Dynamic Loss Probabilities and Implications for Financial Regulation*

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Abstract

Much of financial regulation and supervision is devoted to ensuring the safety and soundness of financial institutions. Such micro- and macro-prudential policies are almost always formulated as capital requirements, leverage constraints, and other statutory restrictions designed to limit the probability of extreme financial loss to some small but acceptable threshold. However, if the risks of a financial institution's assets vary over time and across circumstances, then the efficacy of financial regulations necessarily varies in lockstep unless the regulations are adaptive. We illustrate this principle with empirical examples drawn from the financial industry, and show how the interaction of certain regulations with dynamic loss probabilities can have the unintended consequence of amplifying financial losses. We propose an ambitious research agenda in which legal scholars and financial economists collaborate to develop optimally adaptive regulations that anticipate the endogeneity of risk-taking behavior.

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C M Y K

I. Introduction

In the wake of the Financial Crisis of 2007-2009, it has become clear that financial stability can no longer be taken for granted and there is growing doubt that the existing regulatory framework is sufficient for addressing "systemic risk." Despite the sweeping changes that have been and are yet to be made by the Dodd-Frank Act of 2010, the impact of this new legislation on ensuring financial stability is still unclear, largely because we do not have any single framework in which to define and quantify systemic risk—if it cannot be measured, it cannot be managed.

In this Article, we contribute to the development of such a framework by focusing on the recent failure of a central function of financial regulation—to reduce the probability of financial loss of regulated entities to some acceptable threshold—and proposing methods for ensuring that these regulations function as intended.

The starting point for our analysis is the fact that unanticipated financial losses—especially sudden extreme losses—trigger coordinated responses among the losers that can threaten financial stability when the losers are sufficiently large in size or number. Any financial risk entails the possibility of loss; the relevant question for financial stability is whether the parties at risk can withstand such loss, and this, in turn, depends on whether these parties have correctly anticipated the likelihood of and have properly prepared for the loss. Unanticipated losses can cause widespread panic in the form of flights to safety, rapid price declines, and the evaporation of liquidity that, once triggered, are impossible to contain.

The classic example is, of course, a bank run, for which we have developed elaborate legal and institutional remedies over the past century, e.g., capital requirements, "prudent investment" rules, deposit insurance, and the Federal Reserve as a lender of last resort. Given that losses in financial dealings are both uncertain and impossible to avoid consistently, at best, financial regulation can only affect the likelihood and magnitude of such losses. More formally, Lo and Brennan have proposed a simple but general framework that models financial regulations as a desire to limit the probability of losing more than a certain amount X over some period t to an upper bound γ:[1]

$$\text{Prob}(\text{net profit or loss over period } t < -\$X) < \gamma \tag{1}$$

By determining the magnitude of loss X that can destabilize a regulated entity, a financial regulator can set constraints on the entity's risk-taking ability so as to reduce the likelihood of such a loss to some acceptably small level γ, e.g., 0.5%.[2]

However, the existing regulatory framework was largely crafted over half a century ago and did not anticipate the emergence of the so-called "shadow banking system," which refers to money market funds, insurance companies, hedge funds, and other financial institutions that are largely beyond the reach of bank regulatory oversight but share many of the same functions as banks.[3] More importantly, the bulk of the regulatory framework prior to Dodd-Frank was developed during much simpler times when the pace of financial interactions and innovation was considerably slower, the size of the financial industry was considerably smaller, and the scope of the financial system was considerably narrower. This allowed regulators to respond effectively in real time as crises emerged.

But regulators can no longer count on being able to first observe a crisis, and then intervene. Recent experiences such as the subprime mortgage defaults of 2007-2009, the "Quant Meltdown" of August 2007, the collapse of Bear Stearns, AIG, and Lehman Brothers in 2008, and the "Flash Crash" of May 6, 2010 are examples of unanticipated losses that were too large, too broad, and too fast for existing regulatory bodies and tools to prevent. Recent proposals for "taking away the punch bowl" at the height of the party, i.e., "counter-

1. *See* Andrew W. Lo & Thomas J. Brennan, *Do Labyrinthine Legal Limits on Leverage Lessen the Likelihood of Losses? An Analytical Framework*, 90 TEX. L. REV. 1775, 1777, 1792-93 (2012).

2. If, for example, a bank cannot withstand a loss of $100 million over the course of a month, then its regulator may wish to constrain its risk-taking activities so that the probability that it loses $100 million in any given month is 0.5%. If the constraint is accurately implemented, the bank should breach that critical level of losses only once every 200 months. At such a level of risk, other mechanisms for ensuring the safety and soundness of the banking system such as deposit insurance and a lender of last resort should suffice.

3. The Dodd-Frank Act created the means to bring certain of these shadow banking institutions under the purview of the Federal Reserve System by designating them to be "Systemically Important Financial Institutions" (SIFIs). *See* Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203, 124 Stat. 1376, 1802-21 (codified as amended at 12 U.S.C. §§ 5461-72 (2012)) (defining SIFIs and providing for payment, clearing and settlement supervision, and elsewhere); *Id* at 1822-1955 (codified as amended at 15 U.S.C. § 78a (2012)) (providing for investor protection and improvements to securities regulation, including establishment of a financial oversight council, and elsewhere). However, only a handful of non-bank institutions have received such designations to date, and it will be years before we can determine whether this mechanism is sufficient to address the systemic risks posed by this part of the financial system. In any case, the SIFI designation does not address the mismatch between traditional macroprudential regulation and the speed, scope, and size of today's financial institutions.

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cyclical" capital buffers, implicitly recognize the importance of unanticipated losses and the need for more dynamic regulatory responses, but those proposals do not explicitly model the dynamics of loss probabilities in formulating their policies and, as a result, may not be responsive enough.[4] In particular, if macroprudential regulations are imposed using inaccurate information such as outdated estimates of current risk exposures, then unintended threats to financial stability can easily emerge as economic conditions shift.

In this Article, we extend Lo and Brennan's analysis to cases in which loss probabilities are dynamic and argue that financial regulation must be equally dynamic to be effective.[5] Controlling the likelihood of unanticipated losses as market conditions vary requires a detailed understanding of the behavior of financial asset prices. Although prices are random, they generally have a degree of structure. Simple models often assume that asset returns follow a stable pattern, e.g., a lognormal distribution, over time. In these models, one does not know for sure whether an asset price will fall below a certain level, but one does know with greater certainty the probability that the price will fall below that level. Unfortunately, price processes in the real world are seldom truly stable over time. They can change swiftly, as can their co-movement with other asset prices. As a result, continuous monitoring and rapid updating of leverage and capital requirements are generally necessary to keep losses to within a specified level of statistical confidence.

We illustrate this challenge by investigating the properties of foreign currency exchange rates for seven major currencies through time. Currency markets are among the largest and most active financial markets in the world, affecting virtually every major corporation, industry, and sovereign entity. Because foreign exchange rates are routinely roiled by macroeconomic shocks, central banking interventions, and geopolitical upheaval, the dynamics of foreign-currency loss probabilities are particularly relevant for our purposes. After showing that these loss probabilities change dramatically through time, we illustrate the implications for regulation by examining how the Chicago Mercantile Exchange dynamically changes its margin requirements for foreign exchange futures contracts in response to changes in risk.

4. *See, e.g.*, Markus K. Brunnermeier et al., THE FUNDAMENTAL PRINCIPLES OF FINANCIAL REGULATION 31-38, 57, 72 (2009). The "punch bowl" metaphor for financial regulatory interventions was first used in a speech by Federal Reserve Chairman William McChesney Martin in which he said: "The Federal Reserve . . . is in the position of the chaperone who has ordered the punch bowl removed just when the party was really warming up." William McChesney Martin, Chairman, Bd. of Governors, Fed. Reserve Sys., Address before the New York Group of the Investment Bankers Association of America 12 (Oct. 19, 1955) (transcript available at http://fraser.stlouisfed.org/docs/historical/martin/martin55_1019.pdf).

5. The dynamic nature of financial risk is well known. For an example of dynamic risk management by private parties, see the discussion in Section 3 of the Chicago Mercantile Exchange's system designed for this purpose. For a discussion of the failure of many prior regulations to account for the dynamic nature of financial risk, see Lo & Brennan, *supra* note 1.

However, time variation in asset price dynamics can also be driven by the financial system itself, even by the very regulations designed to constrain that system, and such sources of risk are the subject of extensive study in the economics literature.[6] One simple example is a regulatory capital requirement that constrains a financial entity to maintain a certain amount of equity relative to the amount of risky assets that it holds. If the value of the risky assets decreases, the entity may need to divest itself of some of those assets to comply with the regulation. This sale may have an adverse impact on asset prices, particularly if many entities are in similar situations at the same time. The result may be a so-called "fire sale" of assets that increases losses and drives up asset price volatility, at least in the short term. This effect may also become self-reinforcing, with entities forced to sell even more assets because of their own impact on prices. Thus, an ostensibly salutary regulatory capital requirement can amplify small shocks and destabilize the entire system under certain conditions.

The simple tripping of regulatory limits and induced fire sales is not the only way the statistical properties of market prices can be altered by forces solely within the financial system. The interactions can be much more subtle, as is the case when economic entities engage in sophisticated trading strategies that exploit time-varying market conditions. We illustrate this possibility with the specific example of a class of dynamic trading strategies that consist of buying "losers" and selling "winners," purchasing securities that have experienced recent price declines and short-selling securities that have experienced recent price appreciation. In doing so, such trading strategies are betting on mean reversion—today's losers becoming tomorrow's winners and vice versa—but an unintended consequence of this strategy is to dampen price volatility if many funds are trading using this same strategy in sufficient size to

6. *See, e.g.*, Tobias Adrian & Hyun Song Shin, *Liquidity and Leverage*, 19 J. FIN. INTERMEDIATION 418 (2010) (providing evidence that marked-to-market leverage is procyclical and has aggregate consequences for market risk); Markus K. Brunnermeier & Lasse Heje Pedersen, *Market Liquidity and Funding Liquidity*, 22 REV. FIN. STUD. 2201 (2009) (developing a model that shows that under certain conditions margin requirements are destabilizing with the possibility of liquidity spirals); Jon Danielsson, Hyun Song Shin & Jean-Pierre Zigrand, *The Impact of Risk Regulation on Price Dynamics*, 28 J. BANKING & FIN. 1069 (2004) (using simulations to show that the feedback effects of risk management may exacerbate financial instability); Ana Fostel & John Geanakoplos, *Why Does Bad News Increase Volatility and Decrease Leverage?*, 147 J. ECON. THEORY 501 (2012) (developing a model explaining why leverage decreases during periods of high volatility); Ana Fostel & John Geanakoplos, *Leverage Cycles and the Anxious Economy*, 98 AM. ECON. REV. 1211 (2008) (showing how fluctuations in endogenous leverage levels, referred to as the "leverage cycle," can cause contagion and flight to collateral); Johannes Brumm, Michael Grill, Felix Kubler, and Karl Schmedders, *Margin Regulation and Volatility* (Swiss Fin. Inst. Research Paper No. 13-59, Dec. 2, 2013) (examining the relationship between margin requirements and asset volatility); John Dai & Suresh Sundaresan, Risk Management Framework for Hedge Funds Role of Funding and Redemption Options on Leverage (Mar. 21, 2010) (unpublished manuscript) (modeling hedge fund leverage and returns as constrained by obligations to investors and prime brokers); Jon Danielsson, Hyun Song Shin, and Jean-Pierre Zigrand, Procyclical Leverage and Endogenous Risk (Oct. 4, 2012) (unpublished manuscript) (exploring the connection between fluctuations in leverage and fluctuations in financial conditions).

have an impact on market prices. In such situations, a single macro shock that causes prices to trend instead of mean-revert can generate simultaneous losses among all funds implementing this strategy. This forces the funds to reduce their positions at the same time, which only exacerbates their losses and amplifies volatility as they reduce their volatility-dampening trading. This macro shock can affect investors who had no part in the dynamic trading strategy, but were only passive investors in the underlying securities. Such innocent bystanders may have decided on their investment holdings using historical volatility estimates that are no longer accurate because they did not account for the effect of mean-reversion traders coming into and out of the market.

Of course, the extent to which swiftly varying price distributions and endogenous volatility are problematic is largely an empirical question, and the prospect of unexpected loss, rapid unwinding of positions, and artificial volatility reduction may well be sufficiently remote to be of no concern. However, in this Article we provide empirical evidence to the contrary by simulating the historical performance of a simple mean-reversion trading strategy and documenting the dynamic nature of its probability of loss under various market conditions. We find evidence for a volatility/leverage feedback loop in which the proliferation of mean-reversion trading strategies dampens volatility, facilitating greater leverage that magnifies both gains and losses. To underscore the potential instabilities inherent in this vicious cycle, we provide a specific example involving the "Quant Meltdown" of August 2007, a unique event in which hedge funds and proprietary trading desks that employed mean-reversion strategies all suffered extreme losses over a few days for no apparent reason.

We conclude by proposing that financial regulation be formulated and implemented with these dynamic considerations in mind. More research must be undertaken to understand the full extent to which loss probabilities are dynamic and endogenous to the regulated financial system so that optimal adaptive regulations can be crafted. This poses a fundamental tension for policymakers because the standard for drafting objective, consistent, and easily enforceable securities laws is to propose "clear bright lines," whereas complex goals such as equation (1) can only be achieved through "balancing tests." Moreover, because regulated entities adapt to their environment, regulations can sometimes have the unintended consequence of motivating financial innovations that circumvent poorly designed constraints.

Systemic risk is not exogenous to the financial system but is determined jointly and endogenously by market participants and their regulators, and this endogeneity must be taken into account when formulating new regulations. In particular, the most effective regulatory framework is one that adapts flexibly over time, taking asset price dynamics into account with a self-awareness of its own impact on those dynamics.

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II. Dynamic Loss Probabilities in Currency Markets

To illustrate the extent to which the probability of loss can vary over time, raising the likelihood of unanticipated losses, in this Section we consider the dynamic properties of foreign currency exchange rates. A natural consequence of globalization is that businesses and investors are now more affected by fluctuating exchange rates than ever before. Even individual investors in U.S. mutual funds holding only domestic corporations will see their fortunes rise and fall with the U.S. dollar given the amount of business coming from Europe and Asia. Accordingly, managing currency risk has become one of the highest priorities for both the private sector and regulators. This market thus provides an ideal illustration of the practical relevance of dynamic loss probabilities.

We consider seven major currencies: the Australian Dollar (AUD), the Canadian Dollar (CAD), the New Zealand Dollar (NZD), the Swiss Franc (CHF), the European Euro (EUR), British Pound (GBP), and the Japanese Yen (JPY).[7] For each currency, X, we define its price at the end of day t to be the number of units of that currency that may be purchased by one U.S. dollar, and we write this value as $P_{X,t}$.[8] We compute the daily return for day t as:

$$R_{X,t} = \frac{P_{X,t}}{P_{X,t-1}} - 1 \tag{2}$$

Financial risk is often measured by return volatility—also known as return standard deviation—which captures the degree of variability of returns around its mean:

$$\sigma_{X,t} = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(R_{X,t-k} - \bar{R}_{X,t}\right)^2}\ , \qquad \bar{R}_{X,t} \equiv \frac{1}{n}\sum_{k=1}^{n} R_{X,t-k} \tag{3}$$

In our analysis, we set $n = 125$ days to yield an estimate of volatility that is flexible enough to change as market risk changes, but long enough to yield an accurate estimate, and we multiply this estimate by $\sqrt{250}$ to annualize it.[9]

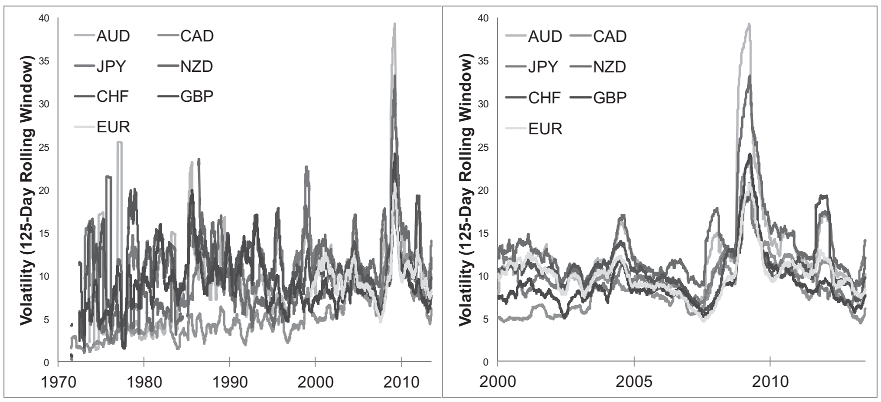
Volatility also plays a critical role in determining loss probabilities given that the calibration of equation (1) almost always depends on a volatility

7. We obtained historical data for these seven currencies from the H10 report of the Federal Reserve Board, which we accessed through Wharton Research Data Services. The data sets analyzed for the currencies generally run from 1971 through 2013, except for the data set for the euro, which runs from its inception in 1999 through 2013.

8. For many currencies, the reciprocal of our price is often the way that quotes of currency value are given. For our purposes, however, our definition of price is most useful because it views the currency as something in which dollars can be invested.

9. There are approximately 250 trading days in a calendar year. *See, e.g.*, *Holidays*, N.Y. STOCK EXCH., http://www.nyx.com/holidays-and-hours/nyse (last visited Dec. 21, 2013) (showing that the NYSE is closed for 9 holidays and approximately 104 weekend days each year, leaving roughly 250 trading days).

parameter. Specifically, higher levels of volatility imply a greater chance of large positive and negative returns. Estimating timely measures of volatility is therefore essential to any risk management protocol. As Figure 1 shows, there is substantial variation in the volatility for each currency over time, implying highly dynamic loss probabilities.



(a) (b)

Figure 1. 125-day rolling-window volatility estimates of seven major currencies, including the Australian Dollar (AUD), the Canadian Dollar (CAD), the New Zealand Dollar (NZD), the Swiss Franc (CHF), the European Euro (EUR), the British Pound (GBP), and the Japanese Yen (JPY). Estimates are based on daily data from: (a) 2000 to 2013; and (b) 1971 to 2013. All estimates are annualized by multiplying by $\sqrt{250}$.

In addition to their time-varying volatilities, currency returns also exhibit time-varying co-movements and these co-movements are important determinants of the overall volatility of portfolios of foreign exchange.[10] To analyze the co-movement of the returns for investments in the seven currencies, we calculate the correlation of the returns for each pair of currencies. At each point in time, we compute these numbers based on the prior 125 days of data.[11] To gauge the degree to which the currencies are all moving together, we calculate the average of the pairwise correlations of returns to investments in the seven currencies:

$$\text{Average of Pairwise Correlations} = \frac{1}{7 \times 6} \sum_{i,j \in C, i \neq j} \text{Corr}(R_i, R_j) \quad (4)$$

10. Specifically, the variance of a portfolio of assets is the weighted sum of the individual assets' variances and all pairwise covariances.

11. Note that there is no need to multiply by a factor to annualize correlation—as was the case with volatility—because the units of correlation are invariant with respect to time. Specifically, correlation is the ratio of covariance to the product of two standard deviations, and both the numerator and denominator in this ratio scale linearly with time. *See* GEZA SCHAY, INTRODUCTION TO PROBABILITY WITH STATISTICAL APPLICATIONS 158 (2007).

where $C \equiv \{\text{AUD, CAD, CHF, EUR, GBP, JPY, NZD}\}$.[12] If the currencies are statistically independent of each other, then we would expect this average to be approximately zero. Alternatively, if the currencies are all highly correlated, we would expect the average to be close to one. In fact, the average has varied significantly over time, as shown in Figure 2. The average since 2000 has frequently been as low as 0.3 and has been as high as 0.7. A more sophisticated analysis using the eigenvalues of the correlation matrices confirms this pattern—periodically, currency movements become highly correlated and are driven by a single common factor.

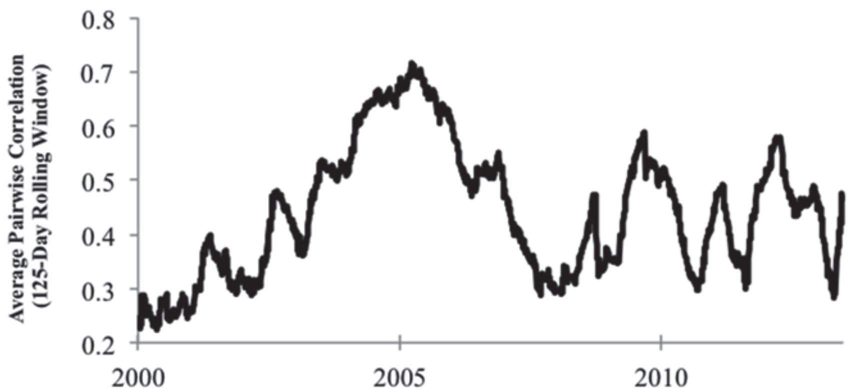


Figure 2. Average pairwise correlations of returns to investments of U.S. dollars in seven major foreign currencies, based on 125-day rolling-window correlation matrices from 2000 to 2013.

III. Dynamic Loss Limits in Practice

A concrete example of dynamic loss limits in practice is the way many organized exchanges set and update margin requirements as market conditions vary, presumably to constrain the probability of loss to an acceptable level. In this Section we describe the approach taken by one of the leading exchanges, the Chicago Mercantile Exchange (CME). As one of the world's largest organized financial exchanges, the CME has developed several industry standards for setting margin requirements dynamically so as to insulate market participants and the exchange from default due to extreme losses.

The CME determines the appropriate amount of collateral for a particular participant using a sophisticated risk management system known as Standard Portfolio Analysis of Risk (SPAN). The margin requirements vary with the investment portfolio, and they are also regularly updated to reflect the current volatility and other attributes of the investment. According to the CME

12. Dividing by 42 is appropriate even though there are only 21 unique pairings because each pair of currencies appears twice in the sum.

website, "SPAN has become the industry standard for portfolio risk assessment. It is the official performance bond (margin) mechanism of over 50 registered exchanges, clearing organizations, service bureaus and regulatory agencies throughout the world."[13]

The key to SPAN's effectiveness is the speed with which it adjusts to changes in market conditions, particularly market risk. During periods of rapid volatility changes, SPAN reflects those changes and triggers corresponding changes in margin requirements. This has the effect of smoothing the changes in loss probabilities, thereby reducing the likelihood of unanticipated losses. Some researchers have argued that sharp increases in margin requirements can trigger financial crises,[14] and this observation underscores the importance of updating margin requirements as frequently as volatility changes. If margin requirements are continuously revised to yield relatively stable loss probabilities as market conditions change, the likelihood of a sudden and substantial increase in margin requirements is reduced.

The SPAN system does not remove all subjectivity and judgment from the process of evaluating portfolio risk exposures. SPAN is designed to compute how risky positions change in value following a variety of possible movements in various markets.[15] To start, SPAN evaluates the gains or losses in a portfolio under a number of scenarios.[16] With these scenarios, SPAN essentially builds a distribution of possible portfolio returns. The shape of the distribution depends upon the choice of such underlying parameters as the size of possible price and volatility movements for underlying assets. For some purposes, parameters must also be specified to determine probabilities of particular scenarios.[17] The various parameters must be frequently updated to reflect changes in market conditions, but such calculations require some judgment, as they are not pinned down by any formula. Similarly, additional modifications must be made for portfolios containing securities that are more vulnerable to extreme movement.[18] Once all the necessary inputs have been

13. *Risk Management Overview*, CME GROUP, http://www.cmegroup.com/clearing/risk-management (last visited Dec. 6, 2013). Further details about the SPAN system are also available on the CME website.

14. *See, e.g.*, Brunnermeier & Pedersen, *supra* note 6.

15. *See generally* CME GROUP, CME SPAN: STANDARD PORTFOLIO ANALYSIS OF RISK (2010), http://www.cmegroup.com/clearing/files/span-methodology.pdf (discussing how SPAN operates and giving examples).

16. According to the CME, "[m]ost SPAN exchanges or clearing organizations use 16 scenarios." *Id* at 6.

17. This is the case, for example, in the computation of "Composite Delta Scenarios." *Id* at 11.

18. As a specific example, "[d]eep out-of-the-money short options may pose significant risk, as unusually large price changes may result in unexpectedly large losses, particularly as expiration nears." *Id* at 10. Applying the SPAN methodology used for other assets to short options thus may not yield appropriate margins. Instead a "Short Option Minimum" can be manually inputted and used to take the place of the usual SPAN method if it is too low. *Id* at 21.

provided, the system determines what the appropriate performance bond, i.e., margin requirement, should be.

Returning to the case of foreign currency investments, we collected the CME's historical margin requirements for investments in currency futures contracts.[19] Figure 3 illustrates the historical levels of the required margin for an initial investment by a speculative investor.[20] We show the margin level as a percent of dollars invested. The actual performance bond requirements of the CME are stated in dollars per contract, with the contract size varying depending on the particular currency at issue. We convert this into a percentage of dollars per contract by dividing the stated performance bond amount by the dollar amount corresponding to the contract on each date.[21] It also overlays 125-day trailing volatility—as measured by annualized standard deviation—for daily investment of dollars in the euro. This volatility curve has the same shape as that of a margin requirement that varies over time to maintain a fixed loss probability under the assumption that returns have zero expected return and volatility equal to the 125-day average.[22] As seen in the Figure, the CME margin requirements generally correlate strongly with recent volatility. Similar relationships hold for the remaining six currencies in our dataset.

19. These contracts represent positions on future prices of the currencies, and historical margin requirements. *See List of Historical Margins by Name,* CME GROUP, http://www.cmegroup.com/clearing/risk-management/historical-margins.html (last visited Dec. 6, 2013). Specific details about the terms of the contracts are available on the CME website.

20. Ongoing maintenance margins are generally lower than initial margins, and investors who are hedging, rather than speculating, have a different set of margin requirements.

21. For euro futures, the contract size is 125,000 euros. To convert this into the corresponding dollar amount, we divide 125,000 by the spot exchange rate of euros per dollar on each day. Therefore, the margin per dollar invested we report for the euro is the stated performance bond divided by the converted dollar amount. *See generally EUR/USD*, CME GROUP, http://www.cmegroup.com/trading/fx/g10/euro-fx_contract_specifications.html (last visited Dec. 6, 2013) (providing further details about the contracts involved).

22. Specifically, consider a model that assumes that returns are normally distributed with mean zero and volatility equal to the 125-day trailing value. To ensure that the probability of loss to the clearinghouse is no more than g, the performance bond should be equal to $-F^{-1}(g)*s_t$, where s_t is the 125-day trailing volatility at time t and F^{-1} is inverse cumulative distribution function for the standard normal distribution with mean zero and unit variance. Thus, the margin requirement in this case is equal to a constant multiple of recent volatility, and it is for this reason that the curves traced out by the margin requirement and by historical volatility have the same shape over time. A similar situation occurs if the normal distribution is replaced by an instance of Student's *t*-distribution.

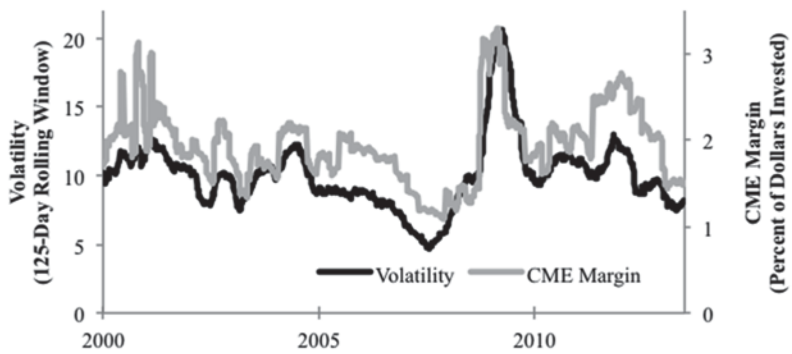


Figure 3. Volatility of daily returns for investment in U.S. dollars in the euro, along with historical margin requirements of the CME for euro futures contracts. The volatility is calculated for the prior 125 days and annualized by multiplying by $\sqrt{250}$. The CME margin is the level required for an initial investment by a speculative investor. The margin reported is the percentage of dollars invested in the contract, as explained further in the text.

Of course, even the most sophisticated risk management techniques of private clearinghouses do not guarantee complete protection in all circumstances. There have been examples of clearinghouse failures in the past,[23] and concerns have been raised recently about clearinghouse risk in light of the increased volume of clearinghouse demand created by Dodd-Frank.[24] Nonetheless, state-of-the-art risk management systems such as SPAN serve as a useful proof-of-concept for the importance of dynamic loss probabilities.

The SPAN system is critical to the CME for protecting its clearinghouse against defaults, and it incorporates the types of adaptive and dynamic updating that regulation of the financial system should also incorporate. It is not, however, concerned with managing systemic risk. Financial regulation should be informed by such private-sector examples and implement systems in the same spirit, but the focus of macroprudential policies is the entire financial system. Therefore, such policies need to account not just for losses at the clearinghouse level, but losses at the level of the macroeconomy. In addition, they need to incorporate changes in pricing dynamics resulting both from

23. For example, Caisse de Liquidation became insolvent in 1974 and Kuala Lumpur Commodity Clearing House was forced to stop trading in 1983. *See* Matthew Leising & Bradley Keoun, *Swaps 'Armageddon' Lingers as New Rules Concentrate Risk*, BLOOMBERG, Dec. 21, 2012, http://www.bloomberg.com/news/2012-12-21/swaps-armageddon-lingers-as-new-rules-concentrate-risk.html. There has also been stress on U.S. futures markets in times of crisis, as witnessed by more than $4 billion in margin calls by Chicago futures markets in October 1987. *Id*; *see also* Ben Bernanke, *Clearing and Settlement During the Crash*, 3 REV. FIN. STUD. 133, 147 (1990).

24. One of the provisions of Dodd-Frank requires many swaps that were previously traded over the counter to be traded through clearinghouses, which will substantially increase the volume of trades and risks handled by clearinghouses. *See* Leising & Keoun, *supra* note 23.

exogenous events and trading strategies, as well as the endogeneity of adaptive behavior and the impact of the regulatory requirements themselves.

A further difference is that the CME deals with highly liquid instruments for which changes in volatility and price processes may be readily observed and incorporated into new margin requirements. Regulation of the entire financial system must deal with investments that may not be as easily valued or traded at all times. The challenges to regulators are thus significantly different in nature from those faced by the private sector. Nonetheless there is much that can be learned from the way sophisticated financial institutions such as the CME use dynamic and adaptive rules to limit their losses.

IV. Proprietary Trading and Leverage Constraints

The fact that leverage, market risk, and loss probabilities are interrelated is only one level of complexity in the dynamics of setting optimal leverage constraints. A more important level of complexity arises from the fact that many investors employ highly dynamic trading strategies that are state-dependent, and these strategies often interact with market risk to yield an even more challenging system that regulators must control. We provide a simple, but surprisingly realistic example in this Section based on a mean-reversion trading strategy first proposed by Lehmann, and Lo and MacKinlay, which can be analyzed directly using historical U.S. equity returns.[25] After describing the strategy and the role that leverage plays in determining its returns, we construct its daily returns from 1926 to 2012 and show how fixed leverage constraints would imply highly variable loss probabilities for the strategy across time.

Given a collection of *N* securities, consider a long/short market-neutral equity strategy consisting of an equal dollar amount of long and short positions, where at each rebalancing interval the long positions consist of "losers" (underperforming stocks, relative to some market average) and the short positions consist of "winners" (outperforming stocks, relative to the same market average). Specifically, if ω_{it} is the portfolio weight of security *i* at date *t*, and if R_{it} denotes the return of security *i* on date *t*, then

$$\omega_{it} = -\frac{1}{N}(R_{it-k} - R_{mt-k}), \qquad R_{mt-k} \equiv \frac{1}{N}\sum_{i=1}^{N} R_{it-k} \tag{5}$$

for some $k > 0$.

Note that the portfolio weights are the negative of the degree of outperformance k periods ago, so each value of k yields a somewhat different strategy. For our purposes, we set $k = 1$ day. By buying yesterday's losers and

25. *See* Bruce N. Lehmann, *Fads, Martingales, and Market Efficiency*, 105 Q.J. ECON. 1 (1990); Andrew W. Lo & A. Craig MacKinlay, *When are Contrarian Profits Due to Stock Market Overreaction?*, 3 REV. FIN. STUD. 175 (1990).

selling yesterday's winners at each date, such a strategy actively bets on mean reversion across all *N* stocks, profiting from reversals that occur within the rebalancing interval. For this reason, (5) has been called a "contrarian" or mean-reversion trading strategy that benefits from market overreaction, i.e., when underperformance is followed by positive returns and vice-versa for outperformance.[26]

However, another source of profitability of mean-reversion trading strategies is the fact that they provide liquidity to the marketplace. By definition, losers are stocks that have underperformed relative to some market average, implying a supply/demand imbalance, i.e., an excess supply that caused the prices of those securities to drop, and vice-versa for winners. By buying losers and selling winners, contrarians are adding to the demand for losers and increasing the supply of winners, thereby stabilizing supply/demand imbalances. Traditionally, designated market-makers such as the NYSE/AMEX specialists and NASDAQ dealers have played this role, for which they are compensated through the bid/offer spread. But over the last decade, hedge funds and proprietary trading desks have begun to compete with traditional market-makers, adding enormous amounts of liquidity to U.S. stock markets and earning attractive returns for themselves and their investors in the process.

As liquidity providers, market-makers are often said to be "long volatility" because market-making profits generally increase with volatility. There are several reasons for this positive relation, but the most common explanation is that market-makers have no proprietary information about the fundamental value of a security and profit mainly from transacting because they earn the bid/offer spread for each round-trip trade in which they participate. Therefore, the most favorable set of market conditions for market-makers is when prices are not trending up or down but swinging back and forth vigorously, generating larger amounts of non-information-based liquidity trades.[27]

As volatility increases, market-makers' profits increase in lock-step, which inevitably draws more competitors into the industry. And as more market-making capital is deployed, its impact on prices becomes more pronounced. In particular, mean-reversion trading strategies tend to reduce market volatility because they attenuate the movement of prices by selling stocks for which there is excess demand and buying stocks for which there is excess supply. Therefore, an increasing amount of capital dedicated to market-making strategies is one potential explanation for the secular decline in U.S.

26. *See* Lo & MacKinlay, *supra* note 24 (giving further details on the strategy); Amir E. Khandani & Andrew W. Lo, *What Happened to the Quants in August 2007?*, 5 J. INV. MGMT. 5, 29 (2007) (providing even further details on the strategy).

27. *See* Lawrence R. Glosten and Paul R. Milgrom, *Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders*, 14 J. FIN. ECON. 71 (1985).

equity-market volatility during the 10 years prior to the 2008 financial crisis. Once this market-making capital is withdrawn from the marketplace, volatility should pick up, as it did after the Quant Meltdown of August 2007. We shall return to this important volatility/leverage feedback loop in the sections below when we consider the endogeneity of volatility.

If mean reversion implies that contrarian trading strategies will be profitable, then momentum implies the reverse. In the presence of return persistence, i.e., positively autocorrelated returns, Lo and MacKinlay show that the contrarian trading strategy (5) will exhibit negative profits.[28] As with other market-making strategies, the contrarian strategy loses when prices exhibit trends, either because of private information, which the market microstructure literature calls "adverse selection," or a sustained liquidation in which the market-maker bears the losses by taking the other side and losing value as prices move in response to the liquidation. Therefore, whether or not (5) is an interesting strategy in its own right, losses with respect to this particular strategy serve as a valuable indicator of broad-based liquidations of long and/or short positions, which occurred during the Quant Meltdown of August 2007, as discussed below.[29]

Note that the weights in (5) have the property that they sum to 0, which means that (5) is an example of an "arbitrage" or "market-neutral" portfolio where the long positions are exactly offset by the short positions.[30] As a result, the portfolio "return" cannot be computed in the standard way because there is no net investment. In practice, however, the return of such a strategy over any finite interval is easily calculated as the profit-and-loss of that strategy's positions over the interval divided by the initial capital required to support margins on those positions. This feature of market-neutral strategies is why leverage is so central to the profitability of hedge funds and proprietary trading desks—more leverage means less capital tied up per dollar of profit-and-loss, hence higher potential rates of return.[31]

28. *See* Lo & MacKinlay, *supra* note 25, at 183-84.

29. *See also* Khandani & Lo, *supra* note 26; Amir Khandani & Andrew C. Lo, *What Happened to the Quants in August 2007?: Evidence from Factors and Transactions Data*, 14 J. FIN. MKT., 1 (2011).

30. Such a strategy is more accurately described as a "dollar-neutral" portfolio since dollar-neutral does not necessarily imply that a strategy is also market-neutral. For example, if a portfolio is long $100 million of high-beta stocks and short $100 million of low-beta stocks, it will be dollar-neutral but will have positive market-beta exposure. In practice, most dollar-neutral equity portfolios are also constructed to be market-neutral, hence the two terms are used almost interchangeably, which is sloppy terminology, but usually correct.

31. Specifically, suppose that a portfolio consisting of $100 million of long positions and $100 million of short positions generated profits of $2 million over a one-day interval. The return of this strategy is simply $2 million divided by the required amount of capital to support the $100 million long/short positions. Under Regulation T, the minimum amount of capital required is $100 million (often stated as 2:1 leverage, or a 50% margin requirement), hence the return to the strategy is 2%. *See* Margin Requirements, 12 C.F.R. §220.12 (2013). If, however, the portfolio manager is a broker/dealer, then Regulation T does not apply (other regulations govern the capital adequacy of broker/dealers, such as SEC Rule 15c3–1), and higher levels of leverage may be employed. For example, under certain

Lo and MacKinlay provide a detailed analysis of the unleveraged returns of the contrarian trading strategy, tracing its profitability to mean reversion in individual stock returns as well as positive lead/lag effects and cross-autocorrelations across stocks and across time.[32] However, for our purposes, such decompositions are of less relevance than simply using (5) as a tool to study the performance of leverage constraints over time and across different market environments. To that end, we apply this strategy to the daily returns of all stocks in the University of Chicago's CRSP Database from December 31, 1925 to September 30, 2012.[33]

Before turning to the performance of the leverage constraints over time, we summarize the strategy's historical performance to provide some intuition for its properties. Figure 4 shows the average return and Sharpe ratio for the strategy for holding periods of 1, 5 and 20 trading dates. The results are impressive. Over the course of the historical time period we consider, the strategy produced an average daily return of 1.96%, or 490% per year, assuming a 250-day year! Of course, this return is unrealistic because it ignores a number of market frictions such as transactions costs, bid/offer spreads, price impact, short-sales constraints, and other institutional limitations.[34] In

conditions, it is possible to support a $100 million long/short portfolio with only $25 million of capital—leverage ratio of 8:1—which implies a portfolio return of $2/$25 = 8%. Note that the technical definition of leverage—and the one used by the U.S. Federal Reserve, which is responsible for setting leverage constraints for broker/dealers—is given as the sum of the absolute values of the long and short positions divided by the capital.

The gross dollar investment I_t of the portfolio (5) under Regulation T and its unleveraged portfolio return R_{pt} are given by:

$$I_t \equiv \frac{1}{2}\sum_{i=1}^{N} |\omega_{it}| \quad , \qquad R_{pt} \equiv \frac{\sum_{i=1}^{N} \omega_{it} R_{it}}{I_t} \tag{6}$$

To construct the leveraged portfolio return $L_{pt}(\theta)$ using a regulatory leverage factor of θ:1, we simply multiply the formula for R_{pt} in (6) by θ/2, so that

$$LR_{pt}(\theta) \equiv \frac{\theta}{2} \times \frac{\sum_{i=1}^{N} \omega_{it} R_{it}}{I_t} \tag{7}$$

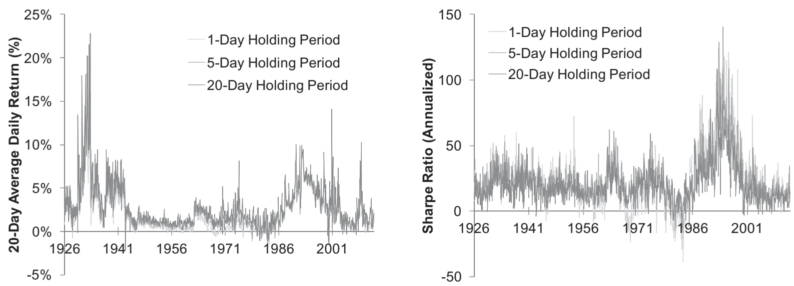
Note that the Regulation T leverage requirement is currently 2:1 (θ=2), and this is equivalent to a multiplier of θ/2=1, For this amount of leverage, $LR_{pt}(\theta)$ is simply equal to R_{pt}.

32. *See* Lo & MacKinlay, *supra* note 25, at 183-84, 201.

33. We use only U.S. common stocks (CRSP share code 10 and 11), which eliminates REITs, ADRs, and other types of securities.

34. However, Lo and MacKinlay provide a thorough analysis of all of these considerations and conclude that none of them can explain away the profitability of these strategies. *See* Lo & MacKinlay, *supra* note 25 192-201; Andrew W. Lo & A. Craig MacKinlay, *Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test*, 1 REV. FIN. STUD. 41, 56-60 (1988); Andrew W. Lo & A. Craig MacKinlay, *An Econometric Analysis of Nonsynchronous Trading*, 45 J. ECONOMETRICS 181, 198-203 (1990); ANDREW W. LO & A. CRAIG MACKINLAY, A NON-RANDOM WALK DOWN WALL STREET 287-346 (1999). Even more convincingly, a number of hedge

particular, a daily rebalancing interval would imply extraordinarily high turnover across the set of thousands of securities in our sample, which was simply not feasible through most of the sample period.[35]



(a) (b)

Figure 4. Historical performance of the contrarian trading strategy with holding periods of 1, 5, and 20 days: (a) average daily returns, computed over non-overlapping blocks of 20 trading days; (b) Sharpe ratio for the same time periods, with the numerator taken to be the average daily return, and the denominator taken to be the standard deviation of the returns during the 20-day block. The Sharpe ratio value is annualized by multiplying by $\sqrt{250}$.

Figure 4(a) also shows a strong trend of declining average daily returns starting in the 1990s and beyond, a reflection of increased competition, changes in market structure, improvements in trading technology and electronic connectivity, the growth in assets devoted to this type of strategy, and the corresponding decline in U.S. equity-market volatility over the last decade.[36] This trend is closely related to the use of leverage, which we shall consider in more detail below.

To develop intuition for the magnitude of time variation in loss probabilities for dynamic trading strategies, consider the margin requirements for the mean-reversion strategy (5) with a 1-day holding period under a number of scenarios. We first derive the margin required under Regulation T, discussed above in note 34.[37] We then consider margin requirements that set the

funds and proprietary trading desks at major investment banks implemented strategies like this one during the 1980s and 1990s and were consistently profitable throughout this period.

35. The average number of securities in our sample from December 1925 to September 2012 is 2,985. During the period from 1972 onward, when both AMEX and NASDAQ stocks were included in the CRSP database, the average number of securities is 5,381. The high turnover and the large number of stocks involved also highlight the importance that technology plays in strategies like (5), and why funds that employ such strategies are predominantly quantitative.

36. Equity market-making profits are usually positively correlated with the level of volatility, see Glosten & Milgrom, *supra* note 27, and most quantitative equity market-neutral strategies have a significant market-making component to their returns, especially at higher trading frequencies.

37. This is the initial margin requirement, rather than the maintenance margin requirement which is generally lower. *See Maintenance Margin*, INVESTOPEDIA, http://www.investopedia.com/terms/m/maintenancemargin.asp (last visited Dec. 21, 2013). The Regulation T initial margin requirements have been changed by the Federal Reserve 24 times since 1934 when the first regulation was promulgated, though the requirements have not been changed since

proprietary trader's probability of a daily loss greater than the margin to 1% and assume that the distribution of returns has a volatility equal to that of the strategy for the previous 120 trading days, with either a normal distribution or a Student-*t* distribution with one or two degrees of freedom (which illustrates the impact of fat tails).

Figure 5 shows the historical margin levels under the various scenarios. Since the 1940s, Regulation T has yielded the highest levels, and the assumption of normality always produces the lowest levels.

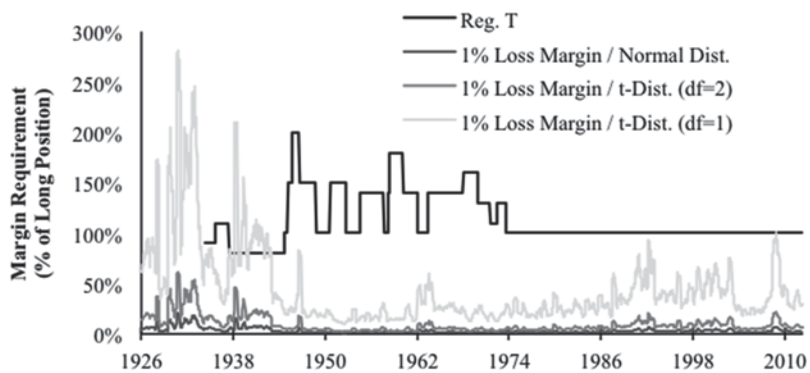


Figure 5. Historical margin requirements for the contrarian strategy with a 1-day holding period under various possible models for return distributions.

These results provide a compelling illustration of the fact that loss probabilities, leverage constraints, and market risk are inextricably intertwined. Hence time variation in one of these quantities necessarily implies time variation in the others. As long as market risk is constant, fixed leverage constraints may yield outcomes that regulators and policymakers expect. But during periods when market risk varies significantly, fixed leverage constraints may produce unexpected outcomes.

V. Volatility/Leverage Feedback Loops

Having established the time series properties of the mean-reversion trading strategy (5) using historical data, we are now able to examine the practical relevance of the self-reinforcing volatility/leverage feedback loop implied by this strategy. To that end, we investigate two simple empirical relations motivated by the market-making characteristics of mean-reversion strategies discussed above: (1) whether the profitability of the mean-reversion strategy is positively related to contemporaneous market volatility; and (2)

1974. *See* 98th Annual Report, Bd. of Governors of the Fed. Reserve Sys., 324 tbl. 8 (2011), http://www.federalreserve.gov/publications/annual-report/files/2011-annual-report.pdf.

whether increases in the profitability of market-makers are associated with subsequent declines in volatility.

Before turning to these two hypotheses, we provide a more detailed discussion of the potential mechanisms by which volatility and leverage are related, and how these mechanisms can affect macroprudential regulation.

Mean-reversion strategies such as (5), known more generally as quantitative equity market neutral strategies, became popular in the mid-1990s and assets under management grew steadily until reaching their peak in 2007 among the funds in the BarclayHedge database.[38] As the amount of assets in these strategies increased, the strategies' impact on market price dynamics also increased, helping to suppress market volatility during this period by placing upward price pressure on the losers and downward price pressure on the winners. Figure 7 contains a graph of the 125-day rolling-window volatility of the S&P 500 Total Return Index from January 2, 2002 to June 29, 2007 (solid line), clearly indicating a downward trend in market volatility in the aftermath of the bursting of the Internet Bubble.[39] As market volatility declined, broker/dealers were willing and able to offer greater amounts of leverage to their clients, including quantitative equity market neutral funds. The mean-reversion strategies pursued by these funds thus facilitated an even greater amount of available leverage, and as these funds took on more leverage, their potential losses would be magnified as well as their potentials gains. This magnification played a critical role in the Quant Meltdown of August 2007, which we describe in more detail below.

38. *See infra* Figure 6. Because hedge funds and proprietary trading desks are not required to report their returns or assets under management, this information is available only on a voluntary basis. However, the figures collected by third parties such as BarclayHedge are likely to be highly correlated with aggregate industry figures.

39. This downward trend is also evident in forward-looking measures of risk such as the VIX Index, hence it is not simply an artifact of lagged information. *See infra* Figure 10. The market's collective wisdom during this period was that equity market risk had declined significantly.

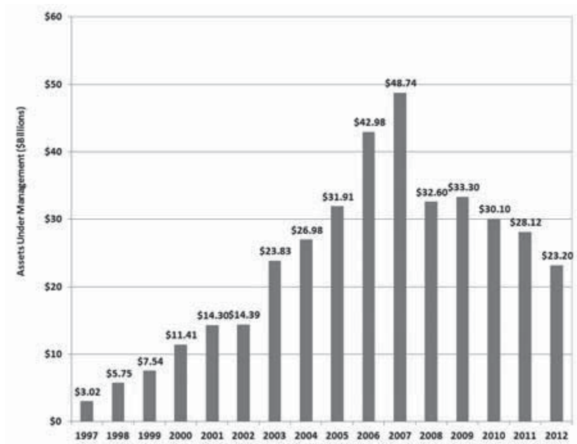


Figure 6. Assets under management among equity market neutral hedge funds in Barclay's Hedge Fund Database from 1997 to 2012.

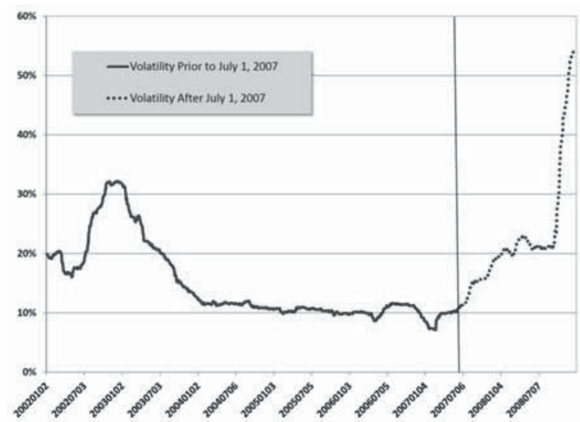


Figure 7. 125-day rolling-window volatility of the daily S&P 500 total return index from January 2, 2002 to June 29, 2007 (solid line) and July 2, 2007 to December 31, 2008 (dotted line).

The dynamic relation between trading strategies, leverage, and market risk may also reduce the effectiveness of fixed leverage constraints and macroprudential regulation. This challenge is a special case of the so-called "Lucas critique"[40] in which the potential impact of feedback effects of policy changes on human behavior can undermine the goals of such changes.[41] In the

40. Robert Lucas, *Econometric Policy Evaluation: A Critique*, *in* THE PHILLIPS CURVE AND LABOR MARKETS 19 (Karl Brunner & Allan H. Meltzer eds., 1976).

41. See Narayana Kocherlakota, *Modern Macroeconomic Models as Tools for Economic Policy*, THE REGION, May 2010, at 5-21, http://www.minneapolisfed.org/pubs/region/10-

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case of leverage constraints, the endogeneity of market risk was demonstrated by Danielsson, Shin, and Zigrand in a simple but compelling dynamic equilibrium model in which the imposition of Value at Risk (VaR) constraints on investors will, in equilibrium, have the perverse effect of increasing the volatility of the risky asset. The intuition for this rather surprising phenomenon is straightforward: imposing a VaR constraint on traders is akin to endowing them with time-varying risk aversion, where they become effectively more risk averse after suffering significant losses and reduce their positions. By unwinding their positions, they exacerbate their losses, leading to greater volatility.[42]

However, the traders in Danielsson, Shin, and Zigrand's framework do not employ particularly sophisticated trading strategies—they are short-term (one-period) expected-utility maximizers with constant absolute risk aversion.[43] In the case of proprietary traders who do engage in more dynamic trading strategies, the feedback effects can be even more complex and unexpected.

Going back to the empirical evidence of a feedback loop between market-making and volatility, to test the first hypothesis—that the profitability of the mean-reversion strategy (5) is contemporaneously related to market volatility—we calculate the historical correlation between changes in the returns to the contrarian trading strategy and changes in the volatility of an equally-weighted market index. Figure 8 illustrates the historical time series of the returns and volatility, and Table 1 shows the correlations of changes in the two amounts, both in the aggregate and by decade. With the exception of 1-day holding periods in the 1990s, all the correlations are positive, implying that increasing market volatility is associated with increasing profitability of the basic mean-reversion strategy (5).[44] These correlations provide significant evidence that the contrarian trading strategy indeed does explain a component of market volatility, and is particularly sensitive to relatively short-term changes in market volatility.

05/2009_mplsfed_annualreport_essay.pdf, for an excellent review of this important idea and its influence on modern macroeconomics and monetary policy.

42. Jon Danielsson, Hyun Song Shin & Jean-Pierre Zigrand, *Impact of Risk Regulation on Price Dynamics*, 28 J. BANKING & FIN., 1069, 1086 (2004).

43. *Id*. at 1073.

44. The sole negative entry, a statistically insignificant value of −0.01, can be explained by the fact that during this period a large influx of capital into long/short equity and equity market neutral hedge funds likely drove down the profitability of these strategies *See* Khandani & Lo, *supra* note 26, at 24.

Figure 8. Historical average daily performance of the contrarian trading strategy with a 1-day holding period and the volatility of the equal-weighted market index. Each average daily return and volatility value is calculated during a block of 20 consecutive trading days, and the 20-day periods considered in the calculations are non-overlapping.

Start	End	Mean (%)	SD (%)	Sharpe Ratio	Holding Period Corr. 1 Day	5 Days	20 Days
12/31/1925	12/31/1929	564.7	51.6	10.95	0.67	0.73	0.64
1/1/1930	12/31/1939	1225.2	79.3	15.44	0.21	0.31	0.33
1/1/1940	12/31/1949	494.0	38.7	12.75	0.28	0.29	0.19
1/1/1950	12/31/1959	107.9	9.1	11.86	0.68	0.38	0.07
1/1/1960	12/31/1969	173.2	17.9	9.70	0.46	0.51	0.40
1/1/1970	12/31/1979	130.3	12.2	10.69	0.13	0.48	0.40
1/1/1980	12/31/1989	232.2	26.4	8.78	0.23	0.49	0.27
1/1/1990	12/31/1999	1121.5	34.5	32.52	0.02	0.08	0.11
1/1/2000	12/31/2009	358.7	27.5	13.03	0.51	0.59	0.41
1/1/2010	9/30/2012	194.3	17.4	11.14	0.50	0.72	0.65
12/31/1925	9/30/2012	490.7	46.7	10.51	0.30	0.40	0.34

Table 1. Means, standard deviations, and Sharpe ratios of the contrarian trading strategy with a 1-day holding period, and correlations between changes in average daily returns for the contrarian strategy and changes in the volatility of the equal-weighted market index, for 10-year subperiods and the entire sample period from December 31, 1925 to September 30, 2012. Means, standard deviations, and Sharpe ratios are computed using daily returns during the relevant time period and then annualized by multiplying by 250 in the case of the average and $\sqrt{250}$ in the case of the standard deviation and the Sharpe ratio. Correlations are computed for contrarian strategies with 1-, 5-, and 20-day holding periods, but each average daily return and volatility value is calculated during a block of 20 consecutive trading days, and the 20-day periods considered in the calculations are non-overlapping. Changes are computed as the difference between one 20-day block of days and the immediately preceding 20-day block.

To test the second hypothesis—that increases in mean-reversion profits are associated with subsequent declines in volatility—we construct a value-weighted index of all broker/dealers[45] and consider its relationship to volatility of the broader market. We hypothesize that broker/dealers derive profits from strategies that provide liquidity and thereby reduce volatility. This may include the contrarian strategy described above, but it may also include other possibilities.

We test our hypothesis by calculating the correlation between returns to broker/dealers and market volatility, as well as the correlation between the changes in these values. We illustrate returns for broker/dealers in Figure 9, and we report the correlations in Table 2. The changes are generally strongly negatively correlated, particularly in the short term. This implies that as broker/dealers become more profitable, market volatility is reduced. While we cannot conclude a causal relationship from mere correlations, the patterns are consistent with a volatility/leverage feedback loop.[46]

Start	End	20 Days	40 Days	60 Days	120 Days	250 Days
7/2/1962	12/31/1969	-0.35	-0.60	-0.44	-0.70	-0.28
1/1/1970	12/31/1979	-0.03	-0.08	-0.24	-0.14	-0.06
1/1/1980	12/31/1989	-0.17	-0.39	-0.22	-0.01	-0.16
1/1/1990	12/31/1999	-0.42	-0.46	-0.32	0.03	-0.09
1/1/2000	12/31/2007	-0.34	-0.17	-0.39	0.03	-0.91
1/1/2007	9/30/2012	-0.18	-0.63	-0.60	-0.43	-0.69
7/2/1962	9/30/2012	-0.22	-0.34	-0.31	-0.21	-0.39

Table 2. Correlations between changes in average daily returns (reflecting dividends and compounding) for the value-weighted index of broker/dealers and changes in the volatility of the equal-weighted index of the entire market. Each average daily return and volatility value is calculated during a block of *n* consecutive trading days, where *n* is 20, 40, 60, 120, or 250 according to the labels at the top of the column, and the *n*-day periods considered in the calculations are non-overlapping. Changes are computed as the difference between one *n*-day block of days and the immediately preceding block of *n* days. The results are reported by decade, as well as in the aggregate since July 2, 1962.

45. We define our universe of broker/dealers equities to be those securities in the CRSP database with an SIC value of 6211. Our index begins on July 2, 1962, when securities of this type first were listed as part of the CRSP database.

46. This empirical evidence is also consistent with the common empirical intuition that short-term volatility is mean-reverting. However, this intuition is typically devoid of any economic justification, but based instead on the time series properties of short-term volatility measures. For example, a simple first-order autoregressive model of volatility,

$$\sigma_t = \mu_\sigma + \rho(\sigma_{t-1} - \mu_\sigma) + \epsilon_t\,, \rho \in (0,1) \tag{8}$$

can generate the pattern observed in Table 2 if we assume that broker/dealers can observe σ_t without error and adjust their leverage constraints appropriately. Our proposed explanation for the dynamics of leverage and volatility endogenizes (8) and provides the mechanism by which volatility changes and institutional and regulatory structures that facilitate those changes.

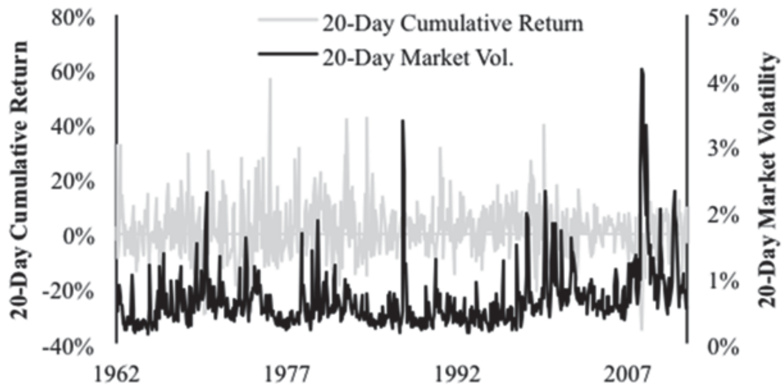

Figure 9. Historical daily performance of the broker/dealer value-weighted index and the volatility of the equal-weighted market index. Each average daily return and volatility value is calculated during a block of 20 consecutive trading days, and the 20-day periods considered in the calculations are non-overlapping.

VI. The "Quant Meltdown" of August 2007

To develop a deeper appreciation for the implications of the volatility/leverage feedback loop, consider the fate of quantitative equity market-neutral funds during the second week of August 2007 when, without any warning, they all suffered significant losses at the same time, including some of the most prominent and consistently profitable firms.[47] One of the hardest hit was the Global Equity Opportunities Fund of Goldman Sachs. David Viniar, Chief Financial Officer of Goldman Sachs, observed that "[w]e were seeing things that were 25-standard deviation moves, several days in a

47. For example, the *Wall Street Journal* reported on August 10, 2007 that:

> After the close of trading, Renaissance Technologies Corp., a hedge-fund company with one of the best records in recent years, told investors that a key fund has lost 8.7% so far in August and is down 7.4% in 2007. Another big fund company, Highbridge Capital Management, told investors its Highbridge Statistical Opportunities Fund was down 18% as of the 8th of the month, and was down 16% for the year. The $1.8 billion publicly traded Highbridge Statistical Market Neutral Fund was down 5.2% for the month as of Wednesday.
> . . . .
> Tykhe Capital, LLC—a New York-based quantitative, or computer-driven, hedge-fund firm that manages about $1.8 billion—has suffered losses of about 20% in its largest hedge fund so far this month. . . .

Gregory Zuckerman, James R. Hagerty & David Gauthier-Villars, *Impact of Mortgage Crisis Spreads*, WALL ST. J., Aug. 10, 2007, A1. On August 14, the *Wall Street Journal* reported that the Goldman Sachs' Global Equity Opportunities Fund "lost more than 30% of its value last week." Henny Sender, Kate Kelly & Gregory Zuckerman, *Goldman Wagers On Cash Infusion To Show Resolve*, WALL ST. J., Aug. 14, 2007, A1.

row . . . There have been issues in some of the other quantitative spaces. But nothing like what we saw last week."[48]

It was no coincidence that all of these funds were engaged in the same type of trading strategy, nor that the strategies used by the funds depended critically on the amount of leverage that was available. This "Quant Meltdown" of August 2007 has been studied by several authors,[49] and with the benefit of hindsight and the simulations and empirical analysis described above, a common narrative has emerged.

During the first half of 2007, rising interest rates and declining U.S. residential real estate prices contributed to the growing losses of fixed-income portfolios with exposure to subprime-mortgage-related debt and its derivatives.[50] By the summer of 2007, investors were beginning to realize the seriousness of the problems in the mortgage market. On June 7, 2007, Bear Stearns suspended redemptions from its High-Grade Structured Credit Strategies Enhanced Leverage Fund in a desperate attempt to forestall disaster in a fast-moving market. By July 31, this fund and its higher-leverage counterpart lost most of their value, filed for bankruptcy under Chapter 15,[51] and were liquidated.

In this increasingly stressful atmosphere of market turmoil, Khandani and Lo conjecture that a single equity market neutral fund or trading desk decided to reduce its market exposure by liquidating a portion of its investments.[52] In doing so, it was either large enough or impatient enough to have moved the

48. Peter Thal Larsen, *Goldman pays the price of being big*, FIN. TIMES, Aug. 14, 2007, at 37.

49. *See, e.g.*, GOLDMAN SACHS GLOBAL QUANTITATIVE EQUITY GRP., THE QUANT LIQUIDITY CRUNCH (2007); MATTHEW ROTHMAN, LEHMAN BROS. RESEARCH, U.S. EQUITY QUANTITATIVE STRATEGIES: VIEW FROM QUANTLAND—WHERE DO WE GO NOW? (2007); MATTHEW ROTHMAN, LEHMAN BROS. RESEARCH, U.S. EQUITY QUANTITATIVE STRATEGIES: REBALANCE OF LARGE CAP QUANT PORTFOLIO (2007); MATTHEW ROTHMAN, LEHMAN BROS. EQUITY RESEARCH, U.S. EQUITY QUANTITATIVE STRATEGIES: TURBULENT TIMES IN QUANT LAND (2007); Kent Daniel, *Anatomy of a Crisis*, 26 CFA INST. CONF. PROC. Q. 11 (2009); Khandani & Lo, *supra* note 26; Khandani & Lo, *supra* note 29; James Montier, *The Myth of Exogenous Risk and the Recent Quant Problems*, BEHAV. INV. BLOG (Sep. 24, 2007), http://behaviouralinvesting.blogspot.com/2007/09/myth-of-exogenous-risk-and-recent-quant.html.

50. Specifically, on February 27, 2007 the Federal Home Loan Mortgage Corporation (Freddie Mac) discontinued its purchases of the most risky subprime mortgages and mortgage-related securities. Press Release, Freddie Mac, Freddie Mac Announces Tougher Subprime Lending Standards to Help Reduce the Risk of Future Borrower Debt (Feb. 27, 2007). On April 2, 2007, New Century Financial Corporation, a leading subprime mortgage lender, filed for Chapter 11 bankruptcy protection. News Release, New Century Fin. Co., New Century Financial Corporation Files for Chapter 11; Announces Agreement to Sell Servicing Operations (Apr. 2, 2007). On June 1, 2007, the two largest bond-rating agencies—Standard and Poor's and Moody's Investor Services—downgraded over 100 bonds backed by second-lien subprime mortgages. *See The Role of Credit Rating Agencies in the Structured Finance Market: Hearing Before the Subcomm. on Capital Mkts. Ins. and Gov't Sponsored Enters.*'s *of the H. Comm. on Fin. Serv's*, 110th Cong. 147 (2007) (statement of Vickie A. Tillman, Exec. Vice President, Standard & Poor's).

51. Bear Stearns was ultimately denied Chapter 15 bankruptcy protection for these two funds. Bruce Nathan & Richard Corbi, *Overseas Bear Stearns Hedge Funds Denied Chapter 15 Relief*, BUS. CREDIT, July/Aug. 2008, at 2, 4.

52. *See* Khandani & Lo, *supra* note 26, at 5.

prices of various securities so as to generate losses for itself and other funds with similarly constructed portfolios. As these losses were realized each day, portfolio managers and their investors grew more nervous, motivating further liquidations that caused greater losses. The unwinding of positions was also likely prompted by the need to avoid exceeding applicable leverage constraints and margin requirements as losses increased. This vicious cycle played itself out from August 6th to 9th, and reversed itself abruptly starting on August 10th, apparently after Goldman Sachs committed $3 billion of additional capital to support its hard-hit Global Equity Opportunities Fund.[53] In the aftermath of this Quant Meltdown, many equity market neutral hedge funds closed down permanently, assets fled to other strategies and safer havens[54] and by the end of 2007, stock market volatility had nearly doubled.

However, in the years since the Financial Crisis of 2007-2009, equity market volatility has declined to pre-Crisis levels,[55] which may very well restart the volatility/leverage cycle once again. Of course, aggregate leverage in financial markets is considerably lower today than in the early 2000s, and the economic climate is considerably less certain, especially for financial institutions. Therefore, a return to a lower-volatility environment does not necessarily imply that quantitative equity market neutral funds will now return to their pre-Crisis levels as well. One reason is that new forms of market-neutral strategies have emerged, e.g., high frequency trading, and given the current market climate and the greater limitations of broker/dealer leverage today as compared to a decade ago, these new strategies are more profitable and less risky than the less technologically sophisticated and slower-moving equity market neutral counterparts.

These considerations underscore the impact that the volatility-leverage feedback loop can have even with exchanged-traded securities in markets that are considered among the most liquid in the world. They also demonstrate the need for dynamic leverage regulation that takes into account feedback effects and the endogeneity of volatility to the regulated financial system. Such regulation would ideally have been able to adjust flexibly and would have required fewer firms to unwind positions so quickly, which in turn may have avoided the extreme level of observed volatility.

53. *See* Sender, Kelly & Zuckerman, *supra* note 47.
54. *See supra* Figure 6.
55. *See infra* Figure 10.

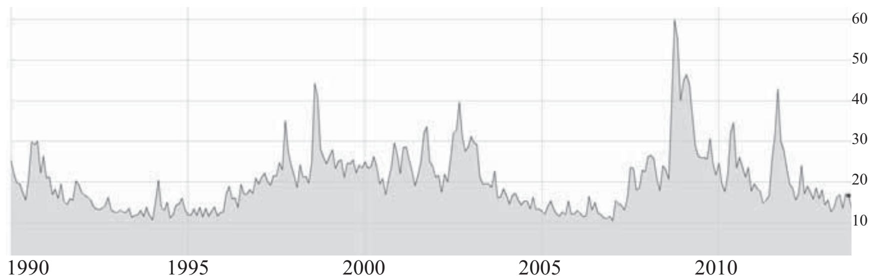

Figure 10. Daily VIX Index from January 2, 1990 to November 1, 2013.[56]

VII. Conclusion

Dynamic loss probabilities in financial markets pose a significant challenge for traditional financial regulation. Unless regulations are sufficiently adaptive to changing economic conditions, they may not be able to perform the role expected of them. As our foreign-exchange example illustrates, neither volatility nor correlation is stable over time, even for very broadly traded assets such as the currencies of major countries. The SPAN system of the CME provides an informative example of how the private sector has addressed some of these dynamics. However, the challenges to macroprudential regulation are significantly more complex because they must address the endogeneity of systemic risk, and also deal with assets that are much less liquid and difficult to price than those of the CME.

Moreover, the empirical properties of the equity mean-reversion trading strategy illustrate the complexity that volatility/leverage feedback loops can pose for regulators, both because of their ability to amplify shocks and their potential impact on aggregate market risk levels. When such strategies trip leverage limits, rapid unwinding and price instability can occur, as it did for the quants in August 2007.

These examples, and the enormous corpus of new regulations mandated by the Dodd-Frank Act of 2010, underscore the growing recognition that measuring and managing systemic risk now involves far more than the traditional banking industry. Our regulatory infrastructure thus needs to be modernized. There is clear consensus among economists, financial industry leaders, regulators, and policymakers that, like national defense, education, and the environment, financial stability is a public good. Therefore, the case for the utility of macroprudential regulation is not controversial. However, the precise form that such regulation should take is highly controversial, largely because we do not yet have a clear scientific understanding of the mechanisms by

56. *Volatility S&P 500 (^VIX)*, YAHOO! FINANCE, http://finance.yahoo.com/q?s=%5EVIX (last visited Dec. 14, 2013).

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which systemic risk is generated and can be moderated. Dynamic loss probabilities are an attempt to provide such scientific foundations.

Addressing the challenges of dynamic loss probabilities is no simple task, and will require a new approach to financial regulation, one that is capable not only of adapting to changing economic conditions but that also properly accounts for its own impact on the behavior of regulated entities. The volatility/leverage feedback loop is only one of many examples of complex adaptive behavior, and new research will likely be needed to create the necessary tools for regulating such systems. Rather than choosing between "clear bright lines" and "balancing tests," a more sophisticated type of regulation might be developed in which balancing tests are formulated via "clear bright principles" such as the objective of constraining loss probabilities to some fixed upper bound. Inventing new forms of regulation will undoubtedly require close collaboration among legal scholars, practicing lawyers, and financial economists, and we hope the analysis in this Article provides sufficient motivation for these collaborations.