loan portfolio data we use for this study comes from the loan accounting system (LAS) data in Moody's Analytics Credit Research Database (CRD). The CRD is one of the world's largest historical time series of private firm, middle-market loan data for C&I borrowers. The dataset collects facility and loan information at the draw level from contributing banks at a quarterly frequency, including origination date/amount, contractual maturity, unpaid balance, delinquency and default status, bank

We calculate the loan loss allowances compliant with the two impairment models as far as back our data allows for each loan in the portfolios of the contributing banks. We then compare the two loss allowance rates with banks' historical reported net charge off (NCO) rates.

Loss Allowance Under the Incurred Loss Model

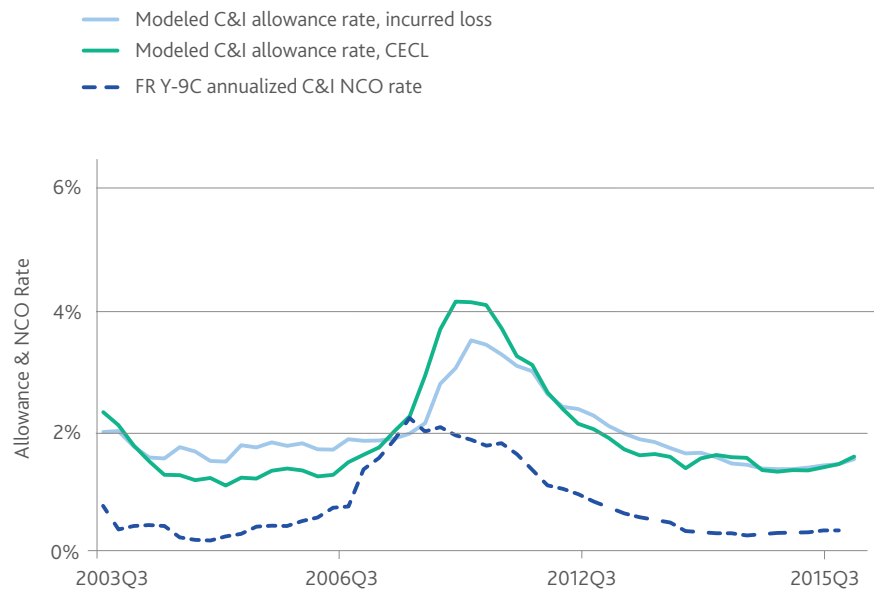
The CRD does not have actual historical loss allowances from contributing banks. In an effort to achieve a uniform treatment across contributing banks, we calculate historical loss allowances based on the loan-level PD and loss given default (LGD). Most of the CRD-contributing banks submit their internal risk rating for the borrowers and the associated PD or PD range of each rating. To ensure consistency with banks' loss allowance calculation processes, we use these internally assigned PDs when available. For loans without internal PDs, we use the one-year TTC PD generated by the RiskCalc

Figure 1 Aggregate C&I allowance rate under the incurred loss model



Source: Moody's Analytics

Figure 2 Aggregate C&I allowance rate vs. NCO rates on C&I portfolios, 15 banks



Source: Moody's Analytics

software. We do not have any information regarding the internal LGD estimates from the CRD contributors. Instead, we use the long-term, loan-level LGD generated by Moody's Analytics LossCalc software.² We calculate the one-year loss rate in quarter t as: $1\text{-year TTC PD}(t) \cdot \text{LGD}(t)$. The goal of the incurred loss model is to estimate those loan losses incurred in the

portfolio but not yet identified and charged off. Most banks use the loss emergence period (LEP) to adjust the annual loss rate in their loss allowance calculations. For example, assume a bank has a loan portfolio in which it takes two years for a loan to move from loss event to charge-off; the bank then has two years of losses inherent in its portfolio at any given point. If

² The required inputs for Moody's Analytics LossCalc software are borrower's PD, loan industry sector, secured vs. unsecured, and evaluation date.

the estimated annual loss rate is 2%, and the bank uses 2% to estimate the allowance for loan and lease losses (ALLL), it will only reserve one year of losses. However, if the bank multiplies the annual loss rate by LEP of two years, it will reserve for two years of losses. In general, the loss allowance rate under the incurred loss model for each loan is calculated as $LEP \cdot (1\text{-year TTC PD}(t)) \cdot LGD(t)$, and the loss rate of a loan portfolio is equal to the balance-weighted sum of loan allowance rates.

Using publicly available information in FR Y-9C reports on C&I portfolio allowance rates for Q1 2013 – Q4 2015, we estimate the LEP for each bank so that the C&I portfolio allowance rate for that bank as calculated based on PD and LGD is as close to the publicly available information as possible. The estimated LEP ranges from 1.33 years to 2.55 years across banks, with an average of 1.90 years. Once we estimate LEP for each bank, we assume the bank used the same LEP prior to Q1 2013, when the C&I portfolio loss allowance rate was not publicly available. Figure 1 compares the modeled C&I portfolio incurred loss allowance rate for the 15 banks in aggregate, with the publicly reported loss allowance rates. The green line represents the modeled C&I loss allowance rate, and the blue line represents the actual loss allowance rate collected from banks' FR Y-9C reports, beginning Q1 2013.³ The green and blue lines match quite well, which suggests that our model assumptions are reasonable and consistent with the banks' internal practices for loss allowance calculation under existing GAAP rules.

Loss Allowance Under the CECL Model

We calculate the CECL loss allowance as the lifetime expected credit losses based on Moody's Analytics RiskCalc PIT PD term structure, Moody's Analytics LossCalc LGD term structure, and the contractual time to maturity of each individual loan at each quarter t :

$$\text{LossAllowance}_{\text{CECL}}(t) = \sum_{i=1}^M LGD(t_i) \cdot (CPD(t_i) - CPD(t_{i-1}))$$

Here $t_i = t + i$ quarter, t_M is the contractual time to maturity of the loan as of quarter t , and $CPD(t_i)$ is the cumulative probability of default from t to t_i . We ignore discounting in this calculation,

because reliable effective interest rates are not available. We do not apply additional qualitative (Q) factors to the modeled CECL loss allowance above, because the RiskCalc and LossCalc models are point-in-time and incorporate information about future credit environments.

CECL Impact on C&I Portfolios

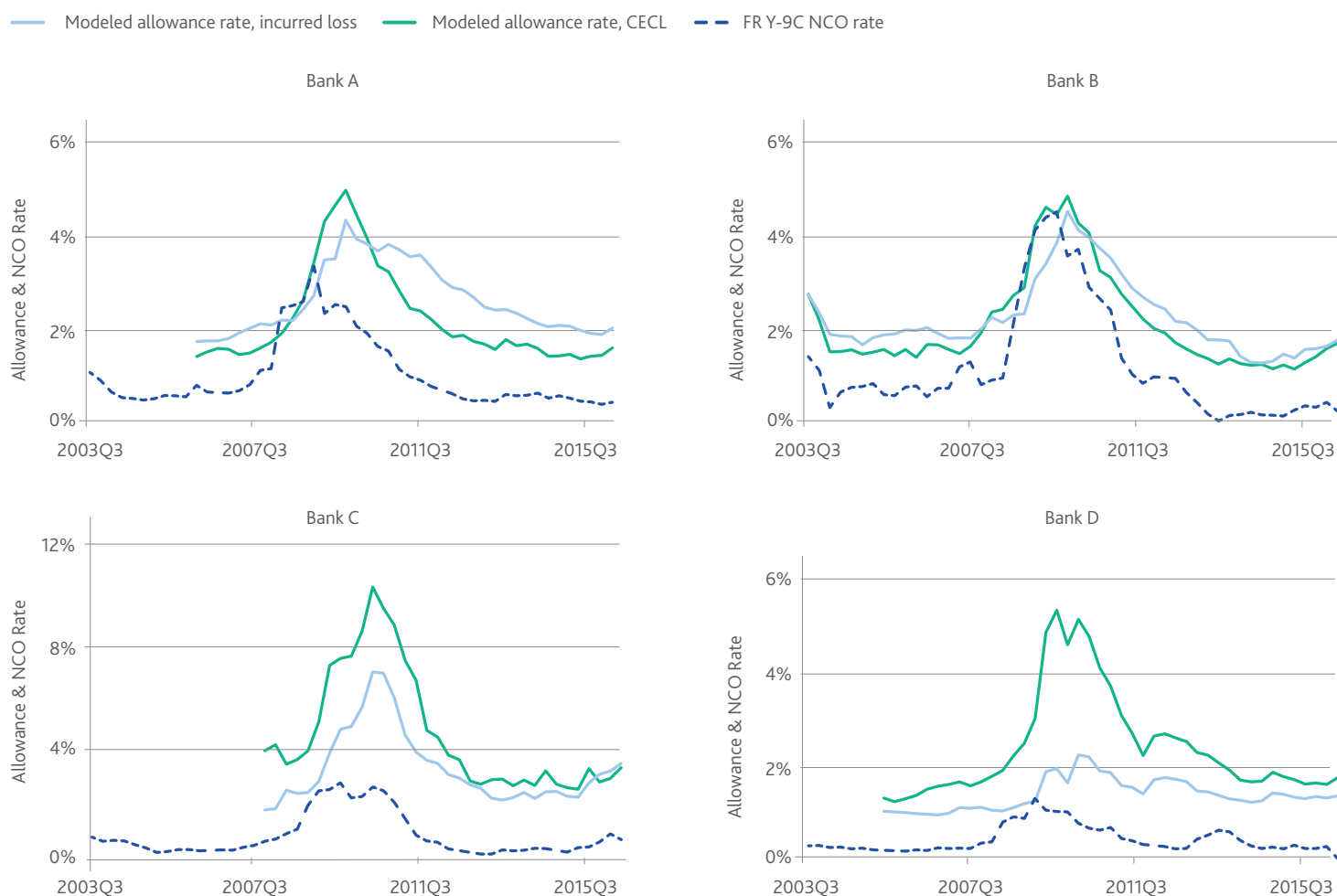
Figure 2 compares the aggregated loss allowance rates of the C&I portfolios from 15 CRD-contributing banks. We also include the historical one-year NCO rates (i.e., NCO over the next four quarters for each time t) for C&I portfolios publicly available for the same 15 banks. The two sets of allowance rates fluctuate over time and cross each other. However, during the financial crisis, the CECL allowance increased earlier and faster than the incurred loss curve and remained above the NCO line. This suggests our modeled CECL loss allowance is more responsive to market deterioration than the incurred loss approach, and the CECL reserve would have been sufficient to absorb the loss during the following year.

Figure 3 shows results for a set of four individual banks selected from our data sample. We see significant variations across the four banks regarding trends and levels for both loss allowance rates and historical loss experiences over time. As shown in Figure 3, the loss allowances created under CECL are generally sufficient to cover the actual losses banks experienced the following year. However, the CECL loss allowances⁴ are not always higher than those seen under the incurred loss model during our analysis period, and the relative change in allowance level varies across banks. The economic cycle is a key driving factor, as indicated by these charts. When retroactively applied to the financial crisis period, the CECL model calls for dramatically higher loss allowance rates than the incurred loss model. Under the current, relatively benign economic conditions, with historically low loss experience, CECL's loss allowance level remains close to banks' existing reserve levels. For some banks, the CECL allowance level may even be lower than the incurred loss allowance.

3 The disaggregated historical loss allowance rates collected from 10-Q and 10-K forms were used for LEP factor calibration but not included for aggregate loss allowance rate calculation in Figure 1 for comparison purposes.

4 Of course, banks can apply additional qualitative adjustments during loss allowance calculation, which further increases or decreases the allowance level from our modeled results.

Figure 3 Incurred loss and CECL C&I allowance rate comparison for individual banks



Source: Moody's Analytics

Figure 4 Volatility of loss allowance rates

Time Period	Standard Deviation	
	Incurred Loss	CECL
2003 Q3 – 2015 Q4	0.55%	0.83%
2007Q1 – 2010 Q4	0.66%	1.04%

Source: Moody's Analytics

We also attempt to better understand CECL's impact on each bank by examining their portfolio characteristics, including (but not limited to) loan maturity, industry sector, credit riskiness, and allowance calculation practices. The average LEP used by Bank A is 2.30 years, the highest among the four banks and very close to the average time to maturity of 2.37 years in its C&I portfolio. Given that PIT PD after the financial crisis is generally lower than the

long-run average TTC PD, it is not surprising to see the CECL loss allowance level lower than the incurred loss allowance level in the current environment. The same argument applies to Bank B, which has an average LEP of 1.95 and an average time to maturity of 1.94 years. Bank B's portfolio is slightly riskier than Bank A's, with a balance-weighted, one-year TTC PD of 3.1%, compared to Bank A's 2.7%. For Banks C and D, the portfolios' lifetimes are much longer than

the LEP used in the incurred loss model. Banks C and D have average times to maturity of 2.62 years and 2.44 years, respectively, compared to LEPs of 1.60 years and 1.46 years. For those banks, the CECL loss allowance level is nearly always above the allowance level generated by the incurred loss model.

Loss Allowance Rate Volatility Under CECL

Market participants have been arguing that the "reasonable and supportable forecast," CECL's forward-looking requirement, may inject

available capital.⁵

Conclusions

We find that the loss allowance levels under the incurred loss model were indeed "too little, too late" during the economic downturn. The loss allowances estimated under the CECL model are much more responsive to market changes and are generally sufficient to cover banks' realized losses at different time periods, even without additional qualitative adjustments. The CECL impact varies significantly across banks and over

The volatility of the loss allowance rate under the incurred loss model is significantly lower than the loss allowance rate volatility under the CECL model, in line with general market expectations. In addition, CECL may significantly affect the level and volatility of banks' earnings and available capital.

additional volatility into banks' loss allowances. Figure 4 lists the standard deviations of the historical loss allowance rates under the two accounting standards for two different analysis periods. The volatility of the loss allowance rate under the incurred loss model is significantly lower than the loss allowance rate volatility under the CECL model, in line with general market expectations. In addition, our research suggests that CECL may significantly affect the level and volatility of banks' earnings and

time. The relative changes in loss allowance levels are driven primarily by a portfolio's loan maturity, credit riskiness, the bank's business, and economic cycle. If CECL is implemented immediately under the current, more moderate economic conditions, allowance levels may actually decrease for some banks. Our results are in line with market expectations that CECL will generally lead to higher volatility in loss allowances as compared to the incurred loss model.

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⁵ See Levy, et al., 2017.

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GLOSSARY OF TERMS

AIC	Akaike information criterion	FRB	Federal Reserve Board
ALLL	Allowance for loan and lease losses	FVS	Fair value spread
ALM	Asset and liability management	GAAP	Generally Accepted Accounting Principles
ANN	Artificial neural network	GAM	Generalized additive model
API	Application program interface	GAO	Government Accountability Office
AR	Accuracy ratio	GC	Gross contribution
ASU	Accounting Standards Update	HQIC	Hannan-Quinn information criterion
BCBS	Basel Committee on Banking Supervision	IAS	International Accounting Standard
BEA	Bureau of Economic Analysis	IBA	ICE Benchmark Administration
BED	Business employment dynamics	ICE	Intercontinental Exchange
BLS	Bureau of Labor Statistics	IFRS	International Financial Reporting Standard
BOC	Bureau of Census	LAS	Loan accounting system
C&I	Commercial and industrial	LEP	Loss emergence period
CCA	Capital cost allowance	LGD	Loss given default
CCAR	Comprehensive Capital Analysis and Review	MAE	Mean absolute error
CECL	Current expected credit loss	MRA	Matters requiring attention
CLV	Customer lifetime value	MRIA	Matters requiring immediate attention
CPI	Consumer price index	NAR	National Association of Realtors
CPO	Certified pre-owned	NCO	Net charge-off
CRD	Credit Research Database	NSA	Not seasonally adjusted
CRE	Commercial real estate	OCC	Office of the Comptroller of the Currency
CV	Cross-validation	PCA	Principal component analysis
DF	Discount factor	PCR	Principal component regression
DFA	Dodd-Frank Act	PD	Probability of default
DFAST	Dodd-Frank Act Stress Test	PIT	Point in time
DPD	Days past due	PPNR	Pre-provision net revenue
DRD	Default & Recovery Database	RMSE	Root mean square error
EAD	Exposure at default	ROA	Return on assets
EBA	European Banking Authority	SA	Seasonally adjusted
EBITDA	Earnings before interest, taxes, depreciation, and amortization	SAAR	Seasonally adjusted annual rate
ECB	European Central Bank	SBA	Small Business Administration
ECL	Expected credit loss	SBCS	Small Business Credit Survey
EDF	Expected Default Frequency	SBIC	Schwarz's Bayesian information criterion
EIR	Effective interest rate	SME	Small and medium-sized enterprises
ERS	Enterprise risk solutions	TTC	Through the cycle
FASB	Financial Accounting Standards Board	VAR	Vector autoregression
FDIC	Federal Deposit Insurance Corporation		
FPE	Final prediction error		

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