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Basel III C:
Internal Risk Models[1]

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Abstract

For financial regulators seeking to use regulatory requirements to manage risk in a banking system, there can be a concern that such requirements crowd out efforts by banks to develop their own risk management systems. One way in which regulators have attempted to solve this problem is to enable banks to use internal risk models to satisfy regulatory requirements. Beginning with the 1996 Market Risk Amendment, the Basel framework has allowed banks to determine the capital charges associated with certain assets using their own internal risk models. But allowing the use of internal risk models has not been without controversy. Where some see an incentive for the development of internal risk management systems better able to address the unique risk profiles of particular banks, others see excessive complexity and uncertainty. And while some financial regulators are beginning to subject banks' models to greater scrutiny, questions remain about the ability of financial regulators to provide effective oversight of such models.

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[1] This module is one of seven produced by the Yale Program on Financial Stability (YPFS) examining issues related to bank capital. The other modules in this series are:

- *Basel III A: Regulatory History*
- *Basel III B: Basel III Overview*
- *Basel III D: The Swiss Finish to Basel III*
- *Basel III E: Synthetic Financing by Prime Brokers*
- *Basel III F: Callable Commercial Paper*
- *Basel III G: Shadow Banking and Project Finance*

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1. Introduction

For financial regulators seeking to use regulatory requirements to manage the risk in a banking system, there can be a concern that such requirements crowd out efforts by banks to develop their own risk management systems. Banks subject to regulatory requirements may perceive the satisfaction of those requirements by itself as a sufficient response to risk. Or banks may believe they lack the resources to both meet regulatory requirements and develop their own risk management systems. Given that such systems, if robust, may be more effective in dealing with the unique risk profile of a particular bank than blanket requirements, there have been calls by regulators to "ensure that regulatory requirements do not impede the development of sound risk management by creating perverse incentives" (Bank for International Settlements 1995, 1-2).

One way in which regulators have attempted to solve the problem of providing effective oversight of financial institutions without stunting the development of the financial institutions' own risk management systems is to enable banks to use internal risk models to satisfy regulatory requirements. Beginning with the 1996 Amendment to the Capital Accord to Incorporate Market Risk (commonly referred to as the Market Risk Amendment), the Basel framework has allowed banks to determine the capital charges associated with certain assets using their own internal risk models rather than standardized capital charges applied by the Basel Committee on Banking Supervision (BCBS) to different categories of assets. With the capital charges produced by internal risk models typically lower than those produced using the standardized approach, the opportunity to use internal risk models has been widely seen as intended to incentivize the development of banks' own risk management systems.

But the incorporation of internal risk models as a cornerstone of the Basel framework has not been without controversy. Where some see an incentive for the development of internal risk management systems better able to address the unique risk profiles of particular banks, others see "a subsidy to complexity," which makes "risk more difficult to monitor and manage, not less" (Haldane 2012, 17). With this complexity has often come uncertainty, with a series of recent studies illustrating the fact that different banks' models can produce very different assessments of the riskiness of the same set of assets.

In response to growing concerns about the use of internal risk models, some financial regulators are beginning to subject banks' models to greater scrutiny. Yet questions remain about the ability of financial regulators to provide effective oversight of such models given their complexity and the difficulty government agencies face in hiring individuals with the necessary expertise in risk modeling. Furthermore, some banks have complained about the amount of resources necessary to respond to this added scrutiny, forcing some banks to run parallel models—one for the banks' actual use and one to satisfy financial regulators.

The remainder of the case is organized as follows: Section 2 provides an overview of the history of internal risk models. Section 3 outlines the adoption of internal risk models as part of the Basel framework. Section 4 discusses concerns that are emerging about the ability of banks to manipulate their internal risk models to achieve desired results. Section 5 concludes with a summary of the current status of efforts by regulators to address the concerns raised by internal risk models.

Questions

1. Is the incorporation of internal risk models into regulatory frameworks a positive trend that incentivizes the development of banks' own risk management systems or

a negative trend that introduces too much complexity and subjectivity into such frameworks (or neither of the above, some of each, etc.)?

2. Are financial regulators capable of providing effective oversight of banks' internal risk models?

2. History of Internal Risk Models

Some commentators date the introduction of internal risk models to the late 1960s, when profound changes to the global economy produced a level of financial market turbulence not experienced since the Great Depression thereby necessitating increased attention to risk. Others argue that internal risk models date to the late 1970s and early 1980s, when high market volatility caused large investment banks to establish risk management departments. Regardless of the specific account selected, the common narrative is that at some point after the economic stability of the 1950s and early 1960s, conditions of market stress caused banks to pay increased attention to the amount of risk involved in their businesses.

Charles Sanford (then head of Resources Management and later CEO) at Bankers Trust undertook early efforts to use modeling techniques to address this risk, developing along with Dan Borge the "risk-adjusted return on capital" metric or RAROC in the late 1970s. This measure compared the return produced by a transaction to the amount of capital that would need to be allocated to the transaction as a buffer against risk. Because the RAROC model determined this amount of capital based on its assessment of the maximum potential loss that could occur during a fixed period of time, many consider Charles Sanford and Dan Borge to be the fathers of the modern Value-at-Risk (VaR) model.

Market Risk Models

In 1994, the VaR approach became an increasingly popular way for banks to measure market risk (i.e., the risk of loss due to fluctuating prices for assets) with the introduction of J.P. Morgan's RiskMetrics model. Widely disseminated by J.P. Morgan, the RiskMetrics model became the basis for much of the market risk modeling that occurred during this period (Nuxoll 1999). J.P. Morgan described the model as consisting of three basic components:

1. A set of market risk measurement methodologies

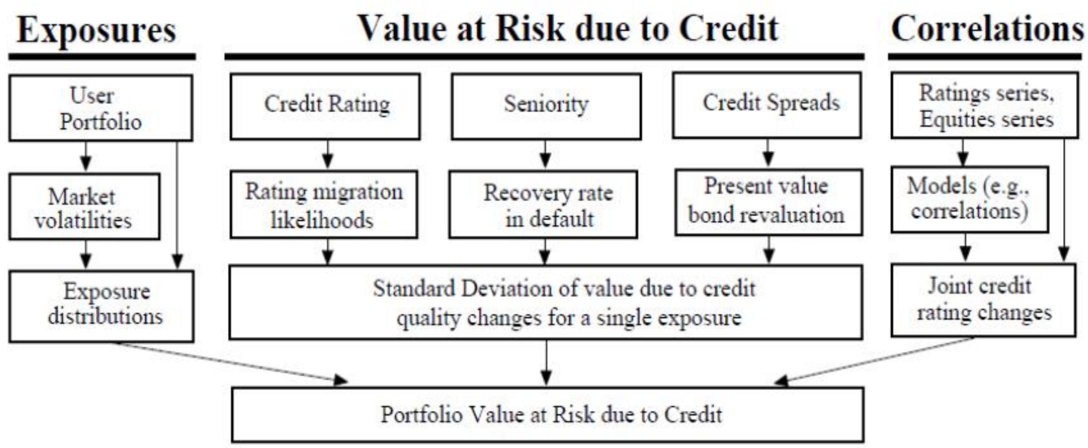
2. Data sets of volatility and correlation data used in the computation of market risk

3. Software systems that implement the methodologies using the data sets

At a very basic level, the RiskMetrics model involves the use of historical data to determine an estimated volatility for each type of risk (interest rate risk, foreign exchange risk, etc.) associated with a given security and the correlation between the various types of risk. In its technical document describing the RiskMetrics model, J.P. Morgan gives the simple example of a U.S. corporation holding a government bond denominated in a foreign currency. Such a bond would be subject to two different, but potentially related types of market risk—interest rate risk (loss to the U.S. corporation resulting from a decline in the price of the bond due to an increase in interest rates) and foreign exchange risk (loss to the U.S. corporation resulting from a decline in the value of the foreign currency relative to the dollar).

Historical data can provide an estimate of the maximum amount that the price of the bond is likely to drop over a given time period as a result of interest rate movement to a given degree of certainty (the interest rate VaR) and it can also provide an estimate of the maximum amount that the foreign exchange rate is likely to drop over the same time period to the same degree of certainty (foreign exchange VaR). But the total risk will not be simply the sum of the interest rate risk and the foreign exchange risk if there is a correlation between these two factors. Therefore, historical data also is used to determine the correlation between the interest rate risk and the foreign exchange risk for this type of bond. Using the RiskMetrics model, the corporation would have to determine the interest rate VaR, the foreign exchange VaR, and the correlation between the two risk factors, before using a formula derived from standard portfolio theory to calculate the total VaR for the bond. (For a detailed discussion of the methodology underlying the RiskMetrics model, see Longerstaey and Zangari 1996.)

Figure 1: CreditMetrics Framework



Source: Gupton et al. 1997.

Credit Risk Models

J.P. Morgan also developed what became the industry standard for models measuring credit risk (i.e., the risk of loss due to a counterparty failing to pay an amount owed), releasing CreditMetrics in 1997 (Nuxoll 1999). While J.P. Morgan describes CreditMetrics as "philosophically similar" to RiskMetrics, it notes one major difference in available data that drives much of the divergence between the models. Whereas when measuring market risk there is "an abundance of daily liquid pricing data on which to construct a model," in the case of credit risk there is "relatively sparse and infrequently priced data on which to construct a model." Therefore, "CreditMetrics seeks to *construct* what it cannot directly observe: the volatility of value due to credit quality changes" (Gupton et al. 1997, iii emphasis in original).

The model does this by seeking to "balance the best of all sources of information in a model which looks across broad historical data rather than only recent market moves and across the full range of credit quality migration—upgrades and downgrades—rather than just default." (The basic framework is depicted in Figure 1.)

In its technical document describing the CreditMetrics model, J.P. Morgan gives the simple example of a portfolio consisting of two bonds:

- Bond #1—BBB-rated, senior unsecured, 6% annual coupon, five-year maturity
- Bond #2—A-rated, senior unsecured, 5% annual coupon, three-year maturity

To determine the credit risk associated with each of the bonds by itself, the CreditMetrics model employs three steps tied to the three headings under the "Value at Risk due to Credit" heading of the framework diagram: Credit Rating, Seniority, and Credit Spreads.

First, the bond issuer's current credit rating determines the likelihood of a default or migration to another credit rating within a given timeframe. Based on historical data, CreditMetrics determines a "transition matrix" setting forth the percentage likelihood of a given migration. For example, the sample transition matrix in Figure 2 indicates that there is a 0.06% likelihood that a AAA issuer will be downgraded to BBB within one year but a 5.52% chance that an A issuer would experience such a downgrade.

Figure 2: CreditMetrics One-Year Transition Matrix

Initial Rating	Rating at year-end (%)							
	AAA	AA	A	BBB	BB	B	CCC	Default
AAA	90.81	8.33	0.68	0.06	0.12	0	0	0
AA	0.70	90.65	7.79	0.64	0.06	0.14	0.02	0
A	0.09	2.27	91.05	5.52	0.74	0.26	0.01	0.06
BBB	0.02	0.33	5.95	86.93	5.30	1.17	0.12	0.18
BB	0.03	0.14	0.67	7.73	80.53	8.84	1.00	1.06
B	0	0.11	0.24	0.43	6.48	83.46	4.07	5.20
CCC	0.22	0	0.22	1.30	2.38	11.24	64.86	19.79

Source: Gupton et al. 1997.

Second, armed with the percentage likelihood of a given credit migration, the CreditMetrics model calculates the value change likely to result from such migrations. Value upon default is determined based on historical data concerning rates of recovery in default given seniority class. For example, the sample chart in Figure 3 based on one set of historical data indicates that senior unsecured creditors can expect to recover an average of 51.13% of face value in the event of default.

CreditMetrics determines value changes tied to non-default credit migrations by revaluing the expected cash flows from a bond (periodic interest payments and principal payment on maturity) using a discount rate tied to credit spreads between rating categories.

Third, with the likelihood of a given migration and the value change that would result from such migration having been determined, CreditMetrics can produce an estimate of the maximum value change to a given degree of certainty. For example, in the table of migration probabilities and value changes in Figure 4, there is only a 1.47% chance that the BBB bond in question will migrate to B, CCC, or default. To this degree of certainty, the value of the bond will not fall below $98.10, or $8.99 below the mean of all scenarios.

Figure 3: Recovery Rates by Seniority Class (% of face value, i.e., "par")

Seniority Class	Mean (%)	Standard Deviation (%)
Senior Secured	53.80	26.86
Senior Unsecured	51.13	25.45
Senior Subordinated	38.52	23.81
Subordinated	32.74	20.18
Junior Subordinated	17.09	10.90

Source: Gupton et al. 1997.

Figure 4: Calculating Volatility in Value Due to Credit Quality Changes

Year-end rating	Probability of state (%)	New bond value plus coupon ($)	Probability weighted value ($)	Difference of value from mean ($)	Probability weighted difference squared
AAA	0.02	109.37	0.02	2.28	0.0010
AA	0.33	109.19	0.36	2.10	0.0146
A	5.95	108.66	6.47	1.57	0.1474
BBB	86.93	107.55	93.49	0.46	0.1853
BB	5.30	102.02	5.41	(5.06)	1.3592
B	1.17	98.10	1.15	(8.99)	0.9446
CCC	0.12	83.64	1.10	(23.45)	0.6598
Default	0.18	51.13	0.09	(55.96)	5.6358
		Mean =	$107.09	Variance =	8.9477
				Standard deviation =	$2.99

Source: Gupton et al. 1997.

The above steps concerned the calculation of the risk associated with a single bond. Returning to our model portfolio of two different bonds, as with the calculation of market risk by RiskMetrics, the total credit risk of the portfolio would not simply be the sum of the individual credit risk of each bond unless there was no correlation between the probability of credit migration and the resulting value changes of the two bonds. Thus, as with RiskMetrics, CreditMetrics relies on a determination of correlation grounded in historical data. (For a detailed discussion of the methodology underlying the CreditMetrics model, see Gupton et al. 1997.)

Despite having been introduced nearly two decades ago, there is evidence that the methodologies underlying the RiskMetrics and CreditMetrics models continue to guide internal risk modeling today. (For more on internal risk models, see the YPFS Case Study Zeissler, et al. 2014C.)

3. Internal Risk Models and Basel

As discussed in greater detail in the YPFS Case Study *Basel III A: Regulatory History* (McNamara, et al. 2014A), the Basel framework as initially established by Basel I was directed primarily at credit risk. It wasn't until 1996 that the Basel Committee on Banking Supervision (BCBS) addressed market risk with the *Amendment to the Capital Accord to Incorporate Market Risk* (commonly referred to as the Market Risk Amendment). Perhaps not surprisingly given its development during the same time period that banks were becoming increasingly active in financial modeling, the Market Risk Amendment added not only market risk to the Basel framework, but also the concept of allowing banks to use their own internal risk models to make determinations of risk. As the BCBS noted, in developing the Market Risk Amendment, it "took account of the fact that the risk management practices of banks have developed significantly since the initial proposals [about incorporating market risk into Basel] were formulated in the early 1990s." Moreover, the BCBS expressed a desire not to impede further development of these practices by establishing regulatory requirements detached from banks' own risk management systems (Bank for International Settlements 1995).

As a result, the Market Risk Amendment provides banks with a choice between "two broad methodologies" in measuring market risk. The first methodology is a standardized approach based on risk measurements developed by the BCBS. The second methodology, available subject to the fulfillment of certain conditions and the explicit approval of a bank's supervisory authority, allows for the use of internal risk models to determine risk measurements. Among the conditions outlined by the BCBS for use of internal risk models are:

- Certain general criteria concerning the adequacy of the risk management system;
- Qualitative standards for internal oversight of the use of models, notably by management;
- Guidelines for specifying an appropriate set of market risk factors (i.e. the market rates and prices that affect the value of banks' positions);
- Quantitative standards setting out the use of common minimum statistical parameters for measuring risk;
- Guidelines for stress testing;
- Validation procedures for external oversight of the use of models; and
- Rules for banks which use a mixture of models and the standardized approach.

(Key elements of the different conditions are outlined in Figure 5.)

With the development of Basel II, the BCBS expanded the ability to use internal risk models to determine risk measurements to credit risk as well. (For an overview of the use of internal risk models in measuring credit risk, see McNamara, et al. 2014D.)

Figure 5: Conditions for Using Internal Risk Models

Condition	Key Provisions
General Criteria	• Supervisory authority should approve use of models only if bank's risk management system is conceptually sound and adequately staffed, with models that have proven track record
Qualitative Standards	• Supervisory authority should set qualitative criteria including requiring independent risk control unit, back-testing, Board involvement in risk control, etc.
Market Risk Factors	• Risk factors must capture risks inherent in bank's trading positions (interest rates, exchange rates, equity prices, commodity prices) • Banks must adhere to guidelines for each type of risk factor
Quantitative Standards	• VaR must be computed daily on 99%, ten trading day basis with minimum sample period of one year • Data sets must be updated at least once every three months • Banks must apply a multiplication factor to model results as set by the supervisory authority (min. 3)
Stress Testing	• Banks must maintain rigorous and comprehensive stress testing program
External Validation	• Banks must have models validated by external auditors and/or supervisory authorities

Source: Bank for International Settlements 1995

4. Internal Risk Models and the Potential for Manipulation

Although grounded in similar approaches, the various internal risk models deployed by different banks are comprised of a variety of components—risk measurement methodologies, historical data sets, software systems, etc.—differences in any one of which could result in models that, when presented with the same set of assets, arrive at very different assessments of risk. While the BCBS has argued that "it is desirable to have some diversity in risk modelling practices; if all banks modelled in the same way, they could create additional financial instability," it has also noted that "it is undesirable for banks' capital calculation inputs to generate excessive variation in risk measurement, as it would undermine the credibility of capital ratios, distort the international playing field and hamper the functioning of financial markets" (Bank for International Settlements 2013b, 3). And indeed, in the wake of the financial crisis there have been a series of studies that show that the risk assessments of banks' internal models do vary drastically.

In December 2013, the BCBS released the results of Phase II of an analysis of banks' trading book risk-weighted assets (RWAs). This analysis presented 17 internationally active banks in nine jurisdictions with 42 different hypothetical trading portfolios to "test for the impact of differences in modelling across banks by controlling for portfolio composition" (Bank for International Settlements 2013b). The 42 different portfolios consisted of both plain vanilla and complex products in the five major asset categories identified by the BCBS: equity, interest rates, foreign exchange, commodities, and credit spread.

According to the BCBS, individual positions contained within the hypothetical trading portfolios generated wide variations in some instances, variations which narrowed somewhat at the portfolio-level with more diversification. Still, even for the two most diversified portfolios in the exercise, the capital requirements calculated by the different models had a standard deviation of between 24% and 30% of the mean, a significant degree of variation. The capital requirements calculated ranged from €8.6 million to €18.5 million for one portfolio and from €6.3 million to €19.7 million for the other. Among the key drivers of this variation were the length of the data period used in a given model and the method used to aggregate general and specific risk (Bank for International Settlements 2013b).

These results confirmed the findings of Phase I of the BCBS's analysis, which presented 15 internationally active banks with 26 hypothetical trading portfolios containing mostly simple products. Even with these more straightforward products, the different models had a standard deviation of 31% of the mean for calculated capital requirements of the most diversified portfolio, with outcomes ranging from €13.4 million to €34.2 million (Bank for International Settlements 2013a).

In August 2013 the European Banking Authority (EBA) released a second interim report on a similar hypothetical portfolio exercise involving credit risk. The EBA's exercise included 35 banks from 13 EU countries and involved low default portfolios consisting of central government, credit institution and large corporate exposures. The EBA's analysis found "significant variation in the [risk weights] and [expected losses] across banks." Drivers of this variation include differences in definitions of default, differences in the granularity of credit ratings used, and data limitations (European Banking Authority 2013).

With the potential for such wide variation of results based in significant part on the modeling choices that banks make (such as the length of data periods used), there have been growing concerns about the achievement of lower capital requirements through the manipulation of models rather than through the actual reduction of RWAs. (For a detailed examination of one possible case of such manipulation, see McNamara, et al. 2014D.)

5. Regulator Response to Model Manipulation

Particularly in light of the increased attention being paid to the complexity of internal risk modeling and the variability or even manipulation that can result, some financial regulators are beginning to subject banks' models to greater scrutiny. For example in May 2014, the U.S. Office of the Comptroller of the Currency (OCC) announced a major expansion of its quantitative analysis function, focusing not only on enhanced evaluation of banks' internal risk models as required by Dodd-Frank, but also on the creation of the OCC's own models to vet the results of the banks' models. The OCC's staff of "quants"—the individuals charged with the OCC's modeling efforts—recently increased from 31 quantitative economists to 53 and from six research associates/financial analysts to seven after the financial crisis (LaCapra 2014).

But the heightened regulatory scrutiny of internal risk models is not without detractors, even among other financial regulators. An anonymous U.S. Treasury official interviewed for the Reuters article announcing the OCC's initiative characterized the effort as a waste of time, owing in part to the fact that government quants lack the experience of their private sector counterparts and would therefore be seconding-guessing models that they do not fully understand (LaCapra 2014). And indeed, recruiting and retaining experienced quants may be a tall order for regulatory agencies when even starting salaries for quants at major financial institutions are several times more than salaries for government quants. Notably, a senior quant recently hired as part of the OCC's push was poached from another agency, not from the private sector (Ibid.).

Banks themselves have also been critical of the move by some financial regulators to take a more active role in policing internal risk models. One major point of concern has been the increasingly large amount of quantitative resources banks must devote to regulatory compliance. The co-head of the quantitative group at Bank of America has estimated that such compliance represents more than half of his group's work (Andersen 2014). Similarly, an industry headhunter believes that the amount of time quants spend on regulatory matters has increased from 30% pre-crisis to 50%-60% today (LaCapra 2014). According to some bankers, much of this additional work is unnecessary. An anonymous bank executive interviewed for the Reuters article described weeks of back and forth with the OCC over minor differences in model design that resulted in almost no difference in model outcome. According to the executive, the bank now runs two models concurrently—its own version of the model (which had already been approved by the Federal Reserve) and a different version to placate the OCC (Ibid.).

Given the critical role internal risk models play in the Basel risk-weighted capital framework, determining how to provide oversight is a key challenge for regulators moving forward. This state of affairs raises the question of whether or not financial regulators are even in a position to provide effective and efficient oversight of banks' internal risk models. This question is made even more urgent by the many new responsibilities being added to regulators' plates around the world.

Commentators have also proposed potential solutions that reduce the ability of banks to rely solely on the results of their internal risk models. First, regulators could establish floors below which capital requirements would not go regardless of the outcome of modeling. A drawback of such an approach is that the higher the floor is set, the less Basel-driven incentive there is for banks to invest time and resources in internal risk models. In extreme examples where the floor is set at what capital requirements would be using a standardized approach, there is no such incentive—using internal risk models to determine capital requirements could only result in higher capital charges, not lower capital charges. Such a situation would nullify one of the chief reasons for introducing the internal-risk-models approach to the Basel framework, which was to incentivize banks to further develop their own risk management systems given the promise of lower capital requirements.

Another potential solution is the strengthening of the leverage ratio as a credible backstop to risk-based capital requirements. Based solely on a bank's total exposures without any adjusting for risk, the leverage ratio is intended to be simpler and more transparent than risk-based capital requirements and is not subject to the same type of manipulation using internal risk models. A bank manipulating its internal risk models to arrive at artificially low risk-based capital requirements could still be reined in by a leverage ratio that is sufficiently robust. Ultimately, given the difficulty involved in effectively overseeing banks' internal risk models and the potential problems with introducing model floors, it could be that the leverage ratio is the most important element of Basel III for addressing bank capital.

References

Anderson, Leif. 2014. *Regulation, Capital, and Margining: Quant Angle*. January.

Bank for International Settlements. 1995. *An internal model-based approach to market risk capital requirements*. April.

Bank for International Settlements. 2013b. *Regulatory Consistency Assessment Programme (RCAP)—Second report on risk-weighted assets for market risk in the trading book*. December.

Bank for International Settlements. 2013a. *Regulatory Consistency Assessment Programme (RCAP) Analysis of risk-weighted assets for credit risk in the banking book*. July.

European Banking Authority. 2013. *Interim results update of the EBA review of the consistency of risk-weighted assets*. August.

Gupton, Greg et. al. 1997. *CreditMetrics—Technical Document*. April.

Haldane, Andrew. *The Dog and the Frisbee*. August.

LaCapra, Lauren Tara. 2014. "Exclusive: U.S. banking regulators hire math geeks of their own." *Reuters*. May.

Longerstaey, Jacques and Peter Zangari. 1996. *RiskMetrics—Technical Document 4th edition*. December.

McNamara Christian M., Thomas Piontek, and Andrew Metrick, 2014A. "*Basel III A: Regulatory History*" Yale Program on Financial Stability Case Study 2014-1A-V1, November.

McNamara Christian M., Natalia Tente, and Andrew Metrick, 2014D. "*Basel III D: Swiss Finish*" Yale Program on Financial Stability Case Study 2014-1D-V1, November.

Nuxoll, Daniel. 1999. "Internal Risk-Management Models as a Basis for Capital Requirements." *FDIC Banking Review* 12, no 1:18–29. (Nuxoll 1999)

Zeissler Arwin G. and Andrew Metrick, 2014C. "*JP Morgan Chase London Whale C: Risk Limits, Metrics and Models,*" Yale Program on Financial Stability Case Study 2014-2C-V1, December.

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