

Washington Law Review

Volume 84 | Number 2

5-1-2009

Code, Crash, and Open Source: The Outsourcing of Financial Regulation to Risk Models and the Global Financial Crisis

Erik F. Gerding

Follow this and additional works at: <https://digitalcommons.law.uw.edu/wlr>



Part of the [Banking and Finance Law Commons](#)

Recommended Citation

Erik F. Gerding, *Code, Crash, and Open Source: The Outsourcing of Financial Regulation to Risk Models and the Global Financial Crisis*, 84 Wash. L. Rev. 127 (2009).

Available at: <https://digitalcommons.law.uw.edu/wlr/vol84/iss2/2>

This Article is brought to you for free and open access by the Law Reviews and Journals at UW Law Digital Commons. It has been accepted for inclusion in Washington Law Review by an authorized editor of UW Law Digital Commons. For more information, please contact lawref@uw.edu.

CODE, CRASH, AND OPEN SOURCE: THE OUTSOURCING OF FINANCIAL REGULATION TO RISK MODELS AND THE GLOBAL FINANCIAL CRISIS

Erik F. Gerding^{*}

Abstract: The widespread use of computer-based risk models in the financial industry during the last two decades enabled the marketing of more complex financial products to consumers, the growth of securitization and derivatives, and the development of sophisticated risk-management strategies by financial institutions. Over this same period, regulators increasingly delegated or outsourced vast responsibility for regulating risk in both consumer finance and financial markets to these privately owned industry models. Proprietary risk models of financial institutions thus came to serve as a “new financial code” that regulated transfers of risk among consumers, financial institutions, and investors.

The spectacular failure of financial-industry risk models in the current worldwide financial crisis underscores the dangers of regulatory outsourcing to the new financial code.

This Article explains how financial institutions used the “new financial code” to shift, spread, and price financial risk using the template of the stages of securitization of consumer-credit products, hedging through credit default swaps, and overall portfolio management. This Article then examines several explanations for the failures of risk models, which contributed to the current crisis, including flaws in the design of risk models and agency costs associated with those models. It also outlines several lessons for regulatory outsourcing from the current crisis, including the following:

- Bank regulators should scrap those provisions of Basel II that allow certain banks to set their own capital requirements according to their internal risk models;
- Regulators should promote “open source” in code (or the models) used to market financial products to consumers, price securitizations and derivatives, and manage financial-institution risk; and
- The failure of risk models used to price securitizations and derivatives reveals some of the comparative advantages of equity securities in spreading risk.

^{*} Assistant Professor of Law, University of New Mexico School of Law. The author may be contacted at gerding@law.unm.edu. He wishes to thank Rainer Boehme, Jim Cox, Larry Cunningham, Jeffrey Gordon, Thomas Lee Hazen, Donald Langevoort, Michael Malloy, Geoffrey Miller, Joseph Norton, Heidi Mandanis Schooner, Arthur Wilmarth, colleagues at the University of New Mexico, and participants in the Financial Institutions and Consumer Financial Services Section meeting of the 2009 American Association of Law Schools Annual Meeting for their comments and Corey Reitz for research assistance.

Introduction	129
I. The Rise of the New Financial Code and Its Crash	136
A. A Primer on Financial Risk.....	136
i. Typology of Risk	136
ii. The Revolution in Quantitative Finance.....	139
B. Code Along the Nodes of the Financial Web: The Stages of Securitization	143
i. Marketing Financial Products to Consumers.....	144
ii. The Pooling and Pricing of Securitizations	147
iii. Purchasers of Asset-Backed Securities: Rating Agencies, Regulated Financial Institutions, Risk Management, and Basel II	151
1. Rating Agencies	151
2. Risk Management	153
3. Basel II	154
4. The SEC, Basel II, and Consolidated Supervised Entities 158	
iv. Hedging Risks: Derivatives and Hedge Funds	160
v. Iterations: CDOs and Derivatives to the nth Power.....	162
C. The Crash of the New Financial Code: A Thumbnail Sketch	164
D. Historical Parallels: The 1987 Crash and the Failure of Long-Term Capital Management.....	167
i. The 1987 Crash.....	167
ii. The Collapse of Long-Term Capital Management	168
II. Model Risk: Diagnostics on the Crash of Code	169
A. Design Flaws.....	170
i. Non-Robust Model Assumptions	170
ii. The Radical Critique: The Failure of Models in the Face of Uncertainty	172
iii. Risk Correlation.....	172
iv. Spillover Effects and Feedback Loops	173
v. Interface Between Codes: Information Gaps.....	175
vi. Flaws in Modeling Human Behavior.....	176
1. Bounded Rationality: The “Killer App” for Behavioral Law and Economics	176
2. Modeling and Complex Adaptive Systems.....	178
B. User Interface: Human Agency and Agency Costs	180

i.	Selecting Code: Model Fit or Fitting the Model?.....	180
ii.	Implementation Errors.....	181
iii.	Inputs to Code: Low-Documentation Loans.....	181
iv.	Gaming the Models	182
v.	Interface between Codes Revisited: Information Destruction & Information Externalities.....	182
vi.	The Risk of Homogeneity Among Risk Models: An Anti- Coordination Problem.....	184
vii.	A Coordination Problem Among National Regulators.	185
III.	Select Policy and Research Implications	186
A.	Scrapping Basel II's Internal Models Approach.....	186
B.	Promoting Open Source Risk Models.....	189
i.	The Outlines of an Open-Source Approach.....	189
ii.	The Benefits of Open Source.....	190
iii.	Potential Drawbacks: Would Open Source Promote Homogeneity?	191
iv.	Extending the Open-Source Approach	192
v.	Open Source and Rating Agencies	193
vi.	Open Source and Consumer Protection.....	194
C.	In Praise of Equity	195
Conclusion.....		197

INTRODUCTION

The revolution in quantitative finance that occurred over the last two decades produced models that enabled the rapid growth of securitization and derivatives.¹ This Article demonstrates that financial regulators delegated or outsourced to these computer-based risk models the responsibility of regulating a wide range of risk transfers in the economy—from consumer finance to global financial markets. These risk models failed spectacularly in the global financial crisis that started in the subprime mortgage market, and this outsourcing of regulation exacerbated the crisis.

1. Ronald J. Gilson & Charles K. Whitehead, *Deconstructing Equity: Public Ownership, Agency Costs, and Complete Capital Markets*, 108 COLUM. L. REV. 231 (2008) (describing how advances in quantitative finance have led to the development of sophisticated derivatives and other financial products that promise both to lead to “complete” capital markets and drain liquidity from equity markets).

To understand the crisis, the failure of risk models, and the dangers of regulatory outsourcing, it is helpful to sketch out the system by which mortgages are connected to asset-backed securities, derivatives, and financial risk to global financial institutions.² Securitization uses the future payment streams from mortgages and other credit products to create securities that are sold to investors. These investors not only acquire the right to these payment streams, but also assume a portion of the financial risk that borrowers will not make payment on the underlying mortgages when due; securitization thus carves up the risk associated with mortgages and other securitized assets into slices, which are then spread among investors.³ Those investors could then use credit derivatives and other derivatives to offload parts of this risk to counterparties in exchange for paying premiums to those counterparties.⁴

Securitization and derivatives created a system for transferring risk and spreading it among those investors who could theoretically bear risk most efficiently.⁵ Each part of this risk-transfer system was enabled by private, computer-based industry risk models that were built using innovations in quantitative finance. These models include the following:

- Data-mining and credit-scoring software used by financial institutions to market mortgages, loans and other financial products to individual consumers (this marketing includes not only setting the price of those products to match the risk of individual borrowers, but also creating complex features in those products that can be tailored for certain categories of consumers);⁶
- Pricing models used by financial institutions to structure and price the securitization of those consumer financial products;⁷
- Models used by credit-rating agencies to assign ratings to the asset-backed securities issued in securitizations;⁸

2. This system is described in detail in Part I.B *infra*.

3. The mechanics of securitization are described in greater detail in Part I.B.ii *infra*.

4. For an analysis of derivative transactions, see Part I.B.iv *infra*.

5. See Gilson & Whitehead, *supra* note 1, at 263.

6. Lauren E. Willis, *Decisionmaking and the Limits of Disclosure: the Problem of Predatory Lending: Price*, 65 MD. L. REV. 707, 719–21, 724–26 (2006) (analyzing how advances in financial industry data collection technology allow lenders to market highly complex financial products to consumers and gain an information advantage over consumers with respect to predicting consumer defaults and penalties under those products). Use of code at the level of consumer finance is examined further in Part I.B.i.

7. See *infra* Part I.B.ii.

8. See *infra* Part I.B.iii.1.

- Models used to price those derivatives that further hedge the risks of asset-backed securities;⁹ and
- Models used by financial institutions to manage their investment portfolios and set their overall risk-management policies.¹⁰

This Article refers to the above-mentioned data-mining software and computer-based risk models as the “new financial code.” As the new financial code proliferated, regulators outsourced to it significant responsibility for regulating financial markets. Regulatory outsourcing occurs at each point in the financial system in which computer-based risk models are used, including in the following areas:

- Regulators have permitted lenders to use sophisticated data-mining and credit-scoring software to tailor and market increasingly complex mortgages and other credit products to consumers, and particularly to those consumers least able to navigate that complexity.¹¹
- Regulators have outsourced oversight of the risk transfer in the securitization of financial products to rating agencies indirectly via regulations that govern the principle investors who purchase asset-backed securities. Numerous financial regulations restrict investments by banks and certain other institutional investors to “investment-grade” debt. These regulations delegate regulation of the risk-taking by these institutions to rating agencies that determine which securities qualify as “investment grade.”¹²

9. Frank Partnoy & David A. Skeel, Jr., *The Promise and Perils of Credit Derivatives*, 75 U. CIN. L. REV. 1019, 1020–22, 1029–30 (2007) (analyzing two of these devices—credit default swaps and collateralized debt obligations (CDOs)—and emphasizing the importance of mathematical models for CDOs). For an earlier article analyzing use of code in constructing derivatives, see Henry T.C. Hu, *Misunderstood Derivatives: the Causes of Informational Failure and the Promise of Regulatory Incrementalism*, 102 YALE L.J. 1457, 1476–81 (1993). Use of code in hedging, including in pricing derivatives, is explored in Part I.B.iii.4 *infra*.

10. Raj Bhala, *Applying Equilibrium Theory and the FICAS Model: a Case Study of Capital Adequacy and Currency Trading*, 41 ST. LOUIS U. L.J. 125, 159–62, 178, 183–87 (1997) (detailing arguments for superiority of banks’ internal models to measure risk and set capital requirements compared to regulatory methods). Use of code for these purposes is discussed in Part I.B.iii.3 *infra*.

11. See *infra* Part I.B.i.

12. See Frank Partnoy, *The Siskel and Ebert of Financial Markets?: Two Thumbs Down for the Credit Rating Agencies*, 77 WASH. U. L.Q. 619, 681 (1999) (characterizing regulations that limit financial institutions to investments that are rated by rating agencies as giving those rating agencies a “regulatory license”).

- Under the Basel II Accord,¹³ certain large banks received authority from regulators to set their capital requirements using the banks' proprietary risk models.¹⁴ The new accord also permits banks to set capital requirements using rating agency ratings as a critical determinant.¹⁵
- In 2004, the U.S. Securities and Exchange Commission (SEC) followed the Basel II model by allowing certain large U.S. financial conglomerates to set their required regulatory capital according to their own proprietary risk models.¹⁶
- Regulators have resisted calls to regulate complex over-the-counter (OTC) credit derivatives, which financial institutions have used to hedge risks from securitizations and financial

13. BASEL COMMITTEE ON BANKING SUPERVISION, INTERNATIONAL CONVERGENCE OF CAPITAL MEASUREMENT AND CAPITAL STANDARDS: A REVISED FRAMEWORK (June 2006) [hereinafter "Basel II"], available at <http://www.bis.org/publ/bcbs128.pdf>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n13.pdf>.

Basel II is the second accord among bank regulators and central bankers from countries that belong to the Basel Committee on Banking Supervision (members come from the so-called "Group of Ten" countries: Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States). The accord consists of a series of recommended bank regulations and principles that national regulators should implement in their home countries. The accord thus attempts to set minimum international banking standards to mitigate both regulatory arbitrage by international banks and financial risks caused by potential bank failure that could spread from one economy to another. For a capsule summary of the Basel accords, see Robert Hugi et al., *U.S. Adoption of Basel II and the Basel II Securitization Framework*, 12 N.C. BANKING INST. 45 (2008); Eric Y. Wu, *Basel II: a Revised Framework*, 24 ANN. REV. BANKING & FIN. L. 150 (2005).

Although non-binding, national regulators exert pressure on one another to comply with the accord, giving it the quality of "soft law." See Michael S. Barr & Geoffrey P. Miller, *Global Administrative Law: the View from Basel*, 17 EUR. J. INT'L L. 15, 17 (2006) (reciting critiques of law-making by networks of bank regulators and international bureaucrats in the Basel Accord as lacking accountability and legitimacy, but arguing that Basel II is subject to a subtle structure of international administrative law); Dieter Kerwer, *Rules that Many Use: Standards and Global Regulation*, 18 GOVERNANCE 611 (2005).

14. Joseph J. Norton, *A Perceived Trend in Modern International Financial Regulation: Increasing Reliance on a Public-Private Partnership*, 37 INT'L LAW 43, 46 (2003).

15. BASEL II, *supra* note 13, at 19 (permitting banks to set regulatory capital for credit risk in part based on rating agency ratings (*i.e.*, "external credit assessment")). See also *id.* at 27 (establishing the requirements that specify when banks can use "external credit assessment" to support capital-requirement assessments for credit risk).

The principle U.S. banking regulators have already issued a final rule setting out the framework for Basel II implementation in the United States. Risk-Based Capital Standards: Advanced Capital Adequacy Framework – Basel II, 72 Fed. Reg. 69,288 (Dec. 7, 2007) (to be codified at 12 C.F.R. pts. 3, 208, 225, 325, 559, 560, 563, 567).

16. Alternative Net Capital Requirements for Broker-Dealers That Are Part of Consolidated Supervised Entities, Exchange Act Release No. 34-49,830, 69 Fed. Reg. 34,428 (June 21, 2004) (codified at 17 C.F.R. pts. 200 and 240).

risk generally.¹⁷

- In addition, regulators have been reluctant to regulate hedge funds, which comprise a significant number of the counterparties to OTC derivatives.¹⁸ Even preliminary attempts at regulating hedge funds¹⁹ were thwarted in the face of the terrible complexity of these funds and uncertainty as to the scope of risk that they posed.²⁰

By outsourcing, financial regulators placed great faith in the new

17. See Lynn A. Stout, *Why the Law Hates Speculators: Regulation and Private Ordering in the Market for OTC Derivatives*, 48 DUKE L.J. 701, 704–07 (1999) (noting that OTC market is largely unregulated, but describing debate on regulation in context of proposed Commodity Exchange Act amendments).

Then-Federal Reserve Chairman Alan Greenspan expressed concern about how over-regulation of OTC derivatives might impair market efficiency and threaten U.S. competitiveness. *Working Group Report on OTC Derivatives: Hearing Before the S. Comm. on Agriculture, Nutrition and Forestry*, 106th Cong. (Feb. 10, 2000) (statement of Alan Greenspan, Chairman, Board of Governors of the Federal Reserve System), available at http://agriculture.senate.gov/Hearings/Hearings_2000/w100210/0029gre.htm, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n17.pdf>.

His position meshed with views among other policymakers and scholars that light regulation was justified given a “set of private mechanisms that facilitate smooth functioning OTC derivatives markets.” GARRY J. SCHINASI, *SAFEGUARDING FINANCIAL STABILITY: THEORY AND PRACTICE* 206 (2006) (“Market discipline, provided by shareholders and creditors, promotes market stability by rewarding financial institutions based on their performance and creditworthiness.”) But, Mr. Schinasi also notes, “Recent research finds market discipline to be strong only during periods of banking sector stress and volatile financial markets.” *Id.*

18. Dustin G. Hall, Note, *The Elephant in the Room: Dangers of Hedge Funds in Our Financial Markets*, 60 FLA. L. REV. 183, 221–26 (2008) (criticizing proposals to regulate hedge funds as too modest). *But cf.* Troy A. Paredes, *On the Decision to Regulate Hedge Funds: the SEC’s Regulatory Philosophy, Style, and Mission*, 2006 U. ILL. L. REV. 975, 977 (2006) (describing possible rationale behind SEC attempt to require registration of hedge funds). The proposed SEC regulation (discussed *infra* note 19) was opposed by Alan Greenspan, who favors leaving hedge funds unregulated. DIMITRIS N. CHORAFAS, *STRESS TESTING FOR RISK CONTROL UNDER BASEL II* 299 (2006) (describing letter Greenspan sent to Congress opposing SEC regulation); ALAN GREENSPAN, *THE AGE OF TURBULENCE: ADVENTURES IN A NEW WORLD* 370 (2007) (arguing that hedge funds are sufficiently regulated by “market surveillance”).

19. In one notable example, the Securities and Exchange Commission passed regulations requiring certain hedge funds to register with the Commission. Registration under the Advisers Act of Certain Hedge Fund Advisers, Investment Advisers Act Release No. 2,333, 69 Fed. Reg. 72,054–01 (Dec. 10, 2004) (codified at 17 C.F.R. pts. 275, 279 (2005)), *invalidated by* *Goldstein v. SEC*, 451 F.3d 873 (D.C. Cir. 2006).

20. The SEC’s hedge-fund registration rule prompted a sharp dissent from two SEC commissioners who argued that the benefits of registration paled in comparison to the costs the rule imposed on hedge funds. Registration under the Advisers Act of Certain Hedge Fund Advisers, Investment Advisers Act Release No. 2,333, 69 Fed. Reg. 72,089 (dissent of Commissioners Glassman and Atkins). The U.S. Court of Appeals for the D.C. Circuit ultimately struck down the SEC rule on statutory interpretation grounds. *See Goldstein*, 451 F.3d at 884.

technology of financial institutions to police the transfers of risk made via complex financial products.²¹ Regulators were both daunted by the complexity posed by new financial instruments and awed by the promise of new financial engineering to shift and spread risk efficiently.

But the financial crisis that began in the subprime mortgage market belied this promise, as risk models failed to anticipate a wave of defaults on consumer mortgages that led to losses on mortgage-backed securities. Massive foreclosures in residential real estate and widespread failures of major financial institutions provide stark evidence of the failure of the new financial code to regulate risk.

Before this Article begins to examine the rise and crash of the new financial code, it is useful to examine briefly a parallel in an altogether different area of legal scholarship to provide context for the problem of the new financial code and suggest possible solutions. The way in which financial institutions came to regulate a large part of financial markets resembles, in several important ways, how proprietary software has come to regulate the internet. In 1999, cyberlaw scholar Lawrence Lessig described how the private sector created software that establishes the “architecture” of the world-wide web, and how this software functions as a kind of private regulation.²² According to Lessig, this software enables private firms (and ultimately governments) to track and regulate the behavior of individuals who use the internet.²³ Yet internet users little suspect the ways in which computer codes constrain them.²⁴

21. See generally Bhala, *supra* note 10. Federal Reserve Chairman Alan Greenspan typified the optimism for the new financial code. He lauded the benefits of code for the consumer credit market:

With these advances in technology, lenders have taken advantage of credit-scoring models and other techniques for efficiently extending credit to a broader spectrum of consumers. . . .

Where once more-marginal applicants would simply have been denied credit, lenders are now able to quite efficiently judge the risk posed by individual applicants and to price that risk appropriately. These improvements have led to rapid growth in subprime mortgage lending.

Alan Greenspan, Remarks at the Federal Reserve System’s Fourth Annual Community Affairs Research Conference (Apr. 8, 2005) [hereinafter Greenspan Apr. 8, 2005 Remarks], available at <http://www.federalreserve.gov/boarddocs/speeches/2005/20050408/default.htm>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n21a.pdf>.

Two years earlier, Greenspan touted the ability of these same risk models combined with loan securitization to increase market efficiency and to open “doors to national credit markets for both consumers and businesses.” Alan Greenspan, Remarks at the JumpStart Coalition’s Annual Meeting (Apr. 3, 2003), available at <https://www.jumpstartcoalition.org/fileup/temp/GreenspanRemarks.htm>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n21b.pdf>.

22. LAWRENCE LESSIG, CODE AND OTHER LAWS OF CYBERSPACE (1999).

23. *Id.* at 41–53.

24. *Id.* at 4–8. The architecture of the internet also facilitates government regulation of the web, which threatens to constrain free speech, *id.* at 164–85, intrude on privacy, *id.* at 142–63, and consolidate industry ownership of intellectual property, *id.* at 122–41.

Because this regulation is embedded within a complex technology, it escaped scrutiny by policymakers until examined by Lessig and other cyberlaw scholars. For the same reason, the new financial code also long escaped detailed scrutiny and criticism.

One of Lessig's recommendations for exposing the darker side of the regulatory potential for internet code is to promote open source in software.²⁵ This Article argues that the same approach should be applied to remedy the failures of the new financial code. It argues for greater disclosure of the algorithms and internal workings of the codes used to market financial products to consumers, price asset-backed securities and derivatives, and set risk-management policies at financial institutions. This increased transparency will allow these various codes to be examined by the marketplace and the wider public, improving the ability of codes to regulate transfers of risk. Greater transparency would also allow the public to examine consumer-lending practices and to root out invasions of privacy and predatory or discriminatory lending.

This Article proceeds as follows: Part I outlines both how the rise of risk models enabled the growth of securitization in the last two decades and how financial regulators increasingly outsourced regulatory responsibility to these industry models. Part I then sketches how the current financial crisis spread, demonstrating the failure of these models. It also draws historical parallels from the failure of risk models in the current crisis to both the 1987 stock-market crash and the failure of the Long-Term Capital Management hedge fund in 1998. Part II examines some of the explanations for the spectacular failures of risk models in the current financial crisis. Part III investigates several policy implications of these failures, and argues that bank regulators should abandon those provisions of the Basel II Accord that allow large banks to set their own regulatory capital according to their internal risk models. It also argues that regulators should promote open source in the proprietary models used to market consumer financial products, price securitizations, and manage financial institution risk. Lastly, Part III responds to a recent article by Professors Gilson and Whitehead noting the decline of equity markets at the expense of complex financial instruments made possible by complex risk models.²⁶

25. *Id.* at 100.

26. Gilson & Whitehead, *supra* note 1.

I. THE RISE OF THE NEW FINANCIAL CODE AND ITS CRASH

Part I details the rise of financial institution risk models in the last two decades and provides a snapshot of how these models failed in the ongoing global financial crisis. Part I.A begins with a short summary of different forms of financial risk and then explains how developments in quantitative finance led to new computer-based models that could estimate and price these different forms of risk.

Part I.B then explains how these computer-based models enabled the development of new financial products that broke risk into pieces that could be transferred and spread to investors in financial markets. Part I.B uses the following chain of securitization and hedging as an organizational template: (i) the marketing of mortgages (and other credit products) to consumers; (ii) the securitization of these mortgages, creating mortgage-backed securities; (iii) the decision by banks and other institutions to purchase mortgage-backed securities and other asset-backed securities; and (iv) the use of derivatives to hedge risks from asset-backed securities. At each link of this chain, Part I.B demonstrates both how financial institutions use computer-based models to price and manage risk, and how regulators outsourced regulatory responsibility to these models for overseeing massive transfers of risk.

Part I.C provides a brief snapshot of how the financial crisis began and how it revealed the failure of industry risk models to anticipate or price financial risk. Part I.D then draws parallels between these failures of the new financial code and factors that contributed to the 1987 crash of the U.S. stock market and the 1998 failure of the Long-Term Capital Management hedge fund.

A. *A Primer on Financial Risk*

i. *Typology of Risk*

One of the principal uses of the new financial code is to help financial institutions manage risk and price financial products given expected risk. Therefore, it is important to first lay out a typology of different financial risks that the new financial code attempts to model. Financial risk means most basically the possibility of losing money due to an event.²⁷ Risk

27. Cf. JOËL BESSIS, RISK MANAGEMENT IN BANKING 11–12 (2d ed. 2002) (analyzing risks faced

models attempt to quantify the probability and extent of a loss.²⁸

As detailed in Part I.A.ii *infra*, risk models make various assumptions in attempting to quantify these probabilities and often use historic loss data to model future losses. But attempts to quantify these probabilities are inherently problematic because future losses may not follow historic patterns. This highlights an important distinction that economists have drawn between “risk” (when the probabilities of future loss are known—for example, when playing a game of dice) and “uncertainty” (when probabilities of future loss are not known).²⁹ The question then becomes how well historic data can predict future losses, or, more generally, how effectively measurements of “risk” serve as a proxy for quantifying “uncertainty.”

This distinction between risk and uncertainty aside, the architects of these models make meaningful predictions by breaking financial risk into categories based on the source of potential loss.³⁰ Two of the most basic forms of risk that financial institutions attempt to model and quantify are credit risk and market risk, which are defined as follows:

Credit risk: For a financial institution, credit risk is the risk that a borrower will default on payment of obligations to that institution.³¹ Credit risk includes counterparty risk in derivative transactions, i.e., the risk that a counterparty which has contractual obligations to make payment to an institution (upon an event specified in the derivative contract) will not perform those obligations.³²

Market risk: Market risk, on the other hand, covers risks that the value of a firm’s investments or other assets will decline (or that its

by banks and defining risk as “uncertainties resulting in adverse variations of profitability or in losses”); NEIL CROCKFORD, AN INTRODUCTION TO RISK MANAGEMENT 5–6 (2d ed. 1986).

28. BESSIS, *supra* note 27, at xi.

29. This key distinction was first made by economist Frank Knight over seventy-five years ago, in FRANK H. KNIGHT, RISK, UNCERTAINTY AND PROFIT (1921). See Craig S. Lerner & Moin A. Yahya, “Left Behind” After Sarbanes Oxley, 44 AM. CRIM. L. REV. 1383, 1392 (2007) (noting that Knight created this distinction).

30. BESSIS, *supra* note 27, at 12.

31. *Id.* at 13. Bessis notes that credit risk also covers the decline in the credit standing of an obligor, or bonds or stock held by the institution even short of default, as this decline “triggers an upward move of the required market yield to compensate [for] the higher risk and triggers a value decline” of the security. *Id.*

32. *Id.* at 499–504 (discussing credit risk in the context of derivatives). For an economic analysis of the effects of counterparty risk on the pricing of derivatives and other complex financial instruments, see generally Robert A. Jarrow & Fan Yu, *Counterparty Risk and the Pricing of Defaultable Securities*, 56 J. FIN. 1765 (2002).

liabilities will increase) due to changes in market prices.³³ Because a firm's investment portfolio may be subject to price fluctuations in different types of markets, market risk includes several different subcategories of risk, including: (1) *interest rate risk*, or the risk exposure from changes in interest rates;³⁴ and (2) *equity risk*, or risk arising from fluctuations in stock returns.³⁵

As detailed in Part I.A.ii *infra*, quantitative finance has created sophisticated means of modeling all of the above forms of risk. Other important categories of risk, such as operational, liquidity, and systemic risk, prove harder to quantify as they are less directly reflected by historical market data. These forms of risk are defined as follows:

Operational risk: Operational risk is a broad term that conveys risk posed by a firm's operations. The Basel II Accord defines operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events."³⁶ Operational risk thus covers everything from potential losses caused by employee mistake or fraud, to losses from hurricanes.

Liquidity risk: Liquidity risk also proves difficult to model with market data, as it occurs when markets seize up. This risk takes two forms. Trading-liquidity risk (also called market liquidity risk) is the risk that a firm cannot find a counterparty in the market willing to buy or sell the asset at fair market value.³⁷ Funding-liquidity risk means "the risk that [a] firm will not be able to meet efficiently both expected and unexpected current and future cash flow and collateral needs without affecting either daily operations or the financial condition of the firm."³⁸

Systemic risk: Systemic risk arises from a broader market failure; this

33. HENNIE VAN GREUNING & SONJA BRAJOVIC BRATANOVIC, ANALYZING AND MANAGING BANKING RISK: FRAMEWORK FOR ASSESSING CORPORATE GOVERNANCE AND FINANCIAL RISK 111 (2003).

34. BESSIS, *supra* note 27, at 17.

35. ASWATH DAMODARAN, INVESTMENT VALUATION 60 (2002) (discussing measurement of equity risk through equity-risk premiums).

36. BASEL II, *supra* note 13, at 144, ¶ 644.

37. This raises the question of what constitutes "fair market value." There are other variations on the definition of "trading-liquidity risk" or "market-liquidity risk" that have their own ambiguities. According to the Bank for International Settlements, market-liquidity risk occurs when "a firm cannot easily offset or eliminate a position at the market price because of inadequate market depth or market disruption." BANK FOR INTERNATIONAL SETTLEMENTS, PRINCIPLES FOR SOUND LIQUIDITY RISK MANAGEMENT AND SUPERVISION 1 n.2 (June 2008).

38. *Id.*

form of risk denotes potential losses that affect the entire market,³⁹ and which thus cannot be mitigated through diversification.⁴⁰ These systemic losses may begin with an external shock that disrupts entire financial markets, or with a chain reaction in which one financial institution fails, causing its creditors to fail as well.⁴¹ Systemic risk represents a prime concern of financial regulators, due to its enormous repercussions and the inability of any individual financial institution to mitigate this form of risk through diversification.⁴²

Other forms of risk: Financial institutions also must manage other forms of specialized risk, including concentration risk (potential losses to a lender due to a high percentage of its total loans concentrated in a small number of debtors),⁴³ and reputation risk (potential losses stemming from a decline in public opinion of the institution).⁴⁴ Reputation risk also encompasses the potential threat of bank runs, which occur when depositors withdraw funds due to an institution's deterioration in creditworthiness, whether actual or perceived (or even the perceived deterioration of the financial health of *other* firms).⁴⁵

ii. *The Revolution in Quantitative Finance*

The capacity (however limited) of models to measure risk in a sophisticated way stems from the revolution in quantitative finance over the past two decades. This revolution began with the widespread use of

39. Systemic risk has been defined as “the risk of a breakdown in an entire system, as opposed to breakdowns in individual parts or components.” George G. Kaufman & Kenneth E. Scott, *What is Systemic Risk, and Do Bank Regulators Retard or Contribute to It*, 7 INDEP. REV. 371, 371 (2003); see also Steven L. Schwarcz, *Systemic Risk*, 97 GEO. L.J. 193 (2008).

40. See Larry E. Ribstein, *Fraud on a Noisy Market*, 10 LEWIS & CLARK L. REV. 137, 142 (2006) (discussing how arbitrageurs cannot diversify away systemic risk).

41. Kaufman & Scott, *supra* note 39, at 372–73.

42. See Schwarcz, *supra* note 39, at 200–02. Professor Schwarcz argues that not only do financial institutions lack the capacity to deal with systemic risk individually (because of an inability to diversify away the risk), but that they also lack incentives due to collective action failure; no one firm can capture all the of the benefit of an action it takes to reduce systemic risk. *Id.*

43. FRANK J. FABOZZI, BOND PORTFOLIO MANAGEMENT 491 (2001).

44. See Konrad S. Alt, *Managing Reputation Risk*, RMA J., Sept. 2002, at 40–41.

45. Richard Herring & Til Schuermann, *Capital Regulation for Position Risk in Banks, Securities Firms, and Insurance Companies*, in CAPITAL ADEQUACY BEYOND BASEL 15, 19–20 (Hal S. Scott ed., 2005). Even non-banks may experience the modern equivalent of a bank run when other firms that have extended credit to them make margin calls. Bhagwan Chowdhry & Vikram Nanda, *Leverage and Market Stability: The Role of Margin Rules and Price Limits*, 71 J. BUS. 179, 182 (1998) (analyzing the potential destabilizing effects of margin calls).

the Black-Scholes model for pricing options.⁴⁶ This model, when combined with incredible increases in computing power, enabled specialists in the new field of quantitative finance to build sophisticated pricing and risk models. These models could churn volumes of market data into nuanced forecasts of expected losses (and returns).⁴⁷ The following paragraphs detail some of the basic risk-modeling tools developed during this revolution.

Value-at Risk: Value-at-risk is a method used to determine potential losses from a given form of risk. One option for measuring potential losses is to determine the maximum possible loss. This is not a useful yardstick, however, because while the maximum loss might be enormous (e.g., 100% of the value of an asset), the probability of that loss occurring might be negligible. By contrast, value-at-risk provides a measure of both the extent and probability of losses occurring.⁴⁸ Simply stated, value-at-risk describes the maximum possible loss over a specified time period with a given level of confidence.⁴⁹ For example, a value-at-risk determination of a maximum of \$1,000,000 of losses over a two-week period with a 95% confidence interval translates into a 5% probability that losses will exceed \$1,000,000 over those two weeks. But value-at-risk numbers say nothing about the magnitude of losses above that confidence interval.⁵⁰ In the above example, there is a 5% chance of losses exceeding \$1,000,000, but the value-at-risk measurement does not specify how large those losses may be.

Diagram A depicts a value-at-risk calculation for the foregoing example. The curve depicts expected losses (or gains) on a portfolio with the probability of losses (or gains) on the vertical axis and the magnitude of losses (or gains) on the horizontal axis. The shaded area represents 5% of the area under the curve and is therefore equivalent to 5% of potential losses. Point x, or \$1,000,000, then represents the maximum possible loss with a 95% confidence interval (i.e., there is only a 5% (100% minus 95%) chance that losses will exceed that amount).

46. DONALD R. VAN DEVENTER ET AL., *ADVANCED FINANCIAL RISK MANAGEMENT* 9 (2005).

47. *Id.* at 8–10.

48. BESSIS, *supra* note 27, at 12.

49. *Id.*

50. *See id.*

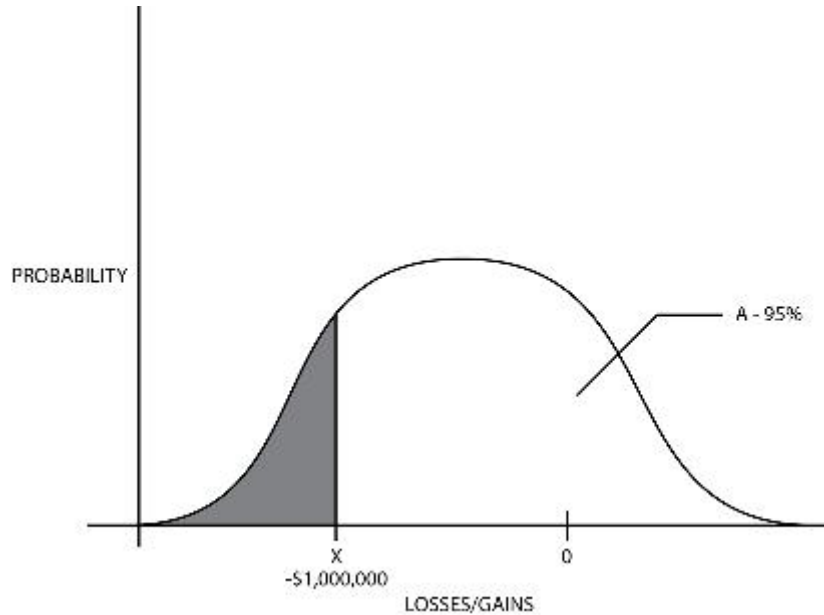


Diagram A

To calculate value-at-risk, modelers must assume the basic distribution of losses, i.e., they must determine the shape of the curve in the preceding diagram. They have three options. First, they can assume that losses fall in a “normal” distribution—in other words, that they follow a bell-curve shape. This assumption may have no basis in reality. Therefore, modelers can take a second approach of using historical data to determine the distribution of losses. This approach has downsides as well; historical data chosen may suffer from sample bias. For example, modelers may not have looked far enough back in time to gather data, and may miss important historical events in which massive losses were incurred. Inputting more historical data would ameliorate this, but financial markets do not always follow historical patterns.⁵¹

In order to form loss distributions, modelers can also employ a third technique—Monte Carlo simulations—which estimates financial losses using sophisticated random sampling driven by advanced computing power. This random sampling proves particularly valuable when several different variables can interact to produce financial loss, i.e., if the

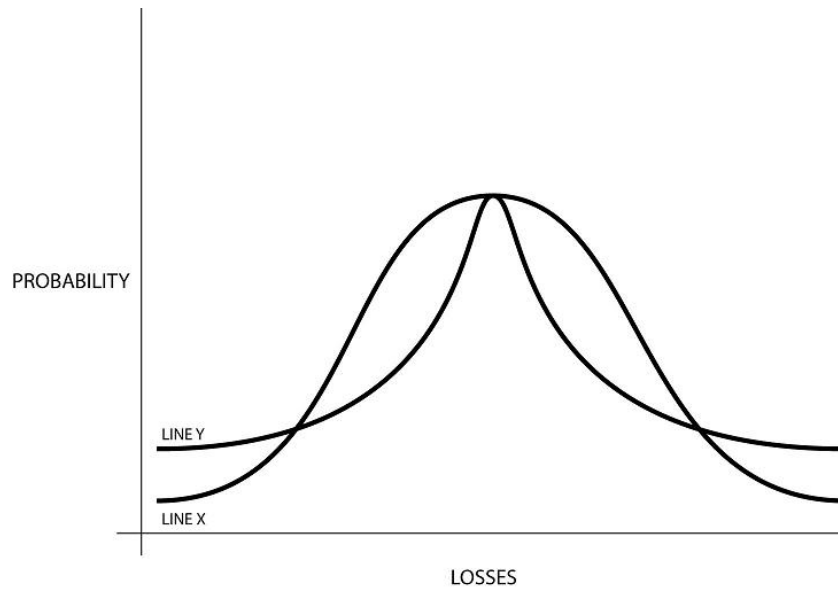
51. Darrel Duffie & Jun Pan, *An Overview of Value at Risk*, 4 J. DERIVATIVES 7, 19–20 (1997).

equation used to calculate losses has multiple variables. But even this sophisticated technique requires that modelers make assumptions about the relationship among these different variables in real-world markets—they must write the equation that transforms the several variables into financial loss. Modelers can assume that this relationship will follow historical patterns (use historical data), which leads back to the problem of whether the historical data selected provide an adequate sample. Modelers could also develop their own algorithm or equations for the relationship, but this in turn leads to the issue of the accuracy of the assumptions behind the algorithm.⁵²

In other words, assumptions in modeling are inescapable, and the strength of a model depends on how well the assumptions match the future behavior of markets. Even the technological wizardry of Monte Carlo simulations cannot transmute uncertainty into risk.

One particular problem faced by value-at-risk models is “fat tails,” or potential large-magnitude, low-probability losses. This phenomenon is so named because the ends of a loss distribution curve, where probabilities are low, have a higher, or “fatter,” magnitude of loss. Diagram B provides a contrast between a normal-shaped distribution of losses (line x) and a distribution of losses with a fat-tail (line y). The left-hand edge of line y represents low-probability but high-loss events, which are often compared to “hundred year storms.”

52. BESSIS, *supra* note 27, at 608–21.

**Diagram B**

Modelers have several options for dealing with potential fat tails. They can “stress test” the models. Stress testing involves changing model assumptions, such as confidence level or the period of time measured, to see if value-at-risk determinations change.⁵³ Stress tests often involve generating worst-case scenarios. Modelers can also judge model performance through “back testing.” This involves modelers making several hypothetical jumps back in time, inputting historical data that were available at those respective times, and then comparing the predictions of the model with how losses actually unfolded.⁵⁴

B. Code Along the Nodes of the Financial Web: The Stages of Securitization

These and other risk-modeling tools developed during the revolution in quantitative finance, when combined with the increases in computing power, enabled financial institutions to develop complex new financial products, including the mortgage-backed securities that lie at the heart of

53. *Id.* at 411–12. Extreme Value Theory represents one mathematically sophisticated version of stress testing for fat tails, but this tool still relies on assumptions to model uncertainty in terms of risk. *Id.* at 78, 411.

54. *Id.* at 411.

the recent subprime crisis. The sections below track the rise of code using the template of mortgage origination, followed by securitization, followed by hedging and risk management in the wake of securitization.

i. Marketing Financial Products to Consumers

The securitization process begins with “origination,” when a lender extends credit to consumers or other borrowers. This credit can come in the form of different kinds of loans or financial products, including mortgages, credit cards, and student loans. For any of these products, the consumer obligation to repay debt creates a prospective cash stream. Originators can then sell the rights to these cash streams. Rights to cash streams from different financial products can then be bundled together and resold in the later stages of a securitization described below.⁵⁵

The use of risk models (or “code”) begins in earnest at this first stage of securitization. Originators employ the combination of advanced marketing software, data mining, and increasingly detailed credit reports to gather information on the creditworthiness of borrowers.⁵⁶ This information is used both to determine whether to approve or deny a loan and to set interest rates to match credit risk.⁵⁷ Many originators use risk modeling and other software more aggressively in actively marketing financial products to consumers. This marketing can include creating complex provisions in a contract that are tailored to different types of consumers.⁵⁸

Consumer-law scholars such as Lauren Willis,⁵⁹ Oren Bar-Gill, and

55. For a primer on securitizations, see Steven L. Schwarcz, *The Alchemy of Asset Securitization*, 1 STAN. J.L. BUS. & FIN. 133, 135 (1994).

56. Willis, *supra* note 6.

57. Patricia A. McCoy, *Rethinking Disclosure in a World of Risk-based Pricing*, 44 HARV. J. ON LEGIS. 123, 126–27 (2007) (comparing “average-cost pricing,” in which lenders set interest rates for the average credit risk of borrowers but may reject loan applicants that pose a higher credit risk with “risk-based pricing,” in which lenders tailor interest rates to the credit risk of individual borrowers). Professor McCoy notes, however, that interest rates that are ostensibly set to match credit risk may also reflect inefficient and socially undesirable motives of lenders, such as rent-seeking and discrimination. *Id.* at 127.

58. Oren Bar-Gill & Elizabeth Warren, *Making Credit Safer*, 157 U. PA. L. REV. 1, 46–52 (2008) (describing data collection by lenders on consumer borrowing behavior); Elizabeth Warren, *The Middle Class on the Brink of Disaster 7–8* (Apr. 17, 2007) (unpublished manuscript, on file with author) (describing interdisciplinary empirical and experimental work by financial industry into consumer borrower behavior).

59. See Willis, *supra* note 6, at 728–29, 737, 768, 829.

Elizabeth Warren⁶⁰ have worried that this data mining gives lenders an information advantage over consumer borrowers, which lenders use to market financial products that may be potentially exploitative or otherwise unsuitable for consumers. (These concerns about consumer-wealth losses dovetail with the privacy concerns expressed by Lessig on the use of code in the internet to track personal data for commercial purposes.⁶¹) These scholars have argued that the information-gathering ability of financial institutions has reversed the traditional information asymmetry between lenders and borrowers. Lenders now have information about a consumer's ability to repay and likelihood of default that the consumer herself does not have.⁶² These scholars have also demonstrated that many originators exploit this information asymmetry to offer complex financial products beyond the understanding of many consumers who buy them.⁶³ The financial institutions can predict when consumers will incur penalties and make higher total payments over the life of a loan when complex features are added. Originators then incorporate select features to extract maximum revenue from less-informed consumers.⁶⁴

This practice became particularly evident in the mortgage market over the last decade. Mortgage lenders began offering home buyers mortgages with novel features. These features allowed prospective buyers to purchase homes that would otherwise lie beyond their means. Most notably, adjustable rate mortgages (or ARMs) offered buyers low fixed rates on an introductory or "teaser" basis, with interest rates converting to a floating, market-based interest rate after a few years.⁶⁵ ARMs and other "exotic" mortgages would cost borrowers substantially more over the life of the mortgages than fixed-rate mortgages, but allowed borrowers to take out mortgages in amounts for which they would not otherwise qualify.⁶⁶ Low-income borrowers could thus afford

60. See Bar-Gill & Warren, *supra* note 58, at 23–25.

61. LESSIG, *supra* note 22, at 151–56.

62. See, e.g., Bar-Gill & Warren, *supra* note 58, at 12–14; Warren, *supra* note 58, at 7–13.

63. Lauren A. Willis, *Against Financial Literacy Education*, 94 IOWA L. REV. 197 (2008) (describing how the revolution in data collection, storage, and processing enable the financial-services industry to model consumer behavior and to market complex products to consumers that exceed consumer understanding).

64. *Id.* See also Bar-Gill & Warren, *supra* note 58, at 23–25; Warren, *supra* note 58, at 13–22.

65. McCoy, *supra* note 57, at 143–44.

66. The costs to consumers of ARM loans were recognized in legal scholarship over two decades ago. See, e.g., William N. Eskridge, Jr., *One Hundred Years of Ineptitude: the Need for Mortgage Rules Consonant with the Economic and Psychological Dynamics of the Home Sale and Loan*

their first home. But these mortgages were not marketed exclusively at the low-income market; the “subprime” crisis may be a misnomer, as middle-class borrowers used ARMs and other exotic mortgages to purchase houses too.⁶⁷

The risk that these borrowers assumed, often without fully understanding it, was that interest rates would significantly rise after the teaser period and push their monthly mortgage expense beyond their budget. (As Part I.C explains, this problem is exactly what befell many borrowers with ARM mortgages.) In other words, ARM mortgages transferred interest-rate risk to borrowers.

As that code enabled mortgage and other lenders to reverse the information asymmetry and shift risk to consumers, regulators took little action. Consumer-law scholars have faulted regulators for doing little in the last decade to protect consumers from complex mortgages (or other financial products that consumers poorly understood), despite evidence that consumers were taking on high levels of debt and were assuming massive interest-rate risk.⁶⁸

The reasons for this regulatory inaction are manifold.⁶⁹ One reason regulators may have become comfortable with the higher levels of risk assumed by consumers is that the lenders also bore a large measure of that risk; if consumers defaulted under their mortgages or other loans, lenders took a loss on whatever they could not recover.⁷⁰ Both lenders and financial markets, many regulators assumed, accurately priced and

Transaction, 70 VA. L. REV. 1083, 1131 (1984).

67. See, e.g., Elizabeth Warren, *The Economics of Race: When Making It to the Middle Is Not Enough*, 61 WASH. & LEE L. REV. 1777, 1793 (2004) (citing lender data that subprime mortgage market included middle-class black and Hispanic families).

68. See, e.g., Bar-Gill & Warren, *supra* note 60, at 70–74.

69. One explanation for regulatory inaction is that the extension of credit with novel features allowed lower-income consumers to buy their first homes and fueled the economy. Cf. Kristopher Gerardi et al., *Do Households Benefit from Financial Deregulation and Innovation? The Case of the Mortgage Market* 35 (Nat'l Bur. Econ. Res. Working Paper No. W12967, 2007), available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=971601, (concluding that deregulation and mortgage innovation made the U.S. housing finance market “less imperfect”). Regulators may have been wary of upsetting either political support for wider home ownership or the financial industry. They also may have been reluctant to disrupt the economic growth stimulated by increased home sales.

70. Cf. THE PRESIDENT’S WORKING GROUP ON FINANCIAL MARKETS, POLICY STATEMENT ON FINANCIAL MARKET DEVELOPMENTS (Mar. 2008), reprinted in 14 L. & BUS. REV. AM. 447, 456 (Spr. 2008) [hereinafter President’s Working Group] (noting that many originators who sold mortgages for securitization still retained some risk of loss if they purchased or guaranteed the resultant asset-backed securities).

managed this risk due to the advances in the risk models they employed.⁷¹

ii. *The Pooling and Pricing of Securitizations*

Many originators did not fully bear this risk, however, because they sold a large portion of mortgages (or other financial products) to special investment vehicles via securitization.⁷² Therefore, the assumption that markets optimally managed risk depends on whether the asset-backed securities issued in those securitizations were accurately priced.⁷³ The accuracy of the pricing of a securitization, in turn, depends on the quality of the code used to model the relevant risks.

Analyzing the role of models in pricing a securitization requires an understanding of the basic structure of securitization and how it transfers credit risk. The following paragraphs describe the process of securitizing mortgages, which lies at the heart of the subprime crisis (but this description could also apply to the securitization of other forms of consumer debt, such as credit card debt and student loans).

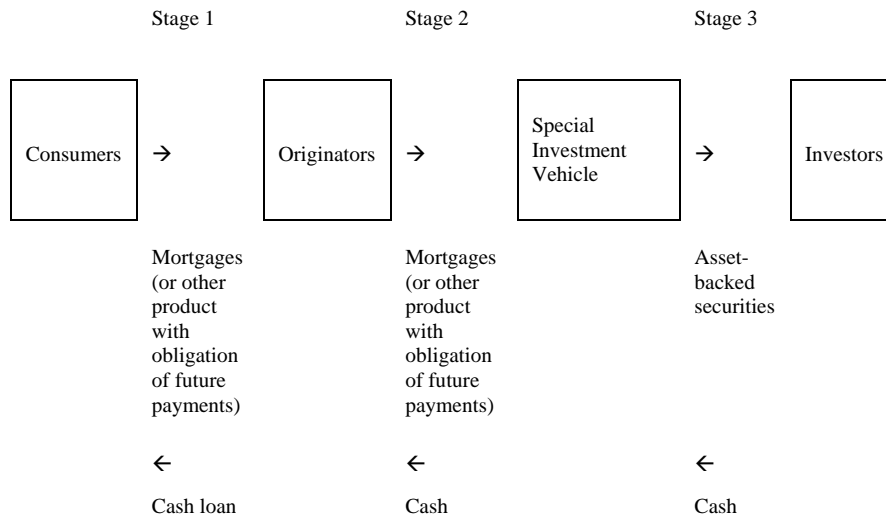
In a mortgage securitization, after mortgage lenders originate mortgage loans (Stage 1 in Diagram C below), special investment vehicles (SIVs) buy pools of mortgages using cash paid by investors who bought securities from those vehicles. (These transactions appear in Stages 2 and 3 in Diagram C below, and occur practically simultaneously.) The securities then pay out to investors based on the cash streams the SIVs receive from the underlying mortgages.⁷⁴

71. See Greenspan Apr. 8, 2005 Remarks, *supra* note 21.

72. Frederic S. Mishkin, Governor, Board of Governors of the Federal Reserve System, Leveraged Losses: Lessons from the Mortgage Meltdown, Remarks at the U.S. Monetary Policy Forum, New York, NY (Apr. 8, 2005), available at <http://www.federalreserve.gov/newsevents/speech/mishkin20080229a.htm>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n72.pdf> (discussing incentive problems created by “originate-to-distribute” model).

73. It also depends on whether purchasers of asset-backed securities and their market counterparties accurately hedged the risks of those securities. See *infra* Part I.B.iv.

74. See Steven L. Schwarcz, *Protecting Financial Markets: Lessons from the Subprime Mortgage Meltdown*, 93 MINN. L. REV. 373, 376–77 (2008). The underlying mortgages serve as collateral for the securities, and, in the event of a liquidation of the SIV, would be sold to satisfy the claims of the security holders.

**Diagram C**

By purchasing these asset-backed securities, investors can invest in the lucrative consumer-credit market (including investing in mortgages, credit card debt, and student loans) while enjoying several benefits that are unavailable when extending credit directly to consumers. First, the purchasers of securities need not collect payments directly from consumers.⁷⁵ Second, these securities are theoretically more liquid than the underlying mortgages.⁷⁶ Third, asset-backed securities allow investors to diversify. This diversification occurs in three different ways.

First, the pooling of mortgages means that the risk of default on any one mortgage is offset by the fact that other mortgages in the pool will continue to pay out. This risk-spreading through pooling is a central benefit of all securitizations. But this assumes that losses among mortgages in the pool will not be highly correlated and that any correlation can be accurately estimated and will remain roughly

75. Collection of monies and enforcement of remedies against consumers would usually be the role of a “servicer,” a firm employed by the SIV to conduct these administrative tasks. Anand K. Bhattacharya & Frank J. Fabozzi, *Expanding Frontiers of Asset Securitization*, in *ASSET-BACKED SECURITIES* 1, 9 (Anand K. Bhattacharya & Frank J. Fabozzi eds., 1996).

76. Leon T. Kendall, *Securitization: a New Era in American Finance*, in *A PRIMER ON SECURITIZATION* 1, 5, 13 (Leon T. Kendall & Michael J. Fishman eds., 1997).

constant.⁷⁷ (These assumptions on correlation have been called into question by the current global financial crisis as noted in Part II.A.iii).

Second, securitization facilitates diversification because investors in asset-backed securities are only buying a sliver of the mortgage pool's risk, and they can diversify away this risk through other investments in their portfolios.⁷⁸ This assumes, however, that losses on the mortgage-backed securities that investors purchase are not highly correlated with losses on other assets (including other asset-backed securities) in their portfolios.

Third, investors can achieve diversification through the terms of the securities being issued. Cash payments on the underlying assets need not simply flow to holders of securities pro rata. Instead, the securities can be “structured” to create different classes, or “tranches,” of securities, with each class having a different level of risk and a different level of reward. To accomplish this, the indenture or other agreement establishing the terms of each tranche often employs a complex “waterfall” rule for payment to different tranches. The waterfall sets the order in which the classes are entitled to receive payments from the underlying assets; in a simple waterfall, holders of senior classes receive amounts due to them in full before holders of junior classes receive anything. Thus, junior classes face a higher risk of not being paid due to defaults on the underlying assets and receive compensation for this risk with a higher interest rate. Different tranches (with different tradeoffs between risk and reward) appeal to different types of investors. More complex waterfall rules than the example above allow securitizations to carve up risk and reward in very finely tuned ways.⁷⁹

Yet even in the most basic securitization, the success of this slicing, dicing, and pricing of risk and reward depends on the capability of those structuring the securitization and those purchasing the securities to accurately model the risks involved. Code—in the form of complex pricing and risk models—again played an integral role. This code might be employed by different financial institutions involved in creating the structure for a securitization, including the following: originators,

77. Joshua D. Coval et al., *The Economics of Structured Finance* 8 (Harv. Bus. Sch. Working Paper No. 09-060, 2008), available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1287363, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n77.pdf>.

78. See Kendall, *supra* note 76, at 13–15.

79. For an explanation of waterfalls and tranching, see Steven P. Baum, *The Securitization of Commercial Property Debt*, in A PRIMER ON SECURITIZATION, *supra* note 76, at 45, 49 (describing commercial mortgage-backed securities).

government-sponsored entities that pool and issue mortgage-backed securities (Freddie Mac and Fannie Mae), and investment banks acting as underwriters for the securities.⁸⁰

All relied on sophisticated modeling to assess risk and price the securities and their institutional services accordingly.⁸¹ (Of course rating agencies and their models played an outsized role in structuring securities as well, which is analyzed in Part I.B.iii.1) Any models for pricing asset-backed securities need to analyze credit risk and, in order to do so, must answer two questions. First, the models need to assess the risk of non-payment (i.e., credit risk) on the underlying assets.⁸² To accomplish this, these models require critical information from the originators on the underlying assets. Given the sheer number and variety of the underlying assets, originators need to provide certain categories of information. For mortgages, these categories might include information on geographic location of the homes, sizes of the mortgage loans, loan-to-value ratios of mortgages, interest rates and other significant terms of the mortgages, and delinquencies on the mortgages.⁸³ When modeling the risk of mortgage-backed securities, an analysis of this information on underlying mortgages in the aggregate (on a pool-wide basis) can miss importance nuances that are apparent when looking at data on the level of individual mortgages.⁸⁴

Second, the models need to assess how risk on the underlying assets would course through the waterfall structure of the securitization and translate into risk on the various tranches of securities.⁸⁵

Certain securitizations might package the securities being issued with some form of credit support, either guarantees from a government-sponsored entity in the case of Fannie Mae and Freddie Mac securities, or a bond insurance policy issued by a bond insurer. Conceptually,

80. For a discussion of the roles of these various players in securitizations, see Kendall, *supra* note 76, at 4–14.

81. For a comprehensive analysis of the modeling that sponsors use for structuring securitizations, see generally ANDREW S. DAVIDSON ET AL., *SECURITIZATION: STRUCTURING AND INVESTMENT ANALYSIS* (2003).

82. *Id.* at 68, 340–42.

83. *Id.* at 307 (discussing types of aggregate data on mortgages that will effect credit risk for mortgage-backed securities). *Cf.* KENNETH G. LORE & CAMERON L. COWAN, *MORTGAGE-BACKED SECURITIES* §§ 4:92–4:104 (describing disclosures on mortgage characteristics that would impact credit risk with respect to mortgage-backed securities), *available on Westlaw* at “Mortsec.”

84. *Cf.* Davidson, *supra* note 81, at 314 (discussing how loan-level data can better predict prepayment risk than pool-level data).

85. *Id.* at 38.

guarantees and bond insurance serve the same function: the guarantor or bond insurer would promise to make certain payments to investors on the securities if the SIV failed to do so, and in exchange, the guarantor or insurer would receive a premium. Of course, to adequately price their premium, the guarantor or insurer would need to apply a risk model to assess the risk of non-payment by the SIV.⁸⁶

In the United States, there is little direct regulation of the supply side of securitization—for example, regulations governing the structure of securitizations or specifying which models the sponsors of securitizations must use. For the supply side of securitization, there is not so much active outsourcing of regulation as an absence of regulation. The SEC does regulate disclosure to investors of asset-backed securities. But the SEC’s Regulation AB, promulgated in 2005, focused principally on SEC registered securitizations and generally did not address the majority of asset-backed securities that are privately placed.⁸⁷ Instead, regulation of securitization occurs indirectly, through banking and other regulations that restrict the investments that banks and other institutions may make. This demand-side regulation, outlined in the next subsection, outsources significant responsibility for overseeing the risk transfers of securitization to rating agencies.

iii. Purchasers of Asset-Backed Securities: Rating Agencies, Regulated Financial Institutions, Risk Management, and Basel II

Thus far, this Article has considered the use of code by those who put together securitizations. But code also plays an integral role in the decisions by investors to purchase these securities, even when investors do not use their own proprietary computer models to price securities.

1. Rating Agencies

Instead, investors in asset-backed securities rely heavily on rating agency analysis. Moreover, regulators outsourced to rating agencies a large measure of oversight over the risk that these investors take on.⁸⁸ In

86. Kendall, *supra* note 76, at 4 (describing insurers’ methods for determining excess collateral or guaranty policy, including relying on body of historical data).

87. Asset-backed Securities, Securities Act Release 33-8518, Exchange Act Release 34-50905, 70 Fed. Reg. 1506-01 (Jan. 7, 2005) (codified in scattered sections of 17 C.F.R.).

88. Kenneth C. Kettering, *Securitization and Its Discontents: the Dynamics of Financial Product Development*, 29 CARDOZO L. REV. 1553, 1674–76 (describing rating agencies as “de facto lawmakers”).

many securitizations, rating agencies are paid by the SIV to issue credit ratings of the asset-backed securities. Rating agencies, for example Moody's, Standard & Poor's, and Fitch, then apply their own proprietary risk models to analyze the securitization.⁸⁹ Like those entities that sponsor securitizations, rating agencies rely on the originators to provide information on the underlying assets. Indeed, rating agencies admit to conducting little independent investigation of securitization beyond the information provided to them by either the originators or the firms sponsoring a securitization.⁹⁰ Some rating agencies have even admitted to conducting little analysis of underlying assets.⁹¹

Rating agencies have a poor track record of predicting credit problems; major ratings downgrades on asset-backed securities and corporate debt have come only after the market has already learned that issuers had serious credit problems.⁹² Several explanations have been offered for this failure, including conflicts of interest created by rating agencies receiving compensation from the companies they rate, and the rating agencies having no monetary liability for poor performance.⁹³

Some scholars, notably Frank Partnoy, have persuasively argued that

89. Professors Partnoy and Skeel describe rating agency models as the driving force behind the structuring of securitizations. Partnoy, *supra* note 12, at 664–68; *see also* Partnoy & Skeel, *supra* note 9, at 1029 (analyzing a type of securitization called collateralized debt obligations).

This may represent a slight overstatement of the role of rating agencies. Some securitizations— for example, certain mortgage-backed securities issuances guaranteed by Freddie Mac or Fannie Mae—are not rated. Kendall, *supra* note 76, at 4. Moreover, concerns have been repeatedly raised that rating agencies adjust their ratings and models to fit the demands of securitization sponsors because of inherent conflicts of interest. *See, e.g.*, U.S. SECURITIES AND EXCHANGE COMMISSION, SUMMARY REPORT OF ISSUES IDENTIFIED IN THE COMMISSION STAFF'S EXAMINATIONS OF SELECT CREDIT RATING AGENCIES 31–32 (July 2008) [hereinafter “July 2008 SEC Rating Agency Report”], available at <http://www.sec.gov/news/studies/2008/craexamination070808.pdf>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n89.pdf>. Sponsors of securitizations remain the primary architects of the structure of securitizations. *Id.* at 31.

Even so, structurers and sponsors must anticipate the analysis and concerns of the rating agencies given the fact that ratings are indispensable to attracting certain investors, as described in Part I.B.iii.1 *infra*.

90. Partnoy, *supra* note 12, at 653.

91. In an oft-repeated quote, Yuri Yoshizawa, the head of Moody's derivative group explained the focus of his group's analysis of collateralized debt obligations: “We're structure experts. . . . We're not underlying-asset experts.” Roger Lowenstein, *Triple-A Failure*, N.Y. TIMES MAGAZINE, Apr. 27, 2008, at 36.

92. Partnoy, *supra* note 12, at 621, 642, 661.

93. Frank Partnoy, *How and Why Credit Rating Agencies are Not Like Other Gatekeepers*, in FINANCIAL GATEKEEPERS: CAN THEY PROTECT INVESTORS? 59, 68–71, 83–89 (Yasuuki Fuchita & Robert E. Litan eds., 2006).

regulation is part of the problem.⁹⁴ Instead of creating incentives for better monitoring, regulators have undermined those incentives by granting rating agencies a kind of oligopoly power.⁹⁵ This power stems from the fact that the securitization market, including the market for mortgage-backed securities, focuses largely on institutional investors.⁹⁶ Many of these institutional investors are restricted by regulation to purchasing only securities with an investment-grade credit rating.⁹⁷ Regulations restrict much of the securities investments of many pension funds,⁹⁸ and regulated financial institutions, including banks⁹⁹ and insurance companies,¹⁰⁰ to investment-grade debt. (These restrictions are designed to ensure the safety of an entity's assets, and, in the case of a bank or other regulated financial institution, to mitigate systemic risk.¹⁰¹) The regulations then provide that only rating agencies that have a special license from the SEC as "Nationally Recognized Statistical Rating Organizations" (NRSROs) can give an investment-grade rating.¹⁰² The handful of NRSROs, and the models they use to rate securities, thus possess great responsibility for regulating the riskiness of investments made by a large number of financial institutions.

2. Risk Management

Purchasers of asset-backed securities not only rely on the code of

94. See, e.g., Partnoy, *supra* note 12, at 681.

95. See *id.* at 698.

96. Kendall, *supra* note 76, at 15.

97. James Hedges, *Hedge Fund Transparency*, in HEDGE FUNDS: STRATEGIES: STRATEGIES, RISK ASSESSMENT, AND RETURNS 315, 316 (Greg N. Gregoriou et al. eds., 2003) (discussing regulations that discourage mutual funds from investing in debt below investment grade).

98. GENERAL ACCOUNTING OFFICE, COMMUNITY AND ECONOMIC DEVELOPMENT LOANS: SECURITIZATION FACES SIGNIFICANT BARRIERS 41 n.41 (Oct. 2003).

99. See, e.g., 12 U.S.C. § 1831e(d)(4)(A) (2009) (provision of Federal Deposit Insurance Act permitting insured savings banks to invest in investment-grade debt, *i.e.*, debt securities "rated in one of the 4 highest rating categories by at least one nationally recognized statistical rating organization").

100. Partnoy, *supra* note 12, at 700–01 (1999) (outlining use by state regulators of rating agencies' ratings in insurance regulations).

101. Cf. Viral V. Acharya, A Theory of Systemic Risk and Design of Prudential Bank Regulation (Jan. 9, 2001) (unpublished manuscript) (analyzing whether prudential bank regulations, including limitations on investments, mitigates systemic risk), available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=236401, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n101.pdf>.

102. Partnoy, *supra* note 12, at 623.

rating agencies to make decisions to purchase individual securities; they also rely on a mix of ratings and their own internal models to manage the risk of their overall portfolio. Many large companies, particularly financial institutions, employ sophisticated proprietary computer-based models to manage the credit and market risk of their investment portfolios.¹⁰³ Some financial institutions also sell risk-management software and services to smaller companies.¹⁰⁴ These models often employ many of the devices described above in Part I.A.ii, particularly tools to calculate value-at-risk.¹⁰⁵

Securities law requires only indirect and summary disclosure of the workings of these internal risk models. Federal securities law requires that publicly registered corporations disclose summaries of quantitative data about their market-risk exposure,¹⁰⁶ and publicly registered financial institutions must make additional disclosure.¹⁰⁷ Of course, numerous SEC and accounting rules govern financial statement disclosure of assets and liabilities, and thus give investors information to assess an issuer's credit risk.¹⁰⁸ But disclosure requirements stop short of substantive review. Moreover, these regulations do not require in-depth disclosure of the details of a company's risk modeling. Even the SEC rule on quantitative disclosure of market risk—one of the more explicit regulations—requires simply “a description of the model, assumptions, and parameters, which are necessary to understand” the numeric disclosures.¹⁰⁹

3. *Basel II*

Whereas federal laws on securities disclosure have taken a light

103. GREG N. GREGORIOU, FUNDS OF HEDGE FUNDS 367–69 (2006) (discussing computer-based models used by hedge funds to make investment decisions).

104. See FRANCESCO SAITA, VALUE AT RISK AND BANK CAPITAL MANAGEMENT 96–97 (2007) (describing portfolio risk-modeling programs developed by Credit Suisse, J.P. Morgan and others).

105. *Id.* at 97 (describing J.P. Morgan product features).

106. 17 C.F.R. § 229.305 (2008) (quantitative and qualitative disclosures about market risk). Accounting standards also require disclosure about a firm's market risk. See, e.g., Financial Accounting Standards Board, Original Pronouncements – Accounting Standards as of June 1, 2008, Vol. II, Statement of Financial Accounting Standards No. 133 “Accounting For Derivative Instruments and Hedging Activities” (FAS 133) Paragraph 44 (requiring disclosure in financial statements on market risk for entities with derivative instruments).

107. SEC-registered bank holding companies must also disclose the information required by Guide 3—“Statistical Disclosure by Bank Holding Companies.” 17 C.F.R. §§ 801(c), 231 (2008).

108. See, e.g., FAS *supra* note 106, at ¶ 44.

109. 17 C.F.R. §§ 229.305 (a)(1)(ii)(B), (a)(1)(iii)(C).

approach to regulating risk models, federal banking regulations in the wake of Basel II actively outsource regulatory responsibility for risk management to these models.

This marks a historic shift, as, until recently, banking and insurance laws had never deferred to the internal risk-management models of financial institutions, but instead set capital requirements according to statutory or regulatory formulae.¹¹⁰ One type of U.S. capital requirement, risk-based capital standards, influenced the creation of international risk-based capital requirements in the international Basel Accord of 1988 (now known as “Basel I”).¹¹¹ Under Basel I, bank regulators (including in the United States) set capital requirements to address credit risk according to a fairly mechanical set of formulae that required financial institutions to maintain capital according to the predetermined level of risk associated with different classes of assets on a bank’s balance sheet. Regulations placed assets in different categories and assigned each category a different “risk weight.”¹¹²

Today, Basel II dramatically alters the scale of outsourcing of setting standards for regulatory capital for banks to private-industry risk models in two ways. First, it increases outsourcing of setting capital standards to ratings agencies (and, by implication, their models).¹¹³ Second, it also outsources the ability to set capital requirements to the internal risk models of banks for the first time; Basel II now permits certain large banks to use internal models to set their own regulatory capital requirements.¹¹⁴ These two trends are reflected in a series of two-part rules that Basel II establishes with respect to how national regulators may set bank capital requirements. In the first part of each rule,

110. Federal bank regulators are required to set minimum capital requirements under 12 U.S.C. § 1831o(c)(1)m (2008) and 12 U.S.C. § 3907 (2008).

111. BASEL COMMITTEE ON BANKING SUPERVISION, INTERNATIONAL CONVERGENCE OF CAPITAL MEASUREMENT AND CAPITAL STANDARDS (July 1988, updated to April 1998) [hereinafter “Basel I”], available at <http://www.bis.org/publ/bcbsc111.pdf?noframes=1>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n111.pdf>. For historical background on adoption of this accord, see Joseph Jude Norton, *Capital Adequacy Standards: a Legitimate Regulatory Concern for Prudential Supervision of Banking Activities?*, 49 OHIO ST. L.J. 1299, 1336–42 (1989). See also JONATHAN R. MACEY ET AL., *BANKING LAW AND REGULATION* 281–82 (3d ed. 2001) (discussing history of U.S. risk-based capital standards leading to Basel I).

112. See BASEL I, *supra* note 111, at Part II. Professor Partnoy notes that, historically, numerous U.S. banking regulations have also keyed off of rating agency ratings. Partnoy, *supra* note 12, at 687–89, 691 n.349.

113. See *supra* notes 13 and 15 and accompanying text.

114. Norton, *supra* note 14, at 53–58.

regulators apply a standardized set of capital requirements for most banks (and these standardized capital requirements rely heavily on rating agency determinations). In the second part of each rule, regulators may allow select banks to use their internal risk-models to set capital requirements. Basel II uses this two-part, bifurcated rule on capital requirements to cover credit risk; Basel II supplements a standardized set of rules that rely on rating agencies with a new “Internal Ratings-Based Approach” that allows certain banks to use internal models to set their capital requirements.¹¹⁵ It then uses a similar bifurcated set of rules—a standard approach and an internal-models exception for certain banks—in its separate capital requirements that cover market risk¹¹⁶ and

115. Under the new accord, national bank regulators may apply one of three approaches to setting requirements for the level of regulatory capital that banks must hold to offset credit risk. Each of the following approaches allows regulators to permit banks to use private-sector risk models to make credit risk calculations, which determine the amount of capital required to cover that risk:

1. *Credit-Risk Standardized Approach*: National bank regulators may continue to apply a modified version of Basel I, with its categorical approach to setting capital requirements for credit risk. This “Standardized Approach” categorizes classes of bank assets into “buckets” according to a rough estimate of the credit risk posed by that class. Regulators then assign a fixed risk weight for all assets in a particular bucket. Banks must then maintain a level of capital for each of its assets equal to the value of that asset multiplied by the asset’s risk weight. Basel II, *supra* note 13, at 19–26. The Basel II Standardized Approach keys the risk weights that apply to many of the buckets to rating agency ratings. *Id.* Furthermore, banks may use certain “external credit assessments”—i.e., rating agency ratings—to lower the risk weights (and thus the capital requirements) for certain classes of assets even further below the amount the Accord specifies for a particular bucket. *Id.* at 27–28.
2. *Credit-Risk Foundation Internal Ratings-Based Approach*: Basel II also gives national bank regulators the option to allow a bank to determine credit risk capital requirements using the bank’s internal credit risk modeling, what the accord labels the “Internal Ratings-Based Approach.” *Id.* at 52. The Internal Ratings-Based Approach has two versions. The “Foundation Internal Ratings-Based Approach” gives banks less flexibility in calculating their risk exposure. In calculating expected losses from borrower default on a given asset, banks can use their own internal models to calculate the *probability* of default. But, to calculate the *magnitude* of loss given a borrower default on an asset, banks must use a categorical, risk-weighted number assigned to all assets of the same class. This mirrors the bucket system of the Standardized Approach. *Id.* at 59–60.
3. *Credit-Risk Advanced Internal Ratings-Based Approach*: The “Advanced Internal Ratings-Based Approach,” by contrast, allows banks to use internal models to calculate *both* probability and magnitude of losses from credit risk for purposes of setting risk weights for assets. *Id.*

116. Basel II also take a bifurcated approach to the standard for regulatory capital that banks must hold to offset market risk, establishing both the following standardized and internal model approaches:

1. *Market-Risk Standardized Measurement Method*: Basel II’s standardized method for market risk specifies a complex mix of bucket risk weights and value-at-risk methodology to set capital requirements covering market-risk exposure. National bank regulators must then ensure that banks follow this standard in determining credit-risk exposure, which then determines capital requirements. For sovereign debt and similar assets, the standardized method again piggybacks on rating agency ratings. *Id.* at 166–90.

operational risk, respectively.¹¹⁷

By giving banks the flexibility to adjust their regulatory capital according to a mix of rating agency ratings and the respective banks' internal models, Basel II outsources significant regulatory authority to the models of rating agencies and banks. To be sure, the Accord sets standards for when national regulators may allow banks to use internal models, and requires regulators to audit those models.¹¹⁸ But these lengthy standards give bank regulators significant discretion in both deciding which banks qualify for the privilege to use internal models and in determining when and how to audit the models of those banks.

In December 2007, the principal federal bank regulators—the Federal Reserve Board, Office of the Comptroller of the Currency (OCC), FDIC, and Office of Thrift Supervision—passed a final rule implementing much of the Basel II Accord.¹¹⁹ Even though Basel II is still being implemented, several studies have indicated that the provisions of Basel II that give banks the ability to set their capital requirements according to internal models would lead to substantial declines in regulatory capital and undercapitalization for credit risk.¹²⁰

-
2. *Market-Risk Internal Models Approach*: As with credit risk, Basel II allows national bank regulators to permit qualified banks to use their own internal risk models to determine market-risk exposure. Basel II favors a value-at-risk approach, and sets standards for these internal risk models, but this “Internal Models Approach” gives banks much more flexibility in using their own methodologies than the standardized approach listed above. *Id.* at 191–203.

117. Unlike Basel I, the Basel II Accord requires banks to set aside capital for operational risk. But again, the newer accord takes a bifurcated approach:

1. *Operational-Risk Basic-Indicator Approach & Standardized Approach*: These two approaches require banks to set aside regulatory capital to cover operational-risk exposure based on a fixed percentage of a bank's income in previous years. The principal difference between these two approaches—the Basic-Indicator Approach & the Standardized Approach—is that the Standardized Approach is slightly more nuanced. It disaggregates a bank's income according to different lines of business and sets distinct capital requirement weights for each of those lines. *Id.* at 144–46.
2. *Advanced Measurement Approach*: This approach gives national regulators the flexibility to allow banks under their jurisdiction to use their internal models based on empirical data of the banks' past operational losses to set operational capital. *Id.* at 147.

118. *See, e.g.*, Basel II, *supra* note 13, at Part 3, Section III (specifying supervisory review process that regulators must undertake to review bank compliance).

119. Risk-Based Capital Standards: Advanced Capital Adequacy Framework – Basel II, 72 Fed. Reg. 69,288 (Dec. 7, 2007) (to be codified at 12 C.F.R. pts. 3, 208, 225, 325, 559, 560, 563, 567).

120. After conducting a “Quantitative Impact Study” of the prospective effects of the Internal Ratings-Based Approach, U.S. bank regulators expressed concern that this new rule would dramatically lower regulatory capital. *See, e.g.*, Pamela Martin, *QIS 4: What Do the Numbers Really Mean?*, RMA J., Sept. 1, 2005; *see also* Paul H. Kupiec, *Basel II: A Case for Recalibration* (FDIC Center for Financial Research Working Paper No. 2006-13, 2006), *available at* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=942301, *permanent copy available at*

4. *The SEC, Basel II, and Consolidated Supervised Entities*

The Basel II Accord explicitly addresses only the regulation of banks and not other financial institutions. Moreover, the accord is still being implemented in the United States and elsewhere. Nevertheless, in 2004, the SEC decided to apply Basel II when setting capital requirements for certain large financial-holding companies as part of the Commission's new Consolidated Supervised Entity (CSE) Program.¹²¹ In particular, the SEC allowed these holding companies to use their internal risk models to set their own regulatory capital. The creation of the CSE Program was driven in part by lobbying by large U.S. financial conglomerates for more flexible capital requirements that would give these firms greater ability to compete with foreign competitors.¹²²

Broker-dealer holding companies could opt into this program, after which the SEC would supervise not only registered broker-dealer entities, which it has historically regulated, but unregulated affiliates and the holding-company parents of those broker-dealers. According to the SEC, the program was "designed to allow the Commission to monitor for financial or operational weakness in a CSE holding company or its

<http://www.law.washington.edu/wlr/notes/84washrev127n120a.pdf>; Paul H. Kupiec, *Capital Adequacy and Basel II* (FDIC Center for Financial Research Working Paper No. 2004-02, 2004), available at http://www.fdic.gov/bank/analytical/cfr/2004/wp2004/CFRWP_2004-02_Kupiec.pdf, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n120b.pdf> (concluding that Basel II's Internal Ratings-Based Approach drastically undercapitalizes portfolio credit risk); Paul H. Kupiec, *Capital Allocation for Portfolio Credit Risk* (Dec. 2006) (unpublished manuscript), available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=681201, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n120c.pdf>.

121. Final Rule: Alternative Net Capital Requirements for Broker-Dealers That Are Part of Consolidated Supervised Entities, Exchange Act Release No. 34-49,830, 69 Fed. Reg. 34,428 (June 21, 2004), available at <http://www.sec.gov/rules/final/34-49830.htm>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n121.pdf>.

122. Stephen Labaton, *Agency's '04 Rule Let Banks Pile Up New Debt, and Risk*, N.Y. TIMES, Oct. 3, 2008, at A1.

The program also responded in part to a European Union (EU) regulatory initiative that would give a non-EU financial conglomerate the ability to obtain a single license to operate across the EU, provided that the firm demonstrated that it (*i.e.*, all the firm's affiliates on a consolidated basis) was subject to sufficient regulatory supervision by a single home-country regulator. Unless U.S. financial conglomerates were bank holding companies and thus subject to ultimate supervision by the Federal Reserve, they would not qualify for special EU status. U.S. investment banks not owned by a bank-holding company thus found themselves at a potential regulatory disadvantage. *Id.* See also OFFICE OF INSPECTOR GENERAL, SEC'S OVERSIGHT OF BEAR STEARNS AND RELATED ENTITIES: THE CONSOLIDATED SUPERVISED ENTITY PROGRAM 4 (2008), Report No. 446-B (Sept. 25, 2008), available at <http://www.sec-oig.gov/Reports/AuditsInspections/2008/446-a.pdf>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n122.pdf>.

unregulated affiliates that might place . . . U.S. regulated broker-dealers and other regulated entities at risk.”¹²³ Ultimately, the following seven financial-holding companies, which included the largest U.S. investment-banking firms, joined the CSE program: the Bear Stearns Companies, Inc., Goldman Sachs Group, Inc., Lehman Brothers Holdings Inc., Morgan Stanley, Merrill Lynch & Co., Citigroup Inc., and JP Morgan Chase & Co.¹²⁴

With respect to these CSEs, the SEC took responsibility for setting regulatory capital. But it decided not to apply the same capital-standard regulatory framework that it had applied to SEC-registered broker-dealers before the CSE Program. That standard framework, also known as the Net Capital Rule,¹²⁵ requires that broker-dealers maintain capital according to fairly mechanical financial ratios that vary according to the types of securities business that a broker-dealer is conducting. Instead of this approach, the SEC allowed CSEs to set capital requirements according to internal risk models. After the CSE rules took effect in 2004, the regulatory capital of those entities admitted to the program dropped. At the same time, these firms dramatically increased their level of borrowing to finance investments, as documented by soaring leverage ratios.¹²⁶

The SEC regulations establishing the program included standards for the SEC in both vetting holding companies applying to join the program (including standards for examining the quality of each applicant’s risk-management policies and risk modeling) and auditing those companies that were admitted to the program. The rules also contained a floor below which a CSE’s capital could not fall. In spite of this, a 2008 SEC Inspector General Report detailed significant lapses by the SEC in following its own regulations in vetting program applicants and the adequacy of their risk models, and auditing the risk management and modeling of those firms admitted to the program.¹²⁷

123. OFFICE OF INSPECTOR GENERAL, *supra* note 122, at 4.

124. *Id.* at iv. The SEC exercised direct oversight, including with respect to capital requirements for five of these firms; Citigroup and JP Morgan continued to have the Federal Reserve as their principal regulator. *Id.* at v.

125. Net Capital Requirements for Brokers or Dealers, 17 C.F.R. § 240.15c3-1 (2009).

126. *See* Labaton, *supra* note 122, at A1.

127. *See* OFFICE OF INSPECTOR GENERAL, *supra* note 122, at ix, xi–xii.

iv. Hedging Risks: Derivatives and Hedge Funds

Banks and non-banks alike use not only capital to mitigate risk, but increasingly use derivatives as well. More particularly, banks and other investors have used derivatives to hedge the risks of asset-backed securities in their portfolios—including the credit risk posed by payment default on those securities. The derivatives employed for this purpose and for hedging other risks have become increasingly complex and esoteric over the last fifteen years. During the same time, trading in over-the-counter (OTC) derivatives has skyrocketed.¹²⁸

Simultaneously, the amount of money under management globally by unregulated hedge funds has exploded.¹²⁹ These three phenomena—risks from asset-backed securities, the expansion of derivatives markets, and the growth of hedge funds—are intertwined, as explained in the following paragraphs. Although derivatives can be used for many reasons, they are often used as a consequence of securitization. Investors can hedge the residual credit risk associated with asset-backed securities in their portfolios by entering into a special type of derivative transaction, called a credit default swap, with a counterparty. Under a credit default swap, this counterparty will pay the investor a specified amount upon the occurrence of a contractually defined “credit event,” e.g., non-payment by the issuing SIV on the asset-backed security held by the investor. In exchange for assuming this measure of default risk, the counterparty receives a premium from the investor.¹³⁰ The transaction thus resembles a form of guarantee or credit insurance policy on the asset-backed security.¹³¹

128. BANK FOR INTERNATIONAL SETTLEMENTS, TRIENNIAL CENTRAL BANK SURVEY: FOREIGN EXCHANGE AND DERIVATIVES MARKET ACTIVITY IN 2007, 2–3 (Dec. 2007).

129. John H. Makin, *Hedge Funds: Origin and Evolution*, AEI POLICY SERIES – AEI ONLINE, May 15, 2006, http://www.aei.org/publications/pubID.24395/pub_detail.asp, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washlrev127n129.pdf>.

130. Aaron Unterman, *Exporting Risk: Global Implications of the Securitization of U.S. Housing Debt*, 4 HASTINGS BUS. L.J. 77, 89 (2008).

131. *See supra* note 86 and accompanying text.

Diagram D sketches out the basic economic bargain of a credit default swap.¹³²

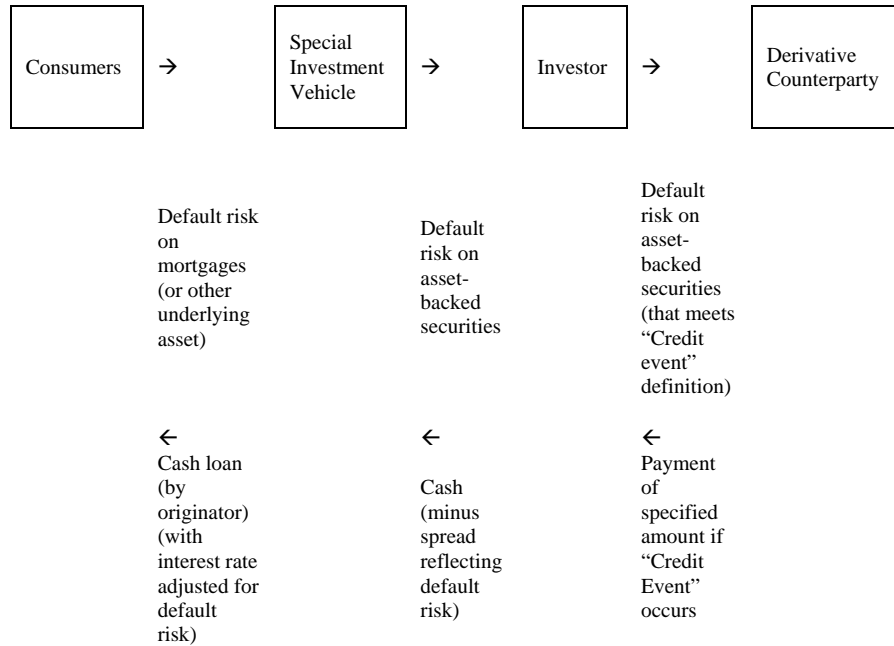


Diagram D

Counterparties thus reap significant rewards but take on significant risks. Because this risk may be too much for regulated financial institutions to bear legally, unregulated hedge funds comprise a significant percentage of counterparties to derivatives.¹³³

Just as in the stages of a securitization, code—in the form of the same types of computer-based risk models—enables and drives hedging. Both

132. For the sake of simplicity, this diagram removes the originator. If the originator is deemed to have made a “true sale” of the assets to the SIV, the assets are no longer considered part of the estate of the originator in bankruptcy. The SIV is then the outright owner of the consumer mortgages, and the originator no longer has any impact on the risk being transferred from borrowers to the SIV and investors. For a discussion of “true sales” in securitizations, see Steven L. Schwarcz, *Securitization Post-Enron*, 25 CARDOZO L. REV. 1539, 1543–48 (2004).

133. For an analysis of the extensive use by hedge funds of credit derivatives, see Noah L. Wynkoop, Note, *The Unregulables? The Perilous Confluence of Hedge Funds and Credit Derivatives*, 76 FORDHAM L. REV. 3095 (2008) (arguing that heavy use of lightly regulated credit derivatives by unregulated hedge funds increases systemic risk).

derivative parties must assess the risks involved to price the contract, yet without sophisticated models, pricing becomes impossible. But modeling becomes more difficult because derivatives lay a further step removed from their underlying assets. Therefore, modeling how risks in the underlying mortgages affect derivatives requires either more powerful models and detailed information on the underlying assets on the one hand, or a set of simplifying assumptions on the other. One simplifying assumption is to rely on previous rating agency determinations; to avoid performing a thorough analysis of the credit risk on the underlying assets, a credit default swap model could simply use a rating agency rating as a proxy for credit risk.¹³⁴

The complexity of credit default swaps and other derivatives led to great deference by regulators, who struggled to keep pace even as derivatives became more complex and the derivative market expanded. Regulators have been reluctant to regulate OTC derivatives for fear of stifling innovation in the spreading of risk.¹³⁵ Regulators have placed great faith in the capacity of the market to self-regulate derivatives, and this self-regulation rests ultimately on the perceived strength of the risk models that are used to price derivatives.¹³⁶

Hedge funds have received similar regulatory deference, as some U.S. regulators have argued that regulation is unnecessary because market counterparties, armed with sophisticated pricing models, provide the necessary discipline against excessive risk-taking.¹³⁷ Meanwhile, the SEC was stymied in its efforts to require hedge funds to register with the Commission and provide basic data to the SEC.¹³⁸

v. *Iterations: CDOs and Derivatives to the nth Power*

The discussion thus far has greatly oversimplified the structure of asset-backed securities and derivatives. For example, securitizations can

134. See Willem H. Buiter, *Lessons from the 2007 Financial Crisis*, CENTRE FOR ECONOMIC POLICY RESEARCH POLICY INSIGHT NO. 18, 2–3 (Dec. 2007) available at <http://www.cepr.org/pubs/PolicyInsights/PolicyInsight18.pdf>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n134.pdf>.

135. See *supra* note 17 and accompanying text.

136. Arthur E. Wilmarth, *The Transformation of the U.S. Financial Services Industry, 1975–2000: Competition, Consolidation, and Increased Risks*, 2002 U. ILL. L. REV. 215, 343–46 (describing flaws in value-at-risk models used to price derivatives, since these models are only “backtested” by regulators).

137. See *supra* note 18 and accompanying text.

138. See *supra* notes 19–20 and accompanying text.

become even more complex when mortgage-backed securities (or other asset-backed securities) are themselves securitized. As Diagram E below illustrates, a new SIV could purchase these mortgage-backed securities and use them as collateral for another securitization, often called a collateralized debt obligation (CDO).¹³⁹

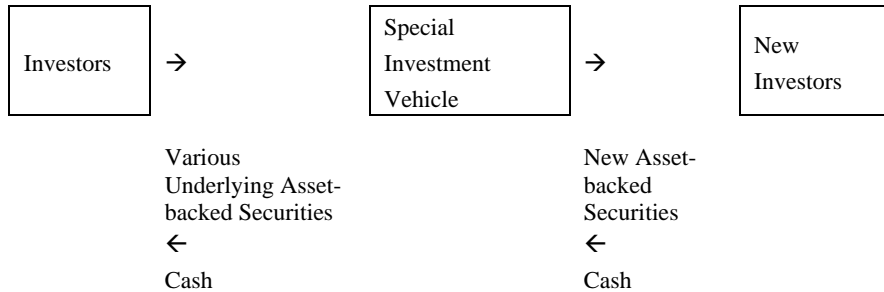


Diagram E

Securities issued in CDOs are often resecuritized themselves, creating what is called a “CDO-squared.”¹⁴⁰ The iterative layering of securitizations of securitizations of securitizations became wildly popular in financial markets in the last seven years.¹⁴¹ Similarly, investors who assumed risks in derivative transactions could then hedge those risks with other derivatives.¹⁴²

But, complexity of securitizations of securitizations and derivatives hedging derivatives makes modeling the risks involved frighteningly difficult. Each layer of a securitization of a securitization moves further away from the underlying assets where risk originates. This makes predicting, for example, the effects of widespread default on the ultimate underlying assets as they cascade through the securitization chain exponentially more complex.¹⁴³

Just as with a basic securitization or credit default swap, modelers looking to measure the credit risk of the securities issued in a CDO-

139. Kendall, *supra* note 76, at 15.

140. Coval et al., *supra* note 77, at 10.

141. Unterman, *supra* note 130, at 70. One presidential commission cited failures of rating agencies to evaluate securitizations of mortgage-backed securities as a key factor in the subprime crisis. President’s Working Group, *supra* note 70, at 449.

142. Hu, *supra* note 9, at 1502.

143. Kendall, *supra* note 76, at 8–11 (describing valuation of “synthetic securities”).

squared face high costs in identifying—let alone finding information about the credit risk posed by—the numerous underlying mortgages and other cash-producing assets that ultimately back the CDO-squared. These modelers again make simplifying assumptions, such as relying on the credit ratings assigned to the securities immediately prior in the securitization chain. Using rating agencies as an analytic shortcut, however, places a great deal of faith in the accuracy and integrity of those ratings.

C. The Crash of the New Financial Code: A Thumbnail Sketch

The proliferation of code throughout the web of financial markets described above in Part I.B had dire consequences, as the crash of multiple codes was a driving factor of the subprime crisis. The crisis has numerous causes and has unfolded (and continues to unfold) in incredibly complex ways that will occupy economists for decades. The following paragraphs present merely a thumbnail sketch of the crisis to highlight the extent to which the various risk models described in Part I.B failed.

The subprime crisis began in 2007, when defaults on ARMs began rising as teaser rates on ARMs expired, leaving many subprime borrowers unable to make payments at the higher reset rate.¹⁴⁴ Rising market interest rates cut off the exit options for borrowers by both making refinancing prohibitively expensive and drying up the resale market; home prices began to level or drop in many markets after years of steady gains.¹⁴⁵ The pricing and risk models of many originators and rating agencies utterly failed to predict the waves of defaults by mortgage borrowers that followed.¹⁴⁶

The wave of defaults swelled enough to affect mortgage-backed securities. First, junior classes plummeted in value.¹⁴⁷ Later waves of defaults undermined the value of senior classes, despite the protections of payment waterfalls and tranching structures.¹⁴⁸ Defaults on asset-

144. Gretchen Morgenson, *Home Loans: A Nightmare Grows Darker*, N.Y. TIMES, Apr. 8, 2007, at C1.

145. *Id.* See also Jia Lynn Yang, *How Bad is the Mortgage Crisis Going to Get?*, FORTUNE, Mar. 31, 2008, at 88.

146. Lowenstein, *supra* note 91.

147. Nelson D. Schwartz & Vikas Bajaj, *Credit Time Bomb Ticked, but Few Heard*, N.Y. TIMES, Aug. 19, 2007, at A1.

148. Greg B. Cioffi, *Collateralized Damage*, DAILY DEAL, Feb. 1, 2008, available at 2008 WLNR 1910083; Robert Stowe, *Anatomy of a Meltdown*, 68 MORTGAGE BANKING 38, Oct. 1,

backed securities triggered guarantees and credit-insurance policies, and unprepared guarantors and credit insurers themselves threatened to falter.¹⁴⁹

Growing losses for financial institutions on mortgages and mortgaged-backed securities created two aftershocks. First, lenders decreased mortgage and other lending, which drove market interest rates higher and started a credit crunch. The higher interest rates created a feedback loop, worsening default rates on ARMs.¹⁵⁰ Second, the plummeting value of asset-backed securities forced many financial institutions to make substantial write-downs of assets on their balance sheets, a process that continues.¹⁵¹ The value of many of these assets has become extremely uncertain, since buyers for asset-backed securities have disappeared.¹⁵² In addition, the iteration of securitization upon securitization meant that default of one class of securitization cascaded and caused losses in subsequent securitizations. The many layers of securitization—CDOs backed by CDOs in an iterative chain—prevented investors later in the securitization chain from calculating the risk they faced from losses on assets earlier in the chain.¹⁵³

The write-down of assets began to affect the creditworthiness, real and perceived, of many institutional investors.¹⁵⁴ Many investors were forced to sell asset-backed securities to improve their balance sheets,¹⁵⁵ but they faced a liquidity risk problem similar to that of mortgage-holders; the initial depression of the prices of asset-backed securities,

2007, available at 2007 WLNR 21537515.

149. Vikas Bajaj & Julie Creswell, *Bond Insurer in Turmoil Turns to Familiar Lender*, N.Y. TIMES, Feb. 20, 2008, at C2.

150. Shawn Tully, *Risk Returns with a Vengeance*, FORTUNE, Sept. 3, 2007, at 50.

151. Charles Duhigg, *A Trickle that Turned into a Torrent*, N.Y. TIMES, July 11, 2008, at C1 (reporting that major banks are writing down twenty to fifty percent of the value of their assets due to losses from mortgage-backed securities).

152. Louise Story, *A Values Debate (Not the Political Kind)*, N.Y. TIMES, May 16, 2008, at C1 (reporting on debate over whether mark-to-market rule in Financial Accounting Statement 157 was leading to overstated write-downs); see also Andrew Ross Sorkin, *Are Bear Counters to Blame?*, N.Y. TIMES, July 1, 2008, at C1 (same).

153. Buiter, supra note 134, at 3. See also Matthew Goldstein & David Henry, *Bear Bets Wrong*, BUSINESS WEEK, Oct. 22, 2007, at 50 (linking Bear Stearns' deteriorating credit situation to uncertain value of "CDO-squared" securities it held).

154. Landon Thomas, Jr., *Run on Big Wall St. Bank Spurs U.S.-Backed Rescue*, N.Y. TIMES, Mar. 15, 2008, at A1 (describing contagious loss of investor and creditor confidence in U.S. investment banks).

155. Liz Rappaport & Justin Lahart, *Debt Reckoning: U.S. Receives a Margin Call*, WALL. ST. J., Mar. 15, 2008, at A1.

combined with the volume of sellers in the market in the same predicament, sent the prices of these securities into a tailspin and dried up liquidity.¹⁵⁶

This created a reputation risk problem for many institutional investors. Creditors, including stock-lending and derivative counterparties, began worrying about the credit risk posed by many institutions and made margin calls.¹⁵⁷ Many large commercial and investment banks were forced to seek emergency equity infusions to shore up their balance sheets, reassure creditors, and meet regulatory capital requirements.¹⁵⁸

A few prominent institutions failed in their attempts to stay afloat.¹⁵⁹ Threats to the solvency of financial institutions and hedge funds created fears of systemic risk and threatened to cause the collapse of other institutions because of the domino effects of credit and counterparty risk. Failure of one firm could trigger the collapse of other institutions because of the complex web of counterparty risk created by derivatives.¹⁶⁰ Moreover, the contagion of depositor or creditor panic exacerbated reputation and systemic risk.¹⁶¹

Some of the most prominent financial institutions that fell victim to the crisis were the financial conglomerates that were able to lower their regulatory capital and increase their leverage under the SEC's CSE Program.¹⁶² The failure or threat of failure to these large institutions, including Bear Stearns and Lehman Brothers, prompted extraordinary federal intervention into financial markets.

A full listing, let alone explanation, of all these interventions is beyond the scope of this Article (and new massive interventions

156. See, e.g., Jenny Anderson, *Hedge Funds Are Squeezed by Investors and Lenders*, N.Y. TIMES, Aug. 20, 2007, at C1.

157. *Id.*

158. See, e.g., Eric Dash, *IndyMac Announces It Will Close Lending Units and Cut Half of Its Work Force*, N.Y. TIMES, July 9, 2008, at C3; David Jolly, *After Losses, UBS Seeks to Raise \$15 Billion*, N.Y. TIMES, May 23, 2008, at C5.

159. Goldstein & Henry, *supra* note 153 (reporting on bailout of Bear Stearns); Dash, *supra* note 158 (reporting on insolvency of IndyMac Bank).

160. Herring & Schuermann, *supra* note 45, at 22 (discussing systemic risk threat posed by securities firms by virtue of OTC derivatives activity).

161. Vikas Bajaj & Julie Creswell, *Bear Stearns Staves Off Collapse of 2 Hedge Funds*, N.Y. TIMES, June 21, 2007, at C1 (reporting that potential failure of Bear Stearns' hedge fund raised investor concerns over systemic risk).

162. See Labaton, *supra* note 122, at A1; Stephen Labaton, *S.E.C. Concedes Oversight Flaws Fueled Collapse*, N.Y. TIMES, Sept. 27, 2008, at A17.

continue to take shape even as it goes to press). Nevertheless, the sheer scope of the federal intervention and the magnitude of financial-institution losses provide lurid evidence of the systemic failure of financial-institution risk models; these models failed to measure the risk of default by mortgage borrowers, price asset-backed securities or derivatives proportionate to their true risks, or ensure adequate hedging and risk management by financial institutions.¹⁶³

The failures of these risk models also signal a failure of the government agencies that outsourced financial regulatory responsibility to the models. As but one example, the SEC's CSE Program has come under withering criticism, including from the Commission's own Office of Inspector General. In a September 2008 study of the SEC's contribution to the collapse of Bear Stearns, the Inspector General criticized the program for allowing CSEs to lower capital to inadequate levels. The study criticized the SEC for failures in both vetting firms (including vetting their risk models) that applied for CSE status and auditing firms (and their risk modeling) once they became CSEs.¹⁶⁴

D. Historical Parallels: The 1987 Crash and the Failure of Long-Term Capital Management

Two financial crises in the last two decades—the 1987 stock market crash and the demise of Long-Term Capital Management in 1998—have sobering parallels to the current crisis. In both earlier events, as in the ongoing “subprime” episode, flawed financial modeling enabled by sophisticated software exacerbated a market crisis, with regulators left unprepared.

i. The 1987 Crash

The 1987 stock market crash was aggravated, if not caused by, the widespread use of novel forms of computer-based hedging of risks called portfolio insurance and program trading.¹⁶⁵ Regulators and

163. Joe Nocera, *Risk Mismanagement*, N.Y. TIMES MAGAZINE, Jan. 2, 2009, at 26–33, 46, 50.

164. See OFFICE OF INSPECTOR GENERAL, *supra* note 122, at 17–23 (criticizing of vetting of CSE risk assessment); 24–27 (criticizing of vetting of CSE risk modeling).

165. Ross M. Miller, *The Leap from Free Markets to Autonomous Markets*, 63 J. ECON. BEHAV. & ORG. 295 (2006); see also Arthur E. Wilmarth, Jr., *The Transformation of the U.S. Financial Services Industry, 1975–2000: Competition, Consolidation, and Increased Risks*, 2002 U. ILL. L. REV. 215, 341.

scholars blamed the crisis on financial institutions that had placed their risk hedging on virtual autopilot.¹⁶⁶ Poorly understood computer-based models were allowed to set major investment and risk management decisions.¹⁶⁷ Homogeneity in these models, combined with poor operational oversight, led many institutional investors to begin selling off the same assets simultaneously at the occurrence of what seemed to be a minor market blip.¹⁶⁸ This caused falling stock market indexes to drop precipitously.¹⁶⁹ In the aftermath, studies criticized regulators for failing to understand and adequately regulate portfolio insurance and program trading.¹⁷⁰

ii. *The Collapse of Long-Term Capital Management*

Misplaced faith in computer-based risk models led to another dire financial crisis over a decade after the 1987 Crash, when the Long-Term Capital Management (LTCM) hedge fund collapsed in 1998. This fund had used mathematical models to set investment strategies in exotic financial products, including asset-backed securities.¹⁷¹ The principals of the fund believed that they could identify outsized profit opportunities with minimal risk because their computer-based models could calculate risk with precision based on massive amounts of data on historic market volatility.¹⁷² But these models made many assumptions, including that:

- future market movements would follow historical patterns;
- historical market data inputted into the models covered a sufficiently long period of time;
- market losses were essentially random instead of correlated; and
- the distribution of gains and losses followed a normal distribution.¹⁷³

166. Miller, *supra* note 165.

167. For an account of the role of portfolio insurance in the 1987 crash, see generally RICHARD BOOKSTABER, *A DEMON OF OUR OWN DESIGN: MARKETS, HEDGE FUNDS, AND THE PERILS OF FINANCIAL INNOVATION* 9–31 (2007).

168. *Id.* at 17.

169. *Id.* at 17–24.

170. See generally David D. Haddock, *An Economic Analysis of the Brady Report: Public Interest, Special Interest, or Rent Extraction*, 74 *CORNELL L. REV.* 841 (1989).

171. ROGER LOWENSTEIN, *WHEN GENIUS FAILED: THE RISE AND FALL OF LONG-TERM CAPITAL MANAGEMENT* 62–69 (2000).

172. *Id.* at 63–65.

173. *Id.* at 64–77. LTCM's models also assumed that the volatility of any security remains

Based on these assumptions, LTCM assumed it could effectively manage a portfolio of complex financial instruments with little risk; if markets moved according to LTCM's models, the fund could readjust its portfolio and enter into and unwind hedges before it incurred major losses.¹⁷⁴

These assumptions and the core faith of LTCM and its investors in the perfection of the fund's models proved disastrously misplaced. Russia's unexpected default on its sovereign debt in August 1998 caused enormous and historically unusual volatility across the world's capital markets and a sudden, sharp increase in credit spreads.¹⁷⁵ This unexpected movement in credit markets caused massive losses for LTCM.¹⁷⁶ Fear that these losses would lead to the cascading failures of major financial institutions prompted the Federal Reserve to orchestrate a bailout of the fund by major investment banks, many of whom faced potentially massive losses due to trades with LTCM.¹⁷⁷

II. MODEL RISK: DIAGNOSTICS ON THE CRASH OF CODE

The scope of the current global financial crisis and the necessity of massive government intervention demonstrate the failure of the risk models throughout the web.

This Part seeks to explain several of the weaknesses inherent in these models—the new financial code—that contributed to this failure. Given that the crisis continues to unfold, and collecting extensive empirical data on model failures remains a work in progress, this Part does not attempt to quantify the relative causal contributions of any one of these weaknesses to the crisis. Instead, it provides a typography of various flaws that contributed to yet another risk—“model risk,” which describes potential losses due to inaccurate risk models themselves.¹⁷⁸

constant and that securities trade in “continuous time” with no significant gaps between the posting of new prices for securities. *Id.* at 68.

174. *Id.* at 68.

175. *Id.* at 140–41, 144–45.

176. *Id.* at 145–47.

177. *Id.* at 185–218.

178. For a discussion of model risk, see Toshiyasu Kato & Toshinao Yoshida, *Model Risk and Its Control*, BANK OF JAPAN MONETARY AND ECONOMIC STUDIES (Dec. 2000), available at <http://www.imes.boj.or.jp/english/publication/mes/2000/me18-2-5.pdf>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n178a.pdf>; see also Ingo Fender & John Kiff, *CDO Rating Methodology: Some Thoughts on Model Risk and Its Implications* (Bank for International Settlements, Working Paper No. 163, 2004), available at <http://papers.ssrn.com/>

These flaws fall into two broad categories: flaws in the technical design of the models, and flaws stemming from the skewed incentives of the parties who select, implement, and use those models. These two sources of weakness are difficult to disentangle. Indeed, aspects of risk-modeling technology, including its inherent complexity, can facilitate its manipulation by self-interested actors. Part II.A examines the failure of the new financial code starting from the vantage point of flaws in technical design. Part II.B analyzes the “user interface” of the code, with a primary focus on the agency costs that affect the incentives of those individuals working in financial institutions who select and use different risk models.

A. *Design Flaws*

i. *Non-Robust Model Assumptions*

The most simple and, at the same time, most complex explanation for the failure of codes is that they were built on flawed assumptions. These models, like any financial or scientific models, make simplifying assumptions about market behavior in order to generate predictions in the face of complexity. Policymakers and scholars have speculated that the root of the failure of risk modeling was simply non-robust assumptions and inadequate stress testing,¹⁷⁹ and back testing¹⁸⁰ of models to root out these faulty assumptions.¹⁸¹

Some policymakers and scholars have faulted the value-at-risk models used by financial institutions for having improper parameters, such as too low of a confidence interval or an unrealistic assumption of the length of the period in which the institution would hold the investment portfolio.¹⁸² Other critics fault modelers for not going back

sol3/papers.cfm?abstract_id=623662, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n178b.pdf>.

179. *See supra* note 53 and accompanying text for a definition of stress testing.

180. *Id.*

181. Oddly, though one of the most outspoken champions of the capacity of risk models (and other aspects of the new financial code), Alan Greenspan (*see supra* notes 17 and 21) now attributes the cause of the subprime crisis to flaws in risk-model assumptions. Alan Greenspan, *We Will Never Have a Perfect Model of Risk*, FIN. TIMES, Mar. 16, 2008; *see also* Jón Danielsson, *Blame the Models*, __ J. FIN. STABILITY __ (forthcoming 2008) *available at* <http://risk.lse.ac.uk/rr/files/JD-33.pdf>, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n181.pdf>.

182. The basic construction of a value-at-risk model is outlined in notes 48–51 *supra*.

far enough in history to gather loss data to be inputted into the model.¹⁸³ Indeed, small sample sizes of historical losses can skew results.¹⁸⁴ For example, a model used in 2006 based on data on market movements in the previous seven years would have missed valuable data points such as the 1998 LTCM crisis.¹⁸⁵ If that same 2006 model had used data from the previous 15 years, it would not have factored data from the 1987 stock-market crash.¹⁸⁶ Some policymakers and scholars also fault models that do not capture risk probabilities that have “fat-tails,” i.e., for not properly measuring lower-probability, but high-magnitude risks.¹⁸⁷

Economists have noted that small errors in assumptions in modeling the risk of the assets underlying a securitization can lead to dramatic errors in modeling the risk associated with asset-backed securities. This initial error is magnified further when modeling the risk of securitizations of those asset-backed securities (CDOs), and magnified even more for subsequent securitizations (CDOs-squared).¹⁸⁸

These technical flaws can be solved with technical fixes, including stress testing value-at-risk determinations using different confidence levels and different model assumptions.¹⁸⁹ However, the argument that risk model approaches basically work, but that technical glitches need to be fixed, offers a dangerously incomplete account of the current financial crisis. The fact that so many financial institutions incurred such large losses (forcing the federal government to make unprecedented interventions in the market) suggests that there was something systemically wrong with either the models or their implementation.

183. BASEL COMMITTEE ON BANKING SUPERVISION JOINT FORUM, CROSS-SECTORAL REVIEW OF GROUP-WIDE IDENTIFICATION AND MANAGEMENT OF RISK CONCENTRATIONS (Apr. 2008), available at http://www.iaisweb.org/__temp/Cross-sectoral_review_of_group-wide_identification_and_management_of_risk_concentrations_April_2008.pdf, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n183.pdf>.

184. See BASEL COMMITTEE ON BANKING SUPERVISION JOINT FORUM, CONSULTATIVE DOCUMENT: PROPOSED REVISIONS TO THE BASEL II MARKET RISK FRAMEWORK (July 2008) (proposing standards for quality control of market risk models).

185. See *supra* Part I.D.ii.

186. See *supra* Part I.D.i.

187. Daníelsson, *supra* note 181.

188. Coval et al., *supra* note 77, at 10.

189. More complicated statistical methods, including Extreme Value Theory, can build further nuance into models to compensate for the potential of “fat-tails.” For a detailed academic work on such statistical techniques, see PAUL EMBRECHTS ET AL., MODELLING EXTREMAL EVENTS FOR INSURANCE AND FINANCE (2003). Technical fixes and additional stress testing and back testing appears to be the approach favored by the Basel Committee on Banking Supervision. See, e.g., *supra* notes 183–184.

ii. *The Radical Critique: The Failure of Models in the Face of Uncertainty*

In stark contrast to the previous explanation, Nicholas Taleb presents a more radical technocratic critique of risk modeling, namely that value-at-risk determinations, including those based on Monte Carlo simulations, are deeply flawed because future losses are unknown and unknowable and cannot be predicted based on historical patterns. In other words, Taleb argues that losses in the future are characterized by “uncertainty” rather than “risk.”¹⁹⁰ He claims that markets continue to evolve and defy historical patterns; “one-hundred-year floods” (what he has famously labeled “black swans”) occur frequently, but the timing, magnitude, and the exact mix of risks posed by these crises defy prediction and probabilistic thinking. Therefore, even sophisticated probabilistic models, such as value-at-risk determinations, according to him, are useless.¹⁹¹

While philosophically provocative, Taleb’s radical critique has uncertain practical implications. If losses are inherently unknowable, it is unclear how investors would ever estimate losses or even make basic investment decisions. It is also unclear how regulators should establish risk regulations, such as traditional regulatory capital requirements.

iii. *Risk Correlation*

There is another fundamental problem with value-at-risk modeling practice that is less ethereal than Taleb’s critique. Risk models often underestimate or completely overlook the correlation of losses among various assets pooled together—whether they are mortgages pooled together to back mortgage-backed securities, or different assets held in a diversified investment portfolio. A high correlation of losses for different assets pooled together means that when losses do occur, they can be massive. A loss on one asset may not be offset by gains on other assets. High correlation of losses—when it rains, it pours—undermines the foundations of diversification and risk pooling on which effective risk management depends.¹⁹²

190. See *supra* note 29 and accompanying text.

191. Nicholas Taleb & Avital Pilpel, *Epistemology and Risk Management*, RISK & REG. (Summer 2007), available at <http://www.lse.ac.uk/resources/riskAndRegulationMagazine/magazine/summer2007/epistemologyAndRiskManagement.htm>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n191.pdf>.

192. Martin Hellwig, *Systemic Risk in the Financial Sector: an Analysis of the Subprime-*

Effective securitization also depends on low correlation of losses on underlying assets. In other words, one of the key benefits of securitization—diversification by pooling assets—may rest on the unfounded assumption that losses on those assets are not correlated. Several economists have noted how the current crisis revealed the fallacy of this assumption. The error in this assumption led to massive losses because of the way in which errors in assumptions with respect to underlying assets are compounded as those assets are securitized and re-securitized.¹⁹³

iv. Spillover Effects and Feedback Loops

Losses within different asset classes—mortgages, mortgage-backed securities, other asset-backed securities—can become highly correlated for several reasons. First, financial losses on one asset can have spillover effects and drag down the value of similar assets. For example, a foreclosed home lowers the value of neighboring properties. Securities that fall in price may drag down the prices of similar securities, particularly when investors do not have adequate information to distinguish how underlying risks may differ among securities. A lack of distinguishing information may lead even rational investors to join a sell-off. Prospects of a deep sell-off increase due to fear by individual investors that other investors will sell.¹⁹⁴

A second form of spillover effect occurs when losses do not stay in the tidy boxes of risk categories outlined in Part I.A.i—credit risk, market risk, liquidity risk, etc.¹⁹⁵ Instead, losses that fall within one

Mortgage Financial Crisis 16 (Nov. 2008) (Max Planck Institute for Research on Collective Goods Bonn 2008/43), *available at* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1309442, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n192.pdf>. *See also* Coval et al., *supra* note 77, at 27–28.

193. Coval et al., *supra* note 77, at 10.

194. Mitchell Y. Abolafia & Martin Kilduff, *Enacting Market Crisis: the Social Construction of a Speculative Bubble*, 33 ADMIN. SCI. Q. 177 (1988). A sell-off need not be explained solely by irrational panic driven by behavioral biases. Investors who sell off may be completely rational in seeking to avoid losses driven by other investors selling in a panic. Information cascades may also offer a partial explanation. Michael P. Dooley & Carl E. Walsh, *Academic Views of Capital Flows: an Expanding Universe*, Reserve Bank of Australia Conference Volume, 89, 100 (1999), *available at* <http://www.rba.gov.au/publicationsandresearch/Conferences/1999/DooleyWalsh.pdf>, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n194.pdf>.

195. Some scholars have argued that because one particular financial loss may qualify as both a credit risk and market risk, models may therefore double-count risk and lead to overly conservative risk management. Bhala, *supra* note 10, at 149–51.

category of risk may spill over and trigger losses from an altogether different form of risk. Consider the following characterization of the spreading financial crisis described in Part I.C:

- *Market risk triggers credit risk:* An unexpected rise in interest rates causes borrowers to default on obligations or become insolvent. This causes their lenders and derivative counterparties to realize credit risk.
- *Credit risk triggers liquidity risk:* The increased credit risk on lenders and counterparties causes them to sell assets to prevent a decline in their own creditworthiness. Market-wide sell-offs of the same class of assets cause prices of those assets to plummet and magnify liquidity risk.
- *Liquidity risk feeds back into credit and market risk:* Plummeting prices from asset fire sales cause holders of those assets to realize additional market risk. The inability of firms to sell assets at historical market prices also deteriorates their creditworthiness and increases the credit risk of their creditors.
- *The above risks compound reputation and systemic risk:* A financial institution's deteriorating creditworthiness (or even *apparent* deterioration among *other* firms) can cause a run on the institution. Runs on multiple financial institutions worsen systemic risk.

The foregoing example demonstrates that spillover effects may create feedback loops. If rising interest rates increase mortgage defaults, which cause larger losses to lenders, who consequently cut back on extending new credit, then interest rates will rise further and provide more fuel to the cycle.

Moreover, the foregoing example illustrates how spillover effects and feedback loops can also transform credit risk and market risk into more complex forms of risk, such as liquidity risk. In the current crisis, when credit and market risk led to sufficient defaults in mortgages and asset-backed securities, owners of both foreclosed properties and asset-backed securities struggled to find buyers for their assets.¹⁹⁶ A loss of liquidity caused markets and credit to seize up, making assets extremely difficult to value and, in some cases, worthless.¹⁹⁷

196. *See supra* note 156 and accompanying text.

197. *See supra* note 152 and accompanying text.

Yet liquidity risk can arise from complex interactions of market and credit risk, including when one form of risk has spillover effects on another or exacerbates the other through feedback loops. Accordingly, it is extremely difficult to model liquidity risk, and the models have not developed to anywhere near the extent of models for credit and market risk. For similar reasons, systemic risk—the granddaddy of all risks—also proves resistant to modeling.¹⁹⁸ Risk models (and regulations) that segregate risks into separate analytic categories of credit, market, and other forms of risk can severely underestimate risk.¹⁹⁹

Homogeneity among risk models exacerbates this problem as it means models at different firms miss the same risks, creating universal blind spots. As Part II.B.vi explains, homogenous risk models also translate into homogenous risk-management practices, meaning that investor reactions to market downturns will be highly synchronized, thereby deepening market disruption.

v. *Interface Between Codes: Information Gaps*

Assuming that originator models were highly robust and based on correct information and extensive data, other financial institutions down the securitization chain often lacked access to these models or their data. Each separate stage in the securitization process creates information gaps; as mortgages are transferred from borrower to originator to SIV to investors, information on the risk of those mortgages is progressively “destroyed.”²⁰⁰ As in a child’s game of “telephone,” the end investors of a securitization receive poor information about the underlying assets.²⁰¹ But even these investors have better information than their counterparties in a credit default swap.

Investor and hedge counterparties alike may take an analytic shortcut by relying on the ratings of rating agencies. Rating agencies also suffer

198. Andrew Haldane et al., *Financial Stability and Bank Solvency*, in SYSTEMIC FINANCIAL CRISES: RESOLVING LARGE BANK INSOLVENCIES 83, 109–10 (Douglas D. Evanoff & George G. Kaufman eds., 2005) (noting methodological challenges to measuring systemic risk).

199. Of course, some scholars argue that segregating risk into different types and different models may lead to overestimation of risk because separate credit and market risk models may overlap and capture the same losses—ultimately leading to double-counting and excessive capital requirements. See Bhala, *supra* note 10, at 150–51. But this contention assumes that the separate models capture the non-linear interactive effects of risks (or, more precisely, that the amount of double-counting outweighs the amount of undercounting).

200. Buiter, *supra* note 134, at 3–4.

201. *Id.*

from asymmetric information, however, and critics have been faulted for a dismal performance in predicting credit problems.²⁰² Part II.B.iv explains how the incentives of originators and rating agencies exacerbated the loss of information in the gaps between models.

vi. *Flaws in Modeling Human Behavior*

1. *Bounded Rationality: The “Killer App” for Behavioral Law and Economics*

At its core, modeling financial risk faces the challenge of modeling individual behavior. For example, securitization begins with models and marketing code employed by originators to determine which loans consumers will purchase, and when consumers will default. Further down the chain, risk-management models employed by financial institutions must factor in how other investors will buy and sell asset-backed securities to calculate market risk and liquidity risk. Modeling behavior is greatly simplified by assuming individuals are rational actors.

But behavioral economics has offered substantial empirical and experimental evidence that the rationality of individuals is bounded. Pioneering work in psychology demonstrated that individuals exhibit various cognitive biases, such as overconfidence, over-optimism and the availability bias, and employ heuristics to estimate probabilities.²⁰³ Consumer-law scholars have argued that these examples of bounded rationality-lead consumers to make suboptimal borrowing choices and to choose financial products that are not in their long-term self interest.²⁰⁴ Behavioral-finance scholars have posited that bounded rationality causes investors to make suboptimal investment choices and leads to financial-market failures.²⁰⁵ A subsequent wave of behavioral-economics scholarship, particularly in behavioral finance, tied behavioral biases to financial-market anomalies that cannot be squared with rational investor behavior and market efficiency.²⁰⁶ In recent years, economists and legal

202. Partnoy, *supra* note 12, at 658–61.

203. Christine Jolls et al., *A Behavioral Approach to Law and Economics*, 50 STAN. L. REV. 1471 (1998).

204. See, e.g., Willis, *supra* note 63.

205. See *supra* note 6 and accompanying text.

206. Nicholas Barberis & Richard Thaler, *A Survey of Behavioral Finance*, in 1B HANDBOOK OF THE ECONOMICS OF FINANCE 1054, 1075–1105 (George M Constantinides et al. eds., 2003).

scholars have explored the particular behavioral biases that affect individuals in the real-estate and subprime-mortgage markets.²⁰⁷

Behavioral economics has faced trenchant criticisms. Notably, Professor Gregory Mitchell²⁰⁸ has argued that behavioral economics presents general tendencies, but has yet to delineate the boundaries of those tendencies.²⁰⁹ In other words, behavioral economics produces evidence that behavioral biases occur, but has not specified when those biases occur.²¹⁰ This failure to specify boundary conditions means that behavioral economics struggles to produce models of human behavior that can lead to testable predictions.²¹¹

This criticism can be flipped and applied not only to the modeling of scholars, but also to the modeling used by financial institutions to predict consumer and investor behavior. Prediction of human behavior by financial modeling is frustrated by the lack of defined boundaries to behavioral biases. This lack of definition obscures the thresholds and magnitude of the effects of behavioral biases. Thus, the higher the probability that a behavioral bias will be salient in a given context, the more uncertainty it threatens to add to risk modeling. Demonstrating the flaws in private industry risk models may prove the “killer application”²¹² of behavioral economics.

Behavioral economics also argues for revisiting the work of consumer law scholars such as Professors Warren, Bar-Gill, and Willis to underscore a nuance in their arguments. When these scholars argue that

207. See Oren Bar-Gill, *The Law, Economics and Psychology of Subprime Mortgage Contracts*, 94 CORNELL L. REV. (forthcoming 2009); Markus K. Brunnermeier & Christian Julliard, *Money Illusion and Housing Frenzies*, 21 REV. FIN. STUD. 135 (2008); Lee Anne Fennell, *Homeownership 2.0*, 102 NW. U. L. REV. 1047 (2008).

208. See Gregory Mitchell, *Tendencies versus Boundaries: Levels of Generality in Behavioral Law and Economics*, 56 VAND. L. REV. 1781 (2003) (arguing that behavioral law-and-economics proponents have documented “tendencies” in behavioral biases, but have yet to specify the “boundaries” of those tendencies, *i.e.*, when, and the extent to which, these biases come into play); Richard A. Posner, *Rational Choice, Behavioral Economics and the Law*, 50 STAN. L. REV. 1551, 1559–60 (1998) (faulting behavioral law-and-economics scholars for failing to offer a theory capable of generating testable predictions that would rival the predictive power of rational-choice economics).

209. Mitchell, *supra* note 208, at 1804–11.

210. *Id.*

211. Gregory Mitchell, *Why Law and Economics’ Perfect Rationality Should Not be Traded for Behavioral Law and Economics’ Equal Incompetence*, 91 GEO. L.J. 67, 122–23 (2002).

212. In its original computer-programming context, a “killer application” (or “killer app”) is a piece of software, the popularity of which drives demand for the underlying platform on which the software runs. STEVE JONES, *ENCYCLOPEDIA OF NEW MEDIA* 172 (2003).

data-mining and computer-based models allow financial institutions to predict consumer defaults, they are writing of a *relative* information advantage compared to consumers.²¹³ The subprime crisis suggests that originator models can also suffer severe flaws in predicting consumer behavior. Severe losses and insolvencies experienced by originators due to mortgages and mortgage-backed securities that they retained suggest that mortgage originators did have an incentive to accurately model consumer behavior, but that they severely miscalculated the level of consumers defaulting on more complex mortgages.²¹⁴

2. *Modeling and Complex Adaptive Systems*

Even assuming the perfect rationality of individuals, models may fail due to the inherent complexity of financial systems. Complexity science is a somewhat amorphous interdisciplinary field in which economists, computer scientists, and natural scientists study how simple interactions between adaptive agents (which could mean anything from investors in a market to organisms in an ecosystem to cells within an organism) can evolve into increasingly complex adaptive systems.²¹⁵ The ability of agents to adapt to the changes in the system, including those caused by the interaction of the agents, leads the overall system—the market, ecosystem or organism—to develop in nonlinear ways.²¹⁶

213. See *supra* notes 62–64, and accompanying text.

214. John Kiff & Paul S. Mills, *Money for Nothing and Checks for Free: Recent Developments in U.S. Subprime Mortgage Markets*, (IMF Working Paper No. 07-188, 2007), available at <http://www.imf.org/external/pubs/ft/wp/2007/wp07188.pdf>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n214.pdf>.

215. Complex adaptive systems are systems in which multiple independent agents interact with one another. The capacity of the agents to adapt to changes in the system causes the system to evolve into progressively more complex forms and to change in a non-linear manner. Simon A. Levin, *Complex Adaptive Systems: Exploring the Known, Unknown and the Unknowable*, 40 BULL. AM. MATH. SOC'Y 3, 4 (2002) (defining complex adaptive systems).

216. *Id.* The complex interactions of agents on the micro level frustrate the prediction of changes to the overall system due to a feature of complex adaptive systems called “emergence.” Emergence has been defined as:

[T]he appearance of unforeseen qualities from the self-organizing interaction of large numbers of objects, which cannot be understood through study of any one of the objects. The key to emergence is understanding that the emergent behaviors of dynamical systems are high-level patterns arising from the indescribably complex interaction of lower-level subsystems. Hence, removing or otherwise changing any interacting component of the system potentially changes the entire system since the interactions leading to the global emergent behaviors may no longer be possible.

J.B. Ruhl, *Complexity Theory as a Paradigm for the Dynamical Law-And-Society System: A Wake-Up Call for Legal Reductionism and the Modern Administrative State*, 45 DUKE L.J. 849, 877–78 (1996) (internal quotations omitted).

A financial market is a complex adaptive system²¹⁷ and may therefore exhibit nonlinear behavior²¹⁸ and suffer bouts of disequilibrium and unpredictable swings.²¹⁹ Accordingly, models of market risk may suffer spectacular failures.²²⁰

The logic of complexity science may have other applications to risk modeling. Risk models and risk management cannot assume a static view of the market. Even acting within a set of risk models and risk-management policies based on those models, individuals at financial institutions have a strong incentive to look for innovative ways to achieve abnormal returns.²²¹ Individuals adapt to the behavior of other players in the market. Individuals also adapt to the set of legal rules designed to constrain their behavior. Their adaptive responses lead to innovations in investment strategies and financial products, which adds new complexities not considered by previous models to the market.²²²

217. See, e.g., Cars H. Hommes, *Financial Markets as Nonlinear Adaptive Evolutionary Systems*, 1 QUANTITATIVE FIN. 149 (2001).

218. Risk models or regulations that rely on linear causality falter when applied to complex adaptive systems. Professor J.B. Ruhl has written extensively on the failures of law to manage non-linear causality. See J.B. Ruhl, *Thinking of Environmental Law as a Complex Adaptive System: How to Clean Up the Environment by Making a Mess of Environmental Law*, 34 HOUS. L. REV. 933, 979 (1997) (criticizing environmental statutes for this flaw).

219. John Foster, *From Simplistic to Complex Systems in Economics*, 29 CAMBRIDGE J. ECON. 873 (2005). Many complex adaptive systems may tend towards disequilibrium because of the concept of emergence (described *supra* note 216). Ruhl, *supra* note 218, at 990–91.

220. See generally Alejandro Reveiz Herault & Sebastian Rojas, *The Case for Active Management from the Perspective of Complexity Theory*, 495 Borradores de Economía, 11 (2008), available at <http://www.banrep.gov.co/docum/ftp/borra495.pdf>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washrev127n220.pdf>. Cf. CARLO C. JAEGER ET AL., RISK, UNCERTAINTY AND RATIONAL ACTION (2001). Legal scholars have analyzed how individuals severely underestimate risk when confronted with complex adaptive systems. E.g., Lawrence A. Cunningham, *Too Big to Fail: Moral Hazard in Auditing and the Need to Restructure the Industry Before it Unravels*, 106 COLUM. L. REV. 1698, 1724–26 (2006) (discussing accounting firms' underestimation of their legal exposure); see also Lawrence A. Cunningham, *From Random Walks to Chaotic Crashes*, 62 GEO. WASH. L. REV. 546 (1994).

221. During asset-price booms, individuals also have a strong incentive to violate internal controls and regulations. See, e.g., Erik F. Gerding, *The Next Epidemic: Bubbles and the Growth and Decay of Securities Regulation*, 38 CONN. L. REV. 393, 424–41 (2006) (analyzing how dynamics of asset-price bubbles and other booms undermine incentives to comply with securities regulation). Non-compliance with laws and other agency costs are discussed in Part II.B *infra*.

222. At the same time, rule-makers and regulators may also be adapting their behavior to meet the adaptive behavior of players in the financial markets. Katharina Pistor & Chenggang Xu, *Incomplete Law — A Conceptual and Analytical Framework and its Application to the Evolution of Financial Market Regulation*, 35 J. INT'L L. & POL. 931 (2003). This adds yet another level of complexity to modeling the behavior of consumers, investors and markets.

One adaptive response is to game-risk models. For example, traders in financial institutions can game-value-at-risk models through a practice called “stuffing risk into the tails.” Under this practice, traders would take “asymmetric risk positions,” *i.e.*, make investments that should average small gains, but have a small probability of very large losses. These large losses lie in the “fat tail” of a loss curve and outside a value-at-risk measurement.²²³

B. User Interface: Human Agency and Agency Costs

The failure of code to adequately model human behavior dovetails with another failure of models in considering the human element. Financial models and other code failed in the subprime crisis not only because of problems with their internal assumptions or with modeling human behavior, but also because of human error in applying the models. The use of the term “code” does not imply that risk models are self-executing. Human agents design, select, and implement models. But along with human agency comes agency costs, as the individuals in charge of designing, choosing, and implementing models can fail to take sufficient care or act selfishly. Agency costs appear first in the design and selection of models and second in how models are implemented.²²⁴

i. Selecting Code: Model Fit or Fitting the Model?

Ideally, individuals who design or select risk and pricing models should choose models based on their accuracy in measuring risk. Instead, evidence suggests that individuals often choose models to justify predetermined business strategies.²²⁵ This risk becomes particularly acute in securitization when firms use a practice known as “mark-to-model” to value underlying assets instead of using market prices.²²⁶ This subversion of the risk-management process stems from

223. Nocera, *supra* note 163, at 46.

224. Regulators have increasingly paid attention to agency-cost theories of explaining rating agency failures during the subprime crisis and have focused, in particular, on potential conflicts of interest created by rating agencies receiving payment from the issuers, whose securities the agencies are rating. *See, e.g.*, July 2008 SEC Rating Agency Report, *supra* note 89, at 23–28, 31–32.

225. Neil Shah, *Can Wall Street be Trusted to Value Risky CDOs?*, REUTERS, July 13, 2007, <http://www.reuters.com/article/reutersEdge/idUSN0929430320070713>, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washlrev127n225.pdf>.

226. One real-estate holding company executive commented on the potentials for abuse with this practice:

When you use a computer model, you’re going to see people make bad decisions . . . Sellers

the pressure on individuals to justify riskier business strategies with higher returns (which, in turn, may increase an individual's compensation).

This bias in selecting models might offer a partial explanation for why the Basel II internal-model approach in the SEC's CSE Program led to investment banks dramatically increasing leverage²²⁷ and having insufficient capital to weather a crisis.²²⁸ If an internal model suggested a higher level of regulatory capital than a standard capital regulation (i.e., a regulation that does not allow a bank to use its internal models, but instead applies categorical risk weights to bank assets), it is questionable whether a financial institution would place itself at a competitive disadvantage and follow the model.

ii. *Implementation Errors*

Even if financial institutions select appropriate models in the abstract, the individuals who write the computer code behind the risk model can make errors. These bugs or implementation errors can propagate themselves when models are copied, and can lead to serious mistakes in computing risk. In 2008, press reports indicated that Moody's blamed a "bug" in some of its computer software for incorrect ratings of several CDOs.²²⁹

iii. *Inputs to Code: Low-Documentation Loans*

Once models have been designed and selected, they require human beings to input information. At this input stage, individuals can subvert the workings of the model by entering incorrect information. Without accurate information, even well-designed models cannot adequately gauge risk. Low-documentation loans—or mortgage loans that were lent without lenders insisting on documentation of the borrower's income or

were incentivized to say the assets were worth a lot, because they made a commission on sales. Many fund managers charge fees in part based on the value of their assets, so they also had incentives to say this stuff was worth a lot. It's not impossible to choose models that support the need for a high-value product.

Tully, *supra* note 150.

227. See Labaton, *supra* note 122 (describing increases in investment-bank leverage in wake of CSE program).

228. Cf. OFFICE OF INSPECTOR GENERAL, *supra* note 122, at xi (recommending that SEC reassess capital requirements in CSE Program in light of Bear Stearns collapse).

229. Sam Jones et al., *Moody's Error Gave Top Ratings to Debt Products*, FIN. TIMES, May 21, 2008.

employment²³⁰—enabled borrowers (or unscrupulous brokers) to supply incorrect information (or no information at all) about income, employment, and other information relevant to establishing a borrower’s creditworthiness. By one estimate, more than fifty percent of subprime loans issued over a two-year period ending in 2007 were made on the basis of such limited documentation.²³¹ These loans greatly increased the credit risk of mortgages and, by extension, related mortgage-backed securities. Consequently, these mortgages defaulted at much higher rates than predicted by rating agency and securitization-pricing models and caused the subprime crisis to mushroom.²³²

The problem of low-documentation loans was enabled by the fact that originators did not insist on documentation, mainly because they transferred the credit risk via securitization. This underscores the need to focus not only on the technical aspects of code, but also on the incentives of actors in designing, inputting data, and using code.

iv. Gaming the Models

As noted above, individuals at financial institutions can also game models by making risky investments designed specifically to avoid detection by the models.²³³

v. Interface between Codes Revisited: Information Destruction & Information Externalities

The problem of low-documentation loans points to a larger problem: different institutions in the securitization and hedging chain may have insufficient incentive to share information they have on the credit risks and other risks with institutions down the chain. Moreover, these institutions have little incentive to share operations of their risk models with one another.²³⁴

This lack of information sharing is suboptimal, as explained by the following discussion of the economic externalities involved with risk modeling. Like risk management in general, the use of effective risk

230. Ann M. Burkhart, *Real Estate Practice in the Twenty-First Century*, 72 MO. L. REV. 1031, 1046 (2007).

231. Alan N. Krinsman, *Subprime Mortgage Meltdown: How Did It Happen and How Will It End?*, 13 J. STRUCTURED FIN. 13 (2007) (discussing data for “past two years”).

232. E. Scott Reckard, *Adjustable Loans Spur New Worries*, L.A. TIMES, Jan. 15, 2008, at A1.

233. Nocera, *supra* note 163, at 46.

234. *See* Buitter, *supra* note 134.

modeling creates positive externalities. A firm that mitigates its own risk reduces credit risk for its creditors.²³⁵ Similarly, systemic risk can be reduced effectively only if institutions throughout the financial system make adequate risk-management decisions. Otherwise, the system is susceptible to domino effects as one institutional failure could cause cascading failures of other firms due to counterparty and reputation risk.²³⁶ Furthermore, providing *information* about a firm's risk models has positive externalities because it allows counterparties and the market as a whole to better evaluate credit risks posed by the firm.²³⁷

Yet firms have disincentives to provide full disclosure about their risk modeling (aside from the fact that they cannot fully capture the benefits of an externality). Detailed information on a firm's risk modeling would allow other firms both to adopt copycat models (and thus free ride on the investment made in constructing the model), and to profit by trading against the firm by reverse-engineering the firm's trading strategies.

On the other hand, incomplete information on a counterparty's risk models reduces the ability of a firm to gather information needed to assess its own credit risk. Moreover, incomplete information may create a lemons problem,²³⁸ if investors or counterparties cannot distinguish firms with good risk models from those with poor ones, even firms with solid models may be assumed to pose excessive credit and systemic risks and may find it difficult to escape the contagion of latter day bank runs.²³⁹ Competent regulators can provide some certification as to the

235. The positive externality becomes clearer when considered in reverse; the financial failure of a firm imposes negative externalities. See GARRY J. SCHINASI, *SAFEGUARDING FINANCIAL STABILITY: THEORY AND PRACTICE* 48–50 (2006).

236. Cf. Schwarcz, *supra* note 39 (positing that because of positive externalities, individual firms have insufficient incentives to mitigate systemic risk).

237. See SCHINASI, *supra* note 235, at 49 (discussing information as positive externality).

238. The “lemons problem” describes how markets can unravel when there are a number of products of varying quality in a marketplace, but consumers cannot distinguish the high-quality products that are more costly to produce (for example, good cars or financial institutions with good risk-management practices) from inferior products produced at lower cost (for example, “lemon” cars or firms with bad risk-management policies). When this situation occurs, consumers will discount the price they are willing to pay for a product and will pay the price for what they perceive to be an average-quality good. This average price will mean sellers of high-quality products will not receive the full value for their products. Many will decide to exit the market (or perhaps produce shoddier, lower-cost products). This will drive the average quality of the product in the marketplace down. This drop in average quality will lead consumers to further discount price, leading above average producers to exit. This creates a vicious cycle. For the seminal work on the lemons problem, see George A. Akerlof, *The Market for “Lemons”: Quality Uncertainty and the Market Mechanism*, 84 Q. J. ECON. 488 (1970).

239. Cf. Guillermo Calvo, *Author's Remarks*, WANTED: WORLD FINANCIAL STABILITY 57

quality of risk modeling, but the failure of regulators to inspect risk models in any depth devalues this certification.

vi. *The Risk of Homogeneity Among Risk Models: An Anti-Coordination Problem*

Even if regulators competently evaluate individual risk models, the interaction of the risk models of different firms creates anti-coordination problems.²⁴⁰ Too much homogeneity among risk-management strategies of financial institutions can increase systemic risk.²⁴¹ If firms have the same strategies and similar portfolios, market shocks can cause the firms to sell the same types of assets at the same time to cover their positions.²⁴² A widespread sell-off would cause values of these assets to plummet and trigger a sell-off of yet another class of assets.²⁴³ Homogeneity of risk management and models can thus lead to spiraling market declines.²⁴⁴ There has been some concern that this is already occurring in the subprime crisis; prices of certain less risky assets have plummeted, as financial firms sell off “good assets” to cover their losses on the “bad.”²⁴⁵ This homogeneity in risk modeling mirrors the risks posed by homogeneity in completely different kinds of systems; for example, homogeneous computer systems are more prone to viruses and security breaches.²⁴⁶

(Eduardo Fernandez-Arias & Ricardo Hausmann eds., 2000) (characterizing cross-border financial contagion, in which financial crises spurred by one sovereign’s default spread to other nations, as a lemon problem).

240. An anti-coordination game is a game in which players adopting the same strategies create losses for all the players. For a more technical definition, see Fuhito Kojima & Satoru Takahashi, *Anti-coordination Games and Dynamic Stability*, 9 INT’L GAME THEORY REV. 667, 668–69 (2007).

241. Carol Alexander, *The Present and Future of Risk Management*, 3 J. FIN. ECONOMETRICS 3 (2005) (positing that regulation may perversely create this homogeneity).

242. *Id.*

243. *Id.*

244. *Id.* The risk posed by homogeneity points to a need for financial institutions and regulators to focus on a second kind of portfolio diversification; each institution needs to analyze not only whether its own portfolio is sufficiently diversified among asset classes, but also whether its portfolio is sufficiently differentiated from the portfolios of other firms in the market.

245. See, e.g., Steven Pearlstein, *Missed Opportunities*, WASH. POST, Aug. 8, 2007, available at 2007 WLNR 15269893.

246. See Rainer Bohme, *Cyber-Insurance Revisited* (2005) (unpublished manuscript), http://www1.inf.tu-dresden.de/~rb21/publications/Boehme2005_CyberInsurance_Revisited_WEIS.pdf, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n246a.pdf>; Rainer Bohme & Gaurav Kataria, *Models and Measures for Correlation in Cyber-Insurance* (June 2006) (unpublished manuscript), <http://www1.inf.tu-dresden.de/~rb21/>

Homogeneity of risk models and risk-management practices has several causes. First, the education of quantitative-finance experts in business schools and economics department can lead to orthodoxies in risk modeling.²⁴⁷ Second, there is a wide literature on herd behavior and mimicry in financial markets.²⁴⁸ If herd behavior leads firms to invest in the same types of assets and firms adjust risk modeling to justify their investment decisions, risk models will tend to converge. Less cynically, if firms find a risk model that gives them a competitive advantage, firms that do not seek to imitate that model may be at a competitive disadvantage. Moreover, widespread reliance on rating agency ratings can create this homogeneity.²⁴⁹

Even disciplined firms that are worried about homogeneity in risk modeling will struggle to ensure that their models are sufficiently different from those of other firms. Without information on the modeling practices of other firms, the anti-coordination problem posed by homogenous modeling is difficult to solve.

vii. *A Coordination Problem Among National Regulators*

In contrast to anti-coordination problems, regulators in different countries face a coordination problem with risk modeling. Under Basel II, banking regulators in each nation have substantial discretion over the extent to which capital requirements may be set according to either internal financial institution models or rating agency ratings. This flexibility permits national bank regulators to refrain (or forbear) from stringently examining and regulating the models used by home-country banks and rating agencies. These banks and rating agencies may press their regulators for lenient treatment in order to take on more risk and make more profit. Yet it is in the collective interest of national regulators to coordinate the level of their regulation—including their level of

publications/BK2006_Correlation_CyberInsurance_WEIS.pdf, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n246b.pdf>.

247. Cf. Nocera, *supra* note 163; Felix Salmon, *Recipe for Disaster: The Formula that Killed Wall Street*, WIRED, Feb. 23, 2009, at 74.

248. ROBERT J. SHILLER, *IRRATIONAL EXUBERANCE* 135–68 (2000).

249. Shadow Financial Regulatory Committee, Statement No. 257: Reliance on Third-Party Credit Ratings 1 (Feb. 11, 2008), *available at* <http://www.aei.org/research/shadow/projectID.15/default.asp>, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n249.pdf> (asserting that widespread use of credit rating models by financial institutions is problematic because the “use of common models is a key source of systemic risk as they are likely to err in the same direction”).

enforcement—to ameliorate systemic risk.²⁵⁰

III. SELECT POLICY AND RESEARCH IMPLICATIONS

Part II examined several factors that contributed to the failure of the new financial code and, consequently, exacerbated the subprime crisis. This final part considers several implications of that analysis for policy and legal scholarship.

Five general points frame the discussion of implications and reverberate throughout Part III. First, law must not defer to the new financial code uncritically. Regulators cannot outsource oversight—whether over consumer lending or over risks posed to financial institutions and global capital markets—to risk models and other codes without thoroughly and continuously auditing those codes. Second, this auditing requires both technical expertise and a constant critical examination of technical assumptions. Regulators cannot abdicate responsibility to examine codes because they are embedded in a complex technology or involve elegant economic models. Third, the best codes are worthless when paired with bad incentives. Codes are designed and used by human agents, which creates agency costs. Codes can only lead to effective risk management with incentive structures that address these agency costs. Fourth, the complexity of code highlights the value of simplicity in the design of both financial instruments and regulation. As engineers have come to realize, sometimes simple designs are the best solutions to complex risks.²⁵¹ Finally, promoting transparency or “openness” in the new financial code promotes efficiency and as well as other normative interests.

A. *Scrapping Basel II's Internal Models Approach*

All five of these general points argue in favor of scrapping those provisions in the Basel II Accord that allow banks to set any capital requirements according to their internal models²⁵² (which this Article collectively refers to as the “Internal Models Approach”).²⁵³ The

250. This coordination problem was the very reason for the first Basel Accord. *See supra* note 13.

251. Henry Petroski has popularized the benefits of simplicity in response to engineering problems. *See, e.g.*, HENRY PETROSKI, INVENTION BY DESIGN: HOW ENGINEERS GET FROM THOUGHT TO THING (1996).

252. *See supra* Part I.B.iii.3.

253. This term thus captures the Internal-Ratings Based Approach for credit risk (*supra* note 115), the Internal Models Approach for market risk (*supra* note 116) and the Advanced

spectacular failure of the proprietary risk models of financial institutions to predict or adequately protect against the current crisis makes entrusting the proprietary risk models of banks with the responsibility of setting regulatory capital seem dangerously misguided. In particular, the dismal record of the Internal Models Approach in the SEC's CSE Program²⁵⁴ provides a warning to U.S. bank regulators to reverse and shelve recent regulations that implement Basel II's Internal Rating-Based Approach.²⁵⁵ Moreover, international bank regulators responsible for the Basel II Accord should revisit the Accord and excise the Internal Models Approach provisions and return to the methods of Basel I for setting regulatory capital.

Basel II should be reversed quickly before it is fully implemented. The SEC's application of the Internal Models Approach led to a disastrous reduction in capital by investment banks.²⁵⁶ Now, because of the ongoing financial crisis, many of those U.S. investment banks have been bought by or converted into commercial banks.²⁵⁷ According to economic studies, Basel II will also lead to undercapitalization when applied to commercial banks.²⁵⁸

Although bank regulators could revise the Internal Models Approach to provide more guidance to national bank regulators on auditing the internal models of banks (as the staff at the Basel Committee on Banking Supervision has already done),²⁵⁹ the fundamental flaws of the Internal Models Approach cannot be overcome. More detailed audit standards would increase the compliance costs to the regulated banks. At the same time, specific rules run the risk of becoming quickly obsolete due to the constant change and increasing complexity of both private industry modeling and financial products.²⁶⁰ Highly specific rules on model standards would also need to be constantly rewritten to address attempts

Measurement Approach for operational risk (*supra* note 117).

254. See *supra* notes 126–127, 164 and accompanying text.

255. See *supra* note 15, at 72 Fed. Reg. 69,288.

256. *Supra* notes 126–127 and accompanying text.

257. Steven Sloan, *Can Even Fed Oversight Alter Investment Banking Giants?*, AMER. BANKER, Feb. 2, 2009.

258. *Supra* note 120.

259. See, e.g., BASEL COMMITTEE ON BANKING SUPERVISION, REVISIONS TO THE BASEL II MARKET RISK FRAMEWORK (Jan. 2009).

260. Shadow Financial Regulatory Committee, Statement No. 238: Basel II: One-and-a-Half Cheers for the Standardized Approach 3 (Dec. 4, 2006), available at <http://www.aei.org/research/shadow/projectID.15/default.asp>, permanent copy available at <http://www.law.washington.edu/wlr/notes/84washlrev127n260.pdf>.

by financial institutions to game the rules.

More detailed rules would also increase the workload of regulators, and financial regulators lack the capacity and incentives to enforce even existing rules. Reviewing the numerous risk models of any one financial institution, let alone back-testing and stress-testing a sample of those models, would require enormous regulator manpower. Regulators responsible for reviewing multiple firms but who are strapped for resources have an incentive to be less rigorous in examining any one firm. Auditing complex models also requires that regulators maintain sufficient technical expertise. Yet regulators face a perpetual disadvantage as the private sector continues to generate technical innovations in financial instruments and modeling.

Even armed with sufficient resources, national bank regulators often lack incentives to audit risk models vigorously. As noted in Part II.B.vii, bank regulators worry whether their foreign counterparts are forbearing from taking regulatory action so as to give their home-country banks a competitive advantage in the international marketplace. Again, this problem was one of the impetuses for the first Basel Accord.

The Basel II Accord makes policing the actions or inaction of regulators even more difficult because of its complexity and lack of transparency. Basel II contains the worst of both rules and standards. It gives national regulators a wide measure of discretion in deciding which banks may use internal models and whether those models satisfy the Accord's standards.²⁶¹ Primary regulatory responsibility can be outsourced to opaque, proprietary models of financial institutions. It is then difficult to assess how thoroughly regulators are auditing these models.²⁶²

Although imperfect, the simpler rules of Basel I have numerous comparative advantages. They are easier to understand, facilitating compliance by banks and auditing by regulators. They are also much more transparent; it is easier not only for regulators to audit a bank, but also for competitors of that bank and regulators in other countries to check whether the bank was cheating (and whether its regulator was adequately performing its job).²⁶³ Furthermore, simpler rules mean that counterparties of banks can more easily understand and model the credit risks posed by banks.

261. *Id.*

262. *Id.*

263. *Id.*

B. *Promoting Open Source Risk Models*

Assuming that Basel II is not repealed, a second-best policy alternative would be to require that banks seeking to use internal risk models for setting their capital requirements publicly disclose the details of those risk models.

i. *The Outlines of an Open-Source Approach*

The disclosure approach to fixing Basel II draws on some of the concepts and arguments that support the open source movement in software.²⁶⁴ Open source software can have different meanings, but a core element of the concept is that the source code²⁶⁵ of the software is openly disclosed.²⁶⁶

This Article's proposal builds on this disclosure element of open source. (Another key element to the definition of open source is that open-source software must be licensed to the public; the license must allow other individuals to use and copy the source code freely and to modify the source code for their own use or for creating derivative software.²⁶⁷ These aspects of open source software are less essential to this paper's proposal.) Here is how disclosure could work with respect to Basel II. Institutions would not be obligated to disclose the internal working of their models; disclosure would be merely a condition of use of these risk models for purposes of setting regulatory capital. In

264. Lawrence Lessig has argued that the transparency of open-source software allows the public to understand and counteract the ways in which internet code allows the private sector and the government to regulate social use of the internet. As noted in the Introduction to this Article, there are parallels between how internet architecture functions as a regulatory code (per Lessig) and how private risk models now function as a new form of financial regulation. *See supra* notes 22–25 and accompanying text.

Lessig's open proposal for checking the regulatory power of internet code has a parallel in this paper's proposal for checking the new financial code. *See supra* note 25 and accompanying text.

265. Source code of software is the text, written in a programming language that is readable to humans and that converts human instructions into computer executions. Apple Public Source License Version 2.0 (Aug. 6, 2003), *available at* <http://www.opensource.apple.com/apsl/>, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n265.pdf>.

266. *See* Open Source Initiative, Open Source Definition (July 7, 2006), <http://opensource.org/docs/osd>, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n266a.pdf>. The Open Source Initiative is a non-profit organization that promotes open source concepts in software, acts as "steward" of the Open Source Definition, and certifies whether software licenses comply with the standards in the Open Source Definition. Open Source Initiative, About the Open Source Initiative (Sept. 19, 2006), <http://opensource.org/about>, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washrev127n266b.pdf>.

267. *See id.*

exchange for this right, institutions would be required to disclose the assumptions, structures, and algorithms used in their models.

To back-test models thoroughly (for the reasons described below), outsiders would also need information about the historic investment portfolio of the financial institution. In addition, gauging the effectiveness of risk models going forward would require some information about the institution's current portfolio, but quite a bit of information on the portfolios of large publicly traded financial institutions is already publicly available online through securities filings.²⁶⁸

ii. The Benefits of Open Source

Using a disclosure-based, open-source inspired approach to fix Basel II would have multiple benefits. First, public disclosure would promote a transparency in risk modeling that would enable the private sector to audit a financial institution's risk modeling. With greater transparency, counterparties could evaluate the adequacy of a financial institution's risk management to assess their own counterparty/credit risk. Opening the source code of risk models would thus mitigate information gaps between the models of different financial institutions, as the counterparties of any bank would better understand the bank's basis for its risk management.²⁶⁹

Public disclosure would also allow an institution's competitors to double-check the work of regulators. Competitors could police whether an institution is "cheating" and adopting weak models to justify taking on additional levels of risk for competitive advantage.²⁷⁰ Policing by a

268. More nuanced and more frequent disclosure (perhaps even close to real-time disclosure) of portfolio information might be facilitated by a recent U.S. securities-disclosure initiative. The XBRL program requires that certain securities issuers present financial data in XBRL format (a special standard for business-related computer files that allows for easy sharing of files among different software applications). This format would facilitate easier uploading of financial disclosures straight from the information systems of a securities issuer to the web and easier downloading of that disclosure by web users straight into analytical software programs. Final Rule: XBRL Voluntary Financial Reporting on the EDGAR System, Securities Act Release No. 33-8,529, Exchange Act Release, 34-51,129, 70 Fed. Reg. 6,556 (Feb. 3, 2005).

Commentators have already lauded the potential of the XBRL Rule to increase transparency in financial markets and allow an "army of citizen regulators" to police risk in financial markets. Daniel Roth, *Road Map for Financial Recovery: Radical Transparency Now!*, WIREd, Feb. 23, 2009, at 81.

269. See *supra* Parts II.A.v and II.B.v.

270. See *supra* Part II.B.vii.

bank's or regulator's competitors would mitigate the problem of regulatory forbearance. Unlike regulators, both counterparties and competitors would have a strong natural incentive to audit a financial institution's risk models thoroughly. Unlike regulators, private auditors would also have sufficient technical expertise.

Another benefit to open-source financial code is that greater disclosure would likely generate more robust financial models—i.e., models with fewer faulty assumptions or otherwise with a lower degree of model risk error. Scholarship in computer science provides evidence that open-source software code is less prone to bugs because open code allows many minds to tackle debugging.²⁷¹

The transparency of open source would help individual financial institutions solve the anti-coordination problems posed by homogenous risk models.²⁷² Even non-banks (which are not subject to Basel II) worried about homogeneity could adjust their own risk models after reviewing open source models.

iii. Potential Drawbacks: Would Open Source Promote Homogeneity?

Opening the source code of financial models faces some potential drawbacks. First, financial institutions would fear surrendering increased profits from proprietary risk models (or even enabling others armed with knowledge of the institution's risk models to trade against them).²⁷³ But this drawback is addressed by the elegance of making opening source code optional. Banks are free to develop their proprietary models. But if they want to use those models to set regulatory capital under Basel II, they must disclose. This might create a powerful disincentive to take advantage of Basel II and use proprietary models to set capital requirements, but this disincentive may be justified given the serious flaws outlined in Part III.A of Basel II's reliance on internal models.

There is a second drawback to the open-source approach; full disclosure of risk models would allow competitors to copy a bank's risk models and imitate their risk-management strategies. This could lead to greater homogeneity in risk-modeling and risk management practices,

271. James W. Paulson et al., *An Empirical Study of Open-Source and Closed-Source Software Products*, 30 IEEE TRANSACTIONS ON SOFTWARE ENGINEERING 246, 252–54 (2004) (finding empirical support for fewer design defects in open-source software than closed-source).

272. *See supra* Part II.B.vi.

273. Another possible, related concern is that dampening the profit motivation to develop risk models might also dampen valuable innovation in risk management.

which, as Part II.B.vi explains, could increase systemic risk.²⁷⁴ This concern is quite valid, but, on the other hand, there is already a large risk of homogeneity in proprietary risk modeling.²⁷⁵ In fact, the risk of homogeneity is heightened under the proprietary approach. Because proprietary models are not publicly disclosed, it is difficult to understand the scope of the current risk. This lack of transparency prevents financial institutions from assessing the risk of whether their internal risk modeling and management are too similar to those of other institutions, raising the anti-coordination problem discussed in Part II.B.vii. Regulators may have access to information about the modeling of different financial institutions, but lack the resources to measure the degree of homogeneity between models adequately. By contrast, greater disclosure of models would allow individual financial institutions, as well as scholars and private watchdogs, to assess thoroughly the risk of homogeneity and raise alarms of increased systemic risk.

iv. Extending the Open-Source Approach

Indeed, to understand the value and risk (including systemic risk) of complex assets, such as asset-backed securities, the marketplace would need greater information about the risk models used by earlier institutions in the chain of securitization. Otherwise, flaws in any model in any link of the long securitization chain (in which mortgages are used to create mortgage-backed securities, which are then used to back CDOs, which then are used to create “CDOs-squared” which are then hedged with credit default swaps) snowball into greater model errors later in the chain.²⁷⁶

Therefore, there is great value in extending the open-source approach all the way back to the data-mining software used to price and structure original consumer mortgages. But encouraging open source of this broader array of risk models would need a different policy lever than the approach outlined above, i.e., using Basel II and the ability to “set your own” capital requirements as a carrot to promote disclosure of models. In short, some degree of regulation would be necessary to require disclosure of the inner workings of those models that are used to price

274. There may be some precedent for open source leading to homogeneity. J.P. Morgan first developed value-at-risk models and then allowed other firms to copy the models, which became an industry standard. Nocera, *supra* note 163, at 33.

275. *Supra* Part II.B.vi.

276. *Supra* note 188 and accompanying text.

asset-backed securities or derivatives.

This extension of the open source approach would have all of the potential efficiency gains outlined above: allowing counterparties and the financial markets to assess the quality of particular firms' risk models, addressing information gaps between models in the chain of securitization and hedging, promoting better, more robust models by allowing many minds to tackle "debugging," and allowing firms to evaluate the risk of excessive homogeneity in modeling.

v. *Open Source and Rating Agencies*

One set of private-industry models, those of rating agencies, would particularly benefit from the open-source approach. Many commentators have noted the dismal track record of rating agencies, particularly with respect to asset-backed securities; there has been a shocking level of default among classes of asset-backed securities with high ratings.²⁷⁷ A full discussion of the potential reasons behind the poor performance of rating agencies is beyond the scope of this Article. But it is clear that either rating agencies are using flawed models to assess the risk of asset-backed securities or they are failing to follow these models when issuing ratings.

In February 2009, the SEC proposed regulations to require that rating agencies disclose certain performance data including statistics tracking the default rates on securities rated by the rating agency.²⁷⁸ This regulation does not go far enough. The SEC should require that registered rating agencies, NRSROs, fully disclose the "source code" of every model (including algorithms and assumptions) used to rate securities. This would allow regulators and investors to assess and troubleshoot flaws in the models used by the rating agencies. The voluntary disclosure made by rating agencies to date, including Standard & Poor's releasing a CDO Calculator,²⁷⁹ does not provide sufficient data.

277. Michel Crouhy et al., *The Subprime Credit Crisis of 07* (July 9, 2008) (unpublished manuscript), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1112467, *permanent copy available at* <http://www.law.washington.edu/wlr/notes/84washlrev127n277.pdf>.

278. *Re-Proposed Rules for Nationally Recognized Statistical Rating Organizations*, Exchange Act Release No. 34-59,343, 74 Fed. Reg. 6,485 (Feb. 9, 2009).

279. *See* Standard & Poor's CDO Interface, <http://www.sp.cdointerface.com/CdoOnlineWeb/login.htm> (last visited Apr. 15, 2009), *permanent copy as site appeared on June 2, 2009, available at* <http://www.law.washington.edu/wlr/notes/84washlrev127n279.pdf>.

Disclosure would not place the NRSROs at a grave competitive disadvantage because of the oligopoly position they enjoy. Again, they enjoy this oligopoly position not only because of the SEC license they hold, but also because myriad financial regulations (including Basel II) place restrictions on financial institutions holding securities other than “investment grade”; these restrictions create a demand for investment-grade securities and for ratings from NRSROs.²⁸⁰

vi. Open Source and Consumer Protection

The open-source model should extend all the way back to the data-mining and credit-scoring software that lenders use to design and market consumer financial products. The Federal Reserve Board recently proposed amendments to Regulation Z (which implements Truth in Lending Act provisions) to improve disclosures to consumers of credit card terms.²⁸¹ Regulation Z and similar regulations could be used to mandate public disclosure by lenders of their data-mining and credit-scoring software and risk models.

Opening the source code of these risk models would allow purchasers of asset-backed securities that are ultimately backed by consumer financial products to gauge the quality of the risk modeling that prices the risk of these products. But opening this source code would have several benefits to consumers as well. First, transparency in data-mining and credit-scoring software would allow consumers to see how financial products transfer risks from financial institutions to consumers. For example, consumers could evaluate risk models used to price adjustable-rate mortgages to determine the extent to which the lender is passing on market risk of interest-rate increases back to borrowers. Similarly, consumers could benefit from access to models used by credit card companies determining which customers should receive complex penalty provisions in their credit card contracts.²⁸² Greater consumer information would allow consumers to detect when lenders are taking advantage of information asymmetries or consumer behavioral biases to

280. See *supra* notes 95–102 and accompanying text. Incidentally, these financial regulations that piggyback on NRSRO ratings may provide another lever to open the source code of rating agencies. If the SEC fails to require that rating agencies open the source code of their models as a condition to NRSRO status, these financial regulations could be amended to specify that acceptable “investment grade” securities would only mean securities given an “investment grade rating” by an NRSRO that has opened the source code of the model used to give the rating.

281. Truth in Lending, 73 Fed. Reg. 28,866 (May 19, 2008) (to be codified at 12 C.F.R. pt. 226).

282. See Bar-Gill & Warren, *supra* note 58.

extract greater value from consumers.²⁸³

Of course, consumers might not be able to make much use of disclosure of data-mining and credit-scoring software by themselves. But, as Professors Richard Thaler and Cass Sunstein recently noted in applauding the Federal Reserve's proposed rules, third parties could audit these disclosures for consumers, alerting them to excessively risky provisions.²⁸⁴ Moreover, consumer watchdog groups could inspect data-mining and credit-scoring software for other concerns, including whether individual privacy is being infringed upon (which is a concern of Professor Lessig with respect to internet code),²⁸⁵ and whether lenders are engaging in subtle racial or other discriminatory lending practices.

C. *In Praise of Equity*

The failures of the new financial code outlined in this Article urge rethinking the growth of asset-backed securities and derivatives at the expense of markets for equity securities. The failures of the risk models used to price asset-backed securities and derivatives indicate that equity securities may enjoy some comparative advantage in providing a cushion against risk.

A recent article by Professors Gilson and Whitehead mapped out the decline of equity markets due to the increasing popularity of complex financial instruments.²⁸⁶ The article noted that these instruments, including securitizations and credit derivatives, enable companies to reduce their cost of capital by disaggregating the residual risk traditionally borne by shareholders; companies can then offload these risks to more efficient risk bearers.²⁸⁷ Derivatives, securitization, and insurance policies separate out specific risks faced by companies, and allow these firms to contract with third parties to assume the distilled risk. Professors Gilson and Whitehead have persuasively argued that growth of asset-backed securities and derivatives have sapped equity markets, as companies now have cheaper options to pass on residual

283. *See supra* notes 58–65, 67–68 and accompanying text.

284. Richard H. Thaler & Cass R. Sunstein, *Disclosure is the Best Kind of Credit Regulation*, WALL. ST. J., Aug. 13, 2008, at A17.

285. Lessig, *supra* note 22, at 142.

286. *See* Gilson & Whitehead, *supra* note 1.

287. *Id.* (positing that derivatives, securitizations and similar novel financial products allow companies to sell their residual risk to more efficient risk bearers than equity investors and thus reduce issuer demand for equity markets).

risk.²⁸⁸

In pricing these instruments, companies rely on the same types of codes that failed in the subprime crisis. The failures of these codes—whether stemming from model risk, information gaps, agency costs, or something else—call into question just how efficiently these novel financial products distill, allocate, and spread risk. In particular, many models for pricing asset-backed securities were unable to process the cocktail of different forms of risk; as noted in Part II.A.iv above, spillover and feedback effects between different forms of risk frustrate risk modeling. Equity holders who bear undivided residual risk have many comparative advantages as risk bearers; they bear residual risk, no matter whether the source is credit, market or liquidity risk or some cocktail of the three.

Equity has other advantages for issuers. First, derivatives, options, and debt instruments allow counterparties to transfer or terminate their bearing of risk through the use of assignment provisions, margin calls and redemption provisions. By contrast, equity has the virtue of being what banking scholars call “patient capital.”²⁸⁹ Capital raised through equity is locked into a company for a longer time, increasing its capacity to absorb risk.

Second, unlike credit derivatives, asset-backed securities and insurance policies, equity securities do not require companies to assess the credit risk of their counterparties. By contrast, the disconnect and distance between the financial instrument and the underlying cash-producing assets in derivatives and other complex financial instruments complicates the assessment of credit risk; recall the long chain from mortgages to mortgage-backed securities to CDOs to credit default swaps.²⁹⁰ Lastly, the complex structure of derivatives and the complex financial modeling used to price them resist easy understanding. As with consumer mortgages and banking rules, complexity in financial devices may thus exacerbate systemic risk.

These points do not contradict the descriptive claim made by Professors Gilson and Whitehead that companies have taken advantage of the completion of capital markets to shift risk using non-equity instruments. Perhaps the problems with asset-backed securities in the

288. *Id.*

289. Richard A. Brealey, *Bank Capital Requirements and the Control of Bank Failure*, in FINANCIAL STABILITY AND CENTRAL BANKS: A GLOBAL PERSPECTIVE 149 (Richard A. Brealey et al. eds., 2001).

290. *Supra* note 200 and accompanying text.

subprime crisis will stem this shift in liquidity away from equity markets,²⁹¹ but that may be a temporary phenomenon. Yet the flaws in modeling complex financial instruments may prove longer lasting. The brief sketch of the comparative advantages of equity securities argues for further study of the circumstances when shareholders may prove to be the most efficient bearers of residual risk after all. If equity's advantages are significant but equity markets are underused due to market imperfections, scholars and policy makers should consider policies to channel issuers and investors back to equity markets.

CONCLUSION

Sophisticated risk models produced by advances in quantitative finance had great promise in allowing financial institutions to measure and manage risk. These models enabled the growth of complex financial instruments—from mortgage-backed securities, to CDOs, to credit default swaps—that allowed financial risk to be transferred and spread to those parties in the economy who theoretically could bear that risk most efficiently. These products lowered the cost of borrowing for consumers and the cost of capital for financial institutions.

Dazzled by the promise of these risk models, financial regulators delegated to them broad authority for regulating risk in the economy. Regulators entrusted private-sector risk models with the duty to manage risk born not only by consumers and financial institutions, but the risk to the entire economy. Private-sector risk models thus became a “new financial code” that displaced traditional legal codes for regulating financial risk.

The severity of the current financial crisis underscored that faith in the new financial code had been misplaced. Consumer borrowers, financial institutions, and financial institutions' creditors and investors have all paid a terrible price for the failure of this code, as have taxpayers, investors at large, workers, and those future generations who face an increased national debt.

This Article unpacked the flaws in the new financial code, including flaws in its internal design and flaws in the incentives of the firms and individuals who used the code. These two types of flaws point to a critical need to reexamine and roll back the outsourcing of financial

291. Professors Gilson and Whitehead believe that the subprime crisis will only slow the shift in liquidity towards these complex instruments temporarily. *See* Gilson & Whitehead, *supra* note 1.

regulation to the new financial code—for example, by jettisoning the Internal Models Approach of Basel II. These two types of flaws also point to a need for greater transparency in the new financial code; this Article proposed harnessing the power of the open-source movement in software to improve both financial-institution risk models and the incentives of those who use them.

These two types of flaws also argue for greater engagement by lawyers and legal scholars with the machinery of risk modeling for three reasons. First, as with internet code, lawyers and legal scholars must also engage technical aspects of the new financial code, because these technical details can shift massive amounts of risk or even magnify risk. Second, the new financial code has come to serve as *de facto* regulation of a vast swath of consumer finance, banking, and capital markets. Third, lawyers and legal scholars can play an invaluable role in designing the incentives of the individuals and firms that use risk models. They must play that role; lawyers and legal scholars bring a needed perspective on how seemingly mechanical rules, when applied and interpreted by human agents, can be manipulated in ways unanticipated by those with an engineering mindset.