2009

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

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

Erik F. Gerding

The widespread use of computer-based risk models in the financial industry in 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 private industry models. The 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 outlines several implications of the current crisis for regulatory outsourcing 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 used to market consumer financial products, 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.

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THE OUTSOURCING OF FINANCIAL REGULATION

I. 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 argues 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,\(^2\) and this outsourcing of regulation exacerbated the crisis.

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.\(^3\) Securitization transformed the future payment streams from mortgages and other credit products into securities to be sold to investors. To accompany those cash streams, securitization carved up the credit risk (and other risks) posed by mortgages and other securitized assets into pieces, which were spread to investors buying the mortgage-backed securities.\(^4\) Those investors could then use credit derivatives and other derivatives to offload parts of this risk to counterparties in exchange for a premium.\(^5\)

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\(^1\) 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).

\(^2\) See infra Part II.c.

\(^3\) This system is described in detail below in Part II.b.

\(^4\) The mechanics of securitization is described in more detail below in Part II.b.ii.

\(^5\) For an analysis of derivative transactions, see infra Part II.b.iv.
Securitization and derivatives created a system for transferring and spreading risk to those investors who could theoretically bear risk most efficiently.\(^6\)

Each part of this risk transfer system was enabled by private, computer-based industry risk models that were built with innovations in quantitative finance. These models include the following:

1. Data-mining and credit scoring software that financial institutions use 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 a borrower, but also creating complex features in those products that can be tailored for certain categories of consumers);\(^7\)

2. Pricing models that financial institutions use to structure and price the securitization of those consumer financial products;\(^8\)

3. Models used by credit rating agencies to assign ratings to the asset-backed securities issued in securitizations;\(^9\)

4. Models used to price those derivatives that further hedge the risks of asset-backed securities;\(^10\) and

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\(^6\) See Gilson & Whitehead, supra note 1, at 263.

\(^7\) Lauren E. Willis, Decisionmaking and the Limits of Disclosure: the Problem of Predatory Lending: Price, 65 Md. L. Rev. 707, 719-721 (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 II.b.i.

\(^8\) See infra Part II.b.ii.

\(^9\) See infra Part II.b.iii.1.

\(^10\) 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-defaults swaps and collateralized debt obligations (CDOs), and emphasizing 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 and otherwise by hedge funds, is explored further in Part II.b.iii.4.
Models used to manage the investment portfolios and set the overall risk management policies of financial institutions.11

This Article refers to the above 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 of the stages in which computer-based risk models are used, including in the following ways:

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.12

Regulators have outsourced oversight of the risk transfer in the securitization of financial products to rating agencies indirectly via regulations of the some of the principal investors in these securitizations. By restricting 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 who determine which investments qualify as “investment grade.”13

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12 See infra Part II.b.i.
13 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”). See also JOËL BESSIS, RISK MANAGEMENT IN BANKING 31-33, 337 (2d ed. 2002) (describing investment restrictions on banks).
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Under the Basel II Accord, certain large banks received authority from regulators to set their capital requirements using the banks’ proprietary risk models. Furthermore, the new accord also permits banks to set capital requirements using rating agency ratings as a critical determinant.

In 2004, the U.S. Securities and Exchange Commission followed the Basel II model in allowing certain large U.S. financial conglomerates to set their required regulatory capital according to their own proprietary risk models.

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 risk generally.

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14 BASEL COMMITTEE ON BANKING SUPERVISION, INTERNATIONAL CONVERGENCE OF CAPITAL MEASUREMENT AND CAPITAL STANDARDS: A REVISED FRAMEWORK (June 2006) (hereinafter “BASEL II”).


16 BASEL II, supra note 14, at 27 (establishing the requirements for when banks can use “external credit assessment,” i.e. rating agency ratings to support capital requirement assessments for credit risk”). See infra Part II.b.iii.3.

In addition, regulators have been reluctant to regulate hedge funds, which represent a significant number of the counterparties to OTC derivatives.\(^\text{19}\) Even preliminary attempts at regulating hedge funds\(^\text{20}\) were thwarted in the face of the terrible complexity of these funds and uncertainty as to the scope of risk that they posed.\(^\text{21}\)

By outsourcing, financial regulation placed great faith in the new technology of financial institutions to police the transfers of risk made via complex financial products.\(^\text{22}\)

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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. at 69 Fed. Reg. at 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 873.

\(^{21}\) See Bhala supra note 11. 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
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 cascading financial crisis that began in the subprime mortgage belied this promise, as risk models failed to anticipate the cascading defaults on consumer mortgages, mortgage-backed securities and other 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.23

Before this Article begins to examine the rise and crash of the new financial code, a parallel in an altogether different area of legal scholarship provides context for both the problem of the new financial code and 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 Larry Lessig described how the private industry created software that establishes the “architecture” of the world-wide web functions as a kind of private regulation.24 According to Lessig, this software enables private firms (and ultimately governments) to track and regulate the behavior of individuals who use the internet. Yet,
internet users little suspect the ways in which computer codes constrain them.\textsuperscript{25} Because this regulation is embedded within a complex technology, it escaped scrutiny by policymakers and scholars 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.\textsuperscript{26} This Article argues that this same approach can 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.\textsuperscript{27} Greater transparency would allow the public to examine consumer lending practices and to root out our invasions of privacy and predatory or discriminatory lending.\textsuperscript{28}

This Article proceeds as follows. Part II 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.\textsuperscript{29} Part II then sketches how the current financial crisis spread, demonstrating the failure of these models.\textsuperscript{30} This Part also draws historic parallels from the failure of risk models in the

\textsuperscript{25} Id at 4-8. The architecture of the internet also facilitates government regulation of the web, which threatens to constrain free speech, intrude on privacy, and consolidate ownership of intellectual property. Id. at 122-85.
\textsuperscript{26} Id. at 100-110.
\textsuperscript{27} See infra Part IV.b.
\textsuperscript{28} See infra Part IV.b.vi.
\textsuperscript{29} See infra Part II.b.
\textsuperscript{30} See infra Part II.c.
current crisis to both the 1987 stock market crash and the failure of the Long-Term Capital Management hedge fund in 1998.  

Part III then examines some of the explanations for the spectacular failures of risk models in the current financial crisis.

Part IV investigates several policy implications of these failures. Part IV 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. This Part further argues that regulators should promote “open source” in these proprietary models used to market consumer financial products, price securitizations and manage financial institution risk. Lastly, Part IV 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.

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

This Part II 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 II.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 II.b then explains how these computer-based models enabled the development of new financial products that broke risk into pieces that could be

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31 See infra Part II.d.
32 See infra Part IV.a.
33 See infra Part IV.b.
34 Gilson & Whitehead, supra note 1. See infra Part IV.c.
transferred and spread to investors in financial markets. Part II.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 to purchase of mortgage-backed securities and other asset-backed securities by banks and other institutions, (iv) the use of derivatives to hedge risks from asset-backed securities. At each link of this chain, Part II.b. demonstrates both how financial institutions use computer-based models to price and manage risk, and how regulators outsourced to these models regulatory responsibility for overseeing massive transfers of risk.

Part II.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 II.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 first to lay out a typology of different financial risks that code attempts to model.
Financial risk means most basically the possibility of losing money due to an event.\(^{35}\) Risk models attempt to quantify the probability and extent of a loss.\(^{36}\)

As detailed below in Part II.a.ii, 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.\(^{37}\) The question then becomes how well historic data can predict future losses, or, more generally, how good of a proxy are measurements of “risk” for quantifying “uncertainty.”

This distinction between risk and uncertainty aside, to make meaningful predictions, the architects of these models break financial risk into categories based on the source of potential loss.\(^{38}\) Basic categories that financial institutions attempt to model and quantify include credit risk and market risk, which are defined as follows:

**Credit risk:** For a financial institution, credit risk means the risk that a borrower will default on payment of obligations to that institution.\(^{39}\) Credit risk includes counterparty risk in derivative transactions, *i.e.* the risk that a counterparty which has

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\(^{35}\) *See Neil Crockford, An Introduction to Risk Management* 5-6 (2nd ed. 1986); *Bessis, supra* note 13, at xi.

\(^{36}\) *Bessis, supra* note 13, at xi.

\(^{37}\) This key distinction was first made by economist Frank Knight over 75 years ago. *Frank H. Knight, Risk, Uncertainty and Profit* (1921).

\(^{38}\) *Id.* at 12.

\(^{39}\) *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.*
contractual obligations to make payment to an institution (upon an event specified in the derivative contract) will not perform those obligations.\textsuperscript{40}

\textit{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 liabilities will increase) due to changes in market prices.\textsuperscript{41} A firm and its investment portfolio may be subject to price fluctuations in different types of markets. Therefore, market risk includes several different subcategories of risk, including the following:

\textit{Interest rate risk}, or the risk exposure from changes in interest rates;\textsuperscript{42} and

\textit{Equity risk}, or risk arising from fluctuations in stock values.\textsuperscript{43}

As detailed in Part II.b below, quantitative finance has created sophisticated means of modeling all of the above forms of risk. Yet, 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:

\textit{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.”\textsuperscript{44} Operational risk thus covers everything from potential losses caused by employee mistake or fraud to losses from hurricanes.

\textsuperscript{40} Id. at 500-04 (discussing credit risk in context of derivatives). For an economic analysis of the effects of counterparty risk on the pricing of derivatives and other complex financial instruments, see Robert A. Jarrow & Fan Yu, \textit{Counterparty Risk and the Pricing of Defaultable Securities}, 56 J. Fin. 1765 (2002).

\textsuperscript{41} HENNIE VAN GREUNING & SONJA BRAJOVIC BRATANOVIC, ANALYZING AND MANAGING BANKING RISK: FRAMEWORK FOR ASSESSING CORPORATE GOVERNANCE AND FINANCIAL RISK 111 (2003).


\textsuperscript{43} ASWATH DAMODARAN, INVESTMENT VALUATION 60 (2002)(discussing measurement of equity risk through equity risk premia).

\textsuperscript{44} BASEL II, \textit{supra} note 14, at 144, ¶ 644.
Liquid 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.\textsuperscript{45} 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.”\textsuperscript{46}

Systemic risk: Systemic risk arises from a broader market failure; this form of risk denotes potential losses that affect the entire market,\textsuperscript{47} and which thus cannot be diversified away.\textsuperscript{48} These systemic losses may begin with an external shock that disrupts entire financial markets or a chain reaction in which one financial institution fails causing its creditors also to fail.\textsuperscript{49} Systemic risk represents a prime concern of financial regulators due its enormous repercussions and the inability of any individual financial institution to mitigate this form of risk through diversification.\textsuperscript{50}

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

\textsuperscript{45} This raises the question of what constitutes “fair market value.” There are other variations on the definition 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.” \textsc{Bank for International Settlements, Principles for Sound Liquidity Risk Management and Supervision} 1, n.2 (June 2008).

\textsuperscript{46} \textit{Id}.

\textsuperscript{47} Systemic risk has been defined by two scholars 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, \textit{What is Systemic Risk, and Do Bank Regulators Retard or Contribute to It}, 7 \textsc{Indep. Rev.} 371, 371 (2003). \textit{See also} Steven L. Schwartz, \textit{Systemic Risk}, 97 \textsc{Geo. L.J.} 193 (2008).

\textsuperscript{48} \textit{See} Larry E. Ribstein, \textit{Fraud on a Noisy Market}, 10 \textsc{Lewis & Clark L. Rev.} 137, 142 (2006)(discussing how arbitrageurs cannot diversify away systemic risk).

\textsuperscript{49} Kaufman & Scott, \textit{supra} note 47, at 372-73.

\textsuperscript{50} \textit{See} Schwartz, \textit{supra} note 47. Professor Schwartz 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 of the benefit of an action it takes to reduce systemic risk. \textit{Id}. 

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percentage of its total loans concentrated in a small number of debtors), and reputation risk (potential losses stemming from a decline in public opinion of the institution). Reputation risk also captures 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).

\[ \text{ii. The Revolution in Quantitative Finance} \]

The capacity of models to measure even risk (let alone uncertainty) in a sophisticated way stems from the revolution in quantitative finance over the past two decades. This revolution began with the widespread use of the Black-Scholes model for pricing options. 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). 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. But, this is not a useful yardstick, because the maximum loss might be enormous (e.g. 100% of the value of an asset), but the probability of that loss

55 Id. at 8-10.
occurring might be negligible. By contrast, value-at-risk provides a measure of both the extent and probability of losses occurring.\textsuperscript{56} Simply stated, value-at-risk describes the maximum possible loss over a specified time period with a given level of confidence.\textsuperscript{57} 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, note that value-at-risk numbers say nothing about the magnitude of losses above that confidence interval.\textsuperscript{58} 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 below 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 (\textit{i.e.}, there is only a 5% (100%-95%) chance that losses will exceed that amount).

\textbf{[Diagram A]}

To calculate value-at-risk, modelers need to assume the basic distribution of losses, \textit{i.e.} they need to determine the shape of the curve in the preceding diagram. They have three options. First, modelers can assume that losses fall in a “normal” distribution, \textit{i.e.} that they follow a bell curve shape. But, this assumption may have no basis in empirical reality. Therefore, modelers can take a second approach of using historical data

\textsuperscript{56} BESSIS, \textit{supra} note 13, at 12.
\textsuperscript{57} \textit{Id.}
\textsuperscript{58} \textit{See id.}
to determine the distribution of losses. This approach has several 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.\footnote{Darrel Duffie & Jun Pan, \textit{An Overview of Value at Risk}, 4 J. DERIVATIVES 7 (1997).
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Modelers can also employ the following third technique to form loss distributions, namely Monte Carlo simulations, which estimate 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, \textit{i.e.} if the equation 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, \textit{i.e.} specifying the equation that transforms the several variables into financial loss. Modelers can assume that this relationship will follow historical patterns (\textit{i.e.} use historical data), which leads back to the problem noted above of whether the historical data selected provides an adequate sample. Modelers could also develop their own algorithm or equations for the relationship, but this in turn leads to the question of how good are the assumptions behind this algorithm.\footnote{BESSIS, \textit{supra} note 13, at 608-21.}

In other words, assumptions in modeling are inescapable and the strength of a model depends on how well the assumptions will 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, but 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 below 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 the line y represents low-probability but high loss events, which are often compared to “hundred year storms.”

[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. 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 into a model the historical data that was available at those respective times, and then comparing the predictions of the model with how losses actually unfolded.

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 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 the recent subprime crisis. The sections below track the

61 BESSIS supra note 13, 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.
62 Id. at 411.
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”, or when a lender extends 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.63

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.64 This information is used both to determine whether to approve or deny a loan and to set interest rates to match credit risk.65 Many originators use this 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 types of consumers.66

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63 For a primer on securitizations, see Steven L. Schwarcz, The Alchemy of Asset Securitization, 1 STAN. J.L. BUS. & FIN. 133, 135 (1994).
64 Willis, supra note 7.
Consumer law scholars such as Lauren Willis, Oren Bar-Gill, and Elizabeth Warren, among others, have worried that this data mining gives lenders an information advantage over consumer borrowers, which lenders use to market financial products that may be unsuitable for consumers and potentially exploitative. (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.69) These scholars have argued 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.70 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.71 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.72

This practice became particularly evident in the mortgage market over the last decade. Mortgage lenders began offering mortgages with novel features to home buyers to allow them 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

67 See Willis, supra note 7.
68 See supra note 66.
69 LESSIG, supra note 24, at 142-63.
70 E.g., Warren, supra note 68, Bar-Gill & Warren, supra note 68.
71 Lauren A. Willis, Against Financial Literacy Education, 94 IOWA L. REV. 197 (2008)(describing how revolution in data collection, storage and processing enables financial services industry to model consumer behavior and to market complex products to consumers that exceed consumer understanding).
72 Id.; Bar-Gill & Warren, supra note 68.
interest rate after a few years.\textsuperscript{73} 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.\textsuperscript{74} Low-income borrowers could thus afford 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 individuals used ARMs and other exotic mortgages to purchase houses too.\textsuperscript{75}

The risk that these borrowers assumed, often without fully understanding it, was that interest rates would rise significantly after the teaser period and push their monthly mortgage expense beyond their budget. (As Part II.c explains, this is exactly what befell many borrowers with ARM mortgages.\textsuperscript{76}) In other words, ARM mortgages transferred interest rate risk to borrowers.

At the same time that code enabled mortgage and other lenders to reverse the information asymmetry and shift risk to consumers, law 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 record levels of debt and were assuming massive interest rate risk.\textsuperscript{77}

\textsuperscript{73} McCoy, \textit{supra} note 65, at 144.

\textsuperscript{74} The costs to consumers of ARM loans was recognized in legal scholarship over two decades ago. \textit{E.g.}, William N. Eskridge, Jr., \textit{One Hundred Years of Ineptitude: the Need for Mortgage Rules Consonant with the Economic and Psychological Dynamics of the Home Sale and Loan Transaction}, 70 VA. L. REV. 1083, 1131 (1984).

\textsuperscript{75} \textit{E.g.}, Elizabeth Warren, \textit{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).

\textsuperscript{76} \textit{See infra} note 151 and accompanying text.

\textsuperscript{77} \textit{E.g.}, Bar-Gill & Warren, \textit{supra} note 68.
The reasons for this regulatory inaction are manifold.\textsuperscript{78} One reason regulators may have taken comfort in 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.\textsuperscript{79} Both lenders and financial markets, many regulators assumed, accurately priced and managed this risk due to the advances in the risk models they employed.\textsuperscript{80}

\textit{ii. The Pooling and Pricing of Securitizations}

But, many originators did not fully bear this risk, because they sold a large portion of mortgages (or other financial products) to special investment vehicles (SIVs) via securitization.\textsuperscript{81} Therefore, the assumption that markets optimally managed risk depends on whether the asset-backed securities issued in those securitizations were accurately priced.\textsuperscript{82} 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 understanding 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

\textsuperscript{78} 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. \textit{Id}. 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.


\textsuperscript{80} See Greenspan Apr. 3, 2005 Remarks \textit{supra} note 22.


\textsuperscript{82} It also depends, as Parts II.b.iii.4 analyzes, on whether purchasers of asset-backed securities and their market counterparties accurately hedged the risks of those securities.
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), the SIVs purchase pools of mortgages using cash paid by investors which 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 received from the underlying mortgages.\textsuperscript{83}

\textsuperscript{83} See Schwarcz, supra note 83. 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.
The following diagram presents this series of transactions graphically:

**Diagram C**

<table>
<thead>
<tr>
<th>Stage 1</th>
<th>Stage 2</th>
<th>Stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Consumers</strong></td>
<td><strong>Originators</strong></td>
<td><strong>Special Investment Vehicle</strong></td>
</tr>
<tr>
<td>→</td>
<td>Mortgages (\text{(or other product with obligation of future payments)})</td>
<td>Mortgages (\text{(or other product with obligation of future payments)})</td>
</tr>
<tr>
<td>←</td>
<td>Cash loan</td>
<td>←</td>
</tr>
</tbody>
</table>

By purchasing these asset-backed securities, investors can invest in lucrative consumer credit market, including mortgages, credit card debt, student loans, while enjoying several benefits compared to extending credit directly to consumers. First, the purchasers of securities need not collect payments directly from consumers. Second, these securities are theoretically more liquid than the underlying mortgages. 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, note this assumes that losses among mortgages in the pool will not be highly correlated and that

---

84 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).

such correlation can be accurately estimated specified and will remain roughly constant.\textsuperscript{86} (These assumptions on correlation have been called into question by the current global financial crisis as noted in Part III.a.iii.).

Second, securitization facilitates diversification because investors in asset-backed securities are only buying a piece of the risk of the mortgage pool and they can diversify away this risk through other investments in their portfolio.\textsuperscript{87} This assumes, however, that losses on the mortgage backed-securities the investor purchases are not highly correlated with losses on other assets (including other asset-backed securities) in their portfolio.

Third, investors can achieve diversification because of the terms of securities being issued. Cash payments on the underlying assets need not simply flow to holders of securities \textit{pro rata}. Instead, the securities issued 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 would often employ a complex “waterfall” rule for payment to different tranches. The waterfall would set the order in which the classes would be entitled to receive payments from the underlying assets. In a simple waterfall, holders of senior classes of securities would receive amounts due to them in full before holders of junior classes received any payments. Thus, junior classes face a higher risk of not being paid due to defaults on the underlying assets and are compensated for this risk with a higher interest rate on their securities. Different classes of securities (with different tradeoffs between risk and reward) might appeal to different types of investors.


\textsuperscript{87} See Kendall \textit{supra} note 85, at 13-15.
More complex waterfall rules than the example above allow securitizations to carve up risk and reward in even more finely tuned ways.\footnote{For an explanation of waterfalls and tranching, see Steven P. Baum, \textit{The Securitization of Commercial Property Debt}, in \textit{A Primer on Securitization}, supra note 85, at 45, 49 (describing commercial mortgage-backed securities).}
Yet the success of this slicing, dicing, and pricing of risk and reward in even the most basic securitization depends on the capability of those structuring the securitization and those purchasing the securities to 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, government sponsored entities (Freddie Mac and Fannie Mae) that pool and issue mortgage-backed securities, and investment banks acting as underwriters for the securities.89

All relied on sophisticated modeling to assess risk and price the securities and their institutional services accordingly.90 (Of course rating agencies and their models played an outsized role in structuring securities as well, which is analyzed in Part II.b.iii.1.) Any model for pricing asset-backed securities needs 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.91 To accomplish this, these models require critical information from the originators on the underlying assets. Given the sheer number and variety of underlying assets, originators typically only provide to the sponsors of securitizations certain categories of information. For mortgages, these categories might include information on location of the homes, sizes of the mortgage, whether the homes are in single family or multiple family structures, interest rates, and other significant terms of the mortgages. Often, the originators will perform a data dump

89 For a discussion of the roles of these various players in securitizations, see Kendall, supra note 85 at 4-14.
90 For a comprehensive analysis of the modeling that sponsors use for structuring securitizations, see Andrew S. Davidson et al., Securitization: Structuring and Investment Analysis (2003).
91 Id.
and give the structurers gigantic electronic files or print outs with this information for each mortgage.\textsuperscript{92} 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.\textsuperscript{93}

Certain securitizations might bundle securities being issued together with some form of credit support, either guarantees from a government sponsored entity in the case of Fannie Mae and Freddie Mac securities, or an bond insurance policy issued by a bond insurer. Conceptually, 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.\textsuperscript{94}

There is little direct regulation in the U.S. of supply side of securitization – for example regulations specifying which models sponsors of securitizations must use. 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.\textsuperscript{95} Instead, regulation of securitization occurs indirectly, through banking and other regulations that restrict the investments that banks and other

\textsuperscript{92} Id.
\textsuperscript{93} Id.
\textsuperscript{94} Kendall, supra note 85, at 4 (describing financial insurance company as alternative to guarantees from Freddie Mac and Fannie Mae).
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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 a large measure of oversight over the risk that these investors take on to those rating agencies. In 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. Like those entities that sponsor

96 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.”)
97 Professors Partnoy and Skeel describe rating agency models as the driving force behind the structuring of securitizations. Partnoy & Skeel, supra note 10 (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 85, 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. 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) available at http://www.sec.gov/news/studies/2008/craexamination070808.pdf. [Hereinafter “July 2008 SEC Rating Agency Report”] Sponsors of securitizations remain the primary architects of the structure of securitizations. Id. at 31.
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 originators or the firms sponsoring a securitization. Some rating agencies have even admitted to conducting little analysis of underlying assets.\(^98\)

Rating agencies have a dismal track record of failing to predict 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.\(^99\) Several explanations have been offered for this failure, including conflicts of interest created by rating agencies receiving compensation from the companies they rate and also having no monetary liability for poor performance.\(^100\)

Some scholars, notably Frank Partnoy, have persuasively argued that regulation is part of the problem.\(^101\) Instead of creating incentives for better monitoring, regulators have undermined those incentives by granting rating agencies a kind of oligopoly power.\(^102\) This power stems from the fact that the securitization market, including the market for mortgage-backed securities, focuses largely on institutional investors.\(^103\)

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 II.b.iii.1 below.

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\(^98\) 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 thus. “We’re structure experts. . . . We’re not underlying-asset experts.” Roger Lowenstein, *Triple-A Failure*, N.Y. Times, Apr. 27, 2008 (Magazine), at 36.


\(^102\) *Id.* at 681-704.

\(^103\) Kendall, *supra* note 97, at 15.
securities they purchase due to regulation. Regulations restrict much of the securities investments of many pension funds, and regulated financial institutions, including banks and insurance companies, 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.) 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. The handful of NRSROs, and the models they use to rate securities, thus possess great responsibility for regulating the riskiness of investments by a large number of financial institutions.

2. Risk Management

Purchasers of asset-backed securities not only rely on the code of rating agencies to make decisions to purchase individual securities, they also rely on a mix of ratings and the purchasers’ own internal models to manage the risk of the purchasers’ overall portfolio. Many large companies, particularly financial institutions, employ sophisticated proprietary computer-based models to manage the credit and market risk of their

106 E.g. 12 U.S.C. § 1831e(d)(4)(A) (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.”)
investment portfolios. Some financial institutions also sell risk management software and services to smaller companies. These models often employ many of the devices described above in Part II.a.ii., particularly tools to calculate value-at-risk.

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, and publicly registered financial institutions must make additional disclosure. 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. 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 one of the more explicit regulations, the SEC rule on quantitative disclosure of market risk, requires simply “a description of the model, assumptions, and parameters, which are necessary to understand” the numeric disclosures.

3. Basel II

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110 GREG N. GREGORIOU, FUNDS OF HEDGE FUNDS 367 (2006) (discussing computer based models used by hedge funds to make investment decisions).
111 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).
112 Id. at 97 (describing J.P. Morgan product features).
113 17 C.F.R. § 229.305 (2008) (Quantitative and qualitative disclosures about market risk). For example, Financial Accounting Standard 133 requires disclosure on concentration of credit risk with respect to financial instruments. FINANCIAL ACCOUNTING STANDARDS BOARD, ACCOUNTING STANDARDS VOL I. 16507-08 (June 1, 2007).
114 SEC registered bank holding companies must also disclose the information required by Guide 3 – “Statistical Disclosure by Bank Holding Companies.” 17 C.F.R. § 802(c) (2008).
115 For example, Financial Accounting Standard 133 requires disclosure on concentration of credit risk with respect to financial instruments. FINANCIAL ACCOUNTING STANDARDS BOARD, ACCOUNTING STANDARDS VOL I. 16507-08 (June 1, 2007).
Whereas federal laws on securities disclosure have taken a light 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 have not shown great deference to the internal risk management models of financial institutions, but instead set capital requirements according to statutory or regulatory formulae. One type of U.S. capital requirements, 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”). Under Basel I, bank regulators (including in the United States) set capital requirements to address credit risk according to a fairly mechanistic set of formulae that required financial institutions to maintain capital according to the predetermined level of risk associated with classes of assets on a bank’s balance sheet. Regulations placed assets in different categories and assigned each category a different “risk weight.” Basel I and U.S. banking regulations keyed certain of these risk weights to rating agency ratings. (This use of rating agency determinations contributed to the problem of rating agency oligopoly outlined by Professor Partnoy and described above.)

117 Federal bank regulators are required to set minimum capital requirements under 12 U.S.C. §§ 1831o(c)(1)m 3907 (2008).
119 BASEL I, supra note 118, at Part II.
120 Id.
Now Basel II dramatically alters the scale of outsourcing of bank capital requirements to private industry risk models in two ways. First, it dramatically increases outsourcing of bank capital requirement regulations to ratings agencies (and, by implication, their models). Second, the accord also outsources for the first time to the internal risk models of banks; Basel II now permits certain large banks to use internal models to set their own regulatory capital requirements. These two trends unfold in 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, the Accord instructs regulators to 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. This bifurcated approach appears in the Basel II rule on capital requirements to cover credit risk; a standardized approach that relies on rating agencies is supplemented with a new “Internal Ratings-Based Approach” that allows certain banks to use internal models. Basel II also takes a similar bifurcated approach

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122 Under the new accord, national bank regulators may apply one of three approaches to setting requirements for 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 14, 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
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– a standard approach and an internal models exception for certain banks – in its separate rules on capital requirements for market risk,123 and operational risk.124

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.125 But, these lengthy standards

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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.

123 Basel II also take a bifurcated approach to 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 off of rating agency ratings. Id. at 166-190.

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.

124 Unlike Basel I, the Basel II accord requires banks to set aside capital for operational risk. But, again, the accord takes the following 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 fixed percentage of a bank’s income in previous years. The principal difference between these two approaches – the Basic Indicator Approach & Standardized Approach – is that the Standardized Approach is slightly more nuanced. It disaggregates 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.

125 E.g. id. at Part 3, Section III (specifying supervisory review process that regulators must undertake to review bank compliance).
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give bank regulators significant discretion in both deciding which banks qualify for the privilege to use internal models auditing the models of those banks.

In December 2007, the principal federal regulators of banks – 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.\(^{126}\) 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 capital according to internal models would lead to substantial declines in regulatory capital and undercapitalization for credit risk.\(^{127}\)

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 U.S. Securities and Exchange Commission decided to apply Basel II to setting capital requirements for certain large financial holding companies as part of the Commission’s new Consolidated Supervised Entity (or “CSE”) Program.\(^{128}\) 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

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\(^{126}\) See supra note 16.


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.\textsuperscript{129}

Broker-dealer holding companies could opt into this program, after which the SEC would supervise not only registered broker-dealer entities, which the Commission 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 unaffiliated affiliates that might place . . . U.S. regulated broker-dealers and other regulated entities at risk.”\textsuperscript{130} Ultimately, the following seven financial holding companies, which include 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.\textsuperscript{131}

With respect to these CSEs, the SEC took responsibility for setting regulatory capital. But, the SEC decided not to apply the same capital standard regulatory framework that it has applied to SEC-registered broker-dealers before the CSE Program.


The program also responded in part to a European Union regulatory initiative that would give a non-E.U. financial conglomerate the ability to obtain a single license to operate across the European Union provided that the firm demonstrated that it (that is all of the firms 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 E.U. status; U.S investment banks not owned by a bank-holding company thus found themselves at a potential regulatory disadvantage. \textit{Id. OFFICE OF INSPECTOR GENERAL, SEC’S OVERSIGHT OF BEAR STEARNS AND RELATED ENTITIES: THE CONSOLIDATED SUPERVISED ENTITY PROGRAM 4} (2008).

\textsuperscript{130} \textit{OFFICE OF INSPECTOR GENERAL, supra} note 129, at 2.

\textsuperscript{131} \textit{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. \textit{Id.} at v.
That standard framework, also known as the Net Capital Rule, requires that broker-dealers maintain capital according to fairly mechanical financial ratios that vary according to the type of securities business that a broker-dealer is conducting. Instead of this approach, the CSE Program 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 borrowing to finance investments, as documented by soaring leverage ratios.

The SEC regulations establishing the program included standards for the SEC in vetting holding companies applying to join the program and their risk management and modeling and in auditing those entities who were admitted to the program. The rules also contained a floor below which a CSE’s capital could not fall. But, a 2008 SEC Inspector General Report details significant lapses in the SEC following its own regulations in both vetting applicants to the program and the adequacy of their risk models and then auditing the risk management and modeling of those firms admitted to the program.

iv. Hedging Risks: Derivatives and Hedge Funds

Banks and non-banks alike use not only capital to mitigate risk, but increasingly derivatives as well. More particularly, banks and other investors have used derivatives to hedge the risks of asset-backed securities in their portfolio – including the credit risk representing the risk of default on payments on those securities. The derivatives employed for this purpose and for hedging other risks have become increasingly complex.
and esoteric over the last 15 years. Over the same time, trading in OTC derivatives has skyrocketed in the last 15 years.\textsuperscript{135}

Simultaneously, the amount of money under management globally by unregulated hedge funds has exploded.\textsuperscript{136} These three phenomena – risks from asset-backed securities, the expansion of the derivatives markets and the growth of hedge funds – are intertwined as explained in the following paragraphs.

Although derivatives can be used for many reasons, often derivatives are used as a consequence of securitization. Investors can hedge the residual credit risk associated with asset-backed securities in their portfolio by entering into a special type of derivative transaction with a counterparty called a credit default swap. 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 the investor holds. In exchange for assuming this measure of default risk, the counterparty receives from the investor a premium.\textsuperscript{137} The transaction thus resembles a form of guarantee or credit insurance policy on the asset-backed security.\textsuperscript{138}

\begin{flushright}
\textsuperscript{137} Partnoy & Skeel, supra note 10.
\textsuperscript{138} See supra note 94 and accompanying text.
\end{flushright}
Diagram D below sketches out the basic economic bargain of a credit default swap.\(^{139}\)

**Diagram D**

<table>
<thead>
<tr>
<th>Consumers</th>
<th>Special Investment Vehicle</th>
<th>Investor</th>
<th>Derivative Counterparty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default risk on mortgages (or other underlying of asset)</td>
<td>Default risk on asset-backed securities</td>
<td>Default risk on asset-backed securities (that meets “Credit event” definition)</td>
<td></td>
</tr>
<tr>
<td>Cash loan (by Originator) (with interest rate adjusted for default risk)</td>
<td>Cash (minus spread reflecting default risk)</td>
<td>Payment of specified amount if “Credit Event” occurs</td>
<td></td>
</tr>
</tbody>
</table>

Counterparties thus reap significant reward but take on significant risk. 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.\(^{140}\)

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\(^{139}\) For 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).

\(^{140}\) 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.
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 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 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.  

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. 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.

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3095 (2008)(arguing that heavy use of lightly regulated credit derivatives by unregulated hedge funds increases systemic risk).


142 See supra note 18, and accompanying text.

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.\textsuperscript{144} Meanwhile, the SEC was stymied in efforts to require hedge funds to register with the Commission and provide basic data.\textsuperscript{145}

\textit{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 become even more complex when mortgage-backed securities (or other asset-backed securities) issued by an SIV 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 or “CDO.”\textsuperscript{146}

\textsuperscript{144} See supra note 19 and accompanying text.
\textsuperscript{145} See supra notes 20-21 and accompanying text.
\textsuperscript{146} Kendall, \textit{Securitization: a New Era in American Finance}, supra note 85, at 15.
Securities issued in CDO are often resecuritized themselves, creating what is called a “CDO Squared.” The iterative layering of securitizations of securitizations became wildly popular in financial markets. Similarly, risks assumed in derivative transactions can themselves be hedged with other derivatives.

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 more complex by an order of magnitude.

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

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147 Coval et al. supra note 86.
148 One Presidential commission cited failures of rating agencies to evaluate securitizations of mortgage-backed securities as key factor in the subprime crisis. President’s Working Group, supra note 79, at 449 (Spr. 2008) [hereinafter, “President’s Working Group”].
149 Hu, supra note 10, at 1502
150 Kendall, supra note 85, at 8-11 (describing valuation of “synthetic securities”).
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 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 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 II.b failed.

The subprime crisis began in 2007, when defaults on ARMs began rising as teaser rates on ARMs expired and many subprime borrowers were unable to make payments at the higher reset rate. 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 continuous gains. Waves of defaults by mortgage borrowers followed, which the pricing and risk models of many originators and rating agencies utterly failed to predict.

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152 Morgenson, supra note 151; See also Jia Lynn Yang, *How Bad is the Mortgage Crisis Going to Get?*,
153 Lowenstein, supra note 98.
The wave of defaults swelled enough to affect mortgage-backed securities. First, junior classes plummeted in value. Later waves of defaults undermined the value of senior classes, despite the protections of payment waterfalls and tranching structures. Defaults on asset-backed securities triggered guarantees and credit insurance policies, and unprepared guarantors and credit insurers themselves threatened to falter.

Growing losses for financial institutions on mortgages and mortgaged-backed securities created two aftershocks. First, lenders cut back on mortgage and other lending, which drove market interest rates higher and started a credit crunch. Higher interest rates created a feedback loop and worsened default rates on ARMs.

Second, the plummeting of the value of asset-backed securities forced many financial institutions to make substantial write-downs of assets on their balance sheets, a process that still continues. Yet the value of many of these assets has become extremely uncertain, as buyers for asset-backed securities disappeared. In addition, the iteration of securitization upon securitization meant that default of one class of securitization cascaded and caused losses in subsequent securitizations. But, the many layers of securitization – CDOs backed by CDOs in an iterative chain – prevented

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158 Charles Duhigg, A Trickle that Turned into a Torrent, N.Y. TIMES, July 11, 2008, at C1 (reporting that major banks are writing down 20% to 50% of the value of their assets due to losses from mortgage-backed securitizations).
159 Louise Story, A Values Debate (Not the Political Kind), N.Y. TIMES, May 16, 2008, at C1 (reporting on debate on whether mark to market rule in Financial Accounting Statement 157 was leading to overstated write downs); See also Andrew Ross Sorkin, Are Bean Counters to Blame?, N.Y. TIMES, July 1, 2008, at C1 (same).
investors later in the securitization chain from calculating the risk they faced from losses on assets earlier in the chain.\textsuperscript{160}

The write-down of assets began to affect the creditworthiness, real and perceived, of many institutional investors.\textsuperscript{161} Many investors were forced to sell asset-backed securities to improve their balance sheets,\textsuperscript{162} but they faced a liquidity risk problem similar to that of holders of mortgages; the initial depression of prices of asset-backed securities, 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.\textsuperscript{163}

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.\textsuperscript{164} 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.\textsuperscript{165}

A few prominent institutions failed in attempts to stay afloat.\textsuperscript{166} 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

\begin{thebibliography}{9}
\bibitem{160} Matthew Goldstein & David Henry, \textit{Bear Bets Wrong}, \textit{Business Week}, Oct. 22, 2007 at 50 (linking Bear Stearn’s deteriorating credit situation to the decline in value of “CDO squared” securities it held).
\bibitem{164} \textit{Id.}
\bibitem{166} Goldstein & Henry, \textit{supra} note 160 (reporting on bailout of Bear Stearns); Dash, \textit{supra} note 165 (reporting on insolvency of IndyMac Bank).
\end{thebibliography}
institutions because of the complex web of counterparty risk created by derivatives. 167 Moreover, the contagion of depositor or creditor panic exacerbated reputation and systemic risk.168

Some of the most prominent financial institutions that fell victim to the crisis were the financial conglomerates who were able to lower their regulatory capital and increase their leverage under the SEC’s CSE Program.169 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 continue to take shape at the time this Article went 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.170

These failures of 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 agency’s contribution to the collapse of Bear Stearns, that office criticized the program

167 Herring & Schuermann, supra note 53, at 22 (discussing systemic risk threat posed by securities firms by virtue of OTC derivatives activity).
169 See Labaton, supra note 129.
170 Joe Nocera, Risk Mismanagement, N.Y. TIMES MAGAZINE, Jan. 24, 2009, at 24;
for allowing CSEs to lower capital to inadequate levels. The study blasted 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.171


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 and two previous financial crises. In both of these 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.172 Regulators and scholars blamed the crisis on financial institutions placing their risk hedging on virtual autopilot.173 Poorly understood computer based models were allowed to set major investment and risk management decisions.174 Homogeneity in these models combined with poor operational oversight led many institutional investors to begin selling off the same assets simultaneously at the

171 See OFFICE OF INSPECTOR GENERAL, supra note 129.
173 Id.
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occurrence of what seemed to be a minor market blip. This caused falling stock market indexes to drop precipitously. In the aftermath, studies criticized regulators for failing to understand and adequately regulate portfolio insurance and program trading.

ii. The Collapse of Long-Term Capital Management.

Faith in code 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 mortgage-backed securities. The principals of the fund believed they could identify outsized profit opportunities with minimal risk because their computer-based models could calculate risk with precision based on massive data on historic market volatility. But, these models made many assumptions (including some of the same assumptions described in Part III.a infra), including the following:

¶ 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.

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

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175 Id. at 17.
176 Id. at 17-24.
179 Id.
180 Id. 64-77. LTCM’s models also assumed that the volatility of any security remains constant and that securities trade in “continuous time” with no significant gaps between the posting of new prices for securities. Id.
models, the fund could readjust its portfolio and enter into and unwind hedges before it incurred major losses.\textsuperscript{181}

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.\textsuperscript{182} This unexpected movement in credit markets caused massive losses for LTCM.\textsuperscript{183} 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.\textsuperscript{184}

\section*{III. 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 III seeks to explain several of the weaknesses inherent in these models – 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. But, instead this Part provides a typography of various flaws

\begin{flushleft}
\footnotesize
\textsuperscript{181} Id. at 68.
\textsuperscript{182} Id. at 134-46.
\textsuperscript{183} Id.
\textsuperscript{184} Id. at 185-218.
\end{flushleft}
that contributed to yet another risk – “model risk,” which describes potential losses due to inaccurate risk models themselves.\textsuperscript{185}

These flaws fall into two broad categories: flaws in the technical design of the models themselves, and flaws because of 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 III.a examines the failure of the new financial code starting from the vantage point of flaws in technical design. Part III.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\textsuperscript{186} and back testing\textsuperscript{187} of models to root out these faulty assumptions.\textsuperscript{188}

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 period in which the institution would hold the investment portfolio.\textsuperscript{189} Other critics fault modelers for not going back far enough in history to gather loss data to be inputted into the model.\textsuperscript{190} Indeed, small sample sizes of historical losses can skew results.\textsuperscript{191} For example, a model used in 2006 that based on data on market movements in the previous seven years would have missed valuable data points such as the 1998 LTCM crisis.\textsuperscript{192} 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.\textsuperscript{193} Some policymakers and scholars also fault models for not dealing with “fat-tails”, \textit{i.e.} those low-magnitude, high probability “100 year storms.”\textsuperscript{194}

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 of

\textsuperscript{186} See supra note 61, and accompanying text for a definition of stress testing.
\textsuperscript{187} See supra note 62, and accompanying text for a definition of stress testing
\textsuperscript{188} Oddly 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 20-21) now attributes the cause of the subprime crisis to flaws in risk model assumptions. Alan Greenspan, \textit{We Will Never Have a Perfect Model of Risk}, FIN. TIMES, Mar. 16, 2008, available at http://www.ft.com/cms/s/0/edbdbcf6-f360-11dc-b6bc-0000779fd2ac.html.
\textsuperscript{190} The basic construction of a value-at-risk model is outline above in notes 56-59.
\textsuperscript{192} 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).
\textsuperscript{193} See Part II.d.ii supra.
\textsuperscript{194} See Part II.d.i supra.
\textsuperscript{194} Danielsson, supra note 188.
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 (CDO Squared).195

These technical flaws can be solved with technical fixes, including stress testing value-at-risk determinations using different confidence levels and different model assumptions.196 But, 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 models or their implementation.

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 futures losses are unknown and unknowable and cannot be predicted based on historical patterns. In other words, Taleb argues that losses in future are characterized by “uncertainty” rather than “risk.”197 Taleb argues that markets continue to evolve and defy historical patterns; “100 year storms” (what he has famously labeled “black swans”) occur on a

195 Coval et al., supra note 86.
196 Id. 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).
197 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 190-191.
198 See supra note 37 and accompanying text.
frequent basis, but that their timing, magnitude, and the exact mix of risks they pose defy prediction and probabilistic thinking. Therefore, even sophisticated probabilistic models such as value-at-risk determinations, according to him, are useless.\textsuperscript{198}

While philosophically provocative, the radical critique of Taleb 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.

\textit{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 potential losses for different types of assets. A high correlation of losses for different assets pooled together – be they mortgages pooled together for a securitization, asset-backed securities pooled together for a CDO, or various securities in a firm’s investment portfolio – 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.\textsuperscript{199}

Securitization is also dependent 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.

\textsuperscript{198} Nicholas Taleb & Avital Pilpel, \textit{Epistemology and Risk Management}, RISK & REG. (Summer 2007) available at http://www.lse.ac.uk/resources/riskAndRegulationMagazine/magazine/summer2007/epistemologyAndRiskManagement.htm;\textsuperscript{199} Coval et al., \textit{supra} note 86.
Several economists have noted how the fallacy of this assumption was revealed by the current crisis. 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 resecuritized.  

\textit{iv. Spillover Effects and Feedback Loops}

Losses within different asset classes – mortgages, mortgage-backed securities, other asset-backed securities – can become highly correlated or 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 in a lemons situation 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.

A second form of spillover effect occurs when losses do not stay in the tidy boxes of risk categories outlined in Part II.a.i – credit risk, market risk, liquidity risk etc. Instead, losses that fall within one category of risk may spillover and trigger losses from an altogether different form of risk. Consider the following characterization of the spreading financial crisis described in Part II.c:

\begin{itemize}
  \item \textit{Id.}
  \item 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.
  \item 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 11, at 149-51.
\end{itemize}
Market risk triggers credit risk: An unexpected rise in interest rates causes borrowers to default on obligations or enter insolvency. 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 default, 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. A loss of liquidity caused markets and credit to seize up, and made assets extremely difficult to value and, in some cases, worthless.

Yet, because liquidity risk can arise from complex interactions of market and credit risk, including non-linear feedback loops and spillover effects, it is extremely difficult to model; accordingly the tools to model and measure liquidity risk have not developed to anywhere near the extent of credit and market risk models. For similar reasons, systemic risk – the granddaddy of all risks – also proves resistant to modeling. Risk models (and regulations) that segregate risks into separate analytic categories of credit, market and other forms of risk can severely underestimate risk.

Homogeneity among risk models, exacerbates this problem as it means models at different firms miss the same risks, creating blind spots. (As Part III.b.vi explains, homogenous risk models also translates into homogenous risk management practices, which means that investor reactions to market downturns will be highly correlated and deepen 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

\[203\] See supra note 163 and accompanying text
\[204\] See supra note 159 and accompanying text
\[207\] Of course, some scholars argue that segregating risk into different types and different model may lead to overestimation of risk, because separate credit risk models and market risk models may overlap and capture the same losses; this overlap would lead to double-counting and excessive capital requirements. See supra Bhala, supra note 11. 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.)
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.” As in a child’s game of “telephone,” the end investors of a securitization receive poor information about the underlying assets. But even, these investors have better information than their counterparties in a credit default swap.

Investors and hedge counterparties alike may take an analytic shortcut and rely on the ratings of rating agencies. But, rating agencies also suffer from asymmetric information and have been faulted for a dismal performance in predicting credit problems. Part III.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 & 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.

\footnote{208 Buiter, supra note 141.}
\footnote{209 Id.}
\footnote{210 Partnoy, supra note 101, at 658-661.}
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But, behavioral economics has offered substantial empirical and experimental evidence that the rationality of individuals is bounded. Pioneering work in experimental psychology demonstrated that individuals exhibit various cognitive biases, such as overconfidence, over-optimism and the availability bias, and employ heuristics (mental shortcuts) to estimate probabilities. 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. Behavioral finance scholars posited that bounded rationality causes investors to make suboptimal investment choices and causes financial market failures. 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. In recent years, economists and legal scholars have explored the particular behavioral biases that affect individuals in the real estate and subprime mortgage markets.

Behavioral economics has faced a trenchant criticism, most prominently articulated in the legal literature by Professor Gregory Mitchell, that behavioral

212 E.g. Willis, supra note 71.
213 Supra notes 7 and 68 and accompanying text.
216 See Gregory Mitchell, Tendencies versus Boundaries: Levels of Generality in Behavioral Law and Economics, 56 VA. L. REV. 1781 (2003) (arguing that behavioral law and economics proponents have documented “tendencies” in behavioral biases, but has yet to specify the “boundaries” of those tendencies, i.e. when, and the extent to which, these biases come into play); See also Richard A. Posner, Rational Choice, Behavioral Economics and the Law, 50 STAN. L. REV. 1551, 1559-1560 (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).
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Economics presents general tendencies, but has yet to delineate the boundaries of those tendencies. In other words, behavioral economics produces evidence that behavioral biases occur, but has not specified when those biases occur. This failure to specify boundary conditions means that behavioral economics struggles to produce models of human behavior that can lead to testable predictions.

But, this criticism can be flipped and applied not only to the modeling of scholars, but to the modeling used by financial institutions to predict consumer and investor behavior, as well. 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” 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 consumer law scholars argue that data mining and computer-based models allow financial institutions to predict consumer defaults, they are writing of a relative information advantage compared to consumers. But, 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

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217 Mitchell, supra note 216 at 1804-1811.
218 Id.
220 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).
221 See supra notes 70-72, and accompanying text.
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.

2. **Modeling and Complex Adaptive Systems**

Even assuming the perfect of rationality of individuals, models may fail due to the inherent complexity of financial systems. Complexity science reveals how certain systems, including financial markets, behave in non-linear ways that frustrate easy modeling. Complexity science denotes 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 produce the evolution of increasingly complex adaptive systems. 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 – develop in nonlinear ways.

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223 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).

224 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...

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

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. 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. The adaptive responses of individuals lead to innovations in investment strategies and financial products, which adds new complexities to the market not considered by previous models. One adaptive response is to game risk models. For

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225 E.g., Cars H. Hommes, Financial Markets as Nonlinear Adaptive Evolutionary Systems, 1 QUANT. FIN. 149 (2001)

226 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. E.g. Ruhl, supra note 227, at 979 (criticizing environmental statutes for this flaw).


229 During asset price booms, individuals also have a strong incentive to violate internal controls and regulations. See 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 III.b infra.

230 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.
example, traders in financial institutions can game value-at-risk 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. But, these losses lie in the “fat tail” of a loss curve and outside a value-at-risk measurement.231

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.232

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.233 This risk becomes particularly acute in securitization when firms use a practice known as “mark-

231 Nocera, supra note 170, at 46.
232 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, the securities of which the agencies are rating. E.g. July 2008 SEC Rating Agency Report, supra note 97 at 23-28, 31-32.
233 Neil Shah, Can Wall Street be Trusted to Value Risky CDOs? Reuters (July 13, 2007).
to-model” to value underlying assets instead of using market prices. This subversion of the risk management process stems from 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 lowering their regulatory capital. If an internal model suggested a higher level of regulatory capital than a standard capital regulation, it is an open question 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 risk model can make errors. These bugs or implementation errors can propagate themselves when models are copied and can lead to serious mistakes in the results of risk models. In 2008, press reports indicated that Moody’s blamed a “bug” in some of its computer software for leading to incorrect ratings of several CDOs.

iii. Inputs to Code: Low-documentation Loans

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234 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 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 157

235 See supra note 133 and accompanying text.


237 Sam Jones et al., Moody’s Error Gave Top Ratings to Debt Products, FIN. TIMES (May 20, 2008).
Once models have been designed and selected, they require human input of 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 employment\textsuperscript{238} enabled borrowers (or unscrupulous brokers) to supply incorrect information about income, employment and other information relevant to establishing a borrower’s creditworthiness (or to avoid providing information). By one estimate, over 50% of subprime loans issued over a two year period ending in 2007 were made on the basis of such limited documentation.\textsuperscript{239} 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.\textsuperscript{240}

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

\textit{iv. Gaming the Models}

As noted above, models can also be gamed by individuals at financial institutions who make risky investments designed specifically to avoid detection by models.\textsuperscript{241}

\textsuperscript{239} Alan N. Kribsman, \textit{Subprime Mortgage Meltdown: How did it Happen and How will it End?}, 13 J. STRUCTURED FIN. 13 (2007)(discussing data for “past two years”).
\textsuperscript{241} \textit{See supra} note 231 and accompanying text.
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v. Interface between Codes Revisited: Information Destruction, Externalities and Information

The low-documentation loan problem points to a large problem that the different institutions in the securitization and hedging chain may have insufficient incentive to share information they have on the credit and other risks associated with assets with institutions later in the chain. Moreover, these institutions have little incentive to share with one another operations of their risk models with one another. 242

This lack of information sharing is suboptimal, as explained by the following discussion of the economic externalities involved with risk modeling. The use of effective risk modeling, like risk management in general, creates positive externalities. A firm that mitigates its own risk reduces credit risk for its creditors. 243 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. 244 Furthermore, information about a firm’s risk models has positive externalities as it allows counterparties and the market as a whole to better evaluate credit risks posed by the firm. 245

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

242 See Buiter, supra note 191.
244 Schwarcz, supra note 47 (characterizing systemic risk mitigation as a public good).
245 See Schinasi, supra note 243, at 49 (discussing information as positive externality).
copycat models (and thus free ride on the investment used to construct 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; 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.246 When they are
competent, regulators can provide some certification as to the quality of risk modeling. 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

But, even if regulators competently evaluate individual risk models, the interaction of the risk models of different firms creates anti-coordination problems.247 Too much homogeneity among risk management strategies among financial institutions can increase systemic risk.248 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.249 A widespread sell-off would cause values of these assets to

246 Cf. Guillermo Calvo, Author’s Remarks, WANTED: WORLD FINANCIAL STABILITY 57 (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’s problem).
247 An anti-coordination game is a game in which the players adopting the same strategies creates 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).
248 Carol Alexander, The Present and Future of Risk Management, 3 J. FIN. ECONOMETRICS 3 (2005) (positing that regulation may perversely create this homogeneity).
249 Alexander supra note 248.
plummet and trigger a sell-off of yet another class of assets.\textsuperscript{250} Homogeneity of risk management and models can thus lead to spiraling market declines.\textsuperscript{251} There has some concern that 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.”\textsuperscript{252} 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.\textsuperscript{253}

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.\textsuperscript{254} Second, there is a wide literature on herd behavior and mimicry in financial markets.\textsuperscript{255} 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.\textsuperscript{256}

\begin{footnotesize}
\begin{enumerate}
\item \textsuperscript{250} \textit{Id.}
\item \textsuperscript{251} \textit{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 portfolios of other firms in the market.
\item \textsuperscript{252} \textit{See} e.g., Steven Pearlstein, \textit{Missed Opportunities}, WASH. POST. Aug. 8, 2007, \textit{available at} 2007 WLNR 15269893.
\item \textsuperscript{254} Cf. Nocera, \textit{supra} note 170; Felix Salmon, \textit{A Formula for Disaster}, WIRED, Mar. 2009 at 74.
\item \textsuperscript{255} ROBERT J. SHILLER, \textit{IRRATIONAL EXUBERANCE} 135-68 (2000).
\item \textsuperscript{256} Shadow Financial Regulatory Committee, Statement No. 257: Reliance on Third-Party Credit Ratings 1 (Feb. 11, 2008) \textit{available at} http://www.aei.org/research/shadow/projectID.15/default.asp (asserting that
\end{enumerate}
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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. This opens the door for regulatory arbitrage by financial firms. Yet it is in the collective interest of national regulators to coordinate the level of their regulation – including their level of enforcement – to ameliorate systemic risk.257

257 This coordination problem was the very reason for the first Basel Accord. See supra note 14.
IV. SELECT POLICY AND RESEARCH IMPLICATIONS

Part III of this paper examined several factors that contributed to the failure of the new financial code and, consequently, exacerbated the subprime crisis. This Part IV now considers several implications of that analysis for policy and legal scholarship.258

Six general points frame the discussion of implications and reverberate throughout Part VI. 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 either because they are embedded in a complex technology or because they involve elegant economic models. As with internet code, legal scholars must also engage technical aspects of the new financial code, because technical details can shift massive amounts of risk or even magnify risk. Moreover, the new financial code has come to serve as de facto regulation of a vast swath of consumer finance, banking, and capital markets.

Third, the best codes are worthless 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. Legal scholars

258 One open question is how much each factor analyzed in Part III contributed to the subprime crisis. Given that the crisis continues to unfold, solid data for econometric and other empirical testing of the causal effects of each factor remains to be collected. But, lack of iron clad data on which factor had the greatest causal effect should not delay discussion of urgent, pragmatic policies designed to address the systemic risk caused by the failure of code.
can and must play an invaluable role in designing these incentives; 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.

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, sometime simple designs are the best solutions to complex risks.\textsuperscript{259}

Sixth, promoting transparency or “openness” in the new financial code promotes both efficiency and other normative interests.

\textit{a. Scrapping Basel II’s Internal Models Approach}

All six 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 models\textsuperscript{260} (which this Article collectively refers to as the “Internal Models Approach”).\textsuperscript{261} The 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 Consolidated Supervised Entities program\textsuperscript{262} provides a warning to U.S. bank regulators to reverse and shelve recent regulations that implement Basel II’s Internal

\textsuperscript{259} Henry Petroski has popularized the benefits of simplicity in response to engineering problems. \textit{See}, \textit{e.g.}, \textsc{Henry Petroski, Invention by Design: How Engineers Get from Thought to Thing} (1996).

\textsuperscript{260} \textit{See supra} Part II.b.3.

\textsuperscript{261} This term thus captures the Internal Ratings-Based Approach for credit risk (\textit{supra} note 122), the Internal Models Approach for market risk (\textit{supra} note 123) and the Advanced Measurement Approach for operational risk (\textit{supra} note 124).

\textsuperscript{262} \textit{See supra} Part II.b.4.
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Rating-Based Approach.263 Moreover, international bank regulators responsible for the Basel II 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.264 Now, because of the crisis, many of those U.S. investment banks have been bought by or converted into commercial banks.265 According, to economic studies, Basel II when applied to commercial banks will also lead to undercapitalization.266

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),267 the fundamental flaws of the Internal Models Approach cannot be overcome. More detailed audit standards would increase the compliance costs of the regulated. 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.268 Highly specific rules on model standards would also need to be constantly rewritten to address attempts by financial institutions to game the rules.

263 See supra note 16 at 72 Fed. Reg. 69,288.
264 Supra notes 133-134 and accompanying text.
266 Supra note 127.
267 See, e.g., BASIEL COMMITTEE ON BANKING SUPERVISION, REVISIONS TO THE BASIEL II MARKET RISK FRAMEWORK (Jan. 2009).
More detailed rules would also increase the workload of regulators. But, 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. Strapped regulators responsible for reviewing multiple firms 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 in an intellectual arms race with financial institutions, 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 III.b.vii, bank regulators worry whether their counterparts in other countries 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.

Yet, the Basel II Accord makes policing the actions or inaction or regulators more difficult due to both 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. 269 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. 270

269 Id.  
270 Id.
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. The simpler Basel I rules are also much more transparent; it is easier not only for regulators to audit a bank, but 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). Furthermore, simpler rules mean that counterparties of banks can more easily understand and model the credit risks posed by banks.

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

Taking a step back, using disclosure approach to fix Basel II draws on some of concepts and arguments for the Open Source movement in software. Open source software can have different meanings, but a core element of the concept is that the source code of the software is openly disclosed.

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271 Id.
272 Larry 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 24-26 and accompanying text.

So too does Lessig’s open proposal for checking the regulatory power of internet code have a parallel in this paper’s proposal for checking the new financial code. See supra note 26.

273 The following is based on the “Open Source Definition” but is not an exhaustive summary of that definition or its concept. See Open Source Initiative, Open Source Definition, http://opensource.org/docs/osd. 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 license comply with the standards in the Open Source Definition. Open Source Initiative, About the Open Source Initiative, http://opensource.org/about.

274 Source code of software is the text, written in a human readable programming language, that converts human instructions into computer executions.
This Article’s proposal builds on this disclosure element of open source. 

(Another key element to the open source definition 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.275 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 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, to gauge 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 on large publicly traded financial institutions is already publicly available online through securities filings.276 

ii. The Benefits of Open Source

275 See Open Source Initiative, Open Source Definition, supra note 273.
276 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 disclosure 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 33-8,529, Exchange Act Release, 34-51,129 (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, The Road Map for Recovery, WIRED, Mar. 2009, at 81.
Using 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.\textsuperscript{277}

Public disclosure would also allow an institution’s competitors to double-check the work of regulators. Competitors could thus police whether an institution is “cheating” and adopting weak models to justify taking on additional levels of risk for competitive advantage.\textsuperscript{278} Policing by a bank’s competitors (and by a 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 – \textit{i.e.} models with less faulty assumptions or otherwise with a lower degree of model risk error. Scholarship in computer science

\textsuperscript{277} \textit{See supra} Parts III.a.v and III.b.iv
\textsuperscript{278} III.b.vi.
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provides evidence that open source software code are less prone to bugs, because open
code allows many minds to tackle debugging.279

The transparency of open source would help individual financial institutions solve
the anti-coordination problems posed by homogenous risk models.280 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 does face 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).281 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 IV.a in 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

279 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).
280 III.b.vi.
281 Another possible, related concern is that dampening the profit motivation to develop risk models might
also dampen valuable innovation in risk management.
management practices, which, as Part III.b.vi explains, could increase systemic risk.\textsuperscript{282} This concern is quite valid, but, on the other hand, there is already a large risk of homogeneity in proprietary risk modeling.\textsuperscript{283} Yet, because proprietary models are not publicly disclosed it is difficult 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 III.b.vi. above. 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.

\textit{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 other institutions earlier in the chain of securitization. Otherwise flaws in any model in any link of the long securitization chain (in which mortgages are converted into mortgages, which are then converted into to mortgage-backed securities, which then back CDOs, which then are used to create “CDOs squared”

\textsuperscript{282} There may be some precedent for open source leading to homogeneity. JPMorgan first developed value-at-risk models and then allowed other firms to copy the models, which became an industry standard. Nocera, supra note 170, at 33.
\textsuperscript{283} Supra Part III.b.vi
which are then hedged with credit default swaps) snowball into greater model errors later in the chain.\textsuperscript{284}

There is therefore great value in extending the disclosure/open source approach all the way back to the credit scoring and 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, \textit{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 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 firm’s 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.

\textit{v. Open Source and Rating Agencies}

One set of private industry models, those of rating agencies, would particularly benefit from the disclosure/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

\textsuperscript{284} Supra note 195 and accompanying text
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high ratings.\textsuperscript{285} A full discussion of the potential reasons for the 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.\textsuperscript{286} This regulation does not go far enough. The SEC should require that registered rating agencies, NRSROs, should 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 rating agency models. The voluntary disclosure made by rating agencies to date, including Standard & Poor’s releasing a CDO Calculator,\textsuperscript{287} does not provide sufficient data.

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 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.\textsuperscript{288}


\textsuperscript{287} Cite.

\textsuperscript{288} Supra notes 102-109, and accompanying text

Incidentally, these financial regulations that piggyback off of 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
vi. **Open Source and Consumer Protection**

The disclosure/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.\(^{289}\) 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 this code 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 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 to determine which customers should receive complex penalty provisions in their credit card contracts.\(^{290}\) Greater consumer information would allow consumers to detect when

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\(^{290}\) See Bar-Gill & Warren, *supra* note 66.
lenders are taking advantage of information asymmetries or consumer behavioral biases to extract greater value from consumers.\textsuperscript{291}

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 argued in applauding the Federal Reserve’s proposed rules, third parties could audit these disclosures for consumers, alerting them to excessively risky provisions.\textsuperscript{292} Moreover, consumer watchdog groups could inspect data mining and credit scoring software for other concerns, including whether individual privacy is being infringed (which is a concern of Professor Lessig with respect to internet code),\textsuperscript{293} and whether lenders are engaging in subtle racial or other discriminatory lending practices.

c. \textit{In Praise of Equity}

The failures of the new financial code outlined in this Article urges 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 argues 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 at the expense of the complex financial instruments.\textsuperscript{294} 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 born by

\begin{flushleft}
\textsuperscript{291} Supra notes 67-75, and accompanying text.
\textsuperscript{293} Lessig, \textit{supra} note 24, at 142.
\textsuperscript{294} See Gilson & Whitehead, \textit{supra} note 1
\end{flushleft}
shareholders; companies can then offload these risks to more efficient risk bearers. 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 risk.

But, to price these instruments, these instruments rely on the same codes that failed in the subprime crisis. These same failures – whether stemming from model risk, information gaps, agency costs or otherwise – 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 III.a.iii 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.” Capital raised

295 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).
296 Id.
297 See Gilson & Whitehead, supra note 1.
298 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).
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, assessing credit risk for derivatives and other complex financial instruments is complicated by the disconnect and distance between the financial instrument and the underlying cash-producing assets; recall the long chain from mortgages to mortgage-backed securities to CDOs to credit default swaps.\(^{299}\) 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 subprime crisis will stem this shift in liquidity away from equity markets.\(^{300}\) 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 outlined above argues for further study of the circumstances when shareholders may prove to be the most efficient bearers or 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.

\(^{299}\) *Supra* note 208 and accompanying text.

\(^{300}\) 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.