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THE IFM RELEASES SPECIAL 2012 ISSUE OF REVIEW OF FUTURES MARKETS

Derivatives markets worldwide increasingly have become a central tool for market users in managing risk, and there has never been a more critical time than now for research and education examining issues that affect trading, clearing, innovation, and competition. This is particularly true as these markets will see a transformation amid the most sweeping reforms in history.

The Institute for Financial Markets, a nonprofit educational foundation founded in 1989, is pleased to have funded six new research studies that take a thoughtful look at innovation, taxation, and regulation — relevant issues facing the industry in U.S. and international markets. The studies contained in this issue of the *Review of Futures Markets* have been subjected to an arduous, academic peer-review process, which demands authors meet quality standards that avoid the dissemination of unwarranted findings, superfluous claims or interpretations, and personal views.

We believe the intelligence shared in these studies increases the public understanding in the purpose, complexities, and nuances of the global markets, which benefits a broad sector of populace — from market-users, policy-makers, regulators, and academics to other stakeholders.

The IFM hopes you enjoy this complimentary issue of the *Review of Futures Markets*, and we welcome your comments.

Trish Foshée
President

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CLEARING AND OTC TRADED DERIVATIVES: A SURVEY

Joseph K.W. Fung and Robert I. Webb*

The financial economics literature on market microstructure — or the way a market is organized — has grown substantially since Garman's (1976) seminal article. Much of the focus of the existing literature is on the impact of market microstructure on price formation and price discovery. Market microstructure characteristics such as settlement and clearing arrangements have received less attention. The 2007–2009 Global Financial Crisis has highlighted the importance of clearing to practitioners, policymakers, and academics alike. A sharp rise in perceived counterparty risk during the financial crisis for some over-the-counter (OTC) traded derivative securities, coupled with uncertainty by regulators over the true size of outstanding positions in such securities by market participants, has led to calls for mandatory clearing through *central counterparties* (CCPs) of some (G-20 Leaders 2009) or virtually all (Hull 2010) OTC traded derivatives and centralized reporting of OTC derivative transactions to *trade repositories* (TRs).[1]

The principal objectives behind such proposals are to increase transparency, reduce counterparty risk, reduce excessive risk-taking by financial institutions and the potential for systemic risk, prevent market abuse, and avert similar financial crises from arising in the future. This study surveys the recent financial economics literature to ascertain whether the desired objectives are likely to be met from mandatory centralized clearing and centralized trade reporting of OTC derivative transactions; which, if any, OTC traded derivatives should be subject to centralized clearing; and, if so, who should clear OTC traded derivatives. In addition, this study

1. In September 2009, leaders of the G-20 nations agreed to the following objective regarding OTC derivatives: "All standardized OTC derivative contracts should be traded on exchanges or electronic trading platforms, where appropriate, and cleared through central counterparties by end-2012 at the latest. OTC derivative contracts should be reported to trade repositories. Non-centrally cleared contracts should be subject to higher capital requirements. We ask the FSB and its relevant members to assess regularly implementation and whether it is sufficient to improve transparency in the derivatives markets, mitigate systemic risk, and protect against market abuse." (See page 9 from the Leaders' Statement, the Pittsburgh Summit, 2009.)

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assesses the likely implications of mandatory clearing of OTC derivatives for the financial innovation process and the prevention of similar financial market crises in the future.

The G-20 Leaders' Statement from the 2009 Pittsburgh Summit leaves the process for the adoption of mandatory clearing of standardized OTC derivatives up to the individual member nations but imposes a requirement for periodic progress reports to G-20 Leaders from the Financial Stability Board.[2] However, even the adoption of mandatory clearing for standardized OTC derivatives in a given country may leave many questions unanswered for market participants. For instance, the passage of the *Wall Street Reform and Consumer Protection Act* (better known as the Dodd-Frank Act) in the United States in 2010 requires standardized OTC derivatives to be centrally cleared or traded on an exchange but leaves many of the important details to be determined by the relevant regulatory agencies charged with enforcing the law. This means that although a decision has been taken mandating centralized clearing of standardized OTC derivatives in the United States, industry representatives still have ample opportunity to influence regulatory policymakers on how that mandate works in practice.

Moreover, as Grant (2011) points out, one unintended consequence of leaving implementation of the mandate to individual G-20 nations is the potential to increase market fragmentation and create *regulatory arbitrage* opportunities by imposing local clearing restrictions on affected OTC derivatives.[3] This has the potential to create additional problems that may impede achievement of the original objectives. For instance, Pirrong (2011) argues: "Fragmentation of clearing on jurisdictional lines will increase the costs and risks of clearing, including systemic risks." Fragmentation in clearing means that potential economies of scale are not exploited

2. A 2010 progress report by the Financial Stability Board reported: "Progress is being made toward achieving implementation of these objectives, including industry efforts to meet commitments made to supervisors; ... At the level of the industry, the so-called G14 major derivatives dealers and a number of buy-side institutions issued a joint letter on 1 March 2010 detailing further commitments to supervisors relating to OTC derivatives market transparency, expanded central clearing, standardization and collateral management. This advance on the commitments made by firms in September 2009 to specific target levels for central clearing of CCP-eligible OTC credit derivatives and CCP-eligible OTC interest rate derivatives. "However, the enhanced clearing targets only partially cover the OTC market, as most derivative contracts are currently not CCP-eligible" (see page 39). It also reported on page 41: "At the [June 2010] Toronto Summit, G20 Leaders pledged to work in a coordinated manner to accelerate the implementation of over-the-counter (OTC) derivatives regulation and supervision and to increase transparency and standardization. OTC derivative contracts should be reported to trade repositories. The G20 will work towards the establishment of CCPs and TRs in line with global standards and ensure that national regulators and supervisors have access to all relevant information."

3. Grant [2011] argues "... In Japan, legislation is already in place that require yen-based over-the-counter (OTC) derivatives to be cleared in Japan; ... and India has developed the Clearing Corporation of India to act as a central counterparty (CCP) and trade repository for the domestic market. ... it looks like efforts to implement the G20 reforms...- are fragmenting all over the place. ... Basically Asian regulators want to ensure that trades in which institutions in their jurisdictions are involved are cleared through entities over which they have some control."

and relevant information about the aggregate positions of market participants may not be understood.[4]

The push for mandatory clearing of OTC traded derivatives is as much a result of the long history of success of exchange traded derivative markets in minimizing counterparty risk and promoting transparency as the presumed failure of certain OTC traded derivative markets to handle counterparty risk during the recent financial crisis. Simply stated, exchange traded derivative markets worked well during the crisis while some OTC derivatives markets either did not or appeared not to work well.

Exchange traded derivatives are contracts where all terms have been standardized, leaving only price to be determined. In addition, exchange traded derivative securities require trades to be processed via a clearinghouse or central counterparty. Mandatory clearing in futures markets, for instance, has made defaults relatively rare and market prices more transparent. Not surprisingly, a common view of how centralized clearing would operate in the OTC derivatives markets mirrors how existing futures clearinghouses operate and manage risk (that is, through imposing margin requirements and daily marking to market of outstanding positions). This is more complex than it first appears, as market prices may not be readily available to determine appropriate margins for counterparties.

I. CLEARING AND THE SIZE OF OTC DERIVATIVES MARKETS

According to the Bank for International Settlements (BIS 2011), the total notional principal of OTC derivatives outstanding at the end of calendar year 2010 stood at $601 trillion. Interest rate swaps, forward rate agreements (FRAs) and options accounted for 77% of all OTC derivatives. This was followed by foreign exchange forwards, forex swaps, currency swaps and options that collectively accounted for $57.8 trillion or over 9.6% of the total. Credit default swaps accounted for $29.9 trillion or about 5% of total OTC derivatives. Equity linked derivatives and commodity derivatives accounted for $5.6 trillion and $2.9 trillion, respectively, or about 1.5% between the two categories. The remaining $38.5 trillion is classified as "unallocated" and represents OTC derivatives of all types from non-reporting institutions from the triennial BIS survey. Notional principal is a poor measure of overall risk exposure. The BIS reports that netting arrangements reduced the gross credit exposure to $3.34 trillion as of the end of 2010.

Although the leaders of the G-20 nations agreed in 2009 to mandate the use of a central counterparty for standardized OTC derivatives, by 2012 the market was already moving in that direction earlier. Culp (2009) points out that "clearing and settling OTC derivatives through CCPs was already becoming popular well before

4. Bliss and Steigerwald (2006) note that the desired benefits from clearing can be achieved with different structures. For instance, they point out, "Economies of scale can be achieved both by cross-border consolidation of CCPs and by cross-border consolidation of dealers. Credit risk management can be done by CCPs or by insurance companies. Operational efficiency can be obtained by centralizing processing in CCPs or in securities depositories."

the advent of the financial crisis in mid-2007.” The fraction of transactions in OTC derivatives that are centrally cleared continues to rise. The International Swaps and Derivatives Association (2011) estimates that “the level of cleared interest rate swaps exceeded 50 percent of interest rate swap notional outstanding at the end of 2010, up from 21 percent at year-end 2007. Over the same time frame, the volume of uncleared interest rate swaps outstanding declined from $201 trillion to $116 trillion, a decrease of $85 trillion or 42 percent.”

It is worth noting that the demand for mandatory clearing of OTC derivatives primarily arose from perceived problems in the credit default swap sector. Other OTC derivatives did not raise the concerns the credit default swap (CDS) market raised. At the height of the financial crisis, the notional value of outstanding credit default swaps was over $60 trillion. However, portfolio compression has reduced the outstanding amount of credit default swaps substantially.

II. THE NATURE OF CLEARING

A. Clearing and the Frequency of Clearing

The term clearing can be used to describe the frequency with which trading is allowed on a market or the process by which ownership is exchanged between counterparties to trades. Both are important market microstructure characteristics. For instance, in a continuous auction market trading is allowed at any time during the trading day. Alternatively stated, the market clears continuously throughout the trading day. In contrast, a periodic call auction market is one in which trades are only allowed at specified times during the trading day and prohibited at all other times. The market “clears” periodically during the trading day. This “batch processing” of trades allows information to accumulate as orders to buy and sell accumulate and arguably leads to more informative prices than from a continuous auction market. Nevertheless, most markets today permit continuous trading while open.

The term clearing is also used to describe the transfer of ownership of security positions between parties. It is this use of the term that is behind the proposals to impose mandatory clearing of certain OTC traded derivatives. In exchange traded derivative markets, the clearinghouse takes the other side or interposes itself between every transaction. This reduces potential counterparty risk in most cases because the presumably stronger clearinghouse takes the other side of every trade. It also makes it easier for markets participants to enter or exit futures positions.

B. Clearing of Equities versus Derivatives

Clearing is needed whenever security positions change hands. However, there is a fundamental difference between clearing on equity markets and clearing on derivatives markets. For example, suppose Party A agrees to buy 1,000 shares of Apple stock from party B. Both parties need a mechanism to transfer ownership from Party B to Party A. That mechanism is clearing. The clearing process of a stock transaction is essentially immediate. The risk associated to the clearinghouse is similarly short-lived. A bookkeeping transaction records the change in ownership and the clearing process is essentially over. The clearing process for an option or futures transaction entails clearinghouse or central counterparty involvement until the position is closed.[5]

This fundamental difference between clearing stock and derivative market trades gives rise to potential economic rents to futures exchanges that not only clear their own futures transactions but disallow clearing of their exchange's products on other markets. Put differently, one consequence of restricted clearing is that it also impedes the fungibility of futures contracts. *Fungibility* means that a futures contract on some commodity, index, or security can be initiated on one exchange and offset on another. It should be noted that the non-fungibility advantage enjoyed by futures markets may not accrue to equity options exchanges as equity options exchanges in the United States are required by their regulator — the Securities and Exchange Commission — to use a common clearing firm, the Options Clearing Corporation, to clear all option trades. This allows exchange traded equity options to trade on multiple exchanges.

C. The Gains from Clearing

The important contribution of the provision of clearing services to the value of an exchange is not commonly recognized. For instance, a significant component of the value of futures exchanges is due to the value of the clearinghouses that they control. Anecdotal evidence of this fact includes the dramatic decline in the value of the CME Group on February 5 and 6, 2008, in response to a U.S. Justice Department, Anti-Trust Division letter suggesting that clearinghouses be separated from exchanges. The *Financial Times* (Weitzman 2008) reported on February 8, 2008:

> Shares of the CME Group and Nymex fell sharply in New York yesterday, as investors digested the implications of the US Department of Justice's call for the separation of clearing houses from the futures exchanges that own them. CME shares fell 12 per cent by mid-day trading to $519.30 on fears that any change would result in severe disruption to the business model that has enabled the CME to become the world's largest futures exchange. Nymex, which CME targeted with a cash-and-share bid last week, saw its shares fall 11 per cent to $94.92.

Another example is the widespread belief that the primary reason the Intercontinental Exchange (ICE) purchased the New York Board of Trade (NYBOT) in 2006 was to obtain the NYBOT's clearinghouse. The *Financial Times* (Morrison

5. Bliss and Steigerwald (2006) provide a detailed analysis of the clearing function for derivatives. They note: "In securities clearing and settlement, the length of time between the execution of a transaction (in which the counterparties undertake reciprocal obligations to deliver a security against payment) is dictated primarily by operational constraints. With derivatives, however, the length of time between the execution of a transaction and settlement is essential to the contract. Put another way, the fundamental economic purpose of a derivatives transaction involves the reciprocal obligations of the parties over the life of the contract."

and Cameron 2006) reported on September 17, 2006:

> Traders said the key attraction of ICE's purchase of Nybot, through $400m in cash and the issue of equity that equates to 15 per cent of its stock, was Nybot's own clearinghouse, the New York Clearing Corporation rather than Nybot's soft commodities such as coffee, cocoa, sugar, cotton and orange juice and its financial futures business. This will give the Atlanta-based electronic commodities exchange the flexibility it wants to compete with its bigger rival the New York Mercantile Exchange.

Both of the foregoing examples illustrate the value that exchange owned clearinghouses contribute to the value of a futures exchange. The mandate that exchange traded derivatives be cleared through a central counterparty has potentially important implications for how profits are made in various financial businesses. To be sure, it creates new potential revenue opportunities in clearing certain OTC derivatives. However, the potential size of the business opportunity is not clear.

D. Risk Management at Clearing Counterparties

Risk management is central to the successful operation of a clearinghouse or clearing counterparty. Clearinghouses manage their risk exposures by imposing margin requirements and marking security positions to market on a daily or more frequent basis, as conditions require.[6] Proper risk management by clearinghouses necessitates the ability to correctly identify the market value of security positions. This may be difficult to do for certain OTC derivatives whose market value is uncertain. It is also important to point out that the choice facing market participants is not clearing everything or clearing nothing, but rather runs the continuum from no clearing to requiring trades be entered into a trading repository (without a mandate for centralized clearing) to clearing OTC derivatives centrally to restricting trading to derivatives exchanges.

III. THE NATURE OF FINANCIAL INNOVATIONS

Smithson (1998) argues that financial innovations arise from attempts to lower transaction costs or reduce risks. He argues that most complex securities can be decomposed into simpler ones. For instance, futures contracts are simply exchange traded forward contracts. That is, futures contracts represent an advance over forward contracts where significant counterparty risk may exist. Other mechanisms also exist as potential solutions for the presence of counterparty risk such as one or both parties posting collateral. It should be noted that, in some cases, a futures position might have more risk than otherwise similar forward contracts. For instance, it may be that the counterparty risk of a large bank trading with another "too large to fail" large bank may be lower than that with the exchange clearinghouse.

Financial markets evolve over time to meet the needs of market participants. The question naturally arises as to why OTC traded derivatives continue to exist if

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6. For instance, during the stock market crash of October 19, 1987, many futures positions were marked to market on an intraday basis.

exchange traded derivative markets represent an improvement over OTC traded derivatives. Trade is voluntary. Trade occurs only because both parties believe that they are better off from engaging in it. The continued co-existence of futures markets with corresponding OTC forward markets suggests that there is a need for many types of derivative products. Simply stated, some of the older techniques still serve the needs of some market participants better than the newer alternatives.

Alternatively stated, there are costs and benefits to both exchange and OTC traded derivatives. Culp (2009) argues the benefits of clearing OTC derivatives through a CCP include "counterparty anonymity," greater "transparency and consistency of pricing for margins and funds settlements," easier "monitoring of market participants' aggregate activity within the CCP across products," and simpler resolutions in the event of defaults, among others. Culp (2009) also argues that the costs of clearing OTC derivatives through a CCP include the potentially high cost of margin and collateral "during periods in which derivatives participants are liquidity constrained;" disagreements with models used to determine margin; disagreement with pricing or valuation of positions; and "limited gains" from the anonymity benefit for large well-capitalized traders.

IV. THE CASE FOR MANDATORY CLEARING OF OTC DERIVATIVES

Acharya et al. (2009) detail "three levels of centralized clearing" for credit derivatives (i.e., trade registry, centralized clearing for OTC derivatives, restricting trading to a derivatives exchange) in order to increase market transparency and reduce counterparty risk. Basically, they argue that such a change is necessary to provide "aggregate information on outstanding deals and risk exposures" to both regulators and market participants. They argue: "We therefore feel that the strongest public policy need in the area of OTC derivatives is to require centralized clearing for <u>all</u> systemically important derivatives."

Acharya and Bisin (2010) advance a competitive two-period general equilibrium model where default by market participants on contracts is possible. They show that opacity in the OTC markets makes counterparty risk more difficult to assess and gives rise to a "counterparty risk externality [that] can lead to excessive default and production of aggregate risk, and more generally, inefficient risk-sharing." However, the introduction of centralized clearing makes markets more transparent. The greater transparency allows market participants to adjust contract terms to reflect the overall positions held by the counterparty — that is, to force the other side "to internalize the counterparty risk externality of its trades" — and results in efficient risk sharing.

Acharya and Bisin (2010) focus on the credit default swap market — a market that some observers argue exacerbated the severity of the 2007–2009 financial crisis. They argue that "the moral hazard that a party wants to take on excessive leverage through short positions — collect premiums today and default tomorrow — is counteracted by the fact that they face a steeper price schedule by so doing." They contend that their "model provides one explanation for the substantial buildup of OTC positions in credit default swaps in the period leading up to the crisis of 2007-09, their likely contribution to over-extension of credit in the economy, and possible remedies for avoiding this excess in future."

As the title of his paper suggests, Hull (2010) examines issues arising from the proposed mandates that OTC derivatives be cleared centrally. Particular attention is directed toward the issue of whether all types of OTC derivatives should be subject to centralized clearing. Hull decomposes OTC derivatives into four major types: (1) plain vanilla derivatives with standard maturity dates; (2) plain vanilla derivatives with non-standard maturity dates; (3) nonstandard derivatives for which there are well-established pricing models; and (4) highly structured deals.

Hull argues that the first two types of OTC derivatives are readily amenable to clearing because market prices are either readily available (Type 1) or can be easily interpolated from readily available market prices (Type 2). Hull recognizes that the third type of OTC derivative is often illiquid due to infrequent trading. Examples include "Asian options, barrier options, compound options, basket options, accrual swaps, and so on." Hull recognizes that valuation of all Type 3 OTC derivatives may be difficult and proposes that "market participants provide the CCP with valuation software when the OTC derivative is traded." Not surprisingly, the fourth type of OTC derivatives, "highly structured deals," is the least amenable to being cleared centrally "because they are usually quite complex and models for valuing them are less readily available." Nonetheless, Hull argues "it is important to find a way of handling them" because "it is often these types of derivatives that lead to huge speculative positions and have the potential to increase systemic risk." Hull argues that one way of doing so is to require counterparties in Type 4 OTC derivative transactions to provide mutually agreed valuation software to the clearinghouse or agree on a third party to appraise the value of the OTC derivative security position.

Hull also envisions some exemptions from central clearing requirements, which he suggests, be called "zero margin trades." Basically, it would include firms that do not currently have to post collateral for their private derivatives market transactions. Hull argues that such transactions would be have to be registered with the central clearing party although no margin would need to be posted. Lang and Madlener (2010) examine the potential impact of mandating centralized clearing of OTC derivatives in the electric power sector. Collateral would be required for derivative positions that currently do not require collateral. This poses a problem for market participants because as Lang and Madlener (2010) note, "collateralization does not come for free."

V. THE CASE AGAINST MANDATED CLEARING OF OTC DERIVATIVES

One concern with mandated clearing of standardized OTC derivatives center on the extension of mandated clearing to illiquid or difficult to price OTC derivatives. Culp (2009) notes that the principal function of a clearinghouse or central counterparty is to substitute its credit risk for the credit risk of the counterparties. This is a meaningful advantage only if the risk of the clearinghouse is lower than the risk counterparties would otherwise face. It is critical that CCPs effectively manage their risk exposure. However, doing so requires CCPs to be able to determine the market price of the derivatives. This is hard to do in an illiquid market. Pirrong (2011) provides a detailed analysis of the role that central counterparties play and considers "what effects increased use of them will have on the financial system." In particular, he argues that central counterparties should limit any OTC derivatives clearing to "liquid standardized products" in order to effectively manage the risks to which the CCP is exposed.

Another concern with mandated clearing of OTC derivatives is that the assumption of counterparty risk by the CCP could aggregate too much risk in one entity — the CCP. This could lead to an "excessive concentration of risk" in the CCP and a belief among market participants that the CCP is "too big to fail" as Culp (2009) and Singh (2011) point out. Culp argues that this, in turn, may induce "a *moral hazard* problem in which derivatives participants manage their risks less prudently because of an expectation that derivatives CCPs would be bailed out."

Pirrong (2011) argues that the actions of CCPs may impact systemic risk. Specifically, Pirrong asserts such actions "can both decrease it" (for instance by reducing the impact of clearing member failure) "and increase it" (for instance by increasing margin requirements during a period of financial stress). He also warns "that CCPs have failed in the past." Culp (2009) draws similar conclusions when he argues that the proposed mandatory centralized clearing of standardized OTC derivatives "might well actually increase the fragility of the financial system by creating new institutions that regulators, and politicians believe are too big or too interconnected to fail. At the same time, mandated clearing and settlement could impose significant costs on various market participants and interfere with financial innovation."

As noted above, the fragmentation of CCPs across international boundaries or asset classes reduces the potential effectiveness of the CCP. Duffie and Zhu (2011) examine whether the addition of a new separate CCP to a "particular class of derivatives increases or reduces counterparty exposures." They report evidence that the introduction of a CCP "reduces netting efficiency, increases collateral demands, and leads to higher average exposure to counterparty default." In addition, they report that the existence of multiple CCPs increases counterparty risk. They recommend a single CCP for "standard interest rate swaps and credit default swaps" to avoid this latter issue.

Culp (2009) dichotomizes financial market regulation into regulation of products and institutions. He contends that mandated clearing of OTC derivatives is a form of product regulation and argues that regulating institutions is a better way of monitoring and controlling systemic risk than regulating financial products. Culp argues that rather than reducing systemic risk mandated clearing "will likely engender significant legal and regulatory uncertainty, impede financial innovation, raise market participants' costs, and adversely impact the competitiveness of U.S. derivatives participants."

Gubler (2009) argues that the requirement for clearing of OTC derivatives is essentially "an attempt to regulate the process of financial innovation itself and that, when viewed in this light, the proposal is neither as modest nor as obviously superior to the status quo as its proponents claim." That said, it is also important to point out that many OTC derivatives were being centrally cleared prior to the proposal that standardized OTC derivatives be centrally cleared or traded on an organized exchange.

VI. MANDATORY CLEARING OF OTC DERIVATIVES AND FINANCIAL CRISES

Although the Acharya and Bisin (2009) "model suggests that excessive leverage and excessive production arising due to the OTC nature of trading can lead to a 'bubble' in the market for goods (e.g., the housing stock), a subsequent crash upon realization of adverse shocks, and a breakdown of risk transfer (credit or insurance markets) in those states," most observers contend that the failure to centrally clear OTC derivatives was not the principal cause of the 2007–2009 financial crisis.[7] Nor would the adoption of centralized clearing for OTC derivatives avert a similar financial crisis in the future. Hull (2010) states emphatically: "The first point to make is that OTC derivatives did not cause the 2007–2009 financial crisis (or previous financial crises). The causes of the crisis are complex and it would be a mistake to imagine that regulating OTC markets will somehow automatically prevent similar crises in the future." Similarly, Culp (2009) argues: "I contend that the proposal to mandate central counterparty OTC clearing for standardized products will not likely avert another potential crisis or failure of a large financial institution, but will likely engender significant legal and regulatory uncertainty, impede financial innovation, raise market participants' costs, and adversely impact the competitiveness of U.S. derivatives participants." Baker (2011) argues that much financial regulation emanating from a financial crisis is driven by stories about particular firms during the crisis.[8] She argues that the mandate that standardized OTC derivatives be centrally cleared has broader and unintended implications for the repo and other markets.

VII. WHO SHOULD CLEAR OTC DERIVATIVES?

Not surprisingly, the literature is largely silent on who should clear OTC derivatives. Nystedt (2004) argues that organized derivatives exchanges (ODE) should clear such contracts. He states: "A potentially important service ODE markets can provide OTC market participants is to extend clearing services to them. Such services would allow the OTC markets to focus more on providing less competitive contracts/innovations and instead customize its contracts to specific investors' risk

7. For instance, see the statement of the Financial Economists Roundtable (2009).

8. Baker (2011) argues: "Memorable tales of financial collapse, such as that of Lehman Brothers (Lehman), Bear Stearns, and American Financial Group (AIG), frequently drive narratives of financial market crises and future preventative regulatory solutions. Much U.S. financial regulation, such as the monumental and historic 'Dodd-Frank Wall Street Reform and Consumer Protection Act,' (Dodd-Frank) can be understood from this perspective."

preferences and needs." According to Culp (2009), many derivatives exchanges are already providing such services, including CME Group, ICE, Eurex, SGX, and NYSE LIFFE, as well as LCH.Clearnet, which formerly cleared a number of future contracts.

VIII. CONCLUSIONS

There is general agreement in the financial economics literature that the absence of centralized clearing for OTC traded derivatives did not cause the Global Financial Crisis of 2007-2009 nor will the imposition of centralized clearing on standardized or virtually all OTC traded derivatives be likely to avert similar financial crises in the future. The demand for centralized clearing for those OTC traded derivatives that are not currently centrally cleared is not coming from the parties to the trades. The push for centralized clearing of standardized is principally coming from regulators and policymakers, not OTC market participants.

Trading in OTC derivatives is voluntary. Existing counterparties have shown by their actions that they are willing to enter into OTC derivative transactions without requiring the transactions be cleared centrally. While the imposition of mandatory centralized clearing of standardized OTC traded derivatives and the requirement that most OTC derivative transactions be reported to trade repositories may not help individual market participants, it is likely to provide regulatory authorities with the information to make better decisions about which actions to take during periods of financial market stress.

Many OTC derivatives are already being cleared centrally. This movement toward greater central clearing of OTC derivatives has been in response to market forces rather than government edict. Futures clearinghouses handle much of that business. One large segment of the OTC derivatives sector — interest rate swaps — is starting to be cleared. Mandatory centralized clearing of standardized OTC derivatives represents a potentially lucrative business opportunity to clearinghouses.

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BEHAVIORAL FINANCE AND PRICING OF DERIVATIVES: IMPLICATIONS FOR DODD-FRANK ACT

Rahul Verma*

This study investigates the relevance of noise in the derivative market by examining the responses of returns and time varying risks in six futures and four stock index options markets to a set of investor sentiments. Consistent with previous studies, the estimation results suggest that noise is systematically priced in a wide variety of futures and options markets. Investor sentiments on gold, crude oil, wheat, copper, live cattle and sugar significantly impact the returns and conditional variances in precious metals, energy, oilseed, industrial metals, livestock and soft agricultural futures markets respectively. Similarly returns and volatilities in VIX, VXD, VXN and VXO are significantly affected by sentiments of professional analysts and institutional investors, while there is no such effect of individuals. There seem to be a significant greater response of these derivative markets to bullish than bearish sentiments. Lastly, there are evidences of positive feedback trading by investors and lead-lag relationships among their sentiments. Noise seems to affect risk and return in the derivative market in a similar fashion in which it affects those in stocks. The direct implication of these findings is that traditional measure of time variation in systematic risk in the derivative market omits an important source of risk: noise. It has wider implications for the newly enacted Dodd-Frank financial reform bill on derivative trading. They also have important implications for policies that seek to reduce spillover effects and investors who aim to improve their portfolio performance.

Over the past decade the evidence that psychology and emotions influence financial decisions have become more convincing. Financial economists are now realizing that investors can be irrational and predictable errors by investors can affect valuations. Studies argue that psychological biases, cognitive errors and emotions affect investor decisions. Most of the theoretical and empirical studies on investors' psychology have focused on stock markets and empirical

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evidences on anomalies are well documented.[1] However, behavioral finance has been applied in derivatives pricing to a lesser degree. The current literature on derivatives and investors psychology merely conjectures or provides inconsistent results on whether behavioral factors are relevant in pricing of derivatives. Little empirical work is done to examine the ways in which greed, fear, and irrationality are priced in the options and futures markets. This research attempts to contribute to the literature by empirically investigating whether tenets of behavioral finance are relevant in the pricing of derivatives.

It is beyond the scope of one single study to examine the applicability of all theories and models of one area of research into another. This paper borrows one of the established paradigms from behavioral finance, the role of investor sentiments (also called noise) to examine if it can forecast the future direction of derivative prices. The noise trader models in behavioral finance imply that often investors do not make investment decisions based on a company's fundamentals and are capable of affecting stock prices due to unpredictable changes in their sentiments.[2] In traditional finance only risk premium matters while in behavioral finance both systematic risks and noise are relevant (Hirshleifer, 2001; Baur, Quintero, and Stevens, 1996). After decades of study the sources of risk premiums in financial markets is well understood; while, dynamic psychology based derivative pricing theories are still in the infancy stage.

Evidence which suggests that investor sentiments are a priced factor in futures and options market equilibrium is still in dispute. The existing empirical tests on investor sentiments and derivative pricing is provided by studies such as Wang (2001; 2003; 2004); Han (2008); Chen and Chang (2005); Simon and Wiggins (2001); Sanders, Irwin, and Leuthold (2000; 2003). These studies have found inconsistent results on the significance and causality of relationship between sentiments and derivative pricing. One of the reasons for this could be that the existing tests focus primarily on first moment contemporaneous correlations between investor sentiments and derivative returns while less attention is given to the impact of noise on time

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1. The role of investor psychology in stock valuation is well documented by Black (1986), Trueman (1988), DeLong, Shleifer, Summers and Waldman (DSSW) (1990, 1991), Shleifer and Summers (1990), Lakonishok, Shleifer, and Vishny (1991), Campbell and Kyle (1993), Shefrin and Statman (1994), Palomino (1996), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subramanyam (1998); Hong and Stein (1999) and Sias, Starks, and Tinic (2001). Nofsinger (2010) provides an extensive review of theoretical and empirical studies on behavioral finance.

2. Studies related to individual investors sentiments find strong co-movements with stock market returns and volatility (Verma, Baklaci, and Soydemir, 2006, 2008; Verma and Verma 2007; Brown and Cliff 2005; De Bondt 1993) and mixed results regarding its role in short term predictability of stock prices (Brown and Cliff 2004; Fisher and Statman 2000). Similarly, studies examining institutional sentiments find strong co-movements with stock market returns (Verma et al. 2006, 2008; Brown and Cliff 2005) and mixed results regarding its short run implications on stock prices (Brown and Cliff, 2004; Lee, Jiang, and Indro 2002; Clarke and Statman 1998; Solt and Statman 1988). Recent behavioral asset pricing models predict linkages between irrational sentiment and risk to reward ratio (Verma and Soydemir 2009; Yu and Yuan 2005; Basak 2005; Cecchetti, Lam, and Mark 2000; Jouini and Napp 2005; Abel 2002; Girard, Rahman, and Zaher 2003; Garrett, Kamstra, and Kramer 2005; Li and Zhong 2005).

varying risks in futures and options markets. The DSSW (1990) and Sias, Starks, and Tinic (2001) suggest that the impact of noise traders' risk is on both the formation of conditional volatility and expected returns of an asset.[3] Therefore, any tests on the effect of investor sentiments on the mean alone are mispecified and at best incomplete. In case of derivative markets, Sanders, Irwin and Leuthold, (2000; 2003) argue that that investor sentiment does not affect expected returns but could impact its volatilities. However, no analysis is done to investigate the manner in which noise trading may affect expected return through its effect on the market's formation of risk (volatility) in derivative markets as suggested by the DSSW(1990).

Further, the evidence on momentum profitability (Jegadeesh and Titman 1993) and reversals suggest the effect of sentiments on financial markets may be asymmetric (Hong, Lim, and Stein 2000; Hong and Stein 1999). Specifically, a market displays an asymmetric response when returns respond differently to market upturns (bullish) than downturns (bearish) in terms of both speed and magnitude. The economic rationale for this asymmetric response can be explained from the behavioral standpoint of investor psychology. Investors, in general, are more concerned about market downturns than upturns, partly due to their risk-aversion and this tendency gets reflected in market prices, causing different responses to downturns and upturns.[4] Also, due to restrictions on short selling there may be an asymmetric relation between sentiment and valuations. That is, when investors are overoptimistic there is upward pressure on prices that is hard for rational investors to overcome while in the case of pessimism, it is easier for rational investors to trade against the irrational investors. This suggests that prices are not as likely to deviate below intrinsic value as they are above or, magnitude of undervaluation may be different from overvaluation. Given these arguments, it is important to empirically examine whether the relationship between sentiments and derivative pricing are asymmetrical during optimistic and pessimistic periods.

This research is designed to fill a void in the literature related to investor sentiments and derivative pricing by examining the role of behavioral finance in futures and options markets' returns, volatilities and asymmetry. Accordingly, the following three research questions are examined: (i) Is there a role of noise in commodity derivative market returns and risk? (ii) Is there a role of noise in stock derivative market returns and risk? (ii) Are there asymmetrical effects of noise on commodity and stock derivative markets during optimistic and pessimistic periods?

This research makes the following contribution to the literature: first, unlike previous studies which examine the relationship between sentiments and the mean

3. DSSW (1990) show that sentiment can affect expected return of an asset through its effect on the conditional variance of returns. Brown and Cliff (2005) argue that noise trading may impact higher moments of returns such as volatility. Lee, Jiang and Indro (2002) and Verma and Verma (2007) find significant relationship between sentiments and conditional variance in the U.S. stock market.

4. The asymmetric effect of sentiments on the stock market is attributed to the limits to arbitrage (Brown and Cliff, 2004), unidentified risk factors (Fama and French, 1992) and overconfidence (Gervais and Odean, 2001). Empirical tests on asymmetric relationship between sentiments and stock valuation is provided by Lee et al. (2002) and Verma and Verma (2007).

of derivative returns, this research tests the impact of noise on both return and volatilities of futures and options markets; second, unlike previous studies, which examine the symmetrical relationship without segregating between optimism and pessimism, this study examines the existence of asymmetrical impact of bullish and bearish sentiments on derivative markets; third, unlike previous studies which employs bivariate static techniques and treats sentiment of each derivative in isolation this research employs an appropriate multivariate technique to model sentiments of several derivatives of a related assets in one system and examines their relative and spillover effects. Treating sentiments in isolation implicitly ignores potential spillover effects of one type of sentiments on another.

The responses of six commodity futures index returns, volatilities and asymmetry to sentiments on a set of 20 separate commodities are analyzed. The six commodity futures markets identified are: energy, precious metals, industrial metal, agricultural products, grains and livestock. In order to link the relevant sentiments with each futures index, the 20 sentiments are factored into the following six groups: energy (crude oil, heating oil, natural gas, unleaded gasoline), precious metals (gold, silver, platinum), industrial metal (copper), agricultural products (cocoa, coffee, orange, sugar), grain (corn, soybean, soybean oil, wheat) and livestock (live cattle, lean hogs, feeder cattle, pork bellies). Similarly, the returns, volatilities and asymmetry of four stock index options to sentiments of three different categories of investors are analyzed. The four stock index options chosen are: VIX (S&P 500 index options), VXO (S&P 100 index options), VXN (Nasdaq 100 index options) and the VXD (Dow Jones options). The three groups of investors whose sentiments are analyzed are: individual investors, institutional investors, and professional analysts.

This study employs data on weekly basis from the following sources: Datastream; CBOE; CRSP; surveys of American Association of Individual Investors, Investors Intelligence, CONSENSUS Inc., Federal Reserve Bank of St. Louis, and Kenneth French Data Library. The estimation results of a set of multivariate EGARCH models indicate that there is at least one kind of sentiment in each market which significantly affects derivatives' returns and volatilities and also has asymmetric spillover effects. Specifically, investor sentiments on gold, crude oil, wheat, copper, live cattle and sugar are found to significant impact the conditional variance in precious metals, energy, oilseed, industrial metals, livestock and soft agricultural futures markets respectively. There seem to be a significant greater response of these futures markets to bullish than bearish investor sentiments. Similar results are obtained in case of VIX, VXD, VXN and VXO responses to investor sentiments. Both returns and volatilities in these stock index options are significantly affected by sentiments of professional analysts and institutions, while there is no such effect from individuals. There are also evidences of positive feedback trading by investors and lead-lag relationships among their sentiments. Overall, consistent with previous studies, the estimation results suggest that noise is systematically priced in a wide variety of futures and option markets.

These results are consistent with behavioral paradigm that suggests that noise affects an assets return through its impact on its conditional variance. The findings of this study could have important implications for the recently enacted Dodd-Frank's financial-system overhaul which includes measures that would bring more derivatives trading onto regulated exchanges. They also have important implications for policies that seek to reduce spillover effects and investors who aim to improve their portfolio performance.

The remainder of this study is organized as follows. Section I presents the theoretical foundation and reviews the relevant literature on derivative and behavioral finance while Section II presents the model. Section III summarizes data and descriptive statistics. Section IV describes methodology and reports estimation results. Section V presents implications and Section VI concludes.

I. THEORETICAL FOUNDATION

Standard derivative pricing models are based on theories of traditional finance and rest on the assumptions that investors make rational decisions and are unbiased in their predictions about the future. In recent years behavioral finance which incorporates the ideas of non-rational and non-risk neutral investors seems to challenge this notion. In derivative pricing literature, the role of behavioral finance stems from limits to arbitrage (Black 1986; DSSW 1990) and the prospect theory (Kahneman and Tversky 1979). A review of these two theories and empirical work is presented below.

An argument in traditional finance on why noise should not affect market prices lies in the mechanism of arbitrage. It is thought that smart investors look to create profits by trading against irrational traders in order to capture mispricing. Following Black (1986), DSSW (1990) present a model in which noise traders acting as a group can influence stock prices in equilibrium. They argue that arbitrage is limited in a market where informed investors have shorter horizons than noise traders. In their model the deviations in price from fundamental value created by changes in investor sentiments can introduce a systematic risk which is priced , that is, unpredictability in investor sentiments can systematically affect returns.

The theoretical framework describing noise trading in financial markets is provided by studies such as Black (1986), Trueman (1988), DSSW (1990), Shleifer and Summers (1990), Campbell and Kyle (1993), Shefrin and Statman (1994), and Barberis, Shleifer, and Vishny (1998). A trader not trading on information is classified as noise trader. A direct implication of these studies is that a certain groups of investors (noise traders) who often do not make investment decisions based on a company's fundamentals are capable of affecting stock prices by way of unpredictable changes in their sentiments. Noise traders acting in concert on non-fundamental signals can introduce a systematic risk that is priced in the market. Specifically noise trading risk exists because movements in investor sentiment are unpredictable and therefore arbitrageurs betting against mispricing run the risk that such sentiment becomes more extreme and prices move even further away from fundamental value. For this reason, the noise trader risk is measured by unpredictability in investor sentiments.

Several empirical studies have investigated the role of noise trading on stock valuation by using investor sentiments data that indicate the expectations of market participants (see Brown and Cliff 2004; Lee, Jiang and Indro 2002; Verma and Soydemir, 2006; 2008, 2009; Verma and Verma 2007.) In derivative markets the role of noise trading is examined by using investor sentiments data by studies such as Simon and Wiggins (2001) and Sanders et al. (2000, 2003).

Based on DSSW (1990), Brown and Cliff (2004, 2005) explicitly describe the mechanism under which investor sentiments can affect valuations. The environment where sentiments can affect valuations is based on three assumptions. First, some of the investors are biased; second, these biases are persistent in nature, and third, there are limits to arbitrage. Similarly, Shleifer and Summers (1990) present an alternative to the efficient market approach and present a model based on two assumptions: first, some investors are not fully rational and their demand for risky assets is affected by their sentiments; and second, trading by rational investors which are not subject to such sentiments is risky and therefore limited. They find that changes in sentiments are not fully countered by rational arbitrageurs and therefore can affect market prices. Palomino (1996) extends the DSSW (1990) model for an imperfectly competitive market and show that in the presence of risk averse investors, trading with rational speculators based on irrational beliefs may be profitable i.e., noise traders may earn higher returns and obtain higher expected utility than rational investors. It suggests that imperfect competition restricts arbitrage mechanism in two ways: first, quantities traded are smaller as compared to perfectly competitive markets which limit the price stabilizing effect of arbitrageurs; second, irrational behavior can impose higher costs on rational investors than noise traders.

Like in the case of the stock market, valuations in derivative markets can also be affected due to limits to arbitrage. In case of financial futures, the valuation of contracts mainly depends on the relationship between expected prices and spot rate of the underlying asset. This relationship is given by the spot-futures parity theorem (Elton and Gruber 1991). Commodity futures prices are also governed by the same general considerations as financial futures. One difference, however, is that the cost of carrying commodities is greater than the cost of carrying financial assets. Any deviation from this parity relationship would give rise to risk free arbitrage opportunities. Behavioral biases would not matter for derivative pricing if rational arbitrageurs could fully exploit the irrationality of noise traders, and thus trades of profit seeking investors would correct any misalignment in prices. However, behavioral advocates argue that, in practice, several factors limit the ability to profit from mispricing in the derivative market. For example, limits to arbitrage in options market are well documented by Stein (1989), Poteshman (2001), Poteshman and Serbin (2003), and Mahani and Poteshman (2004).

Limits to arbitrage can also be caused due to positive feedback trading in the derivative market. Positive feedback trading or trend chasing is generally considered to be an irrational behavior and associated with noise trading, which has potential to nullify the price stabilizing effect of arbitrage. Kurov (2008) provides evidence on the linkage between investors' attitude and trading behavior at the microstructure level in the futures market. It investigates the response of traders' order flows in S&P500 futures and NASDAQ100 futures indexes and finds that index futures traders use positive feedback trading strategies, that is, buy (sell) index futures contracts after price increases (decreases). It also finds a positive relationship between intensity of such positive feedback trading and individual and institutional investor sentiments. On similar lines, Manaster and Mann (1996) provide a reason as to why irrational behavior can affect trading and thus prices in futures contracts. They argue that index futures markets have a different microstructure as market makers tend to hold relatively small positions and quickly reduce their inventory exposure. Such microstructure characteristics of futures market may affect the propensity of traders to engage in positive feedback trading and limit the arbitrage mechanism of stabilizing prices. However, Antoniou, Koutmos, and Pericli (2005) did not find any evidence of positive feedback trading in index futures, concluding that rational arbitrageurs are able to correct the mispricing by way of arbitrage.

Sanders et al. (2003) examine the lead-lag relationship between returns and sentiments in 28 futures markets. They find that sentiments are increasing function of past returns (positive feedback trading), and noise trader sentiments are useful in predicting futures returns only when sentiments are at extreme level otherwise insignificant. Earlier Sanders et al. (2000) use similar analysis with Market Vane's bullish sentiment index and find consistent results. They argue that sentiment could impact other aspects of price behavior, such as volatility. This argument is consistent with Brown and Cliff (2005), which recognizes that noise trading may impact higher moments of returns, especially volatility. Similar arguments in favor of relationship between sentiments and time varying risk are presented by DSSW (1990) and Sias et al. (2001). These studies find a significant role of noise traders' sentiments in predicting future volatilities in the U.S. stock market. Motivated by these studies, an investigation of linkages between sentiments with conditional volatilities and expected returns in futures and options markets is the primary objective of this research.

Limits to arbitrage and psychological factors can also cause asymmetric behavior of an asset returns to bullish and bearish sentiments (Brown and Cliff 2005). Recent behavioral asset pricing models predict linkages between sentiment and the market price of risk during optimistic and pessimistic periods (Yu and Yuan 2005; Basak 2005; Cecchetti et al. 2000; Jouini and Napp 2005; Abel 2002; Girard et al. 2003; Garrett et al. 2005; Li and Zhong 2005) to be asymmetrical. These studies suggest that irrational investors and rational arbitrageurs hold opposite beliefs: When noise traders are pessimistic, rational arbitrageurs are optimistic. In such a scenario, the compensation for bearing risk should be higher to attract more wealth from rational arbitrageurs, thus adjusting market price of risk upwards. Conversely, when irrational investors are optimistic, market price of risk should be lower to deter rational investors from making investments.

Han (2008) tests the relationship between three types of sentiments and skewness of risk neutral S&P 500 index return and finds results that support the idea that sentiments is an important determinant of index option prices. It also find that index returns have asymmetric response to bullish and bearish sentiments.

Prospect theory describes how people frame and value a decision involving uncertainty. It modifies the analytic description of rational risk averse investors found in standard finance theories. There are four features of prospect theory that appear to be relevant for behavioral finance based derivative pricing models: (i) investors frame their choices in terms of potential gains and losses relative to a specific reference point (either recent highest or purchase price); (ii) investors value the gains/losses according to an S-shaped value function which is concave (convex) for gain (loss); (iii) the value function is asymmetric or steeper for loss than gain; and (iv) investors view each investments separately (also called mental accounting) rather than using a portfolio approach which limits investors' ability to minimize risk and maximize return.

Studies have shown that prospect theory is operative in the options market, and evidence for a concave (convex) value function, as suggested by the prospect theory, is much stronger than standard concave utility function. Actual option prices tend to show systematic and persistent deviation from the prediction of the Black and Scholes (1973) model. Several improvements have been proposed to correct this anomaly. Shefrin and Statman (1993) is one of the earlier behavioral studies to analyze covered call options and find that perceived value and choice from it is consistent with the value function of prospect theory.

Blackburn and Ukhov (2006) investigate the shape of the investors' utility function by examining the index options of Dow Jones and find support for non-concave utility function consistent with the prospect theory. On similar lines, Poteshman and Serbin (2003) analyze call option exercises and argue that a large number of these exercises are irrational in nature, motivated by positive feedback trading and not consistent with generally acceptable market equilibrium models.

Howell and Jagle (1997) argue that behavioral biases affect the subjective valuation as professionals tend to deviate from the Black-Scholes model. Likewise, Miller and Shapira (2004) find that both buyers and sellers price options below its expected values. Verslius, Lehnert, and Woff (2009) design a behavioral model of option pricing by incorporating risk attitude, mental accounting, and probability perceptions. They argue that the result of their behavioral model is better than the traditional Black-Scholes and stochastic volatility model of Heston (1993). Following this, Alemanni, Pena, and Zanotti (2010) find that behavioral version of Black-Scholes is able to better capture option prices than Heston (1993) stochastic volatility model.

Simon and Wiggins (2001) examine the predictive power of three measures of investor sentiments: VIX, put-call ratio, and trading index (TRIN) on 10, 20, and 30 days returns of S&P 500 futures contract. They find a positive relationship between these subsequent returns with the three measures of sentiments. They also find that lagged S&P500 futures contract return is negatively related to VIX and TRIN, a finding consistent with linkage between higher subsequent volatility due to large negative market returns (Nelsen 1991).

Chen and Chang (2005) employed VIX, put-call ratio, and TRIN as sentiment indicators and analyzed their predictive power over S&P 500 futures returns. They employ extended classifier system, one of the artificial intelligence models and find that sentiments are contrarian in nature and can significantly predict the S&P 500 futures returns. Similarly, Brown and Cliff (2004) regress individual and institutional investor sentiments against a set of derivative variables. They find that both VIX and CBOE equity put to call ratio are negatively related to institutional investor sentiments while positively related to individual investor sentiments. They also find that changes in net positions in SPX futures of non-commercial traders and small traders are positively related to institutional investor sentiments.

Wang (2003) uses the COT (Commitment of Traders) report, an indirect measure of sentiments to investigate the forecasting power of actual traders' position over S&P 500 index returns. It finds that both large speculators and large hedgers are useful market timing indicators but provide opposite forecasts. Speculators (hedgers) sentiments are price continuation (contrarian) in nature. It argues that large speculators have superior forecasting ability than hedgers and small traders. Earlier, Wang (2001) did similar analysis with COT data to forecast returns of six major agricultural futures and finds consistent results. Likewise, Wang (2004) investigates the predictive power of COT data on five major currencies — British pound, Canadian dollar, Deutsche mark, Japanese yen, and Swiss franc over their futures returns and find similar results.

In summary, theoretical studies suggest a significant relationship between sentiments and returns which is asymmetric in nature. However, empirical tests on noise and derivative valuation have found inconsistent results on significance and causal relationship between sentiments and options and futures pricing. For example, Sanders, Irwin, and Leuthold (2000, 2003), Antoniou, Koutmos, and Pericli (2005) find insignificant results; Kurov (2008), Han (2008), Simon and Wiggins (2001) suggest significant positive relationships; Chen and Chang (2005) find significant negative relationship; and Brown and Cliff (2004) and Wang (2001, 2003, 2004) find both positive and negative significant relationships.

One of the probable reasons previous studies do not provide any coherent answer is because existing tests focus only on first moment bivariate contemporaneous correlations between sentiments and valuation and ignore conditional volatilities.However, theoretical studies make a strong argument that sentiments can affect derivative valuation through its impact on time varying risk; no empirical test exists. Currently, it is merely conjectured that sentiments might affect both volatilities and returns in options and futures markets. Also, there is little test on how limits to arbitrage and other behavioral factors can cause derivative prices to behave asymmetrically during optimistic and pessimistic periods. This research is positioned to address these voids in the derivative pricing and behavioral finance literature.

II. MODEL

This study follows the approach suggested by DSSW (1990) and Sias et al. (2001) to model the impact of noise on derivative returns, volatility, and asymmetry. Recent empirical studies (Lee et al. 2002; Brown and Cliff 2005) have analyzed similar relationships in case of the stock market. Under this approach sentiments can impact an asset price through the interaction of four effects: (i) price pressure,

(ii) hold more, (iii) Friedman, and (iv) create space. The "price pressure" and "hold more" effects of sentiments directly impact expected returns of an asset. On the other hand, the "Friedman" and "create space" effects of sentiments indirectly impact expected returns through their influence on conditional volatilities of asset returns.

The "price pressure" effect represents the pricing error caused due to noise traders' misperceptions as their bullishness (bearishness) bids up (down) purchase (selling) prices thereby leading to lower expected returns. The "hold more" effect causes the expected returns to be higher (lower) since greater (lower) level of risk is borne by bullish (bearish) irrational investors due to increased (decreased) demand of assets. The "hold more" effect stems from the price pressure effect as irrational traders tend to hold more (less) of those assets whose prices are higher (lower) than their fundamental values. These two effects suggest that sentiments can impact expected returns by moving prices away from intrinsic values and cause a change in the level of market risk. The net impact of these two effects depends on whether noise traders are bullish or bearish. In case of bullishness, when the "hold more" effect is greater (lower) than the "price pressure" effect, expected returns would be higher (lower). However, during bearishness it does not matter which effect is greater since both effects would lead to lower expected returns.

The "Friedman" effect represents the loss which noise trades have to bear due to trade with rational arbitrageurs during the arbitrage mechanism. This is caused by noise traders' misperceptions about the risk of an asset, which makes them buy and sell at wrong time and suffer extreme losses. Like "price pressure," the "Friedman" effect also always leads to lower expected returns. The greater is the irrationality or misperceptions about risk, the larger is loss on noise trading.

The "create space" effect is the heart of the noise trader model. It suggest that assets on which irrational investors are active tend to trade at prices below their intrinsic values and expected to generate higher returns than securities on which noise traders play a less active role. The logic is that noise trading on certain assets increases the price uncertainty, making rational investors to shun those causing prices to fall and expected returns to increase. Noise traders thus create their own space. This variability in returns due to greater create space brings an additional systematic risk that is priced in equilibrium. Noise traders thus gain more by trading on these securities and consequently these assets exhibit greater volatility and mean reversion than the ones which are mainly held by rational investors and trade close to their fundamental values. The greater (lower) the create space than "Friedman" effect; greater (lower) would be the expected returns due to effect of sentiments on conditional volatilities.

The four effects also suggest an asymmetric effect of bullish and bearish sentiments on asset returns. In "price pressure" and "Friedman" effects, it does not matter whether noise traders are bullish or bearish since irrationality causes the expected returns to be always lower. This is in contrast to "hold more" effect where expected returns would be higher or lower depends on bullish or bearish sentiments. Similarly "create space" effect causes an increase in expected returns only when noise traders are bullish while there is no negative effect of bearish sentiments on expected returns. Overall, noise traders can earn higher returns in the presence of "hold more" and "create space" effects only when they are bullish.

In summary, the "price pressure" and "hold more" effects are short-term in nature due to the effect of *directions* of sentiments on the *mean* of excess returns, while the "Friedman" and "create space" capture the long run impact of noise on excess returns due to the effect of *magnitude* of sentiments on the formation of future *volatilities* of returns. In order to examine long term relationship between sentiments and asset valuation, there is a strong case to model both returns and volatilities of futures and options while analyzing the effect of noise on derivative valuation.

This research employs an appropriate multivariate technique to model sentiments of several derivatives of related assets in one system and examines their relative and spillover effects. Treating sentiments in isolation implicitly ignores potential spillover effects of one type of sentiments on another. For example, shocks originating from sentiments of one related asset (say gold) not considered might mistakenly be seen as a disturbance originating from sentiments of other asset (say silver) included in the analysis. Since studies such as Brown and Cliff (2004, 2005) and Verma and Verma, (2007) suggest that risk, returns, and sentiments may act as a system, the multivariate version of Nelson's (1991) Exponential Generalized ARCH (EGARCH) model is employed.

In order to model asymmetric effects of bullish and bearish sentiments on returns and volatilities, the multivariate version of Nelson's EGARCH extended by Koutmos and Booth (1995) is used.[5] This model is estimated separately to investigate the postulated relationships in six commodity futures markets (energy, precious metals, industrial metal, agricultural products, grains and livestock) and four stock index options markets (VIX, VXO, VXN and VXD) with 22 commodities and 3 stock market based investor sentiments, respectively. Table 1 details the list of variables included in each model.

The Vector Autoregressive (VAR) model (Sims 1980) in the mean equation is appropriate when estimating unrestricted reduced-form equations with a uniform set of dependent variables as regressors. The model is also appropriate for analyzing the postulated relationships because it does not impose a priori restrictions on the structure of the system and can be viewed as a flexible approximation to the reduced form of the correctly specified but unknown model of true economic nature.

The mean equation takes the following form:

$$R_{i,t} = \beta_{i,0} + \sum_{i=1,\, j=1}^{K} \beta_{i,j} R_{j,t-m} + \varepsilon_{i,t}; i, j = 1..K; i \neq j \tag{1}$$

5. Nelson's EGARCH model is a univariate one and it only considers the asymmetric impacts of positive and negative innovations of a previous period on current conditional volatility. It does not examine the asymmetric impact of positive and negative innovations of one variable on the volatility of another variable.

Table 1. List of Variables Included in Each Model.

Models		Variables
Model 1: Energy futures market	i	Returns on Reuters-CRB energy sub-index
	ii	Sentiments on crude oil
	iii	Sentiments on heating oil
	iv	Sentiments on natural gas
	v	Sentiments on unleaded gasoline
Model 2: Precious metals futures market	i	Returns on Reuters-CRB precious metals sub-index
	ii	Sentiments on gold
	iii	Sentiments on silver
	iv	Sentiments on platinum
Model 3: Industrial futures market	i	Returns on Reuters-CRB industrial sub-index
	ii	Sentiments on copper
	iii	Sentiments on silver
	iv	Sentiments on platinum
Model 4: Soft agricultural futures market	i	Returns on Reuters-CRB soft agriculture produce sub-index
	ii	Sentiments on cocoa
	iii	Sentiments on coffee
	iv	Sentiments on orange
	v	Sentiments on sugar
Model 5: Grain and oil seed futures market	i	Returns on Reuters-CRB grain and oil seed sub-index
	ii	Sentiments on corn
	iii	Sentiments on soybean
	iv	Sentiments on soybean oil
	v	Sentiments on wheat
Model 6: Livestock futures market	i	Returns on Reuters-CRB livestock seed sub-index
	ii	Sentiments on live cattle
	iii	Sentiments on lean hogs
	iv	Sentiments on feeder cattle
	v	Sentiments on pork bellies
Model 7: Stock index derivative market	i	Returns on VIX
	ii	Returns on VXO
	iii	Returns on VXN
	iv	Returns on VXD
	v	Sentiments of individual investors
	vi	Sentiments on institutional investors
	vii	Sentiments of professional analysts

Here $R_{i,t}$ is the column vector of variables under consideration. $\beta_{i,0}$ is the deterministic component comprised of a constant. $\beta_{i,j}$ is matrix of coefficients, *m* is the lag length and $\varepsilon_{i,t}$ is a vector of random error terms.

This equation is estimated seven times separately to examine the role of noise in the seven derivative markets: energy, precious metals, industrials, soft agricultural, grain and oil seed, livestock, and stock index. In total, these seven models include 25 different types of investor sentiments related to 25 commodities and stock indexes. For example, in Model 1, which examines the role of noise in the energy futures market, sentiments on the following four commodities are used: crude oil, heating oil, natural gas, and unleaded gasoline. Similarly, in Model 2, which investigates the effect of noise in the precious metals futures market, sentiments on the following three commodities are used: gold, silver and platinum.[6]

In the first model, $K = 5$ since there are five variables and thus $i,j = 1,2,3,4,5$. Similarly, in the second model, $K = 4$, or $i,j = 1,2,3,4$ and so on. Here, the parameter $\beta_{ii,j}$ captures the degree of mean spillover effects across sentiments and returns. A significant $\beta_{ii,j}$ coefficient would mean that variable *j* leads variable *i*, or equivalently, that current *j* can be used to predict future *i*. Since the purpose of the paper is not to analyze how market return and volatility are affected by its past innovations, but rather to investigate the spillover effects between sentiments and volatility, the constraint $i \neq j$ is specified.

Following multivariate EGARCH (Koutmos and Booth 1995) the conditional variance equations takes the following form:

$$\sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{K} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-m}^2)\}; i, j = 1...K, i \neq j \tag{2}$$

$$f_j(Z_{j,t-m}) = (\left|Z_{j,t-m}\right| - E\left|Z_{j,t-m}\right| + \delta_j Z_{j,t-m}); j = 1..K \tag{3}$$

where $Z_{j,t-1}$ is the standardized residual at time *t-m* which is defined as $\varepsilon_{j,t-m}/\sigma_{j,t-m},$ and $E|Z_{j,t-m}|$ is the expected value of $Z_{j,t-m}$. The parameters $\alpha_{i,j}$ captures the volatility spillover among the variables, that is, the effect of innovations from variable *j* to variable *i*.

The asymmetric effect of negative and positive on conditional volatility is measured by the ratio $|-1 + \delta_j|/(1 + \delta_j)$. A negative value of δ_j will lead to a larger value of the ratio indicating that negative innovations will have greater effects on conditional volatility than positive innovations. A significant positive (negative) $\alpha_{i,j}$ coupled with a negative (positive) δ_j implies that negative (positive) innovations in variable *j* have a higher impact on volatility of variable *i* than positive (negative) innovations. This implies that the volatility spillover mechanism is asymmetric.

Following Bollerslev (1990), Koutmos and Booth (1995), and So (2001), a time invariant correlation matrix is assumed while estimating these multivariate EGARCH

6. A description of variables included in each of the seven models is shown in table 1 and their descriptive statistics are shown in Table 2.

models. Under this specification, the covariance is equal to the product of the standard deviations ($\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\,\sigma_{j,j}$ for i, j = 1,2,3; $i \neq j$). This specification reduces the number of parameters and makes the estimation more tractable.

III. DATA AND DESCRIPTIVE STATISTICS

The data for this research are obtained from May 1990 to December 2010 in weekly intervals.[7] A common sample is identified during this period to match all the variables. The description of the data source is as follows:

A. Futures Market Data

This study employs six commodity indices benchmarks to test the effect of noise on futures market. These commodity futures indices attempt to replicate the return available to holding long positions in commodities such as agriculture, metal, energy, or livestock investments (Schneeweis and Spurgin 1997). The futures benchmark therefore serves as an index of the expectations of the commodity market participants towards the future valuation of the underlying assets. Valuations of these indices are based primarily on the following three factors: (i) price return derived from changes in a relative commodity futures contract; (ii) roll return, which is the return associated with rolling over a futures contract prior to its expiration date, and re-investing the entire proceeds in order to keep the portfolio fully invested; and (iii) collateral return, which is the interest earned on any cash value during the investment period.

The commodity futures indices are from the Reuters Commodity Research Bureau Index (CRB). CRB is a leading industry index, and it has served as the most widely recognized measure of global commodities markets and a widely recognized broad measure of overall commodity price trends. Since 2005, the CRB is also known as the Reuters/Jefferies-CRB index. The source for CRB data is the Thomson Financials Datastream database. The details of the CRB component groups (sub-commodity index) used in this study are as follows:

- The benchmark for the energy index is the Reuters-CRB energy sub-index which comprises of crude oil, heating oil, and natural gas, and it accounts for 18% of the overall CRB Index.

- The benchmark for the grains and oilseed index is the Reuters-CRB grains and Oilseeds sub-index which is comprised of corn, soybeans, and wheat, and accounts for 18% of the overall CRB Index.

- The benchmark for industrial materials is the Reuters-CRB industrials sub-index which comprises of copper and cotton, and it accounts for 12% of the overall CRB Index.

- The benchmark for livestock is the Reuters-CRB livestock sub-index

7. The exception is CBOE volatility indices, which started at later dates.

which comprises live cattle and lean hogs and accounts for 12% of the overall CRB Index.

- The benchmark for precious metals is the Reuters-CRB precious metals sub-index which comprises gold, platinum, and silver, and it accounts for 17% of the overall CRB Index.

- The benchmark for soft agriculture produce is the Reuters-CRB soft agriculture produce sub-index which comprises of cocoa, coffee, orange juice, and sugar, and it accounts for 23% of the overall CRB Index.

This paper employs the CRB index returns instead of returns of assets included in each index due to the following two reasons: replacing index with multiple assets comprising each index would substantially increase the number of variables in each multivariate EGARCH models which might make them overparameterized, and for consistency purposes, the CRB index returns is employed in all the models. There would be a substantial increase in the relevant parameters that might lead to loss of generalizability of results if these indexes are replaced with several assets.

B. Options Market Data

This study employs the four options volatility indices from Chicago Board Options Exchange (CBOE) dataset. The CBOE volatility indices are key measures of market expectations of 30 days (near-term) volatility conveyed by different stock index option prices. These indices are based on stock index option prices and incorporate information from the volatility skew by using a wider range of strike prices rather than just at-the-money series. Specifically, the four stock index options chosen are the following: VIX, which tracks the S&P 500 index options; VXO, which tracks the S&P 100 index options; the VXN, which tracks the Nasdaq 100 index options; and the VXD, which tracks the Dow Jones index options.

C. Futures Market Sentiments Data

To measure the expectations of informed investors, this study employs Consensus Bullish sentiment index provided by Consensus Inc. This index gives the attitudes of professional brokerage house analysts and independent advisory services on major financial markets. Consensus Inc. surveys these advisory services on bullishness or bearishness of a particular asset. It compiles a sentiment index for each of these assets by dividing the number of bullish counts to the total number of opinions. This index is compiled on every Friday and released during the early part of the following week. Specifically, this research uses sentiments on 22 different commodities, which can have a bearing on the returns and volatilities in six futures markets chosen for this study. These 22 assets for which sentiments are obtained are (i) for energy futures market (crude oil, heating oil, natural gas, unleaded gasoline); (ii) for precious metals futures market (gold, silver, platinum); (iii) for industrial metal futures market (copper, silver, platinum); (iv) for agricultural products futures market (cocoa, coffee, orange, sugar); (v) for grain futures market (corn, soybean, soybean oil, wheat); and (vi) for livestock futures market (live cattle, lean hogs, feeder cattle, pork bellies).

D. Stock Index Options Sentiments Data

To measure sentiments of market participants on index options, this study employs three different survey data similar to the ones used in the literature on behavioral finance and stock valuation. The three kinds of investors chosen are institutional investors, who participate in the market for a living; individual investors, whose primary line of business is outside the stock market; and professional analysts, who provide advisory services (i.e., informed investors).

The choice of institutional investor sentiment index is survey data of *Investors Intelligence (II)*, an investment service based in Larchmont, New York. *II* compiles and publishes data based on a survey of investment advisory newsletters. To overcome the potential bias problem towards buy recommendation, letters from brokerage houses are excluded. Based on the future market movements, the letters are labeled as bullish, bearish, or correction (hold). For consistency purposes, the sentiment index for the institutional investor is computed as the percentage of bullish responses to the total number of opinions. Since authors of these newsletters are market professionals, the *II* series is interpreted as a proxy for institutional investor sentiments.

The choice of individual investor sentiment index is the survey data of *American Association of Individual Investor (AAII)*. Beginning July 1987, *AAII* conducts a weekly survey asking for the likely direction of the stock market during the next six months (up, down, or the same). The participants are randomly chosen from approximately 100,000 AAII members. Each week, *AAII* compiles the results based on survey answers and labels them as bullish, bearish, or neutral. These results are published as "investor sentiment" in monthly editions of *AAII* Journal. The sentiment index for individual investors is computed as the percentage of bullish investors to total number of opinions. Since this survey is targeted towards individual investors, it is primarily a measure of individual investor sentiments.

The choice of informed investor sentiments is the index provided by Consensus Inc., which gives the attitudes of professional brokerage house analysts and independent advisory services on future stock market movements. Consensus Inc. surveys these advisory services on bullishness or bearishness of stock market. It compiles a sentiment index by dividing the number of bullish counts to the total number of opinions. This index is compiled on every Friday and released during the early part of the following week.

Table 2 reports the descriptive statistics of the above- mentioned 33 variables. In the case of futures and options markets log first differences are used to capture weekly returns while sentiments are at their levels. Overall, the mean returns of commodity futures indices are somewhat higher than those of stock index options (except for VXN). Specifically, precious metals and energy futures have higher mean returns accompanied by higher standard deviation, suggesting that investors are being compensated for bearing additional risk. That these higher statistics are observable in the two futures market may be due to high volatility in crude oil and gold prices during the last few years. The sentiments related to the commodity markets are somewhat in the range of 41%–51%, suggesting that expectations have been almost same for bullishness and bearishness/neutral. The only exception is sentiments related to the natural gas, approximately 20%, indicating that almost 80% of the market participants were either bearish or neutral during the last two decades. Consistent with the volatility in energy and precious metals futures prices, the sentiments related to crude oil, gasoline, heating oil, and gold have higher standard deviation than other expectation indicators. Of the three stock market related sentiments, institutional investors and professional analysts seem to be more bullish than individual investors. The sentiments of institutional investors appear to be more volatile than those of individuals and analysts.

IV. ESTIMATION

In accordance with equations (1, 2, and 3), a set of seven multivariate EGARCH models are estimated. The first model examines the role of noise in the energy market by linking the energy futures market return with sentiments on four energy related assets: crude oil, heating oil, natural gas and unleaded gasoline. Table 3 reports the estimated coefficients of the mean and variance equations. The parameter $\beta_{i,j}$ captures the degree of mean spillover effects across sentiments and returns. Specifically, a significant $\beta_{i,j}$ coefficient would mean that variable *j* leads variable *i*, or equivalently, current *j* can be used to predict future *i*. The significant positive coefficients $\beta_{12,}$ $\beta_{13,}$ $\beta_{14,}$, and β_{15} suggest investor sentiments for the four energy related assets play a significant role in the energy futures market returns. The crude oil sentiments seem to have the maximum impact on energy futures returns. The volatility spillover effects among variables is captured by the parameters $\alpha_{i,j}$, that is, the effect of innovations from variable *j* to variable *i*. A significant and negative α_{12} indicates spillover effects from crude oil sentiments to energy futures market volatility. Unlike the results for energy futures returns, where all four energy related assets have significant effects, in the case of variance only α_{12} is significant and negative. Insignificant volatility spillover effects of heating oil, natural gas and unleaded gasoline sentiments reiterate the dominant effect of crude oil in the energy market.

The possibility of asymmetric impact of investor sentiments on futures market volatilities can be ascertained by examining the coefficients $\alpha_{i,j}$ coupled with δ_j. A significant negative $\alpha_{i,j}$ coupled with a significant positive δ_j would imply that volatility spillover mechanism from j^{th} variable to i^{th} variable is asymmetric or there is greater effect of bullish than bearish sentiments on the conditional variance of returns. In Table 3, a negative and significant $\alpha_{1,2}$ exists with a positive and significant δ_2, suggesting that there is greater response of energy futures volatilities to bullish than bearish crude oil sentiments. Although the parameters δ_3, δ_4, and δ_5 are significant,

Table 2. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel A: Futures markets returns						
CRB_EGY	0.0016	0.1575	-0.2591	0.0377	-0.7378	7.8725
CRB_IND	0.0007	0.0908	-0.0805	0.0216	-0.0300	4.0453
CRB_GR	0.0009	0.1122	-0.0986	0.0270	0.3317	3.8508
CRB_LIV	0.0004	0.1077	-0.0948	0.0224	0.0693	4.6715
CRB_PR	0.0012	0.0866	-0.1021	0.0233	-0.4611	5.0158
CRB_AG	0.0006	0.0893	-0.0813	0.0256	0.1393	3.4799
Panel B: Stock index options returns						
VIX	0.0003	0.3294	-0.2968	0.0843	0.4315	3.9886
VXD	-0.0001	0.2984	-0.2335	0.0842	0.5125	3.8346
VXN	-0.0018	0.2904	-0.2375	0.0734	0.4074	3.8738
VXO	0.0002	1.2514	-0.5040	0.0936	2.0855	29.5143

Table 2, continued. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel C: Commodity market sentiments						
Energy:						
S_CRUDE	0.4402	0.9600	0.0000	0.2277	-0.1669	2.3305
S_HEAT	0.4348	0.9400	0.0400	0.2074	0.1116	2.0523
S_NG	0.1940	0.9300	0.0000	0.2496	0.7969	2.1491
S_GASO	0.4116	0.9500	0.0000	0.2329	-0.0517	2.1586
Precious metals:						
S_GLD	0.4804	0.9600	0.0300	0.1898	0.1177	2.2280
S_SLV	0.4709	0.9500	0.0400	0.1783	0.2756	2.6018
S_PLT	0.4909	0.9500	0.0600	0.2034	-0.0838	2.1438
Industrial:						
S_CU	0.4856	0.9600	0.0800	0.1966	0.0236	2.0488
S_SLV	0.4709	0.9500	0.0400	0.1783	0.2756	2.6018
S_PLT	0.4909	0.9500	0.0600	0.2034	-0.0838	2.1438

Table 2, continued. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel C, continued: Commodity market sentiments						
Agricultural:						
S_COCOA	0.4363	0.9400	0.0400	0.1857	0.3227	2.4439
S_COFFEE	0.4580	0.9600	0.0400	0.1997	0.2195	2.2030
S_OJUICE	0.4238	0.9400	0.0500	0.2091	0.2331	2.1422
S_SUGAR	0.5088	0.9400	0.0500	0.2025	-0.0071	2.1232
Grain and oil seed:						
S_CORN	0.4895	0.9500	0.0500	0.1939	0.1377	2.2009
S_SOY	0.5130	0.9400	0.1200	0.1758	0.0071	2.1301
S_SOYOIL	0.4605	0.9600	0.0500	0.2052	0.1843	2.1291
S_WHEAT	0.4858	0.9200	0.0300	0.1794	0.0410	2.3422
Livestock:						
S_LCATTLE	0.5138	0.8700	0.1200	0.1501	-0.0160	2.2946
S_HOGS	0.4591	0.9300	0.1300	0.1565	0.1400	2.2874
S_FCATTLE	0.4688	0.9500	0.0600	0.1861	0.1650	2.2807
S_PORK	0.4261	0.8900	0.0400	0.1807	0.2334	2.3358

Table 2, continued. Descriptive Statistics.

	Mean	Max	Min	S.D.	Skewness	Kurtosis
Panel D: Stock market sentiments						
AA	0.3984	0.3980	0.6860	0.1280	0.0991	0.1394
II	0.4806	0.4890	0.6290	0.2224	0.0764	-0.6827
CONS	0.4667	0.8600	0.0300	0.1580	-0.0198	2.3193

The variables included in panel A are weekly returns on CRB futures indices related to energy (CRB_EGY), industrial metals (CRB_IND), grains and oil seeds (CRB_GR), livestock (CRB_LIV), precious metals (CRB_PR) and soft agricultural products (CRB_AG) .The variables included in panel B are weekly returns of CBOE volatility index for S&P500 (VIX), Dow Jones (VXD), NASDAQ (VXN) and S&P100 (VXO). The variables included in panel C are % of bullish professional analysts on cocoa (S_COCOA), coffee (S_COFFEE), corn (S_CORN), crude oil (S_CRUDE), copper (S_CU) , feeder cattle (S_FCATTLE), unleaded gasoline (S_GASO), gold (S_GLD), heating oil (S_HEAT), hogs (S_HOGS), live cattle (S_LCATTLE), natural gas (S_NG), orange juice (S_OJUICE), pork (S_PORK), platinum (S_PLT), silver (S_SLV), soybean (S_SOY), soy oil (S_SOYOIL), sugar (S_SUGAR) and wheat (S_WHEAT). The variables included in panel D are % of bullish individual investors (S_AA), institutional investors (S_II) and professional analysts (S_CONS).

Table 3. Multivariate EGARCH Estimation Results for Sentiments and Energy Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0090	0.0106	0.8462
β_{12}	0.0873***	0.0280	3.1144
β_{13}	0.0559***	0.0148	3.7851
β_{14}	0.0470***	0.0133	3.5347
β_{15}	0.0465**	0.0235	1.9796
β_{20}	0.1260***	0.0094	13.4188
β_{21}	0.2025***	0.0558	3.6283
β_{23}	-0.0012	0.0036	-0.3437
β_{24}	0.0092	0.0153	0.6036
β_{25}	0.0064	0.0222	0.2867
β_{30}	0.0403***	0.0075	5.3599
β_{31}	0.0195	0.0182	1.0728
β_{32}	0.0361***	0.0066	5.4629
β_{34}	0.0334***	0.0015	22.6893
β_{35}	0.0187	0.0129	1.4523
β_{40}	0.0025	0.0213	0.1160
β_{41}	-0.0561	0.1119	-0.5009
β_{42}	0.2101***	0.0313	6.7197
β_{43}	0.0207	0.0215	0.9656
β_{45}	0.0428	0.0280	1.5311
β_{50}	0.0959***	0.0086	11.1328
β_{51}	0.2520***	0.0811	3.1090
β_{52}	0.1359**	0.0568	2.3911
β_{53}	0.0199***	0.0058	3.4456
β_{54}	0.2208***	0.0161	13.7025
α_{12}	-0.1797***	0.0625	-2.8752
α_{13}	-0.1493	0.2375	-0.6289
α_{14}	-0.0436	0.0498	-0.8764
α_{15}	-0.0857	0.1939	-0.4417
α_{21}	0.2067	0.1754	1.1783
α_{23}	0.0560	0.1246	0.4497
α_{24}	0.0057	0.0250	-0.2278
α_{25}	0.0846	0.1109	0.7633
α_{31}	-0.1183	0.0966	-1.2246
α_{32}	-0.0685	0.0426	-1.6073
α_{34}	-0.0392**	0.0184	-2.1287
α_{35}	0.3274***	0.0828	3.9557

Table 3, continued. Multivariate EGARCH Estimation Results for Sentiments and Energy Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	0.2324	0.1773	1.3108
α_{42}	-0.1043	0.1036	-1.0071
α_{43}	0.2151	0.2560	0.8401
α_{45}	-0.0313	0.1671	-0.1873
α_{51}	0.2844*	0.1670	1.7025
α_{52}	0.0236	0.0352	0.6711
α_{53}	-0.0287	0.0967	-0.2971
α_{54}	-0.1258***	0.0349	-3.6085
α_{55}	0.5040***	0.1131	4.4545
δ_1	0.3003***	0.0731	4.1090
δ_2	0.7122***	0.0450	15.8273
δ_3	-0.5722***	0.0580	-9.8700
δ_4	1.4381***	0.2580	5.5732
δ_5	-0.3011***	0.0787	-3.8281

The five variables included are: CRB energy futures index returns (i,j=1), investor sentiments on crude oil (i,j=2), heating oil (i,j=3), natural gas (i,j=4) and unleaded gasoline (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{12,}$ $\beta_{13,}$ β_{14} and β_{15} captures the effect of sentiments of crude oil, heating oil, natural gas and unleaded gasoline respectively on energy futures market returns. Similarly, $\alpha_{12,}$ $\alpha_{13,}$ α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of crude oil, heating oil, natural gas and unleaded gasoline respectively on energy futures market volatilities. The asymmetric effects of these four sentiments on energy futures market volatility is captured by $\delta_{2,}$ $\delta_{3,}$ $\delta_{4,}$and δ_5. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of energy futures market.

they do not imply asymmetric effects of other sentiments on energy futures volatilities since coefficients α_{13}, α_{14}, and α_{15} are statistically insignificant.

Some other significant coefficients also reveal linkages among sentiments of different energy related assets. For example, significant positive parameters $\beta_{32,}$ $\beta_{42,}$ and β_{52} indicate that sentiments of heating oil, natural gas and unleaded gasoline are formed in part due to investors' perceptions about the future direction of the crude oil prices. However, crude oil sentiments do not seem to be developed in response to expectations about the other three energy related assets (insignificant $\beta_{23,}$ $\beta_{24,}$ and β_{25}). Similarly, heating oil sentiments seems to be impacted by bullishness/bearishness in natural gas. There is also some evidence of positive feedback trading or trend chasing by investors. Specifically, coefficients β_{21} and β_{51} are positive and significant, suggesting that past futures index returns are an important

Table 4. Multivariate EGARCH Estimation Results for Sentiments and Precious Metals Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0016	0.0207	0.0773
β_{12}	0.0901***	0.0278	3.2410
β_{13}	0.0382	0.0377	1.0133
β_{14}	0.0429	0.0405	1.0593
β_{20}	0.0779***	0.0225	3.4622
β_{21}	1048.0159	584501.4514	0.0018
β_{23}	0.0082	0.1594	0.0514
β_{24}	0.2216	0.2139	1.0360
β_{30}	0.0539	0.0655	0.8229
β_{31}	12440.7844	104018.4407	0.1196
β_{32}	0.3418**	0.1478	2.3126
β_{34}	-0.1498	0.2123	-0.7056
β_{40}	0.0067	0.0778	0.0861
β_{41}	78693.1284	90090.3503	0.8735
β_{42}	0.0782	0.0674	1.1602
β_{43}	0.0451	0.1865	0.2418
α_{12}	-2.5718***	0.8359	-3.0767
α_{13}	-0.5461	0.5169	-1.0565
α_{14}	2.4384	3.7948	0.6426
α_{21}	0.9442	0.9203	1.0260
α_{23}	0.1239	0.5064	0.2447
α_{24}	5.0691	4.6322	1.0943
α_{31}	-0.6950	0.7483	-0.9288
α_{32}	-0.1437	0.6720	-0.2138
α_{34}	-1.5136	2.1564	-0.7019
α_{41}	0.1369	0.5449	0.2512
α_{42}	-0.0431	0.3742	-0.1152
α_{43}	-0.0475	0.5321	-0.0893
δ_1	-0.0413	0.6549	-0.0631
δ_2	0.9875***	0.3561	2.7731
δ_3	-0.3294	0.2544	-1.2948
δ_4	-0.7961***	0.1535	-5.1863

The four variables included are: CRB precious metals futures index returns ($i,j=1$), investor sentiments on gold ($i,j=2$), silver ($i,j=3$), and platinum ($i,j=4$). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{12,}$ $\beta_{13,}$ and β_{14} captures the effect of sentiments of gold, silver and platinum respectively on precious metal futures market returns. Similarly, $\alpha_{12,}$ $\alpha_{13,}$ and α_{14} captures the volatility spillover effects or innovations from sentiments of gold, silver and platinum respectively on precious metals futures market volatilities. The asymmetric effects of these three sentiments on precious metals futures market volatility is captured by $\delta_{2,}$ $\delta_{3,}$

determinant of sentiments for crude oil and unleaded gasoline.

The second multivariate EGARCH model consists of four variables related to the precious metals asset class. It includes precious metals futures index returns and sentiments for gold, silver and platinum. The estimation results are presented in Table 4. The effect of gold sentiments on precious metals futures returns and volatilities is similar to the impact of crude oil sentiments on the energy futures market. Significant β_{12} and α_{12} indicate that sentiments induced noise trading on gold can affect precious metal futures returns and volatilities respectively. Specifically, the effect of gold sentiments is positive on mean while negative on the conditional variance of CRB futures index returns for precious metals. Moreover, α_{12} coupled with a significant and positive δ_2 suggests the presence of asymmetric response of these volatilities to the bullish and bearish sentiments on gold. The sentiments of other two precious metals (silver and platinum) seem to have an insignificant effect on the returns and volatilities of futures index. Moreover, a significant β_{32} coefficient means that sentiments of silver are significantly driven by traders' expectations about gold.

Table 5 reports the estimation of a five variable multivariate EGARCH model, which includes grain and oil seed futures index returns and sentiments for corn, soybean, soybean oil, and wheat. Three out of four sentiments (corn, soybean and wheat) have significantly positive effect on oil seed futures index returns. Similarly, the conditional variance of futures index returns is significantly affected by soybean and wheat sentiments. Negative and significant coefficients α_{12}, α_{15} mean that optimistic expectations on soybean and wheat prices can negatively affect the volatility in oil and seed futures market. However, since δ_{35} is significant while δ_2 is insignificant, an asymmetric response of futures market volatilities can only be attributed to the sentiments of wheat. The magnitude of coefficients related to wheat in both the mean and variance equations suggest that noise in wheat prices can cause greater effect in this derivative market. There are also evidences of lead-lag relationships among sentiments of the four assets. Significant positive parameters β_{32} and β_{45} suggest that sentiments on soybean and soybean oil are somewhat also caused by expectations about corn and wheat prices respectively. Of the four assets, sentiments on wheat seem to have the most dominant effect on oil and seed derivative market. Also, there is an evidence of positive feedback trading as wheat sentiments are significantly related to past movement in the oil and seed futures index prices.

The fourth model links the sentiments on four soft agricultural produce (cocoa, coffee, orange, and sugar) with Reuters-CRB soft agriculture produce futures index returns. The estimation results are reported in Table 6. Similar to results of other derivative markets in this study, there are significant positive effects of investor sentiments on futures index returns. The coefficients β_{13} and β_{15} are positive and significant suggesting that expectations on coffee and sugar can impact soft agricultural futures market returns. However, in the case of variance, only sentiments on sugar have a significant negative impact. Also, a significant δ_5 suggests that the volatility spillover effect from the sentiments of sugar on futures index market

Table 5. Multivariate EGARCH Estimation Results for Sentiments and Grain and Oilseeds Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	-0.0285***	0.0035	-8.1824
β_{12}	0.0115*	0.0062	1.8580
β_{13}	0.0163***	0.0066	2.4705
β_{14}	0.0036	0.0049	0.7199
β_{15}	0.0217***	0.0061	3.5784
β_{20}	0.0497***	0.0112	4.4238
β_{21}	-0.0471	0.1037	-0.4543
β_{23}	0.0357***	0.0025	14.2971
β_{24}	0.0091	0.0145	0.6302
β_{25}	0.0111	0.0185	0.6028
β_{30}	0.0722***	0.0137	5.2815
β_{31}	-0.0265	0.1101	-0.2406
β_{32}	0.0413*	0.0221	1.8721
β_{34}	-0.0136	0.0117	-1.1565
β_{35}	0.0138	0.0214	0.6455
β_{40}	0.0575***	0.0165	3.4914
β_{41}	0.0297	0.1649	0.1802
β_{42}	0.0220	0.0246	0.8968
β_{43}	0.0190	0.0303	0.6284
β_{45}	0.0445***	0.0044	10.1400
β_{50}	0.0935***	0.0118	7.9165
β_{51}	0.2258**	0.0967	2.3347
β_{52}	-0.0158	0.0186	-0.8474
β_{53}	0.0183	0.0197	0.9269
β_{54}	-0.0185	0.0160	-1.1575
α_{12}	-0.3142***	0.0791	-3.9696
α_{13}	0.1098	0.0888	1.2366
α_{14}	-0.1221	0.0766	-1.5939
α_{15}	-0.4086***	0.0786	-5.2017
α_{21}	-0.0836	0.0697	-1.1988
α_{23}	0.1606***	0.0616	2.6082
α_{24}	0.0532	0.0643	0.8271
α_{25}	-0.2964***	0.0592	-5.0028
α_{31}	-0.1387**	0.0583	-2.3801
α_{32}	-0.0164	0.0497	-0.3308
α_{34}	0.0458***	0.0009	51.7931
α_{35}	-0.0531	0.0502	-1.0578

Table 5, continued. Multivariate EGARCH Estimation Results for Sentiments and Grain and Oilseeds Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	-0.0916***	0.0356	-2.5748
α_{42}	0.1843***	0.0461	3.9974
α_{43}	-0.0443	0.0386	-1.1491
α_{45}	-0.0375	0.0399	-0.9393
α_{51}	-0.0656***	0.0216	-3.0369
α_{52}	0.1059***	0.0269	3.9402
α_{53}	-0.0001	0.0216	-0.0026
α_{54}	0.1601***	0.0299	5.3496
δ_1	-0.1292	0.1567	-0.8248
δ_2	0.0139	0.0979	0.1415
δ_3	-0.2261	0.2072	-1.0913
δ_4	0.2748***	0.1116	2.4628
δ_5	0.3251***	0.0906	3.5891

The five variables included are: CRB grain and oilseeds futures index returns (i,j=1), investor sentiments on corn (i,j=2), soybean (i,j=3), soybean oil (i,j=4) and wheat (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters β_{12}, β_{13}, β_{14} and β_{15} captures the effect of sentiments of corn, soybean, soybean oil and wheat respectively on grain and oil seeds futures market returns. Similarly, α_{12}, α_{13}, α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of corn, soybean, soybean oil and wheat respectively on grain and oil seeds futures market volatilities. The asymmetric effects of these four sentiments on grain and oil seeds futures market volatility is captured by δ_2, δ_3, δ_4 and δ_5. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of grain and oil seeds futures market.

might be asymmetric in nature. Further, sentiments on sugar are positively related to past returns in the derivative market and also to expectations on oranges prices.

The next volatility model analyzes the role of noise in the industrial metals futures market. Since silver and platinum are utilized as industrial metals; the sentiments on these two metals are also included in this model. The four variables included are industrial metal futures index returns and expectations on copper, silver and platinum. The estimation results are reported in Table 7. The industrial metal futures index is almost identically affected by the sentiments of all the three metals included in the analysis. The coefficients β_{12}, β_{13}, and β_{14} are positive and significant of approximately similar magnitude. However, in the variance equation only α_{12} is significant and negative suggesting that there are volatility spillover effects from sentiments of copper on industrial metal future index market. This coupled with a

Table 6. Multivariate EGARCH Estimation Results for Sentiments and Soft Agriculture Produce and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	-0.0109	0.0143	-0.7590
β_{12}	0.0350	0.0210	1.6634
β_{13}	0.0650***	0.0166	3.9191
β_{14}	0.0221	0.0141	1.5709
β_{15}	0.0564***	0.0167	3.3733
β_{20}	0.0990***	0.0292	3.3856
β_{21}	0.1513	0.2070	0.7309
β_{23}	0.0474	0.0424	1.1184
β_{24}	0.0589	0.0359	1.6429
β_{25}	0.0471	0.0367	1.2835
β_{30}	0.1433***	0.0399	3.5888
β_{31}	0.4034	0.4454	0.9057
β_{32}	-0.0125	0.0544	-0.2298
β_{34}	-0.0318	0.0508	-0.6248
β_{35}	0.0885	0.0658	1.3453
β_{40}	0.1157***	0.0393	2.9425
β_{41}	-0.0938	0.3593	-0.2611
β_{42}	-0.0062	0.0595	-0.1049
β_{43}	-0.0623	0.0478	-1.3035
β_{45}	0.0169	0.0589	0.2882
β_{50}	0.0903***	0.0185	4.8671
β_{51}	0.1400***	0.0449	3.1156
β_{52}	-0.0352	0.0274	-1.2844
β_{53}	0.0078	0.0076	1.0389
β_{54}	0.0847***	0.0123	6.8954
α_{12}	0.0970	0.0614	1.5802
α_{13}	0.0070	0.0069	1.0150
α_{14}	-0.0179	0.0613	-0.2912
α_{15}	-0.8130**	0.3626	-2.2420
α_{21}	0.3110**	0.1302	2.3881
α_{23}	0.0054***	0.0012	4.5081
α_{24}	0.0781***	0.0535	1.4589
α_{25}	-0.1146	0.1935	-0.5924
α_{31}	-0.3989	0.4694	-0.8497
α_{32}	0.0788	0.1191	0.6615
α_{34}	0.0744*	0.0386	1.9278
α_{35}	0.6119	0.3917	1.5620

Table 6, continued. Multivariate EGARCH Estimation Results for Sentiments and Soft Agriculture Produce and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	0.0637	0.4435	0.1436
α_{42}	0.2222	0.1948	1.1409
α_{43}	-0.0018	0.0086	-0.2044
α_{45}	0.2940	0.4712	0.6239
α_{51}	0.1515**	0.0722	2.0985
α_{52}	0.0706*	0.0416	1.6975
α_{53}	0.0028	0.0027	1.0412
α_{54}	0.0265**	0.0124	2.1314
δ_1	0.3992*	0.0683	5.8477
δ_2	0.4611	0.6895	0.6687
δ_3	14.1606*	7.6182	1.8588
δ_4	1.3280*	0.7185	1.8484
δ_5	0.8250***	0.0686	12.0230

The five variables included are: CRB soft agriculture produce futures index returns (i,j=1), investor sentiments on cocoa (i,j=2), coffee (i,j=3), orange (i,j=4) and sugar (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters β_{12}, β_{13}, β_{14} and β_{15} captures the effect of sentiments of cocoa, coffee, orange and sugar respectively on soft agriculture produce futures market returns. Similarly, α_{12}, α_{13}, α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of cocoa, coffee, orange and sugar respectively on soft agriculture produce futures market volatilities. The asymmetric effects of these four sentiments on soft agriculture produce futures market volatility is captured by δ_2, δ_3, δ_4 and δ_5. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of soft agriculture produce futures market.

significant parameter δ_2 indicates that the effect of copper sentiment on the derivative volatility might be asymmetric in nature. Since copper is more widely used industrial metal, it might explain the significant impact of its sentiments on silver and platinum based expectations (significant β_{32}, β_{42}). Unlike results obtained in other derivative markets, there seems to be no evidence of positive feedback trading here.

The role of behavioral finance in the livestock futures market is investigated by jointly modeling sentiments of live cattle, feeder cattle, lean hogs and pork bellies with livestock futures market returns. Table 8 reports the estimation results for this model. Three out of four sentiments are positively and significantly related to livestock futures index returns. The magnitude of feeder cattle based sentiments is the highest followed by those of live cattle and lean hogs while pork bellies expectations seem to have no impact. On the variance side, only coefficient α_{12} is significant, which

Table 7. Multivariate EGARCH Estimation Results for Sentiments and Industrial Metals and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0136	0.0090	1.5128
β_{12}	0.0488***	0.0079	6.1823
β_{13}	0.0335**	0.0153	2.1911
β_{14}	0.0424***	0.0122	3.4799
β_{20}	0.1730***	0.0312	5.5502
β_{21}	3408.2632	32971.1958	0.1034
β_{23}	-0.0597	0.0923	-0.6473
β_{24}	-0.0656	0.0750	-0.8737
β_{30}	0.0772***	0.0268	2.8875
β_{31}	-15320.1625	74702.4187	-0.2051
β_{32}	-0.0199*	0.0117	-1.7035
β_{34}	-0.0221	0.0637	-0.3472
β_{40}	0.0846***	0.0092	9.2336
β_{41}	5571.9452	5588.5554	0.9970
β_{42}	0.0052*	0.0031	1.6851
β_{43}	0.0120	0.0193	0.6205

means that live cattle based sentiments also impact livestock futures index volatilities negatively. There is also a significant δ_2 indicating asymmetric volatility spillover effects of live cattle on the derivative volatilities. The sentiments of live cattle seem to be driven by the sentiments of other three assets and futures market, suggesting existence of sentiment based noise trading and lead lag relationships among these expectations.

The last multivariate EGARCH model investigates the relevance of noise trading in the stock index options market. Here sentiment of three distinct groups of investors (individual, institutional and professional analysts) and four measures of stock index options (VIX, VXO, VXN, and VXD) are included in the analysis. In order to avoid over parameterization and irrelevant feedback relationships of relatively large number of variables, the model is estimated twice with five variables in each. Specifically, the first model includes changes in VXD, VXN, and three classes of investor sentiments and the second model replaces VXD and VXN with VIX and VXO. The estimation results for these two five variables models are reported in panel A and B respectively of Table 9. In panel A, the coefficients related to the sentiments of professional analysts (β_{14}) and institutional investors (β_{15}) are negative and significant while in panel only β_{14} is negative and significant. The effect of institutional investor sentiments seems to be greater than those of professional analysts. There is a significant negative β_{24} indicating similar effects of professional analysts'

Table 7, continued. Multivariate EGARCH Estimation Results for Sentiments and Industrial Metals and Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{12}	-0.1666***	0.0467	-3.5683
α_{13}	-0.1355	0.1730	-0.7836
α_{14}	-0.1377	0.1173	-1.1740
α_{21}	0.6231	0.9743	0.6395
α_{23}	0.0009	0.2358	0.0040
α_{24}	0.0791	0.3402	0.2325
α_{31}	0.6286	0.7585	0.8287
α_{32}	0.1761	0.1493	1.1794
α_{34}	-0.4798	0.3069	-1.5631
α_{41}	0.5080***	0.1243	4.0883
α_{42}	-0.0137	0.0498	-0.2755
α_{43}	-0.0350	0.0826	-0.4233
δ_1	0.6045***	0.0484	12.4890
δ_2	0.7577*	0.3969	1.9093
δ_3	-0.1368	0.6339	-0.2159
δ_4	-1.7749***	0.1266	-14.0211

The four variables included are: CRB industrial metals futures index returns (i,j=1), investor sentiments on copper (i,j=2), silver (i,j=3), and platinum (i,j=4). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{12,}$ $\beta_{13,}$ and β_{14} captures the effect of sentiments of copper, silver and platinum respectively on industrial metal futures market returns. Similarly, $\alpha_{12,}$ $\alpha_{13,}$ and α_{14} captures the volatility spillover effects or innovations from sentiments of copper, silver and platinum respectively on industrial metals futures market volatilities. The asymmetric effects of these three sentiments on industrial metals futures market volatility is captured by $\delta_{2,}$ $\delta_{3,}$ and $\delta_{4.}$ A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on volatility of industrial metals futures market.

expectations on changes in VXO. However, there are insignificant effects of individual investor sentiments on all the four volatility indices returns. Institutions have a large presence in the derivative market, and that might explain the significant effects of professional analysts and institutional investor sentiments. On the other hand, individuals tend to hold a smaller portion of derivatives in their portfolios, which may cause individual investor sentiments to have insignificant impacts.

The negative effect of investor sentiments in case of options market is in contrast to the results obtained in the six futures markets where sentiments positively affect the mean of returns. A negative relationship between sentiments and changes in volatility measures means that bullishness in the marketplace causes these indices to fall and vice versa. A possible reason for this negative reason could be that

Table 8. Multivariate EGARCH Estimation Results for Sentiments and Livestock Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
β_{10}	0.0102***	0.0020	4.9789
β_{12}	0.0390***	0.0042	9.2355
β_{13}	0.0321***	0.0040	7.9788
β_{14}	0.0795***	0.0040	20.1173
β_{15}	-0.0031	0.0032	-0.9764
β_{20}	0.4367***	0.0155	28.1494
β_{21}	0.0530***	0.0116	4.5699
β_{23}	0.0489***	0.0179	2.7341
β_{24}	0.0486***	0.0165	2.9514
β_{25}	0.0486***	0.0163	2.9844
β_{30}	0.1436***	0.0612	2.3469
β_{31}	0.1849	0.4781	0.3866
β_{32}	0.0763	0.0826	0.9242
β_{34}	0.0039	0.0666	0.0580
β_{35}	0.0467	0.0863	0.5408
β_{40}	0.2000**	0.0911	2.1957
β_{41}	0.3491	0.8155	0.4280
β_{42}	-0.0292	0.1463	-0.1996
β_{43}	0.0011	0.1892	0.0060
β_{45}	-0.0205	0.1435	-0.1432
β_{50}	0.2614***	0.0841	3.1075
β_{51}	0.6024	0.7611	0.7915
β_{52}	-0.0092	0.1403	-0.0655
β_{53}	0.1789	0.1795	0.9967
β_{54}	-0.1535	0.1063	-1.4444
α_{12}	-0.2672**	0.1211	2.2059
α_{13}	-0.0029	0.0297	-0.0985
α_{14}	0.0915	0.2016	0.4537
α_{15}	-0.0294	0.0895	-0.3288
α_{21}	0.0601	0.1534	0.3919
α_{23}	-0.0103	0.0441	-0.2346
α_{24}	-0.0286	0.2041	-0.1399
α_{25}	-0.0192	0.0768	-0.2500
α_{31}	0.0441	0.1639	0.2691
α_{32}	0.1144	0.0954	1.1993
α_{34}	-0.0416	0.1000	-0.4157
α_{35}	-0.0350	0.0584	-0.5993

Table 8, continued. Multivariate EGARCH Estimation Results for Sentiments and Livestock Futures Index Returns.

Variables	Coefficients	Standard errors	t-Statistics
α_{41}	0.1901	0.2707	0.7021
α_{42}	0.0979	0.2309	0.4243
α_{43}	0.0491	0.1906	0.2576
α_{45}	0.0585	0.1647	0.3556
α_{51}	0.2018	0.2152	0.9375
α_{52}	0.0815	0.1457	0.5591
α_{53}	0.0261	0.1075	0.2425
α_{54}	0.0389	0.0416	0.9355
δ_1	0.1070***	0.0310	3.4565
δ_2	0.1069***	0.0463	2.3106
δ_3	3.6350	16.4972	0.2203
δ_4	-0.0799	0.4703	-0.1699
δ_5	1.6898	2.9739	0.5682

The five variables included are: CRB livestock futures index returns (*i,j*=1), investor sentiments on live cattle (*i,j*=2), lean hogs (*i,j*=3), feeder cattle (*i,j*=4) and pork bellies (*i,j*=5) . Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters β_{12}, β_{13}, β_{14} and β_{15} captures the effect of sentiments of live cattle, lean hogs, feeder cattle and pork bellies respectively on livestock futures market returns. Similarly, α_{12}, α_{13}, α_{14} and α_{15} captures the volatility spillover effects or innovations from sentiments of live cattle, lean hogs, feeder cattle and pork bellies respectively on livestock futures market volatilities. The asymmetric effects of these four sentiments on livestock futures market volatility is captured by δ_2, δ_3, δ_4 and δ_5. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable *j* have a higher impact than positive innovations on volatility of livestock futures market.

CBOE volatility indices are linked with bearishness in the market. Based on Black-Scholes model, these indices compute the markets' expectations of 30-day volatility and are meant to be forward looking measures of market risk. For this reason they are viewed as fear index and thus high VIX measures higher anticipated volatility and are interpreted as bearish. These volatility indices have the tendency to spike during pronounced market weakness or sharp sell offs as investors hedge their equity portfolios by buying stock index puts. For example, the VIX surged to around 80% during the stock market crash in October 1987, compared with a mean level of approximately 20% over the sample period examined in this article (similarly, means of VXO, VXN, and VXD are 21%, 31% and 20%, respectively). Conversely, the VIX typically registers low levels during smoothly upward trending markets because of increased complacency and a lower demand for insurance against market declines. This finding is consistent with Brown and Cliff (2004), which finds that

Table 9. Multivariate EGARCH Estimation Results for Sentiments and Stock Index Options.

Variables	Coefficients	Standard errors	t-Statistics	Coefficients	Standard errors	t-Statistics
	Panel A				Panel B	
β_{10}	0.0102	0.0600	0.1698	0.0395	0.0130	3.0389
β_{12}	0.0508	0.3557	0.1427	0.0721	0.0570	1.2645
β_{13}	-0.0500	0.1043	-0.4797	-0.0202	0.0236	-0.8563
β_{14}	-0.0503***	0.0063	-7.9841	-0.0479***	0.0150	-3.1900
β_{15}	-0.0488***	0.0127	-3.8425	-0.0285	0.0264	-1.0804
β_{20}	0.0940	0.1155	0.8143	0.0724***	0.0072	10.0862
β_{21}	0.0513	0.7026	0.0730	0.0381	0.0248	1.5356
β_{23}	0.0481	0.2298	0.2093	0.0303	0.0210	1.4118
β_{24}	0.0501	0.1581	0.3165	0.0327***	0.0072	4.5798
β_{25}	0.0519	0.3251	0.1595	0.0005	0.0107	0.0468
β_{30}	0.0198	7.4366	0.0027	0.2211***	0.0190	11.6620
β_{31}	0.1025	17.1455	0.0060	0.1461	0.1388	1.0528
β_{32}	0.0112	16.8943	0.0007	0.3054**	0.1450	2.1067
β_{34}	0.0442	9.5755	0.0046	0.01742	0.0253	0.68911
β_{35}	-0.2295	15.3716	-0.0149	-0.01362	0.0488	-0.2790
β_{40}	0.0191	7.8165	0.0024	0.1656***	0.0197	8.4172
β_{41}	0.0481	12.8247	0.0037	0.2567*	0.1369	1.8748
β_{42}	0.0417	12.4044	0.0034	-0.2233	0.1485	-1.5040

Table 9, continued. Multivariate EGARCH Estimation Results for Sentiments and Stock Index Options.

Variables	Coefficients	Standard errors	t-Statistics	Coefficients	Standard errors	t-Statistics
		Panel A			Panel B	
β_{43}	0.0018	9.5195	0.0002	-0.1258***	0.0196	-6.4036
β_{45}	-0.0263	12.1204	-0.0022	-0.0472	0.0457	-1.0332
β_{50}	0.1325	1.8373	0.0721	0.1643***	0.0108	15.2348
β_{51}	-0.0140	1.4883	-0.0094	0.0833	0.0423	1.9671
β_{52}	0.1023	1.5616	0.0655	-0.0841*	0.0478	-1.7602
β_{53}	-0.0920	1.1873	-0.0775	-0.0417***	0.0070	-5.9984
β_{54}	0.0763	0.9362	0.0816	0.0232***	0.0110	2.1089
α_{12}	0.0489	1.3310	0.0367	-0.1053	0.2828	-0.3723
α_{13}	0.0338	5.1610	0.0066	0.0704	0.1077	0.6533
α_{14}	-0.0266	14.3663	-0.0019	0.0754	0.3201	0.2355
α_{15}	-0.0682	0.8707	-0.0783	-0.0608*	0.0346	-1.7572
α_{21}	0.0505	1.2727	0.0397	0.0907	0.0695	1.3049
α_{23}	0.0226	4.1444	0.0055	0.0102	0.0137	0.7488
α_{24}	0.0193	10.4958	0.0018	0.2269	0.1703	1.3325
α_{25}	-0.0852	0.8193	-0.1040	-0.0717***	0.0245	-2.9261
α_{31}	0.0338	6.6495	0.0051	-0.8346***	0.2589	-3.2233
α_{32}	0.0687	7.6947	0.0089	1.0513***	0.2969	3.5406
α_{34}	0.0913	51.5081	0.0018	-0.1673***	0.0556	-3.0118
α_{35}	-0.0060	2.4188	-0.0025	-0.0837**	0.0414	-2.0215
α_{41}	0.0786	5.7654	0.0136	-0.1401	0.4090	-0.3425
α_{42}	0.0078	6.9584	0.0011	0.9608**	0.4470	2.1498
α_{43}	-0.0034	13.5412	-0.0002	0.0382	0.1645	0.2325
α_{45}	-0.2395	1.4161	-0.1692	-0.0827**	0.0410	-2.0183

Table 9, continued. Multivariate EGARCH Estimation Results for Sentiments and Stock Index Options.

Variables	Coefficients	Standard errors	t-Statistics	Coefficients	Standard errors	t-Statistics
	Panel A				Panel B	
α_{51}	0.0313	2.8163	0.0111	-0.1217	0.2428	-0.5014
α_{52}	0.0744	3.0718	0.0242	0.1309	0.2778	0.4712
α_{53}	0.0496	10.7834	0.0046	-0.1465*	0.0828	-1.7689
α_{54}	-0.1077	58.5100	-0.0018	-1.1795**	0.5237	-2.2523
δ_1	0.1011	0.2444	0.4134	0.1060	0.0700	1.5153
δ_2	0.1017	0.4206	0.2417	0.0414	0.0415	0.9975
δ_3	0.4743	178.0140	0.0027	0.6284**	0.2867	2.1918
δ_4	0.8746	1014.7419	0.0009	-0.7083***	0.0687	-10.3075
δ_5	1.4567	12.1890	0.1195	3.1230***	1.1631	2.6850

The five variables included in panel A are: VXD (i,j=1), VXN (i,j=2), individual investor sentiments (i,j=3), professional analysts sentiments (i,j=4) and institutional investor sentiments (i,j=5). The five variables included in panel B are: VIX (i,j=1), VXO (i,j=2), individual investor sentiments (i,j=3), professional analysts sentiments (i,j=4) and institutional investor sentiments (i,j=5). Note *, ** and *** denote significance levels at the 10%, 5% and 1%, respectively.

The parameters $\beta_{13,}$ β_{14} and β_{15}captures the effect of sentiments of individual investors, professional analysts and institutional investors respectively on VXD (panel A) and VIX (panel B) returns. Similarly, parameters $\beta_{23,}$ β_{24} and β_{25} captures the effect of sentiments of individual investors, professional analysts and institutional investors respectively on VXN (panel A) and VXO (panel B) returns. The parameters, $\alpha_{13,}$ $\alpha_{14,}$ and α_{15} captures the volatility spillover effects or innovations from sentiments of individual investors, professional analysts and institutional investors on VXD (panel A) and VIX (panel B) volatilities. Similarly, the parameters, $\alpha_{23,}$ $\alpha_{24,}$ and α_{25} captures the volatility spillover effects or innovations from sentiments of individual investors, professional analysts and institutional investors on VXN (panel A) and VXO (panel B) volatilities. The asymmetric effects of these three sentiments on these options volatilities are captured by $\delta_{3,}$ δ_4 and δ_4 . A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in variable j have a higher impact than positive innovations on option volatilities.

VIX is negatively related to institutional investor sentiments.

In the variance equations, only parameter α_{15} in the second model is significant and negative. This suggests that similar to the results of the futures markets, there are significant volatility spillover effects from the institutional investor sentiments on the VIX. However, there are similar insignificant effects on VXN, VXD, and VXO probably due to the fact that VIX is relatively more widely followed indicator than the other there. There is also a significant δ_5 coupled with this α_{15} in panel B, which means that bullishness and bearishness of institutional investor sentiments have dissimilar effects on the VIX changes.

In both these models there are other significant coefficients which lend support to the argument that noise also stems from past market performance or investors engage in positive feedback trading. All three types of investors seem to follow one or more of the volatility indices' past performance while forming their expectations about the future. This indicate that like in the case of stock market, irrespective of their class to a large extent investors are irrational in the derivative market also. Consistent with previous findings, there is also a significant lead-lag relationship among three kinds of investor sentiments. The coefficients β_{43} and β_{53} are negative and significant indicating that both professional analysts and institutions tend to exploit individual investor sentiments as contrarian indicators. This is in contrast to β_{54}, which is positive and significant, suggesting that institutions tend to positively track professional analysts' expectations.[8]

Overall, the significant positive effects of sentiments on mean of six futures market returns is consistent with the *price pressure* and *hold more* effects of sentiments and similar to findings of empirical tests carries in the stock market. The significant negative effects on conditional variance of derivative market returns is in line with the *Friedman* effect and consistent with negative price of time varying risk (Glosten, Jagannathan, and Runkle 1993; DeSantis and Gerard 1997; Verma and Soydemir 2008) and with results obtained in empirical tests on noise and stock market volatilities. The asymmetric effect of bullish and bearish sentiments on derivative volatilities is consistent with the DHS model and other behavioral explanations, which suggest that the effect of bullish and bearish sentiments on asset valuations can be dissimilar in magnitude and pattern (Gervais and Odean 2001; Hong et al. 2000). Significant responses of sentiments of some assets to their

8. DSSW (1990) model suggest that individual investors are more likely to be noise traders than institutional investors. However, whether these two types of noise trading (sentiments) affects stock valuation are investigated by studies such as Nofsinger and Sias (1999), Schmeling (2007), and Verma and Verma (2007). Overall, these studies find that the effect of institutional investor sentiments on stock returns and volatilities are greater than those of individual investors. It is suggested that although both individuals and institutions display significant sentiments, only institutions have enough market power to affect the valuations. These studies also indicate that institutional investors while devising their investment strategies already factor in the sentiments of individual investors. Another reason suggested is that it is much easier for domestic institutional investors to engage in herding behavior than for individual investors, because similar information circulates among funds, allowing them to follow other institutions' decisions more easily. Our findings of greater significant effect of institutional investor sentiments than those of individual investors on stock index options markets are consistent with these empirical studies.

past prices provide support the argument of DeBondt (1993) that sentiments may show extrapolation bias such that increased bullishness can be expected after a market rise and increased bearishness after a market fall. A direct implication of this evidence is “positive feedback trading by investors. This is also consistent with the “bandwagon” effect (Brown and Cliff 2004), which implies that sentiments-induced noise trading is significantly affected by past returns and Clarke and Statman’s (1998) argument that institutional investors form their sentiments based on expected continuation (reversals) of short (long) term returns.

V. IMPLICATION

The recently enacted Dodd-Frank financial system overhaul has noble intentions in bringing transparency and accountability to the derivative market. It includes measures that would bring more OTC derivatives trading onto regulated exchanges. This study provides evidence that noise is present in the exchange-traded derivative market where irrational sentiments induced noise trading by institutions and professional investors can systematically affect their valuations. Based on these findings and past literature, it can be argued that shifting OTC derivatives into regulated exchanges might have some unintended consequences due to the introduction of noise. Although it is difficult to identify the exact outcomes and magnitudes of such transition, this study presents a few possible scenarios which might have bearing on the financial system.

Studies have shown that introduction of new kinds of securities in regulated exchanges can attract a new set of uninformed traders. Stein (1987) finds that introduction of futures contracts allows new trader groups to speculate in the derivative market, since due to certain constraints they are restricted to trade in the underlying assets. Stein points out that there is asymmetric information between this new group and existing investors in the spot market on the supply conditions, and as such these new traders bring noise into the derivative market causing mispricing. Gammill and Perold (1989) and Subrahmanyam (1991) argue that uninformed traders avoid trading with informed traders in stock market and when provided opportunities migrate to index-based derivative instruments such as index futures or options. Such migration happens due to the fact that the index is intact from private information advantage and form a convenient trading medium for uninformed traders.

Also, the informational asymmetries that arise due to firm-specific private information are considerably less severe in the index futures and options markets than in the underlying stock market. VanNess, VanNess, and Warr (2005) examine the impact of introduction of Diamond index securities on the underlying Dow Jones stocks and find movement of uninformed investors to these new index securities followed by significant impact of their speculations on the liquidity. Likewise, Jegadeesh and Subrahmanyam (1993) examine the effect of introduction of S&P 500 futures contracts on the spreads of the underlying stocks and find similar results. In international markets, Leemakdej (2002) finds that motivated by greater liquidity and higher informational asymmetry there is migration of uninformed investors from stock market to derivative market in order to speculate in newly introduced warrants.

The situation of moving OTC to regulated exchanges is very similar to the ones described in above mentioned studies. A large part of the derivative market is constituted by OTC derivatives contracts that are traded (and privately negotiated) directly between two parties, without going through an exchange or other intermediary. These contracts are tailor-made to cater to specific requirements of the two involved parties and mainly used for hedging purposes. Shifting these tailor-made OTC derivative contracts — meant for two hedgers to a platform that would allow multiple bids and offers to be made by multiple participants — might attract a new set of investors (mainly noise traders). This might altogether open a new market accessible to a large group of noise traders for assets that were originally designed for hedgers. In all probability this new group of investors might be uninformed or purely profit seeking speculators with no hedging objectives whatsoever. It is well established that uninformed investors tend to be noise traders and primarily deal in speculation and cause pricing misalignment. As such, this move of trading OTC derivatives on regulated exchanges could lead to greater irrational trading activities and cause higher volatility and mispricing and thus potentially refutes the very purpose of the regulation to remove irrational behavior. Alternatively, assuming even if noise traders are not attracted to these new derivatives or their effects are nullified, these tailor-made contracts for two parties designed for over the counter markets might not survive in regulated exchanges in the long run due to lack of liquidity. Noise traders induce necessary liquidity in the market and therefore provide incentives for informed investors to trade (Black 1986; Trueman 1988). As such, nonexistence of noise or any subsequent attempt to artificially remove it from the derivative market might lead to lower returns for rational investors.

Following Black (1986) and Kyle (1985) and more recently Greene and Smart (2009), which links noise with liquidity and the fact that OTC markets have low liquidity, an argument can be made that noise trading is less prevalent in these markets. Studies on OTC markets such as Duffie, Garleanu, and Pedersen (2005) and Lagos, Rocheteacu, and Weill (2009), find that these markets have lower liquidity due to higher opportunity costs, trading frictions of search and bargain, and high transaction costs. Liquidity in OTC markets of mortgage backed securities, collateralized debt obligations, and credit default swaps are provided on a voluntary basis by broker dealers such as large investment banks who match buyers and sellers. Unlike an exchange, an OTC market is more restrictive and has no market maker to provide liquidity. In addition, OTC markets for derivatives related to interest rate swaps and foreign exchanges have lower asymmetric information. Tetlock (2008) shows that markets with greater liquidity are associated with greater price anomalies such as overpricing low probability events and underpricing high probability events while less liquid markets do not exhibit these anomalies. He argues that these results are consistent with the idea that liquidity is a proxy for noise trading, which can impede market efficiency, and mispricing is largely confined to liquid markets and not to illiquid markets. All these findings indicate lower noise trading in

OTC markets compared to an exchange.

Moreover, the Dodd-Frank Act and Volcker rule call for greater capital requirement and lower trading revenues for large institutions. New regulations governing different lines of business, in addition to the substantial increase in the amount of liquid capital banks must hold, might make it too expensive for financial institutions to stay at their current size. It could lead to the end of some Wall Street practices and create new opportunities for speculations. Necessity is the mother of invention. In order to survive and with a motivation to compensate loss in their cash flows, large institutions subjected by new regulations may reinvent their strategies and not only become active speculators in new exchange traded products but also display irrational and risky behavior elsewhere. This may lead to development of riskier innovative instruments that can escape the new regulations. An analogy could be the linkage between Federal Reserve's decision to keep federal funds rate extremely low for an extended time and the origin of subprime mortgage crisis. In a world of very low real returns, individuals and investors tend to seek higher-yielding assets. Investors desiring higher nominal rates might get tempted to seek more speculative, higher-yielding investments. During years preceding the financial crisis, many large investors facing similar choices chose to invest heavily in subprime mortgage-backed securities since they were perceived at the time to offer relatively high risk-adjusted returns. In the current scenario, large financial institutions may end up taking greater risks to compensate for their losses under the new regulation and thus expose the financial system to a greater risk.

An example of ineffectiveness of government regulation on margin in reducing speculation in stock and derivative markets is provided by Kupiec (1989, 1997). Kupiec did not find any evidence that federal regulations can be systematically altered to manage risk in the stock and derivative instruments. On similar lines, Stein (1987) argues that the presence or absence of a futures market does not reduce speculators by altering their leverage constraint. Rather, misinformed speculators who are unable to trade in the spot market can trade in the futures market, and their noise trading may affect the information content of spot market prices. The opening of a futures market allows the imperfectly informed speculators to trade, and their trading distorts the information content of market-clearing spot prices. Stein interprets his model as a formal counter-example to the conjecture that the addition of speculators to an existing market will add to the depth and liquidity of a market and thereby reduce the price effects created by transitory shocks to demand or supply. Even though agents voluntarily trade with the new futures market speculators, they can be made worse off. Stein's results are a specific example of Hart's (1975) general finding that, when markets are incomplete, opening an additional market may make agents worse off if markets remain incomplete.

The implications of this study are consistent with Pirrong (2009), who provides an argument against derivative trading on the exchanges. He argues that exchange facilitates anonymous trade and operates continuous markets and these features would make it impossible for traders to ascertain the motives of their counterparties. It is impossible to design a market in which speculators exist and always trade with hedgers and never with each other. He mentions that some of the biggest speculative failures (such as Barrings, Metallgesellschaft, Hunts) took place primarily on exchanges, and thinking that trading on exchanges will constrain speculation is contrary to centuries of history. Similarly, Wallison (2009) suggests that credit default spreads that trade on OTC market reflect real market judgments on credit quality and effective price discovery. These implications are in line with Kane (1988), which argues that regulatory reformers need to look beyond immediate problems to assess the long run consequences of the policies they wish to install. In the long run, survival patterns of regulation must be economically efficient ones. But even though the invisible hand eventually punishes over and under-regulator alike, in real time the process can produce considerable turmoil. The sequential search for efficiency can take a long time to unfold and can impose substantial plan of financial services firms, their customers and the general taxpayer.

Based on the above arguments, one can argue the ineffectiveness of regulations (such as Dodd-Frank) in removing inherent risk from the financial system and possible introduction of a new set of noise traders. Once financial institutions have adjusted to the new reality, future research with substantial data points is recommended on this subject.

VI. CONCLUSION

This study investigates the relevance of behavioral finance in the derivative market. It employs a set of multivariate EGARCH models to uncover the impact of noise on returns time varying risks in futures and options markets. The response of six futures markets (energy, precious metals, industrial metal, agricultural products, grains, and livestock) to a set of investor sentiments on 20 different commodities is analyzed. Similarly the impact of three distinct categories of investors on stock index options is investigated. Consistent with previous studies, the estimation results suggest that noise is systematically priced in a wide variety of futures and option markets.

There is at least one of a kind sentiment in each derivative market that significantly affects both returns and volatilities and also has an asymmetric spillover effects. Specifically, sentiments on gold, crude oil, wheat, copper, live cattle and sugar are found to significant effects on the mean and conditional variance in their respective futures index markets. There seems to be a significant greater response of futures markets to bullish than bearish sentiments. Similar results are obtained for VIX, VXD, VXN, and VXO responses to investor sentiments. Returns and volatilities in these stock index options are significantly affected by sentiments of professional analysts and institutions, while there is no such effect from individuals.

These results are consistent with a behavioral paradigm which suggests that noise affects an asset's return through its impact on its conditional variance. Tenets of behavioral finance also apply to futures and options markets. Noise seems to affect risk and return in the derivative market in a similar fashion in which it affects those in stocks. The direct implication of these findings is that traditional measure of time variation in systematic risk in the derivative market omits an important source of risk: noise. The findings of this study could have important implications for policymakers on the recently enacted Dodd-Frank financial system overhaul, which includes measures that would bring more derivatives trading onto regulated exchanges. They also have important implications for investors that seek to reduce spillover effects and investors who aim to improve their portfolio performance.

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OPTIMIZING THE COST OF CUSTOMIZATION FOR OTC DERIVATIVES END USERS

Sean Owens*

This paper examines the regulatory treatment of OTC derivatives under the Dodd-Frank Act and the Basel III accord for market participants and financial institutions in the United States and abroad. It evaluates the capital and margin required for OTC derivative transactions under both frameworks and examines the potential impact on transaction costs applicable to end users for bilateral and centrally cleared transactions. Firms face a tradeoff between the costs associated with initial margin, regulatory capital, execution and structural factors for bilateral transactions relative to SEF-executed centrally cleared transactions. For many end users, minimizing these costs will be the primary objective behind their derivative hedging strategies. To illustrate this, we quantify many of the implicit and explicit costs for standardized cleared swaps and customized bilateral swaps for end users and examine the impact on them according to their credit quality. The paper evaluates transactions predominantly on a stand-alone basis, without the effects of risk netting. While this overstates both the capital and margin required for participants with offsetting portfolios, it reflects the marginal impact for many end users who hedge predominantly one-sided risk in the markets. It evaluates the limit of regulatory impact on participants, which many will seek to reduce through targeted hedging strategies and counterparty netting.

Governments and regulators alike acted prudently to implement financial system safeguards intended to reduce the likelihood of future shocks and mitigate the systemic risk in the wake of the financial crisis of 2008.

The U.S. response was the Dodd-Frank Act which, for the first time, brought the over-the counter (OTC) derivatives markets under regulatory oversight. The international response was put forth by the Basel Committee, which revised capital standards for financial institutions in a series of proposals that comprise the Basel III accord. Both frameworks incorporate changes to the regulatory treatment of OTC derivatives and require banks and regulated financial institutions to hold greater capital for derivative transactions.

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The impact of these changes will be felt by non-financial firms as well. These entities face higher costs passed on to them by financial firms acting as their trading counterparties. The frameworks set forth by both the Dodd-Frank Act and the Basel III accord address systemic risk inherent in the markets from counterparty credit risk. Both seek to ensure that the vast majority of OTC derivative contracts are cleared through central counterparties using a combination of legal mandate and economic incentives that increase the cost of customization and bilateral trading.

I. THE DODD-FRANK ACT

In July 2010, Congress passed the Dodd-Frank Act, which brought regulation to the over the counter (OTC) derivative markets by establishing a broad framework for the treatment of risk related to these transactions. The Act established joint oversight for OTC derivative transactions by the Commodities Futures Trading Commission (CFTC) and the Securities Exchange Commission (SEC) and allows for continued bank oversight from the current prudential regulators including the Federal Reserve Board (Board), Federal Deposit Insurance Company (FDIC), the Office of the Comptroller or Currency (OCC), and other agencies in their respective jurisdictions. Banks, bank holding companies (BHCs) and other regulated financial institutions will continue to adhere to existing prudential regulation. In most circumstances the capital treatment of OTC derivative transactions for bank and BHCs under the Act is governed by existing regulation.

The Act categorizes market participants according to their size, role, and systemic significance in the derivative markets. The application of the Act differs for each category and sets the terms under which institutions are allowed to transact in the OTC markets. Participants fall into three primary categories: Swap Dealers (SD), Major Swap Participants (MSPs), and End Users (EUs). Different requirements exist for each category, with heightened requirements for SDs and MSPs that include the collection of both initial and variation margin from their counterparties for bilateral transactions that are not cleared. SDs ad MSPs are required to clear all transactions that are accepted as “clearable” by a derivatives clearing organization and are also required to execute clearable transactions on a swap execution facility (SEF).

End users have considerably more flexibility handling their transactions than SDs or MSPs and are classified as financial or non-financial. “Financial end users” are those financial entities whose OTC derivative transactions fall below threshold levels set for designation as a MSP. They are further divided according to their risk level: high risk and low risk. “Non-financial end users” are given an exemption from both clearing and execution. Those hedging commercial risk have full discretion over clearing, execution and collateralization of their transactions. Non-financial end users may elect to clear and execute on SEFs, but are not required to do so. They are also exempt from collateralizing transactions.

Under this framework, it will become increasingly important for all end users to evaluate the relevant costs incurred with derivative transactions. Firms face increased costs, which include funding collateral used for initial and variation margin, capital (both internal and that of their counterparties), structural and execution costs. Each of these factors will influence end users' hedging decisions and determine how they chose to execute transactions.

A. Capital Requirements

The Act sets minimum capital requirement for financial entities, including SDs and MSPs that are subsidiaries of regulated banks, BHCs and financial institutions. It includes separate requirements for entities that are not currently regulated. It also establishes guidelines for SDs and MSPs that are registered as Futures Commission Merchants (FCMs) handling customer margin for cleared transactions.

Most SD and MSPs that either directly or indirectly fall under jurisdiction of a prudential regulator will continue to adhere to applicable prudential guidelines. For many, this constitutes supervision by one or more of the FDIC, OCC, Board, or other agency. These institutions calculate their regulatory capital, including that for OTC derivatives, using either a foundation rules-based approach or an advanced approach. Banks that calculate their economic capital through internal models seek the approval of their regulator for the flexibility to use these models to calculate their regulatory capital. Many prefer more risk-sensitive methodologies to the formulaic approach because they more accurately reflect their specific risk characteristics and allow them to take advantage of multi-product counterparty netting.

For those SDs and MSPs that are not currently regulated and are not registered as an FCM (and otherwise not under the jurisdiction above), the CFTC has established capital requirements that mirror those for BHCs under existing prudential banking regulations.

The Act sets a permanent floor on aggregate bank capital equal to the level at the time of its enactment. This floor is calculated using what is referred to as the "general risk based capital rules." It requires BHCs using the advanced approach methodology, in the United States and abroad, to determine their capital requirements to also perform a calculation under these rules and use the more conservative of the two measures.[1] The "general risk based capital rules" are analogous to the rules proposed in the first Basel accord and subsequently used in Basel II's foundation approach, which forms the basis for U.S. regulation. The general rules are standardized across regulatory agencies and are contained in the federal code of regulations (see 12 CFR Part 3 Appendix A-OCC, Part 208 & 225 Appendix A-FRB, Part 325 Appendix A-FDIC).

Given the requirement for dual calculations, banks and affiliated SDs and MSPs will face two possible measures for their regulatory capital, and two measures for the capital required for OTC derivative transactions. Their marginal cost of regulatory capital will be either that which is calculated from the "general rules" or that which

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1. U.S. regulations for bank and BHC capital adequacy are derived from the Basel accords (Basel I & II). The Code of Federal Regulations largely reflects the standards and requirements set forth in the accords, with some modifications. For example, Basel II's standardized approach to calculate counterparty exposure for OTC derivatives is not permitted for U.S. institutions.

is calculated internally using the advanced approach methodology. Bank capital will be determined by the rules that produce a more conservative measure for the institution as a whole, across all product lines and asset classes. In most cases the general rules should yield a more conservative measure of capital adequacy and will determine the amount of regulatory capital required.

B. Prudential Regulation

Current U.S. bank regulation and international capital adequacy standards are based on the principles detailed in the Basel II accord. Financial institutions are allowed to calculate regulatory capital for credit risk under two approaches: the foundation approach or the internal ratings based approach. Banks may use three methods to calculate their counterparty credit risk: the current exposure method (CEM), the standardized method, or the advanced approach, of which two (CEM and advanced approach) are permitted for U.S. institutions. Those with less sophisticated modeling capabilities can use the formula-based approach. Those seeking more risk sensitive measures do so using internally modeled parameters under the advanced approach to calculate their regulatory capital requirements.

C. General Risk Based Capital Rules

The general risk based rules were detailed in the first Basel accord and form the basis of the CEM for calculating capital under Basel II. The methodology is used in the United States as the default method for calculating capital requirements for OTC derivatives for firms that do not or are not allowed to use their own internal models for the calculation. Under the CEM, firms calculate counterparty credit risk from the sum of a transaction's current and potential future exposure. Current exposure is the replacement cost of a transaction after including applicable collateral. Future exposure is calculated by multiplying the notional value of a transaction by a conversion factor from Table 1.

$$\text{Capital Required} = \text{Risk Weight} \times \text{Counterparty Credit Risk (CCR)}$$

$$\text{CCR} = \text{MTM or Replacement Cost} + \text{Potential Future Exposure (PFE)}$$

$$\text{PFE} = \text{Notional Value} \times \text{Conversion Factor}$$

Netting is calculated using the formula: $A_{net} = 0.4 \times A_{gross} + 0.6 \times (NGR \times A_{gross})$ where NGR is the ratio of net exposure to gross exposure. This is the same methodology used to calculate capital under the general risk-based capital rules. Current and future exposures are offset by collateral, which is adjusted by applicable haircuts for quality, liquidity, and tenor.

D. Advanced Approach

Under the advanced approach, firms may use internal model methodologies (IMM) to estimate many of the parameters used to calculate their regulatory capital, including: the probability of default (PD), loss given default (LGD), expected positive exposure (EPE) and exposure at default (EAD). The EAD is scaled by a capital

Table 1. Conversion Factors (in percent).*

Remaining maturity	Interest rate	Exchange rate and gold	Equity	Commodity, excluding precious metals	Precious metals, except gold
One year or less	0	1	6	10	7
Over one to five years	0.5	5	8	12	7
Over five years	1.5	7.5	10	15	8

*Code of Federal Regulations, Title12, Appendix A to Part 225, Capital Adequacy Guidelines for Bank Holding Companies: Risk-Based Measure.

factor "K" to determine the capital required for a particular counterparty or netting set.[2]

$$\text{Capital Required} = K \times EAD$$

$$EAD = \alpha \text{ x effective EPE}$$

Alpha (α) is a scaling parameter equal to 1.4 or may be calculated internally, but not less that 1.2. EPE is the expected positive exposure of the trade or netting set.
Where:

$$K = \left[LGD \times N\left(\frac{N^{-1}(PD) + \sqrt{R} \times N^{-1}(0.999)}{\sqrt{1-R}} \right) - (LGD \times PD) \right] \times \left(\frac{1 + (M - 2.5) \times b}{1 - 1.5 \times b} \right)$$

- N (.) is the cumulative distribution function for a standard normal random variable.
- N^{-1} (.) is the inverse cumulative distribution for a standard normal random variable.
- R is a correlation factor, $R = 0.12 \times (1 - e^{(-50 \times PD)}) / (1 - e^{(-50)}) + 0.24 \times [1 - (1 - e^{(-50 \times PD)}) / (1 - e^{(-50)})]$.
- B is a maturity adjustment, $b = (0.11852 - 0.05478 \times \ln(PD))^2$
- M is the effective maturity of the counterparty netting set.

Table 2 highlights the relative capital requirements for US \$100mm notional interest rate swaps under the applicable regulatory frameworks. The CVA Var charge implemented in Basel III leads to a significant increase in the capital necessary, particularly for long-dated transactions.

E. Clearing

Under U.S. regulation and Basel II, trades with a central counterparty receive a risk weighting of zero. This weighting applies to both current and future exposure from derivative transactions. Under the general risk-based capital rules, current

2. *Code of Federal Regulations*, Title 12, Appendix G to Part 225, "Capital Adequacy Guidelines for Bank Holding Companies: Internal Ratings-Based and Advanced Measurement Approaches."

Table 2. Capital Comparison (US$).

	General Risk-Based Rules	U.S. Prudential Regulation Uncollateralized	U.S. Prudential Regulation Collateralized	Basel III Collateralized w/ CVA Charge
5 yr Swap	100,000	39,949	20,465	67,858
10 yr Swap	300,000	79,742	38,089	195,000

Single 'A' rated counterparty at 20% risk weight.
10 day collateral holding period.

exposures collateralized with cash also receive a risk weighting of zero. Potential future exposure, however, is only partially offset within netted portfolios, up to a maximum of 60% of the gross risk (see the netting formula above). The residual exposure is floored at 40% of the gross PFE based on the gross notional value of individual transactions in the netting set. The capital required under the general rules is much greater than that required by firms using Basel II's advanced approach for large offsetting portfolios.

F. Collateral and Margin

One of the significant provisions of Dodd-Frank is the requirement for participants to post a combination of initial and variation margin to their counterparties for non-cleared transactions. The Act requires financial end users to collateralize most transactions with their counterparties. Non-financial end users are generally not required to collateralize exposure. In its current form, there are two different standards for the collateral and margin relating to bilateral swaps. A firm's regulatory supervisor determines the applicable standard: either that of the prudential regulators, or the CFTC and SEC.

G. Prudential Regulators Margin

SDs and MSPs supervised by the Board, FDIC, OCC, or other agency are required to collect and segregate initial and variation margin from their counterparties for all bilaterally executed swaps. Low risk financial end users and non-financial end users are not required to post initial margin until their exposure exceeds specified threshold levels, initially proposed to be US $15mm to $45mm in mark-to-market exposure, or 0.1% to 0.3% of a firm's Tier I capital. Non-financial end users operate under an identical threshold for variation margin. Other financial firms must operate with CSAs and are required to post initial margin for bilateral trades.

Dealers and MSPs required to receive initial margin from their counterparty have the option to determine the amount through a standard look-up table or through their own calculation. In both scenarios cross-product netting is not permitted across asset classes.

Firms choosing to calculate margin internally must calculate potential future exposure to a confidence level of at least 99% using a minimum 10-day holding period. Data used to calibrate the model must be greater than one year and incorporate periods of financial shock. Notwithstanding, the margin amount must be greater than that which would be required by a central counterparty for a similar transaction.

H. CFTC Margin

The primary difference under CFTC rules is an exemption granted to non-financial end users from the requirement to post initial margin under any circumstances. For all other participants, SDs and MSPs are offered two similar options to calculate initial margin. Rather than a look-up table, firms may calculate margin for bilateral trades as double that required by a CCP for a similar trade based on its risk characteristics. Alternatively, they may calculate margin internally, to the same 99% confidence over a 10-day holding period.

I. CCP Margin

CCPs calculate margin to a minimum confidence interval of 99%, assuming a five-day or greater holding period. For example, LCH Swapclear calculates for 100% loss coverage based on a historical data set and a five-day holding period for its members. IDCG calculates for 99.7% coverage over five days using historical and stressed data. CME Clearing and ICE Credit Clearing use similar specifications with their respective internal models. We expect regulators to set margin for non-cleared transactions at a minimum of 140% of the cleared equivalent, which would reflect the longer holding period.

II. BASEL III

Internationally, the Basel Committee on Banking Supervision responded to the financial crisis with its own revised framework for capital adequacy. It addressed many of the shortcomings that exist in the current Basel II framework through revisions that increase both the overall quantity and quality of bank capital. It includes a more comprehensive set of guidelines for the calculation of a bank's risk-based capital requirements. Basel III includes significant changes to the capital adequacy framework, particularly for counterparty credit risk embedded in OTC derivative transactions. The new accord encourages banks to centrally clear derivative transactions and will require banks to significantly increase the amount of capital held against bilateral transactions that are not cleared.

Basel III is expected to become effective in January 2013 and should be phased in over the next several years. It is the committee's response to the financial crisis and includes a variety of measures to improve the quality of bank capital and to increase the quantity of capital relative to risk weighted assets. It employs more stringent criteria for measuring and evaluating various types of risk.

In the trading book, it provides for increased capital to be held against market risk, particularly for OTC derivative and securitization transactions by requiring stressed Var calculations based upon historical data. It strengthens the counterparty credit risk framework and includes incentives for firms to use central counterparties. The methodology for calculating exposure is revised to be more stringent and includes evaluating Var during scenarios of significant financial stress. A CVA Var capital charge is added to Basel II "default" capital for counterparty credit risk. Transactions with CCPs are risk weighted according to the financial strength and structure of the clearinghouse and its compliance with International Organization of Securities Commissions (IOSCO) standards. The accord addresses systemic risk among financial firms by raising the risk weight for transactions between financial firms relative to non-financials. Other enhancements include the use of capital buffer and a non-risk based leverage buffer and new liquidity standards.

Several of the changes implemented under Basel III will directly impact the calculation of capital for counterparty credit risk inherent with OTC derivative transactions. CCR will include Var calculations using stressed input parameters that reflect the most recent three years of historical data. Institutions active in the derivative markets will be significantly affected by the addition of a new CVA Var capital charge that is added to the existing Basel II default capital requirements. It requires them to hold capital against potential mark-to-market losses resulting from a deterioration of counterparty credit quality. The CVA Var charge will only be calculated for bilateral transactions and will serve as an added incentive for firms to use CCPs.

The framework strengthens the treatment of collateralized exposure by increasing the minimum margin period of risk for collateralized transactions in large netting sets and those containing illiquid trades or collateral. It prohibits the use of rating downgrade triggers in calculating expected exposures. It also increases the risk weighting to financial institutions relative to non-financial institutions through a correlation adjustment to reflect the systemic risk among financial firms.

A. Aggregate Capital Requirements

Similar to Dodd-Frank, Basel III imposes heightened capital requirements for systemically important institutions. They are subject to an additional capital buffer of up to 2.5%. Basel III also changes both the composition and quantity of bank capital. It adds a countercyclical buffer of up to 2.5% and a conservation buffer of 2.5% to institutions' capital requirements. The increase in aggregate capital required across banks as a whole could lead to a greater focus on internal capital allocation to respective business lines at both a macro and micro level within financial entities.

B. CVA Var Charge

The adoption of a CVA Var capital charge is one of the more significant changes implemented in Basel III. The charge will lead to a substantial increase in the capital required for bilateral OTC derivative transactions, even for those that are collateralized. Conceptually, the charge is intended to capture the potential MTM losses from deterioration in counterparty credit quality that could occur short of a default. Regulators require firms to calculate the charge using a 99% Var estimate resulting from changes in credit spreads over a one-year horizon. Firms are required to use market-based spreads and LGD assumptions in their models and are permitted to include CVA hedges, including both single name and index CDS, in the calculation.

Banks have the option to calculate the CVA charge internally or using a standardized formula detailed in the framework. In both approaches, the methodology involves calculating the EAD for a counterparty according to the bank's selected method (CEM, standardized, IMM), incorporating the effects of collateral and netting. The bank will then calculate the Var in a manner similar to that of a bond with a notional equal to the EAD and a maturity equal to the notional weighted effective maturity of a counterparty's netting set. Var must be calculated solely from the volatility of the counterparty's credit spreads and measured over a one-year horizon. The CVA charge is a stand-alone charge that is added to the Basel II default capital calculation for each counterparty.

Banks using the IMM approach to calculate the CVA Var charge are required to use a specified formula as the basis for their model's calculation of a counterparties CVA (see Appendix A). The formula uses currently available market rates, including CDS spreads and recovery values, to estimate PD and LGD and incorporates CVA hedges. CVA is calculated by applying marginal default probabilities to expected exposures over the life of the netting set. The CVA Var charge is then calculated to a confidence level of 99% over a one-year horizon.

For those firms not able to calculate CVA Var internally, a standardized formula is provided that uses a simplified approach which specifies a risk weight according to a counterparty's credit rating and estimates the charge using EAD and the notional weighted maturity of the counterparty (see Appendix A).

C. Collateralized Counterparties

Basel II sets a floor of 10 days on the minimum margin period of risk used to calculate the exposure for collateralized transactions that are marked-to-market on a daily basis. Basel III increases it to 20 days for counterparties with large netting sets (greater than 5000 trades) when a transaction is not easily replaceable or where illiquid collateral is used. Not easily replaced OTC transactions are those with illiquid risk positions that are difficult to hedge, such as certain types of correlation risk or long dated volatility skew. Firms required to use longer margin periods when calculating EAD will be affected by the increase in EE that is the basis for the CVA Var charge. The potential cost increase resulting from the lengthened margin period will serve as an incentive for dealers to collapse offsetting risk in their portfolios and to more closely monitor trade and collateral liquidity. A detailed comparison is summarized in Table 3.

D. CCP Risk Weighting

Under Basel II, bank exposures to CCPs are given a zero risk weight. Basel III imposes a 2% risk weight to exposures to qualifying CCPs, which includes trade exposure, initial margin and default fund contributions of CCP members. The risk

Table 3. Collateralized Capital Requirements 10 year IRS.

Credit Rating	10 Day Holding Period			20 Day Holding Period		
	Capital	CVA Charge	Total	Capital	CVA Charge	Total
AAA	17,580	98,069	115,649	26,048	145,309	171,358
AA	17,580	98,069	115,649	26,048	145,309	171,358
A	27,207	112,079	139,286	40,312	166,068	206,380
BBB	56,069	140,099	196,167	83,077	207,585	290,662
BB	86,923	280,198	367,120	128,793	415,170	543,963
B	114,922	420,297	535,219	170,281	622,755	793,035
CCC	181,364	1,400,989	1,582,353	268,728	2,075,850	2,344,578

weighting will be determined by the CCP's compliance with revised Committee on Payment and Settlement Systems (CPSS) and IOSCO guidelines. The 2% risk weight provides a nominal addition to bank capital and is intended to ensure that banks measure and monitor their overall CCP exposure.

E. Financial Correlation Adjustment

Basel III increases the correlation factor "R" used in the calculation of the capital requirement "K" (see the equation above under Basel II) by a multiple of 1.25 for transactions among financial institutions. The correlation increase applies to exposures with financial firms whose total assets are greater than or equal to US $100 billion. It also applies to transactions with any unregulated financial firm. This translates into an approximately 25% corresponding increase in capital for affected transactions.

III. END USER TRANSACTIONS

End users face a significantly different cost structure for OTC derivative transactions under the combined effects of Dodd-Frank and Basel III. Increased capital requirements for dealers and financial institutions and initial margin for both cleared and non-cleared transactions will have a direct impact on end user derivative pricing. Firms will want to evaluate the costs associated with bilaterally executed, non-cleared transactions and compare them with those of a SEF-traded and cleared alternative. Financial end users will face an entirely one-sided cost structure that penalizes customized and discretionary bilateral transactions in favor of cleared vanilla trades. In many instances, customized transactions can be restructured into a combination of centrally cleared and bilateral transactions that require less capital and are less costly to execute.

End users face a tradeoff between efficient, cost-effective risk transfer and the need for hedge customization. The costs implicit in this tradeoff include: regulatory capital, funding initial margin, market liquidity and structural factors. All of these will affect cleared and non-cleared transactions much differently. Dealers and financial participants will be required to hold increased amounts of regulatory capital and higher levels of initial margin against bilateral transactions versus those which are centrally cleared.

Customized swaps, as a result of their unique nature, will not be clearable. While they could theoretically be executed on a SEF, they will more likely trade bilaterally between counterparties, as per current practice. End users are likely to pay a liquidity premium for bilateral execution compared to that on a SEF, where liquidity is likely to be greatest. Structural costs may also exist, to the extent that dealers are unable to find a natural non-cleared hedge for bilateral trades and are left with a structural margin position at CCPs from hedging customers' transactions. The cost of dealers' margin would be passed along to end users adding to the position. End users will want to evaluate the impact of these costs on the incremental risk introduced by each new transaction to both maximize the amount of nettable risk at dealer counterparties and minimize their associated hedging costs.

A. Further Discussion

In the remainder of the paper, we illustrate many of the explicit and implicit costs associated with execution, clearing, and capital that are expected to exist under the framework created by Dodd-Frank and Basel III. We estimate many of these costs for end users according to their credit quality. For non-financial end users, we examine the impact of the framework on the cost of collateralized and non-collateralized trades. For all others, we compare the cost of capital and initial margin for non-cleared bilateral transactions with that of an SEF-traded centrally cleared equivalent. This includes assessing the potential impact of liquidity and structural costs on end user transaction pricing.

B. End User Costs

The additional amount of regulatory capital required for OTC derivatives is one of the more significant changes affecting market participants. Dodd-Frank sets a floor on aggregate bank capital; however, it is not likely to directly alter the marginal cost allocated by dealers to OTC derivative transactions at the counterparty level. This is due to the disconnect between the regulatory formulas under the general rules and market practices for economic and regulatory capital calculations (Basel II and III advanced approach methodologies). Instead, it is likely to be treated as an immediate and interim measure to increase aggregate bank capital while regulators work to incorporate Basel III capital adequacy standards into U.S. regulation. While cleared trades are granted capital relief under both Basel II and III (0% and 2% risk weighting, respectively), the cost of bilateral transactions will increase substantially from the combined effects of the CVA Var charge, financial correlation adjustment, stressed calculations, and potentially longer margin periods of risk. Bilateral trades will be scrutinized for their contribution to credit risk and capital, and dealer prices will reflect their anticipated costs over the life of a transaction.

Funding the collateral required for initial margin is another significant cost facing most participants. Non-financial end users are expected to remain exempt from mandatory margin requirements. Low risk financial end users may also remain exempt below established regulatory thresholds. All other participants will be required to post initial margin for both cleared and bilateral transactions. Bilateral margin is likely to be at least 40% higher than corresponding CCP levels, which should lead to increased trade standardization as participants will be forced to pay more of a premium for customization.

Beyond the cost of initial margin, end users will face an operational cost associated with central clearing imposed by their FCMs. Competition should limit the administrative portion of operational cost to a nominal charge. It will, however, include specific terms dependent on the credit quality of the clearing customer and capital involved. Many clearing customers will face FCM margin requirements that are credit sensitive and exceed those required for CCP members. FCMs are required to comply with existing capital rules under CFTC and SEC regulations, requiring them to carry capital equivalent to 8% of their customers' initial margin posted for cleared transactions.

End users face potential liquidity driven execution costs in a market that will be split between vanilla SEF-executed trades and customized bilateral transactions. Currently, nearly all interest rate swaps trade bilaterally between participants. Dodd-Frank changes execution by requiring all clearable swaps to trade on SEFs. The concentration of trading on these platforms should lead to increased liquidity among swaps with standard size and tenor. We think this will result in tighter bid-ask spreads for SEF executed transactions than those transactions executed bilaterally. Standard vanilla transactions, traded on SEFs and cleared through a CCP, will become the market convention adopted by participants. Bilaterally executed swaps, whether the result of their customized nature or due to end user discretion, are likely to be priced less favorably, incorporating a concession or liquidity premium, that reflects a decrease in liquidity relative to that available on a SEF.

There is the potential for a structural imbalance to develop in the market that affects end user transaction prices. The market for end user transactions will be segregated between those that are cleared and those that are transacted bilaterally. There is the potential for a risk mismatch to develop within each of these categories. Aggregate risk in the market should be largely offsetting, essentially resembling a matched book. The mismatch would occur if end user non-cleared risk becomes predominantly one-sided and dealers are not able to find a natural non-cleared offset for the risk. Dealers would be left with non-cleared risk positions that are hedged by cleared trades, which would leave them with an aggregate "captive" structural margin position at CCPs. The cost associated with this margin would be passed along to end users adding to the position. It would ultimately lead to a bifurcated market between cleared and non-cleared transactions with a substantial pricing bias. In the near term, it is likely to create greater price variation among dealers and add an additional dimension to the counterparty-specific costs of a transaction.

C. Capital Calculations

In order to illustrate and evaluate the impact of the framework under Dodd-Frank and Basel III on end users and their dealer counterparties, we estimated the capital required for vanilla US $100mm notional, at-the-money 5-year and 10-year interest rate swaps for counterparties of varying credit quality. We modeled forward rates using an initial flat yield curve of 3.00%, with parallel shifts in rates governed by Brownian motion with a constant annual volatility of 30%. Expected exposures were calculated for one year and used to calculate the effective EPE and EAD as per regulatory guidelines. We used PD estimates by rating category taken from Deutsche Bank's Pillar 3 Disclosure in its 2010 Annual Report. LGD was set at 50% for an uncollateralized claim. We calculated capital according Basel II's Advanced IRB Approach.

The CVA Var charge was calculated using the Standardized Method contained in Basel III with the associated counterparty risk weightings. We added the CVA

Var charge to the amount of Basel II default capital to arrive at the total capital required under the new framework. The total capital amount is the capital a firm must hold today against a bilateral swap. To estimate the cost of capital that a firm must hold over the life of the transaction, we assumed a blended dealer cost of capital of 8.0%.

We made several assumptions to arrive at the capital estimates contained in this paper. In aggregate, the assumptions and methodologies used likely result in higher capital calculations and lower margin calculations. Banks calculating the CVA Var charge using an IMM approach may arrive at a smaller charge than under the Standardized Formula due to differences in credit Var parameters. Similarly, exposures calculated with a lagged collateral model are likely to be lower than our estimates. End user clearing costs are likely to be higher than our estimates, which reflect the margin requirement for CCP members. Customer margin requirements are generally higher than those for members and will reflect specific terms agreed with an end user's FCM. The net result is an upward bias in the capital cost estimates and a downward bias in those for clearing cost.

D. Uncollateralized Transactions

Non-financial end users that are not required to implement CSAs for bilateral transactions will face a much more punitive execution cost going forward as a result of the additional capital that must be held by their trading partners. The cost of capital implicit in the price of their transaction is largely unchanged under Dodd-Frank but will increase significantly with the inclusion of the CVA Var charge under Basell III. It is likely that dealers will increase their capital "charge" for a swap in anticipation of the adoption of the new Basel framework. This added charge is expected for hedging transactions with end users who hedge predominantly one-sided risk or long-dated transactions that are likely to remain in place and overlap with the implementation of Basel III.

Non-financial end users have discretion to forgo clearing for vanilla as well as customized trades and execute them bilaterally. They also retain discretion over collateralization. Tables 4 and 5 show the capital required for uncollateralized US $100mm notional, at-the-money 5- and 10-year interest rates swaps for end users according to their credit rating. The current Basel II default capital will increase under Basel III by 400%, as a result of the CVA Var charge.[3]

The magnitude of the CVA Var charge is substantial and its impact will significantly increase the cost for firms operating with and without CSAs. The dealer's capital cost attributed to CCR for a single "A" counterparty on a 10-year swap is $32,660 for the first year of the trade under Basel III and estimated at $140,043 over the life of the trade or 1.63 basis points running (140,043/85,800), of which 80% pertains to the CVA Var charge.

While we assume dealers will charge end users upfront for their cost of capital

3. The CVA Var charge was calculated using the Standardized Method, shown in detail in Appendix A.

Table 4. Uncollateralized 5-year IRS.

Credit Rating	PD	Year One Basel II Capital	Year One Basel III CVA Var Charge	Year One Total CCR Capital	Year One Capital Cost	Capital Cost Life of the Trade
AAA	0.03%	25,814	80,954	106,768	8,541	24,651
AA	0.03%	25,814	80,954	106,768	8,541	24,651
A	0.07%	39,949	92,519	132,468	10,597	30,585
BBB	0.32%	82,329	115,649	197,977	15,838	45,710
BB	1.12%	127,634	231,297	358,931	28,714	82,871
B	3.93%	168,747	346,946	515,693	41,255	119,065
CCC	22.00%	266,308	1,156,485	1,422,794	113,823	328,501

Table 5. Uncollateralized 10-year IRS.

Credit Rating	PD	Year One Basel II Capital	Year One Basel III CVA Var Charge	Year One Total CCR Capital	Year One Capital Cost	Capital Cost Life of the Trade
AAA	0.03%	51,527	287,439	338,966	27,117	115,165
AA	0.03%	51,527	287,439	338,966	27,117	115,165
A	0.07%	79,742	328,502	408,244	32,660	140,043
BBB	0.32%	164,336	410,627	574,963	45,997	201,178
BB	1.12%	254,768	821,254	1,076,023	86,082	372,496
B	3.93%	336,835	1,231,881	1,568,716	125,497	540,434
CCC	22.00%	531,576	4,106,271	4,637,847	371,028	1,562,574

over the life of the trade, Tables 4 and 5 do not include the bank's CVA for the credit risk of the swap. The CVA credit charge is listed in Table 6 using average CDS spreads for corporate firms by rating category, assuming a constant marginal probability of default based on the CDS spread and recovery value applied to the expected exposure of the swaps.

What was previously a costly transaction becomes even more punitive. This should compel most non-financial end users who do not already do so to operate under CSAs.

E. Collateralized Transactions

The current requirement under Basel II, which is carried forward to Basel III, is to model collateralized exposure using a 10-day margin period of risk, during which a defaulting counterparty's position will be re-hedged and its collateral liquidated. Collateralized capital requirements are contained in Table 7 and 8.

F. Central Clearing

Non-financial end users lobbied successfully to be exempted from the requirement to clear or even post initial margin for non-cleared transactions. Cost and capital scarcity were cited as being prohibitive to both growth and investment. The cost to fund initial margin is substantial, particularly for those firms without offsetting risk. Funding costs are computed from aggregate corporate CDS spreads according to rating category.

Non-financial end users have limited outright economic incentive to use CCPs. The cost of funding initial margin outweighs the charge for dealer capital cost. Existence of a sufficiently large liquidity premium or structural charge would alter the economics, particularly for short dated transactions as shown in Tables 11 and 12. The net clearing cost expressed as running basis points represents the aggregate break-even liquidity and structural costs. It is likely that discretionary use of CCPs by non-financial end users will not be driven by cost, but rather by end users' desire to reduce counterparty risk.

G. Financial End Users and Bilateral Margin

Under Dodd-Frank, low risk financial end users are not required to post initial margin for bilateral transactions. They face a similar situation to that of non-financial end users, but if regulated, are required to hold capital for their own capital adequacy. Their internal capital requirements lead to a much closer relationship for the costs of cleared and bilateral transactions, as shown in Tables 13 and 14. We doubled the capital cost estimate as a proxy for the overall cost affecting financial end users. This is admittedly a rough approximation of the cost they will face from dealers plus the cost of their own capital adequacy requirement.

Given the comparable costs for cleared versus non-cleared transactions, financial end users will be more sensitive to potential liquidity and structural costs and their impact on their hedging strategies. The net cost expressed as running

Table 6. Uncollateralized Bilateral CVA Credit Charge.

Credit Rating	CDS Spread	5 Yr Swap Credit Charge	10 Yr Swap Credit Charge
AAA	0.41%	17,665	94,616
AA	0.57%	24,526	131,365
A	0.74%	31,796	170,303
BBB	1.11%	45,547	254,671
BB	2.68%	113,315	606,931
B	4.44%	185,024	991,017
CCC	7.88%	319,254	1,709,967

Table 7. Collateralized Capital Requirements 5 year IRS.

	Year One Capital Requirements			
Credit Rating	Capital	CVA Var Charge	Total	Capital Cost Life of the Trade
AAA	9,445	29,621	39,066	9,020
AA	9,445	29,621	39,066	9,020
A	14,618	33,853	48,470	11,191
BBB	30,124	42,316	72,440	16,726
BB	46,701	84,632	131,333	30,323
B	61,745	126,948	188,693	43,567
CCC	97,443	423,160	520,602	120,201

Table 8. Collateralized Capital Requirements 10 year IRS.

	Year One Capital Requirements			
Credit Rating	Capital	CVA Var Charge	Total	Capital Cost Life of the Trade
AAA	17,580	98,069	115,649	40,204
AA	17,580	98,069	115,649	40,204
A	27,207	112,079	139,286	48,912
BBB	56,069	140,099	196,167	70,330
BB	86,923	280,198	367,120	130,156
B	114,922	420,297	535,219	188,793
CCC	181,364	1,400,989	1,582,353	545,279

Table 9. Five-Year IRS - Cleared Initial Margin.

Credit Rating	CDS Spread*	Year One CCP IM 5 yr Swap**	Year One Margin Cost	Margin Cost Life of the Trade
AAA	0.41%	1,800,000	7,380	17,205
AA	0.57%	1,800,000	10,260	23,919
A	0.74%	1,800,000	13,320	31,053
BBB	1.11%	1,800,000	19,980	46,579
BB	2.68%	1,800,000	48,240	112,462
B	4.44%	1,800,000	79,920	186,318
CCC	7.88%	1,800,000	141,840	330,672

*Moody's.
**Initial margin percentages taken from International Derivative Clearing Group.

Table 10. Ten-Year IRS - Cleared Initial Margin.

Credit Rating	CDS Spread*	Year One CCP IM 10 yr Swap**	Year One Margin Cost	Margin Cost Life of the Trade
AAA	0.41%	3,730,000	15,293	77,173
AA	0.57%	3,730,000	21,261	107,289
A	0.74%	3,730,000	27,602	139,288
BBB	1.11%	3,730,000	41,403	208,932
BB	2.68%	3,730,000	99,964	504,448
B	4.44%	3,730,000	165,612	835,727
CCC	7.88%	3,730,000	293,924	1,483,227

*Moody's
**Initial margin percentages taken from International Derivative Clearing Group.

Table 11. Non-financial End User 5 year IRS Capital vs. Margin.

Credit Rating	Capital Cost Non-cleared	Margin Cost Cleared	Net Clearing Cost (NCC)	NCC Running BP
AAA	9,020	17,205	8,185	0.18
AA	9,020	23,919	14,899	0.32
A	11,191	31,053	19,862	0.43
BBB	16,726	46,579	29,854	0.65
BB	30,323	112,462	82,139	1.78
B	43,567	186,318	142,751	3.10
CCC	120,201	330,672	210,471	4.57

Table 12. Non-financial End User 10 year IRS Capital vs. Margin.

Credit Rating	Capital Cost Non-cleared	Margin Cost Cleared	Net Clearing Cost (NCC)	NCC Running BP
AAA	40,204	77,173	36,969	0.43
AA	40,204	107,289	67,085	0.78
A	48,912	139,288	90,376	1.05
BBB	70,330	208,932	138,602	1.62
BB	130,156	504,448	374,292	4.36
B	188,793	835,727	646,934	7.54
CCC	545,279	1,483,227	937,948	10.93

basis points is the break-even liquidity premium and structural cost for bilateral versus SEF execution. In the case of an A-rated end user trading a five-year swap, if the execution savings on a SEF relative to a bilateral trade is greater than 0.2 bpa running on a swap, it will compensate them for the added cost of clearing margin. These institutions evaluating transactions at the margin will be sensitive to execution and potential structural costs. The economics behind a transaction will likely determine whether it is traded bilaterally as a customized swap or replicated with a combination of cleared and bilateral trades.

High credit quality firms should find comparable costs for clearing margin versus capital, while lower rated firms will find funding costs outweigh capital savings. Structural costs from dealer's margin to hedge bilateral trades could have a significant impact on the economics for AAA-rated through BBB-rated firms. This has the potential to add $23,919 or 0.52 bpa to the cost of a five-year swap and $107,289 or 1.25 bpa to the cost of a 10-year swap, using the margin cost of associated with an AA-rated firm. This is the limit to the charge end users could experience; however,

Table 13. Financial End User 5 year IRS Capital vs. Margin.

Credit Rating	Capital Cost Non-cleared	Margin Cost Cleared	Net Clearing Cost (NCC)	NCC Running BP
AAA	18,040	17,205	(835)	(0.0)
AA	18,040	23,919	5,879	0.1
A	22,382	31,053	8,670	0.2
BBB	33,451	46,579	13,128	0.3
BB	60,647	112,462	51,815	1.1
B	87,134	186,318	99,184	2.2
CCC	240,402	330,672	90,270	2.0

Table 14. Financial End User 10 year IRS Capital vs. Margin.

Credit Rating	Capital Cost Non-cleared	Margin Cost Cleared	Net Clearing Cost (NCC)	NCC Running BP
AAA	80,408	77,173	-3,235	(0.0)
AA	80,408	107,289	26,881	0.3
A	97,824	139,288	41,464	0.5
BBB	140,660	208,932	68,272	0.8
BB	260,312	504,448	244,136	2.8
B	377,586	835,727	458,141	5.3
CCC	1,090,558	1,483,227	392,669	4.6

its combination with potential execution costs could be sufficient to influence highly rated financial end users.

We should point out that the capital calculations do not include the 25% increase to the correlation factor for transactions with large financial counterparties. This would increase the default capital amount (with no effect on the CVA Var amount) and lead to an approximate 5% to 10% increase in the total capital cost amounts listed in the tables.

To this point, we have not mentioned the impact and importance of netting. The numbers in the table assume zero netting benefit and estimate the maximum capital and margin cost associated with a single transaction. The capital and clearing costs (and any structural costs) will decrease with a corresponding increase in risk netting. For the A-rated end user five-year swap with 50% netting benefit, the NCC in Table 13 will drop to 0.1 bpa. As the netting benefit increases, the impact of a liquidity premium will become more significant, since it is based on the total market risk executed by the end user. Even the existence of a very small liquidity premium between bilateral and SEF execution could be a significant factor in end user transaction cost comparisons. In largely netted portfolios it could overshadow capital and margin considerations.

In the example above, we assumed that the netting benefit is equal for both the customers cleared portfolio and its bilateral portfolio at a particular dealer. Netting and end user portfolio composition will play an influential role in determining the trading counterparty as firms try to minimize the amount of net risk outstanding with each counterparty.

High risk financial end users and all other participants are required to post initial margin for bilateral trades. For these firms, it is not a question of whether or not to use CCPs, but rather one of minimizing bilateral costs. These firms have every incentive to maximize the amount of risk they clear relative to that which is executed bilaterally. They stand to benefit from a reduction in initial margin, 40% by our estimates; minimized Basel II and Basel III default capital (0% and 2% respective risk weighting); avoiding the CVA Var charge, which does not apply to cleared transactions; and avoiding the financial correlation adjustment. They also avoid any potential structural costs and are likely to find better execution. For these reasons many will adopt hedging strategies that allow them to maximize the amount of risk transferred through standardized cleared swaps and minimize that which is traded bilaterally.

IV. HEDGING STRATEGIES

Financial end users stand to benefit most from financial engineering to reduce the impact of these factors affecting their overall transaction cost. We expect them to employ strategies that minimize the amount of risk transferred bilaterally in favor of SEF-executed, centrally cleared transactions. Participants will want to compare the incremental cost of a cleared trade at their FCM and CCP against the incremental cost to their bilateral portfolio at each selected dealer. This comparison will include evaluating the impact of liquidity and structural market costs. We expect many to separate their market risk from customized transactions, execute on SEFs, and use CCPs to the extent possible, limiting the use of bilateral trading primarily for customization.

We have outlined two possible approaches end users may pursue going forward. The first involves replicating a customized hedging trade with a portfolio of vanilla trades for risk transfer and one or more basis swaps for customization that in aggregate will be identical to the customized hedging trade. The vanilla trades can be SEF-executed and cleared, reducing both the capital cost and initial margin required, while the basis swap(s) can be executed bilaterally. The second, albeit similar strategy, is to take the customized hedging trade and subtract a vanilla delta hedge from it and then execute the delta hedge independently on a SEF where it is also cleared. The objective of both approaches is to maximize the portion of the market risk that is SEF-executed, resulting in lower overall cost than an entirely bilateral transaction.

In the example below we take an irregularly amortizing 10-year interest rate swap with a risk profile shown in Figure 1. The current trade would be executed bilaterally and subject to the costs and capital outlined earlier. A replicating hedge portfolio of vanilla trades could be SEF-executed and cleared, leaving a basis swap with minimal delta containing a customizing profile of cash flows. Counterparty risk, margin, and capital are significantly reduced (likely negligible in this instance), while the market risk is transferred in a less costly manner. The customized trade is replaced with 10 vanilla swaps and one customized basis swap that replicates the cash flows, payment dates, and risk of the original transaction.

The less clean but more realistic scenario shown in Figure 2 would be to net a delta hedge from the customized transaction. It could be easily replicated as: [the original trade less a 7 year bullet swap] executed bilaterally plus a 7 year bullet swap executed on a SEF and centrally cleared.

The residual swap has a delta of 7k per basis point and a butterfly risk position that is fairly benign. This leads to significantly smaller expected exposures on the residual bilateral trade. Similarly, the cleared delta hedging trade, with a market risk of 50k per basis point will be risk weighted for a CCP, which saves the participant and its counterparty significant capital and bilateral margin.

The higher costs associated with the original bilateral trade would be reduced for 78% of the market risk and apply only to the 12% remaining on the residual butterfly as shown below:

<u>Delta Hedged Cost:</u>

[Bid/Ask + Liquidity premium] for Residual butterfly
+ Bid/Ask for 7-year IRS
+ Capital charge for 7 yr IRS (2% risk wt.)
+ Capital charge [CVA Var & default] for Residual butterfly
+ Cleared margin for 7 yr IRS
+ Non-cleared margin for Residual butterfly
+ Structural charge for Residual butterfly

versus

<u>Original Customized Trade Cost:</u>

[Bid/Ask + Liquidity premium] for Custom hedge
+ Capital charge [CVA Var & default] for Custom hedge
+ Non-cleared margin for Custom hedge
+ Structural charge for Custom hedge

The same delta hedge approach can be applied to more complex transactions, such as those with non-linear risk profiles, where a portion of the market risk can be hedged in a less costly, more capital efficient manner. It can also be applied in more detail to achieve the desired cleared versus residual bilateral risk positions. The end user is not changing the original customized trade but is instead separating a portion of the market risk to be traded independently and cleared. The amount of cost reduction is determined by the risk remaining on the residual bilateral swap.

Figure 1. Irregular Swap – Perfect Hedge.

Year	Customized Trade Notional (mm)	Risk Sensitivity	Vanilla Hedge Notional (mm)	Hedge Risk Sensitivity	Residual Risk Sensitivity
1	106.3	1,000	10.2	(1,000)	0
2	96.1	1,000	5.2	(1,000)	0
3	90.9	1,000	3.5	(1,000)	0
4	87.4	1,000	2.7	(1,000)	0
5	84.7	2,000	4.3	(2,000)	0
6	80.4	8,000	14.7	(8,000)	0
7	65.7	30,000	47.9	(30,000)	0
8	17.9	10,000	14.2	(10,000)	0
9	3.7	2,000	2.6	(2,000)	0
10	1.2	1,000	1.2	(1,000)	0
Total		57,000	106.34	(57,000)	0

Figure 2. Irregular Swap – Delta Hedge.

Year	Customized Trade Notional (mm)	Risk Sensitivity	Delta Hedge Notional (mm)	Hedge Risk Sensitivity	Residual Risk Sensitivity
1	106.3	1,000	0	0	1,000
2	96.1	1,000	0	0	1,000
3	90.9	1,000	0	0	1,000
4	87.4	1,000	0	0	1,000
5	84.7	2,000	0	0	2,000
6	80.4	8,000	0	0	8,000
7	65.7	30,000	80	(50,156)	(20,156)
8	17.9	10,000	0	0	10,000
9	3.7	2,000	0	0	2,000
10	1.2	1,000	0	0	1,000
Total		57,000	80	(50,156)	6,844

A. Netting

The reduction in aggregate counterparty risk through single and multi-product netting will become even more critical under the capital and margin requirements of Dodd-Frank and Basel III. Risk netting remains one of the principal considerations for participants striving to reduce both risk and transaction cost. Firms will seek to minimize bilateral exposure with each of their counterparties. While the impact of netting is significant for some market participants, particularly banks and dealers, who transact in largely offsetting market and credit risk, it has less of an impact on a subset of end users whose hedging transactions are predominantly one sided. They will experience the largest impact from the marginal costs illustrated. For them, the stand-alone trade analysis provided is a relevant representation of the incremental risk and capital associated with their derivative transactions.

As netting benefits increase due to offsetting risk within an end user's portfolio, the relative costs associated with clearing, capital, and market structure will shrink for end users and their counterparties. Execution cost resulting from a liquidity premium will not, and will play an increasing role in the overall cost of the transaction. End users should gravitate toward those venues providing the best liquidity at the lowest cost.

V. IMPLICATIONS

A. Non-financial End Users

Those firms that do not already do so are likely to trade on a collateralized basis. They are not required to clear standard or customized transactions and, despite the increased capital costs levied on them, by dealers are likely to find bilateral execution less expensive than the use of a CCP. Two things could change this: a sufficiently high structural cost in which dealers charge end users for the captive initial margin on their hedge, or a large liquidity premium for bilateral transactions. Both would have to be substantial to make central clearing economically attractive. Non-financial end users electing to clear are likely to do so purely for the reduction of counterparty risk.

Non-financial end users hedging predominantly one-sided risk will likely seek lower cost hedging alternatives or may choose not to hedge at all. Corporate end users might change the structure of their funding and increasingly issue securities that meet their liability risk targets without the use of a swap. It is possible that some will increase their issuance of floating rate and callable or structured notes. Alternatively, some could shorten the duration of derivatives used for hedging purposes, reflecting the relatively high cost associated with long-dated transactions.

B. Low Risk Financial End Users

Low risk financial end users are likely to remain exempt from posting margin below preset regulatory thresholds. For non-cleared transactions, there is less of a trade-off between margin and capital costs, which will increase the impact of potential structural and liquidity costs. Financial end users hedging strategies are likely to be driven by the credit quality and size of the organization, trading volume, and risk characteristics. Larger firms with lower funding and capital costs are more likely to benefit from CCP use, as are those with high trade volume and offsetting risk. Smaller institutions may continue to execute bilaterally even if it means at a higher cost to avoid the operational and infrastructure requirements for clearing.

C. High Risk Financial End Users

For all other institutions the equation is very simple. Customized bilateral transactions will face an entirely one-sided cost structure that is significantly higher than achieved with SEF-executed centrally cleared trades. Initial margin is expected to be at least 40% greater. Capital costs for both the end user and dealer counterparty will be much greater that the 2% risk weighting of CCPs, largely due to the CVA Var charge addition to CCR. Transactions may be more costly to execute, incurring a liquidity premium relative to those traded on a SEF. Participants may also face a structural premium for captive dealer margin. In addition, transactions facing large financial institutions will face the additional 25% correlation increase to default capital. All of these should compel participants to reduce the amount of risk transacted bilaterally and increase the risk transferred using vanilla SEF-executed and cleared transactions. Institutions are able to accomplish this is by extracting the market risk from customized transactions or replicating it with standardized trades that can be executed and centrally cleared in a more capital and cost efficient manner. They are likely to continue to trade bilaterally to achieve customization, while minimizing the amount of risk transferred through that medium.

D. Concentration Risk

The increased cost for bilateral transactions makes netting critical for firms wishing to minimize hedging costs. A byproduct of this could be an increase in the concentration of risk for non-cleared trades with a small number of dealers. Firms with offsetting risk will maximize netting among dealers to reduce costs but may ultimately seek to transact with a select group of dealers. It is possible that we could see a much larger percentage of bilateral customer transactions concentrated with a small handful of dealers to maximize multi-product netting.

E. Dodd-Frank Capital Floor

The floor imposed on bank capital under Dodd-Frank reflects the desire by regulators to increase aggregate bank capital and bring it closer to that which is required under Basel III. It serves as an interim measure until U.S. rules are amended to incorporate the new Basel ratios. Regulators have expressed their intention to incorporate the Basel III requirements into U.S. regulations and are expected to begin to draft these rules in 2012. The marginal capital required for OTC derivative transactions under the general rules is generally higher than that which is required for large institutions using the advanced approach methodology, but has little if any correlation with current risk management practice at most sophisticated financial institutions. Going forward, we do not think it will have any impact on market pricing, which is more likely to reflect the risk sensitive measures detailed in Basel III that more closely coincide with current practice.

VI. CONCLUSIONS

The regulatory framework created by the Dodd-Frank Act and the Basel III accord will significantly change the economics and pricing of OTC derivative transactions. Mandatory clearing and initial margin for non-cleared transactions, combined with increases in regulatory capital requirements, will affect end user transaction costs for both vanilla and customized transactions. Bilaterally executed transactions will become increasingly expensive, which should prompt many participants to adopt hedging strategies that minimize the amount of risk executed in that manner. We have shown how this can be done by replicating customized transactions with a combination of vanilla and customized basis trades.

Firms can significantly reduce their margin, capital, structural, and execution cost by maximizing the amount of market risk transferred through SEF-executed, cleared transactions relative to the amount of risk traded bilaterally. Central to this will be an approach that allows firms to maximize the amount of bilateral netting with dealer counterparties. Those firms able to net significant portions of their incremental risk will be less affected by capital, margin, and structural costs.

They will, however, be increasingly affected by differences in liquidity existing between SEFs and bilateral execution. This is mitigated through the same approach, which separates risk transfer from customization and executes the two separately whenever possible.

Ultimately, we expect many end users to employ hedging strategies that separate risk and execution from customization, enabling them to achieve the most cost effective and capital efficient transaction. This should lead to increasingly standardized SEF-executed transactions for transferring market risk and bilateral basis transactions for customization.

APPENDIX A

In order to illustrate and evaluate the impact on participants and their counterparties, we have estimated the capital charge for vanilla at-the-money 5-year and 10-year interest rate swaps for counterparties of varying credit quality. Future interest rates were modeled by Brownian motion with a constant volatility of 30% and zero drift. Expected exposures are calculated assuming a flat yield curve of 3.00%, with parallel shifts in rates. EEPE is calculated according to the formulas used in the Basel framework and observed for one year to estimate EAD. PD estimates according to rating category were taken from Deutsche Bank’s Pillar 3 Disclosure in its 2010 Annual Report. LGD is set at 50%. CVA Var is calculated using the Standard Method from Basel III as listed below. End user funding levels are aggregate CDS spreads for corporate firms taken from Moody’s.

EEPE Calculation

Expected exposure as a percentage of notional is calculated in the table below. Forward rates were modeled from a flat interest rate curve of 3.00% using an annualized volatility equal to 30.0%. Expected exposures were calculated by simulation of rates over 1,000 paths.

5 year swap Expected Exposures			**10 year swap Expected Exposures**		
Years	Forward Rates	Expected Exposure	Years	Forward Rates	Expected Exposure
0.25	3.1645	0.72	0.25	3.1645	1.37
0.5	3.2281	0.95	0.5	3.2281	1.85
0.75	3.2896	1.14	0.75	3.2896	2.30
1	**3.3202**	**1.19**	**1**	**3.3202**	**2.47**
1.25	3.3619	1.27	1.25	3.3619	2.73
1.5	3.3956	1.30	1.5	3.3956	2.90
1.75	3.4230	1.29	1.75	3.4230	3.02
	EEPE	**0.80**		**EEPE**	**1.60**

EEPE was calculated as the time weighted average over the first year horizon.

Capital Calculation

Capital was calculated according to the formula contained in Basel II and this paper. PD estimates were obtained from the Pillar 3 Disclosure from Deutsche Bank's 2010 Annual Report. LGD was assumed equal to 50%.

EAD = alpha (1.4) * EEPE			**Capital Requirement: No collateral**	
			Notional	100,000,000
		Maturity	5 year swap	10 year swap
Credit Rating	PD	LGD	**EAD = 0.80**	**EAD = 1.60**
AAA	0.03%	50%	25,814	51,527
AA	0.03%	50%	25,814	51,527
A	0.07%	50%	39,949	79,742

EAD = alpha (1.4) * EEPE			**Capital Requirement: No collateral**	
			Notional	100,000,000
		Maturity	5 year swap	10 year swap
Credit Rating	PD	LGD	**EAD = 0.80**	**EAD = 1.60**
BBB	0.32%	50%	82,329	164,336
BB	1.12%	50%	127,634	254,768
B	3.93%	50%	168,747	336,835
CCC	22.00%	50%	266,308	531,576
	r value	b value	k value	
AAA	0.24	0.32	0.02	
AA	0.24	0.32	0.02	
A	0.24	0.27	0.04	
BBB	0.22	0.19	0.07	
BB	0.19	0.13	0.11	
B	0.14	0.09	0.15	
CCC	0.12	0.04	0.24	

			Capital Requirement: Collateral 10 Day	
			Notional	100,000,000
		Maturity	5	10
			5 yr swap	10 yr swap
Credit Rating	PD	LGD	**EAD = 0.41**	**EAD = 0.76**
AAA	0.03%	50%	9,445	17,580
AA	0.03%	50%	9,445	17,580
A	0.07%	50%	14,618	27,207
BBB	0.32%	50%	30,124	56,069
BB	1.12%	50%	46,701	86,923
B	3.93%	50%	61,745	114,922
CCC	22.00%	50%	97,443	181,364
	r value	b value	k value	
AAA	0.24	0.32	0.02	
AA	0.24	0.32	0.02	
A	0.24	0.27	0.04	

			Capital Requirement: Collateral 10 Day		
			Notional		100,000,000
		Maturity		5	10
			5 yr swap	10 yr swap	
Credit Rating	PD	LGD	**EAD = 0.41**		**EAD = 0.76**
	r value	b value	k value		
BBB	0.22	0.19	0.07		
BB	0.19	0.13	0.11		
B	0.14	0.09	0.15		
CCC	0.12	0.04	0.24		

Collateralized Holding Period EE

The EAD for collateralized transactions were calculated as the expected exposure at the end of the collateral holding period (“H”) using a scaled volatility (30% × (H/250)^0.5).

CVA Var Charge

The CVA Var capital charge was calculated using the formula listed below. The charge was calculated assuming no CVA hedge, using EADs calculated for uncollateralized and collateralized swaps. The counterparty weights from the standardized formula were used.

CVA Var Charge: Uncollateralized				
Standard method		M =	5	10
		EAD =	1,121,943	2,239,499
		Discounted EAD	992,691	1,762,348
Credit Rating	Basel III Weights		Std CVA Chg (K)	
AAA	0.70%		80,954	287,439
AA	0.70%		80,954	287,439
A	0.80%		92,519	328,502
BBB	1.00%		115,649	410,627
BB	2.00%		231,297	821,254
B	3.00%		346,946	1,231,881
CCC	10.00%		1,156,485	4,106,271

CVA Var Charge: Collateralized 10 day holding period				
Standard method		M =	5.00	10
		EAD =	410,521	764,078
		Discounted EAD	363,227	601,283
Credit Rating	Basel III Weights		Std CVA Chg (K)	
AAA	0.70%		29,621	98,069
AA	0.70%		29,621	98,069
A	0.80%		33,853	112,079
BBB	1.00%		42,316	140,099
BB	2.00%		84,632	280,198
B	3.00%		126,948	420,297
CCC	10.00%		423,160	1,400,989

CVA Var Charge: Collateralized 20 day holding period				
Standard method		M =	5.00	10
		EAD =	608,269	1,132,137
		Discounted EAD	538,195	890,923
Credit Rating	Basel III Weights		Std CVA Chg (K)	
AAA	0.70%		43,890	145,309
AA	0.70%		43,890	145,309
A	0.80%		50,160	166,068
BBB	1.00%		62,700	207,585
BB	2.00%		125,399	415,170
B	3.00%		188,099	622,755
CCC	10.00%		626,997	2,075,850

Standardized CVA risk capital charge:[4]

$$K = 2.33 \times \sqrt{h} \times \sqrt{\Big[\sum_I 0.5 \times w_i \times (M_i \times EAD_i^{total} - M_i^{hedge} \times B_i) - \sum_{ind} w_{ind} \times M_{ind} \times B_{ind})^2 + \sum 0.75 \times w_i^2 \times (M_i \times EAD_i^{total} - M_i^{hedge} \times B_i)^2 \Big]}$$

4. *Basel Committee on Banking Supervision, Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems*, Bank for International Settlements, December 2010 (rev. June 2011).

Where:

- **h** is the one-year risk horizon (in units of a year), h = 1.

- $\mathbf{w_i}$ is the weight applicable to counterparty 'i'. Counterparty 'i' must be mapped to one of the seven weights wi based on its external rating, as shown in the table of this paragraph below. When a counterparty does not have an external rating, the bank must, subject to supervisory approval, map the internal rating of the counterparty to one of the external ratings.

- $\mathbf{EAD_i^{total}}$ is the exposure at default of counterparty 'i' (summed across its netting sets), including the effect of collateral as per the existing IMM, SM, or CEM rules as applicable to the calculation of counterparty risk capital charges for such counterparty by the bank. For non-IMM banks the exposure should be discounted by applying the factor (1-exp(-$0.05*M_i$))/($0.05*M_i^{hedge}$). For IMM banks, no such discount should be applied as the discount factor is already included in M_i.

- $\mathbf{B_i}$ is the notional of purchased single name CDS hedges (summed if more than one position) referencing counterparty "i" and used to hedge CVA risk. This notional amount should be discounted by applying the factor (1-exp(- $0.05*M_i^{hedge}$))/($0.05*M_i^{hedge}$).

- $\mathbf{B_{ind}}$ is the full notional of one or more index CDS of purchased protection, used to hedge CVA risk. This notional amount should be discounted by applying the factor (1-exp(-$0.05*M_{ind}$))/($0.05* M_{ind}$).

- $\mathbf{w_{ind}}$ is the weight applicable to index hedges. The bank must map indices to one of the seven weights wi based on the average spread of index 'ind'.

- $\mathbf{M_i}$ is the effective maturity of the transactions with counterparty "i." For IMM banks, M_i is to be calculated as per Annex 4, paragraph 38 of the Basel Accord. For non-IMM banks, M_i is the notional weighted average maturity. M_i should not be capped at five years.

- $\mathbf{M_i^{hedge}}$ is the maturity of the hedge instrument with notional B_i (the quantities $M_i^{hedge}*B_i$ are to be summed if these are several positions).

- $\mathbf{M_{ind}}$ is the maturity of the index hedge "ind." In case of more than one index hedge position, it is the notional weighted average maturity. For any counterparty that is also a constituent of an index on which a CDS is used for hedging counterparty credit risk, the notional amount attributable to that single name (as per its reference entity weight) may, with supervisory approval, be subtracted from the index CDS notional amount and treated as a single name hedge (B_i) of the individual counterparty with maturity based on the maturity of the index.

The weights are given in this table, and are based on the external rating of the counterparty:

Rating Weight w_i	
External Rating	w_i
AAA	0.7%
AA	0.7%
A	0.8%
BBB	1.0%
BB	2.0%
B	3.0%
CCC	10.0%

Basel III CVA Formula:

$$CVA = (LGD_{MKT}) \cdot \sum_{l-1}^{T} Max\left(0; exp\left(-\frac{s_{l-1} \cdot t_{l-1}}{LGD_{MKT}}\right) - \exp\left(-\frac{s_l \cdot t_l}{LGD_{MKT}}\right)\right) \cdot \left(\frac{EE_{l-1} \cdot D_{l-1} + EE_l \cdot D_l}{2}\right)$$

Where:

- **t_i** is the time of the i-th revaluation time bucket, starting from $t_0 = 0$.
- **s_i** is the credit spread of the counterparty at tenor t_i.
- **LGD_{MKT}** is the market-based loss given default of the counterparty.
- **EE_i** is the expected exposure to the counterparty at revaluation time t_i.
- **D_i** is the default risk-free discount factor at time ti, where $D_0 = 1$.

APPENDIX B

List of Acronyms

Act	The Dodd-Frank Act
BHC	Bank Holding Company
Board	Federal Reserve Board
CCP	Central Counterparty
CCR	Counterparty Credit Risk

CDS	Credit Default Swaps
CEM	Current Exposure Method
CFR	Code of Federal Regulations
CFTC	Commodity Futures Trading Commission
CME	Chicago Mercantile Exchange
CSA	Credit Support Annex
CVA	Credit Value Adjustment
EAD	Exposure at Default
EPE	Expected Positive Exposure
EU	End User
FCM	Futures Commission Merchant
FDIC	Federal Deposit Insurance Company
ICE	InterContinental Exchange
IDCG	International Derivatives Clearing Group
IM	Initial Margin
IMM	Internal Models Methodology
IOSCO	International Organization of Securities Commissions
IRS	Interest Rate Swap
LCH	London Clearing House
LGD	Loss Given Default
MSP	Major Swap Participant
NCC	Net Clearing Cost
NGR	Net to Gross Ratio
OCC	Office of the Comptroller of Currency
OTC	Over the Counter
PD	Probability of Default
PFE	Potential Future Exposure
SD	Swap Dealer
SEC	Securities Exchange Commission
SEF	Swap Execution Facility
Var	Value at Risk

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A HALF-CENTURY OF PRODUCT INNOVATION AND COMPETITION AT U.S. FUTURES EXCHANGES

Michael Gorham and Poulomi Kundu*

This paper explores the last 55 years of product innovation and competition at U.S. futures exchanges. We find that in general innovations perform better than imitations and product extensions. We find that one exchange has been a more aggressive innovator, imitator, and product extender than other exchanges and has grown to dominate the market. We find that interest rate contracts have generally outperformed others, that the 1980s was the golden decade of successful product innovation, and that there is evidence of a first mover advantage in product competition and of a liquidity driven monopoly effect.

In 1955, there were 61 futures contracts listed on U.S. futures exchanges. By the end of 2010, there were 916 contracts listed (not including futures on individual stocks).[1] This 11-fold growth in the number of listed futures products and the accompanying 668-fold increase in the volume of trading attests to the vigorous amount of product innovation and the dramatically increased importance of futures in the financial and commercial life of the country. U.S. futures exchanges have

1. There are approximately 2,000 futures contracts listed on individual stocks and exchange traded funds (ETFs) at OneChicago, the only surviving U.S. exchange that lists such products. These contracts are not included in the FIA database we will describe shortly, and this estimate was obtained from the OneChicago website on October 22, 2011. In addition, we do not include 632 OTC executed and NYMEX cleared products that are booked into NYMEX clearing via ClearPort. While these products are registered with the Commodity Futures Trading Commission as futures products and are included in the raw FIA database, they are not competing with other futures exchanges but rather with the Intercontinental OTC exchange. In addition, under regulations proposed under Dodd-Frank, most of the ClearPort products will likely not meet a test that requires that certain percentage of trading must occur on the floor or the exchange's electronic platform.

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been listing new products since they were first created in the 1860s. This process of product innovation has often been vitally important to growth of an exchange; for example, the 112-year-old Chicago Mercantile Exchange, would be 1% of its current size, had it ceased listing new products in the early 1970s. In other cases, new products provided the path for an exchange to rise from the ashes of disaster. In 1976, the New York Mercantile Exchange lost its most important product, Maine Potatoes, due to a major default caused by a reckless game of bluff by the parties on both sides of an expiring contract. The exchange shrunk to a sliver of its former self and could well have shut down if it had not listed No. 2 Heating Oil futures and reinvented itself as the world's biggest energy exchange (Gorham and Singh 2009).

While exchange turnarounds make for a good story, innovation plays a more fundamental role as a key to the ongoing growth and profitability of an exchange. The fortunes of futures exchanges depend largely upon the trading and clearing fees earned from trading volume.[2] CME Group, which now accounts for over 95% of U.S. futures volume, derived 82.7% of its revenues from trading and clearing fees in 2008 through 2010 (CME Group Annual Report 2010). Organic growth in trading volume[3] can come from two sources: increased trading in existing products and trading volume in new products. While exchanges may have some influence over the first source, via effective marketing, improvements in contract design or creating pricing incentives for both market makers and traders, trading in existing products is often driven by factors external to the exchange, such as the market dynamics of increased price volatility and significant price trends. Exchanges can have a much greater effect on their total trading volume by creating successful new futures contracts that fill some market need.

Launching successful new products involves significant uncertainty. Most fail, though really precise statistics on success and failure of futures contracts have not been readily available, a situation we intend to remedy in this paper. Few would have guessed that pork belly futures would be the Chicago Mercantile Exchange's (CME) leading contract for a decade. And the fact that the CME and the Chicago Board of Trade (CBOT) each spent about $1 million marketing their new over-the-counter (OTC) stock index contracts in the mid 1980s only to see both contracts fail miserably because the market was not yet ready for them illustrates the potential cost of failure.

There has long been both industry and academic curiosity regarding how to create successful products and how to measure that success. Most new contracts

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2. In the new world of for-profit, stockholder-owned, publically-traded exchanges, the relevant performance metric is that profits and trading volumes directly drive the revenue side of profits through per-contract trading fees. In the old world of member-owned, not-for profit exchanges, which began to disappear with the Chicago Mercantile Exchange's demutualization in 2000, trading volumes drove exchange fortunes in a different way. More customer volume translated into more commissions for the floor members acting as brokers as well as more revenue for the members acting as market makers.

3. Mergers and acquisitions have been a major source of volume growth for both derivatives and stock exchanges over the past decade as the shift to electronic trading has significantly increased economies of scale in the industry, but this is outside the scope of this paper.

stop trading within a few years. And while there would be universal agreement that zero trading volume constitutes failure, there has been much less agreement on where to draw the line between success and failure. The definition of success has typically relied on the longevity (or lifespan) of contracts or on whether trading volume has reached some specified level within a specified period of time, generally three years. And the bar has generally risen over time. For example, the following definitions of success have been used in the literature:

- 1,000 contracts per year (Sandor 1973).
- 10,000 contracts per year (Silber 1981).
- 1,000 contracts per day (250,000 per year) plus open interest of 5,000, the *Wall Street Journal* requirement for including a contract in its market activity listing (Carlton 1984; Black 1986).
- 10,000 contracts per month (Holder, Tomas, and Webb 1999).

Both Black (1986) and Hung et al. (2011) argue that in studies of the effect of various factors (such as size of the underlying market and volatility of spot market prices), it is best to forgo these arbitrary measures and simply use actual volume levels achieved by new contracts. Black, for example uses average daily volume through the first three years as the dependent variable in her attempt to explain success. While this is correct, if we wish to make statements about the numbers or percentages of new contracts that are successful, we have no choice but to choose some standards of success.

Early articles were case studies focusing on why a particular contract succeeded or failed. These include Sandor (1973), who explored factors that contributed to the performance of plywood futures, and Johnston and McConnell (1989), who found bad design behind the failure of the GNMA CDR contract. Nothaft and Wang (2006) later studied the design of the GNMA CDP futures contract. Silber (1981) looked at the entire U.S. market and found that of the 130 new contracts listed between 1960 and 1977 only 24.6% had become successful, measured by trading at least 10,000 contracts in the third year after launch. He also found that both exchange size and being the first mover mattered. The five largest exchanges had success rates twice the level of the five smallest exchanges. And newly innovated contracts were 50% more successful than were similar contracts created by imitating contracts at other exchanges.

Carlton (1984) looked at contracts between 1921 and 1983 and measured contract success by average lifetimes and survival rates. Black (1986) measured success using the *Wall Street Journal's* criteria for listing a futures contract, specifically daily open interest above 5,000 contracts and daily trading volume above 1,000 contracts.

Corkish, Holland, and Vila (1997) focused on product innovation at the London International Financial Futures Exchange (LIFFE) from 1982 to 1994. They measured success using contract life spans and trading volume and found that most futures contract succeeded in the early years of the exchange. They found that contract success was highly correlated with the size and volatility of the underlying market and confirmed the existence of a first mover advantage. The study draws the conclusion that the determinants of success are large and volatile spot market and competition.

Industry statements about success and failure in product innovation have often been seat-of-the-pants estimates. This paper makes use of a largely overlooked goldmine of data, converts it into a product innovation database and uses it to generate concrete, hard data answers to a number of questions regarding the innovation process. A careful analysis of this data will allow us to begin to answer such questions as:

1. What is the expected lifespan and lifetime volume of a new futures contract?
2. Whether a new future contract's success depends on the contract's
    a. underlying asset class.
    b. listing exchange.
    c. the decade in which the product was listed.
    d. degree of innovation, that is, whether the contract is
        i. a true innovation.
        ii. a product extension listed at the same exchange.
        iii. an imitation product listed at a competing exchange.
3. Do new listings in a particular asset class come in clusters as exchanges compete for market share?
4. To what extent do exchanges have monopoly positions in specific product listings?
5. When exchanges compete head-to-head with nearly identical products, how long does it take for one exchange to emerge as the dominant or exclusive market?
6. Are competitions between exchanges for nearly identical contracts always winner-take-all events? When are they not?
7. To what extent do these monopoly positions in individual products extend to asset classes?
8. With increased innovation and proliferation of products, has the share of trading volume concentrated in the highest volume products declined significantly over time?

The purpose of this paper is two-fold. First we will update some conventional metrics and present some previously uncalculated metrics on the process and performance of product innovation in U.S. futures markets over the past 55 years. Second, we will examine the extent to which a first mover (or innovator) advantage and liquidity-driven monopoly play a role in exchange competition over products. The paper is organized as follows. Section I describes the original FIA data source and how we have created a product innovation database that should be useful to other researchers. Section II lays out the descriptive statistics of a half century of product innovation in U.S. futures markets, something heretofore not readily available.

Section III examines the role of first mover advantage and liquidity-driven monopoly in product competition among exchanges. Section IV explores the paper's conclusions.

I. THE DATA: SOURCE AND ENHANCEMENTS

Since 1955 the Futures Industry Association (FIA) has been collecting monthly and annual volume data directly from exchanges. In its annual version, the data consists of all futures contracts that had some trading volume during the prior year. Contracts are organized by the listing exchange. So for each year, the FIA provides: the exchange name, the contract name, the contract size (e.g. 5,000 bushels for wheat), the contract category (five categories including agricultural, equity, interest rate, etc.) and volume of trade (i.e., the number of contracts traded that year). There are no other descriptors in the raw data.

Our objective was to use this data to build a database useful for describing and studying product innovation and competition in the U.S. futures industry. While this study focuses on the U.S. futures market, the FIA data also include the volume of options contracts traded at U.S. futures and options exchanges.

We have inferred from this data that a contract started life in the first year for which a volume number is displayed and ended its life in the last year in which a non-zero volume number was displayed. For example, Anhydrous Ammonia futures first show volume in 1992 and continue to do so through 1997 when 19 contracts were traded. In 1998 and subsequent years no volume is shown. We infer from this that this fertilizer contract started sometime in 1992, died sometime in 1997, and had a life of 6 years. Because the data are annual and do not tell us the date on which the contract started and stopped, the actual life could have been as little as four years or as much as six years.[4]

In cases where contract volume numbers appear for one or more years, then stop, then start showing volume again without a change in size, we calculate the contract's life span as the number of years for which the contract shows non zero volume. For example, French Franc futures started trading at the CME in 1974 and traded till 1990. There was no volume during 1991 and 1992. However, the years 1993 and 1994 show volume again. In such cases, we consider the life to be 19 years.

A. Innovations, Imitations, and Product Line Extensions

The major enhancement we have made to the FIA data is to tag every one of the 916 new contracts with one of three labels:

- An innovation.

4. The actual life would have been just over four years (if it started at the end of 1992 and died in the first days of 1997) or as much as six years (if it started on January 2 and died on December 30). Given a 1992 start and a 1997 end, we can thus infer that the life of this contract was four, five, or six years. Which is most reasonable? Assuming that contract births and deaths are uniformly distributed over the year, the inference that minimizes errors and gets closest on average would be the middle one.

- An imitation – an imitation of a contract previously traded at another exchange.
- A product extension – a variation on a contract previously listed at the same exchange.

Deciding the definition of "innovation" was the most difficult part of preparing the contracts for analysis. At one extreme, one could argue that there have only been a handful of true innovations in futures markets: the first agricultural product, the first currency, the first interest rate, the first equity index. While this might seem reasonable, it is not useful for analyzing the competition among exchanges to offer products that satisfy customer needs. While cattle, hog, corn, and wheat futures are all agricultural products, each offers price risk management tools for very different needs, and we considered the first futures contract in each one of these categories as an innovation.

Likewise, the first interest rate futures contract was the mortgage-backed security issued by Ginnie Mae, the GNMA collateralized depository receipt (GNMA CDR) in 1975 at the CBOT, clearly an innovation. The following year, U.S. Treasury bill futures were launched at the CME, which we also tagged as an innovation, because it was a different issuer. When the U.S. Treasury bond was launched a year after T-bills, we tagged it as a separate innovation, because though it was the same issuer, it was a short-term discount issue as opposed to the longer-term coupon instrument. Finally, when two-year Treasury note futures were launched at NYMEX in 1980, because this was another longer-term, coupon Treasury issue, it was tagged not as an innovation but as an imitation, because it was listed at an exchange different from the innovating exchange. NYMEX T-Note failed within a year, and when the CBOT started its own 6.5-10 year T-Note in 1982, it was tagged as a product extension of the T-bond innovation at the same exchange.

In order to ensure consistency of treatment, we had to establish detailed rules for categorizing the level of innovation of all the products we reviewed.

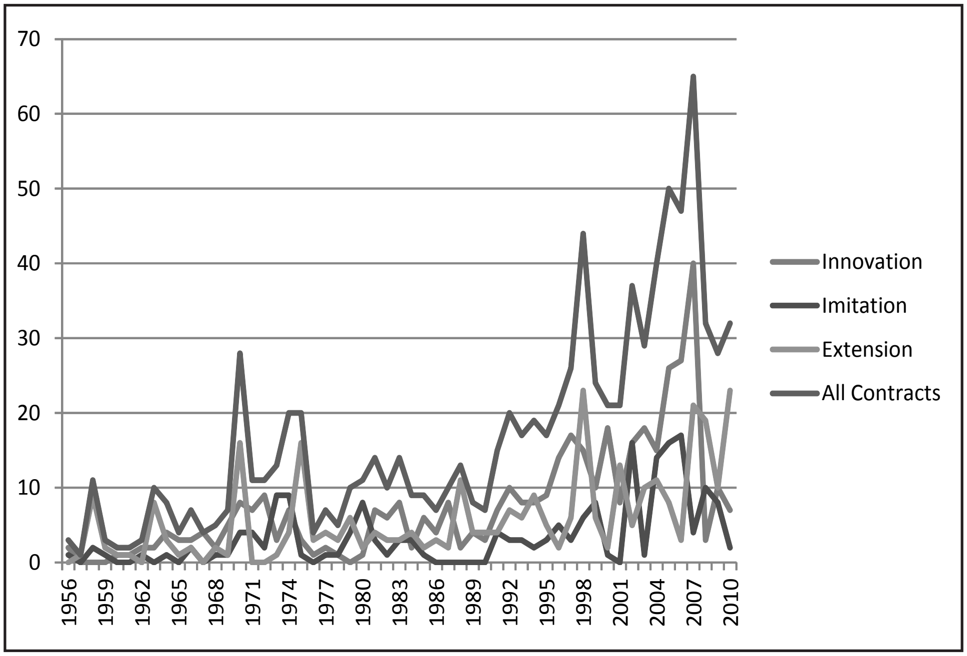
An **innovation** includes:

1. The first time a new product appears at any exchange.
2. A switch from physical delivery to cash settlement of any product. The CBOT introduced 10 versions of the GNMA contract with minor changes. All but the first were product extensions, except for a cash-settled version introduced in 1986, which we count as an innovation.
3. A movement up or down the processing chain. Gasoline and heating oil are produced from crude oil, but the first contract in each of these three distinct products was tagged an innovation.
4. A reduction in contract size to retail mini. Most futures contracts have been designed to appeal to a commercial hedging audience. Exchanges will make modest changes in contract size to better fit commercial needs. The creation of new, much smaller, retail-oriented versions of existing contracts was a trend, often highly successful, that began in the mid 1990s.

We have labeled these new contracts that are at least 50% smaller than the parent contract as innovations. (About 10% of all innovations were minis, and if the 46 minis were classified as product extensions rather than innovations, innovations would fall to 362 and extensions would rise to 365.)

5. A switch from U.S. to foreign delivery, thus reflecting price in a different market (e.g., CBOT's South American Soybeans were an innovation).
6. Switch from single par grade to index of multiple grades and locations (generally captured under the cash settlement change mentioned earlier).
7. For currencies: different currency pair. Same currency pair switching from American to European pricing is not an innovation.
8. For interest rates:
   a. Different issuer. The U.S. Treasury, U.S. government agencies, municipal entities, corporations, and each foreign entity are different issuers. So, the first German government bond and Argentine FRB bond are both innovations, but the Brazilian EI bond and Brazilian C bond would not both be innovations unless they were issued in the same year. (They were in fact both issued by the CME in 1996 and because we could not tell which came first, they were both tagged as innovations.) CBOT Commercial paper futures listed by the CBOT in 1997 was the first corporate issue of short-term paper and was tagged an innovation.
   b. Different currency of issue. Eurodollars, Euroyen, Euromark and EuroCanada were all tagged as innovations.
   c. Short-term, discounted instruments are different from longer-term, coupon instruments. (The maturity divide is typically at one year.) So Treasury notes and bonds of all maturities are all considered the same type instrument and only the first of all these, the 1977 listed T-bond is tagged an innovation.
9. For stock indexes: We explored criteria like market capitalization, style, sector, and publisher as ways to segment the 132 equity indexes into different homogenous groups, and it may be possible to do this in a reasonable way. However, unlike most assets underlying futures contracts, equity indexes are generally protected intellectual property and most indexes are licensed by publishers to exchanges on an exclusive basis (with exceptions like Russell, which for years granted only non-exclusive licenses). This makes head-to-head competition difficult. Two exchanges can list identical corn contracts, but only the CME can list the S&P 500. So we have taken the approach of treating most equity indexes as innovations. Exceptions include:
   a. When an exchange changes the dollar multiplier on its stock index, we tag that an extension. For example, the CME listed the S&P 500 in 1982 with a multiplier of $500. In 1994, it listed a new version with

Figure 1. New Contracts Launched Annually 1956-2010.



a multiplier of $250, because the index had increased so much that the contract value and associated margins had gotten quite large. We tagged the new contract as an extension of the first.

b. When an exchange lists an index that had already been listed at another exchange. The CBOT licensed and listed the Nasdaq 100 index in 1985 when there was not sufficient interest in the market and the product died the next year. Eleven years later in 1996, the CME licensed and listed the same index. We tagged this as an imitation.

A **product extension** is when an exchange makes a size, grade or location change in one of its previous innovations, other product extensions, or imitations. The only exceptions as noted above are when the size change is to a retail mini, or the delivery location is switched to a foreign country, either of which causes the product to be considered an innovation. Note also that there are only two sources of information regarding contract specifications: the contract size or index multiplier (which is generally given in the FIA reports) and the contract name (which might indicate a change in delivery location). For example, in 1964 the CME listed the first Live Cattle contract, clearly an innovation. The following year it listed a Live Cattle Western contract alongside the first. From the name, we knew this referred to a different delivery location and tagged it an extension. However, if a contract undergoes a significant change that is captured in neither the size nor the name, our system will not capture it as a product extension.

An **imitation** occurs when an exchange lists a product previously listed by another exchange, whether the new product is identical to or differs by size, grade, or location from that of the other exchange. The only exceptions as noted above are when the size change is to a retail mini, or the delivery location is switched to a foreign country, either of which causes the product to be considered an innovation.

II. DESCRIPTIVE STATISTICS ON PRODUCT INNOVATION IN U.S. FUTURES MARKETS

Before we examine the metrics generated from the 1955–2010 data, we must first make a general point. During the first 110 years of organized futures trading in the United States, all futures contracts were based on physical commodities, mainly agricultural products. Then, in a concentrated period of a single decade (1972 to 1982), there were three key, and overlapping, waves of innovation that literally reshaped the industry. Foreign exchange futures began in 1972, interest rate futures in 1975, and stock index futures in 1982. While there has been a tremendous amount of innovation during the subsequent 28 years, today's blockbuster contracts, which have been the main drivers of growth, are those that were either created during this decade, or are product extensions of those earlier contracts.

A. Innovative Activity

1. Creation of New Contracts 1956–2010

During the 55-year period, U.S. exchanges listed 916 new contracts, about 17 per year on average. Most prevalent were actual innovations (44%), followed by product extensions (35%), with imitations by other exchanges as the least common type of new contract listed (21%).

Figure 1 makes clear that the frequency of new contract launches has changed markedly over the years. First, there has been a secular increase in annual new product launches during this half century period. The 1950s and 1960s were rather sleepy with new launches averaging about five per year. There was a burst of activity in the 1970s, when the number of new product launches tripled to about 15 per year. There was a bit of a lull in the 1980s, but beginning in the 1990s, there was another explosion in new product development that peaked at 65 new products in 2007. While there was a lot of year-to-year variation, almost every decade has had more new products listed than the decade prior.

Why did the growth in new product launches accelerate from 2001 to 2008? There were two major forces that made the process of product innovation easier, cheaper, and more enticing during the last decade of our study period. The first was the passage of the Commodity Futures Modernization Act in December of 2000, which allowed exchanges to list products much more quickly and easily and with less labor. In the old world, exchanges wishing to list new products were required to create a thick document that explained and justified every term and condition in the contract and explain the economic purpose of the new contract, specifically how it would be used to reduce commercial risk. It would take months, and sometimes over a year, to create this document, referred to as the Contract Justification. Once the CFTC received the proposed futures contract, it then had up to 12 months to approve it.

Exchanges argued to Congress that they were at a competitive disadvantage to European exchanges, which could get new products approved in a matter of weeks. So Congress inserted a provision in the new legislation that said only two things needed to be given to the CFTC: a copy of the proposed contract and a letter from the exchange certifying that the new product was consistent with all applicable laws and regulations. Having so certified the contract, they could list it the next day. It was now up to the CFTC to do the research required to see if the contract did actually comply with all laws and regulations.

The second force that made product innovation easier was the switch from floors to screens, which began more seriously at the two large Chicago exchanges in 2003–2004 when they were faced with serious competition from a new Chicago subsidiary of the giant, all-electronic, German exchange, Eurex. Electronic exchanges significantly reduce the cost of listing new products. In the earlier floor-based world, new products needed floor space and bodies on the floor to make markets in the new products. In the electronic world, all that is needed is a little space on a server. Economies of scale in an electronic world become huge, and exchanges try to race each other down the average cost curve.

2. New Contracts by Commodity Category

Even though they were not introduced until 1972, over half of all new contracts listed during the 55-year study period were financial (see Table 1) and the most frequently listed categories of product were foreign exchange (238), followed by agricultural products (200), equity products (132) and interest rates (129). Energy futures contracts, after excluding the OTC ClearPort products, which are cleared but not traded on NYMEX, were ranked sixth out of eight. Metals were last.

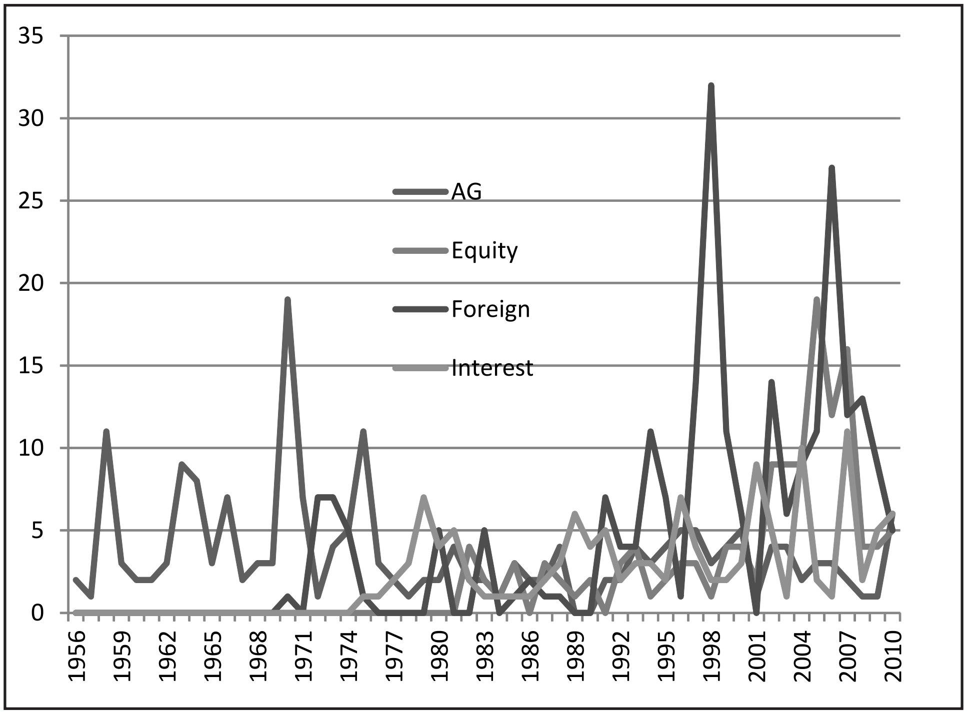
We noted earlier that overall new products were largely innovations (44%), then product extensions (35%) and finally imitations by other exchanges (21%). It is striking that none of the individual commodity groups followed that pattern. Agricultural products were mainly product extensions — not a surprise as cash market grades, weights, and delivery procedures evolve over time and futures contracts are redesigned to reflect these changes. Also, many of the agricultural innovations took place before 1955. Only foreign exchange and equities had more innovations than imitations and extensions. And the fact that 92% of all equities were innovations is a manifestation of our classification of each exclusively licensed stock index as an innovation. Russell stood out from other index publishers by granting non-exclusive licenses until just recently. There are just under 200 countries in the world and the fact that there were 98 FX innovations suggests that there are futures contracts on close to half those currencies.

Looking at the pattern of new contract launches over the 1956–2010 period (Figure 2), new products were almost exclusively agricultural until the 1972 launch of seven new currency futures contracts by the CME, and in 1970 U.S. exchanges listed an all time record 19 agricultural contracts. Financial products (currencies, then interest rates, and then equities) took over most of the new product momentum

Table 1. Number of New Contracts by Innovation Type and Commodity Category: 1956-2010.

	FX	Ag	Equity	Interest Rate	Other	Energy	Precious Metals	NP Metals
Innovations	98	60	121	49	37	28	11	3
Imitations	87	32	6	24	10	13	15	3
Extensions	53	108	5	56	42	33	17	5
All New Contracts	238	200	132	129	89	74	43	11

Figure 2. New Contracts by Commodity Category.



beginning in the mid 1970s, and after 1975 the number of new agricultural contracts never exceeded five in any year.

3. New Contracts by Exchange

Only six of today's futures exchanges existed at the beginning of our study: the two large Chicago (CBOT and CME) and two smaller New York exchanges (NYMEX and ICE, both the results of mergers and purchases along the way) and the two tiny regional exchanges (KCBT and MGE). The larger exchanges were much more aggressive at listing new contracts than were the tiny regional exchanges (Table 2). Could the regionals have become large exchanges had they worked harder at launching new contracts? It is doubtful. During the floor trading era, all important financial exchanges, both for securities and derivatives, were located only in the biggest financial and commercial centers. Only in the more recent electronic era did non-New York securities exchanges such as BATS start developing serious market shares. So no matter how many new contracts Kansas City and Minneapolis listed, it is doubtful they could have won serious market share. In addition, Minneapolis listed about twice as many new contracts as Kansas City but had less than one-third the volume of its Midwestern rival.

What is absolutely clear is that the CME, the exchange that eventually won the decades-long battle with the older and larger CBOT, trumped its larger opponent, and everyone else, in all measures of new products. Over the 55-year period, the

Table 2. New Contracts – by Exchange (1956-2010).

Exchange	Years Exchange in Business (1956-2010)	Total New Contracts	Innovations	Imitations	Extensions
CME	56	279	131	54	94
ICE	56	217	99	48	70
CBOT	56	161	70	17	74
NYMEX	56	101	38	17	46
Others*	54	74	22	37	15
CFE	7	24	23	1	
CCFE	5	20	10	1	9
MGE	56	17	6	3	8
KCBT	56	9	5	2	2
NYSE LIFE	3	8	4	4	
ELX	2	6		5	1
Total		**916**	**408**	**189**	**319**

Other* exchanges (orphaned exchanges) include ACE, BTEC, InCuEx, MBOTCA, MWGE, NFX/PBOT, SGE, SLM, US Futures Exchange/EUREX US and WCCE.

Table 2a. New Contracts – Orphaned Exchanges (1956-2010).

Exchange	Years Exchange in Business (1956-2010)	Total New Contracts	Innovations	Imitations	Extensions
USFE/EUREX US	5	40	15	17	8
PCE	5	10	3	3	4
WCCE	5	8	3	5	
NFX/PBOT	9	8		8	
ACE	3	3		3	
BTEC	3	3			3
InCuEx	4	1	1		
SLM	1	1		1	
SGE	5	0	0	0	0
MWGE	11	0	0	0	0
MBOTCA	10	0	0	0	0
Total		**74**	**22**	**37**	**15**

CME had 90% more innovations, 218% more imitations, and 27% more product extensions than its cross-town rival. In 2007, the CME bought the long-time world's largest derivatives exchange.

Note that Table 2 lists all exchanges that were active at the end of the study. The group of exchanges under the label "Others" are all the orphaned exchanges, exchanges that had active trading at some point during the 1955–2010 period, were not absorbed by another exchange, but just turned out their lights and went out of business. These exchanges are listed in Table 2a. Note that most were not in business long, at least during our study period, and did not list many new contracts. The three

Table 3. Average New Contracts Per Year by Exchange: 1956-2010.

Exchange	Years Exchange in Business	Total New Contracts	Innovations	Imitations	Extensions
CME	55	5.1	2.4	1.0	1.7
CBOT	55	2.9	1.3	0.3	1.3
NYBOT	55	2.4	1.0	0.4	1.0
NYMEX	55	1.8	0.7	0.3	0.8
ICE	51	1.7	0.8	0.6	0.3
USFE	5	8.0	3.0	3.4	1.6
CFE	7	3.4	3.3	0.1	0.0
CCFE	5	4.0	2.0	0.2	1.8
MGE	55	0.3	0.1	0.1	0.1
KCBT	55	0.2	0.1	0.0	0.0
NYSE LIFE	3	2.7	1.3	1.3	0.0
NFX	9	0.9	0.0	0.9	0.0
ELX	2	3.0	0.0	2.5	0.5
InCuEx	4	0.3	0.3	0.0	0.0
Others	42	0.6	0.1	0.3	0.2

orphaned exchanges that started before 1956 did not list a single contract during the 5 to 11 years they were in business during the study period. The exception was the very aggressive USFE, which listed more contracts per year of life than any other exchange. This was not good enough to keep the USFE from going out of business.

But given that the CME and other exchanges were in business during the entire 55-year study, while others have been around less than a decade, it is appropriate to take a look at the rate of innovation per year during the period each exchange conducted trading operations (Table 3). By this measure, several of the newer exchanges were more aggressive developers of new products. The CBOE Futures Exchange (CFE) listed the most innovations per year. New exchanges start out with no business, and it is risk reasonable that they would be fairly aggressive at listing new contracts, since they know that only a portion of new contracts succeed. But aggressive listing of new products is not sufficient to ensure an exchange's success. Of the four new exchanges that were most active, CCFE lost volume rapidly after it was clear that the U.S. Congress was not going to adopt cap and trade legislation, thus making its emissions contracts much less compelling. And the CFE, which listed 3.3 innovations each year during its seven years of life, hit on only one winner, the VIX, which in 2010 accounted for 99.8% of its trading. ELX,

Table 4. Number of New Contracts by Exchange and Commodity Category: 1956-2010

	FX	Ag	Equity	Interest Rate	Other	Energy	Precious Metals	NP Metals
CME	72	62	56	39	40	6	3	1
ICE	126	50	24	7	7	3	0	0
CBOT	9	42	16	55	15	7	15	2
NYMEX	8	17	2	3	2	49	13	7
Others	23	11	8	19	4	0	8	1
CFE	0	0	18	0	1	5	0	0
CCFE	0	0	0	0	20	0	0	0
MGE	0	15	0	0	0	2	0	0
KCBT	0	3	4	0	0	2	0	0
NYSE LIFE	0	0	4	0	0	0	4	0
ELX	0	0	0	6	0	0	0	0

which copied the strategy of Broker Tec and the USFE, by listing the major Treasury contracts of the CBOT, had an average record of launching new contracts, but had by far the highest volume of all the new entrants. A likely reason for this is because ELX is owned by some of the biggest financial trading institutions in the world, which have an interest in creating competitive pressure on CME Group to keep trading fees down and are thus likely to direct a portion of their orders to ELX.

It is also useful to take a look at which commodity categories each exchange has chosen to specialize in (Table 4). For example, while there were eight exchanges that listed 238 foreign exchange contracts, 83% of these contracts were at two exchanges: the CME and ICE/NYBOT. The CME was the innovator, listing the first successful currency contracts in 1972. The first currency futures was actually listed in 1970 at the International Currency Exchange (which called itself ICE, but which we have listed as InCuEx, to avoid confusion with the modern ICE Futures U.S. owned by the Intercontinental Exchange and listed simply as ICE in these tables). Because this was during the time that the Bretton Woods fixed exchange rate system was still in place, this first contract was premature and failed. Realizing that the CME had already created liquid markets in the major currency pairs, the FINEX subsidiary of the Cotton Exchange, which became absorbed into NYBOT and was later purchased and renamed ICE Futures US, decided to specialize in the dollar versus a trade weighted basket of currencies as well as in currency pairs that did not include the dollar, the latter referred to as cross rates.

There are similar stories in each commodity group. Take equity index futures. The innovator was the KCBT which listed the Value Line index a few months before the CME listed the S&P 500 in 1982. The original KCBT innovation is now dead and the CME's S&P 500, or more specifically the E-Mini S&P 500, a 1997 version with a multiplier one-tenth the size of the original contract's multiplier, is the largest in the world. While nine U.S. exchanges have listed 132 equity indexes since 1982, only five now have contracts. One contract, the E-Mini S&P 500, accounted for 75% of all U.S. equity index futures trading volume in 2010 and the CME's total market share of equity index futures was 89%.

In some instances a government action drives exchanges to list products all at one time. There is no better example than Congress' decision, effective December 31, 1974, to repeal the Gold Reserve Act of 1934, making it again legal for Americans to own gold. Five exchanges launched gold contracts on December 31.[5] By 2010, only one of the original five exchanges still listed gold (COMEX) as did one new competitor (NYSE LIFFE).

5. There was actually an earlier attempt. One exchange, the West Coast Commodity Exchange (WCCE), believing it had found a loophole in the Gold Reserve Act that allowed Americans to hold gold coins minted prior to 1934, launched a gold coin futures contract on July 20, 1971. Under very heavy pressure from the U.S. Treasury, the WCCE halted trading in less than a week. And two New York exchanges which were planning their own contracts on placer gold, the gold nuggets found in rivers and streams, decided not to move forward. (*The Gazette*, Emporia, Kansas, August 4, 1971, p. 4, reprinted from *Barron's*).

Table 5. Lifespan of New Contracts (in Years) 1956-2010.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Innovation	1	2	3	5.8	6	54
Imitation	1	2	3	4.8	6	37
Extension	1	2	3	6.0	7	41
All New Contracts	1	2	3	5.7	7	54

B. Success of New Contracts

As mentioned, prior research measured success by product lifespan, by comparing the volume of trading in a specific year following launch to some specific benchmark like 1,000 contracts or 10,000 contracts or by volume over some specified period, like three years. We will show a variation on all these measures plus one additional measure, the discounted value of estimated trading fees earned by the exchange for a specific product.

1. Lifespan of Contract

Lifespan of contract is a measure that tells us how long a contract proved to be useful to the marketplace, but it says little about how broadly useful the contract is. For example, we cannot say that a low-volume contract that lasts 50 years is more successful than a very high volume contract that lasts 20 years. What may be most surprising about our 55-year sample is that the average contract lasts only 5.7 years (Table 5). And while product extensions have the longest lives and imitations the shortest, the differences are a little over a year. Note that the shortest life possible is one year, which could be anywhere from one day to 364 days because we are using annual data. Any contract showing volume in one year only is given a lifespan of one year. The longest life possible is 55 years for a product that was launched in 1956 and still trading in 2010. In fact, the longest lived innovation was 54 years, while the longest lasting product extensions and imitations were over a decade shorter.

2. Lifetime Volume of New Contracts

A much better measure of contract success is the total lifetime volume generated by that contract. This measure should be proportional to the value the market puts on the contract and to the revenues earned by intermediaries, by market makers and by exchanges. This is where the true innovations stand out, generating almost three times the volume of imitations and 50% more than product extensions (Table 6). These numbers suggest that on average the first mover (the exchange with the innovation) does much better than an imitation or extension of that same contract. Note that the means are as much as one to two thousand times the medians. This results from the fact that many contracts generate almost no volume. There were,

Table 6. Lifetime Volume of New Contracts 1956-2010.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Innovation	1	1,236	15,730	31,330,000	306,300	4,977,000,000
Imitation	1	1,623	18,250	11,450,000	172,100	799,700,000
Extension	1	1,578	24,540	21,630,000	349,800	2,262,000,000
All New Contracts	1	1,430	18,868	23,830,000	288,800	4,977,000,000

Table 7. Lifetime Present Value of Trading Fees from New Contracts ($).

	Min	1st Qu	Median	Mean	3rd Qu	Max
Innovations	0	151	1,592	2,091,000	25,450	300,600,000
Imitations	0	170	1,762	832,700	15,550	62,879,000
Extensions	0	168	2,420	1,478,000	39,780	121,200,000
All New Contracts	0	163	1,743	1,617,000	25,940	300,600,000

for example, 104 new contracts that had lifetime volumes of less than 100 contracts. There were, on the other hand, five contracts that delivered lifetime volumes of over one billion contracts: Eurodollars, 5.0 billion; E-mini S&P 500, 3.1 billion; 10-year Treasury notes, 2.3 billion; Treasury bonds, 1.7 billion; and 5-year Treasury notes, 1.2 billion.

The shortcomings of both this and the following measure are that they biased in favor of contracts launched earlier, since earlier launches have more time to build up their lifetime volume. So new exchanges should often do worse by this measure, and any comparison across contracts risks false results due to this bias.

3. Present Value of Trading Fees Paid to Exchanges

The logic of this measure is consistent with mainstream financial decision making. A firm will engage in projects for which the net present value (PV) is positive. Ideally we would take the costs of creating, listing, and maintaining a new product and then calculate the revenues the new product brings in and subtract the present value of the revenues from the present value of the costs. Traditionally, the bulk of exchange revenues came from trading and clearing fees, followed by sales of market data, followed distantly by interest earned, fines levied on misbehaving members, membership fees, and other modest sources. While there is some anecdotal information available on costs, accurate information is not readily available, even in the annual reports of the publicly traded exchanges. But it would still be helpful to rank contracts by the present value of the revenues they generated to see if there were significant differences in revenues among types of contracts.

We should start by saying that we do not know the trading fees that were paid to each exchange for each contract over the past half century. We also do not know when fees were discounted for new contracts for market making and other reasons.These things might be knowable, but it would be difficult to find out. We have therefore made two simple assumptions. First we assume that the fee structure maintained by the CME for a decade or more through the 1980s was used by all U.S. exchanges from 1955 to 2010. This trading/clearing fee was 75 cents for customers and 25 cents for members. Second, we assume that the trading mix between members and non-members was 50-50, which gives us an average $1 fee collected per contract traded for both sides of the trade.

We would use the weighted average cost of capital to discount these fees, if exchanges were stockholder-owned firms that issued equity and bonds to raise cash to fund product development. But for about 80% of the 1955 to 2010 period, exchanges were not-for-profit, member-owned entities that paid for operations out of current revenues and avoided the stock and bond markets. So we approach this by asking what the opportunity cost for member-owners who bought seats was, and we argue that they would have invested in the stock market, allowing us to use the compound annual growth rate of the S&P 500 from 1955 to 2010, which was 6.13%. So we use a discount rate of 6% to discount future fees resulting from new contracts.

Based upon these assumptions, we calculate that the present value of lifetime

Table 8. Success Level – Volume in Fifth Year by Innovation Types 1956-2006.

	Innovation	Innovation (%)	Imitation	Imitation (%)	Extension	Extension (%)
Highly successful	79	19%	94	30%	32	17%
Successful	26	6%	38	12%	6	3%
Moderately	105	26%	68	21%	53	28%
Dead	197	48%	119	37%	99	52%
Total	407	100%	319	100%	190	100%

Table 9. Success Level in Fifth Year (% 1956-2006).

	Highly Successful	Successful	Moderately Successful	Dead	Total
CME	8%	8%	25%	59%	100%
ICE	1%	8%	34%	57%	100%
CBOT	6%	14%	23%	58%	100%
NYMEX	11%	7%	24%	58%	100%
Others	1%	1%	15%	84%	100%
All Exchanges	**5%**	**8%**	**25%**	**62%**	**100%**

Table 10. Success Level in Fifth Year by Category 1956-2006.

	Highly Successful	Successful	Moderately	Dead	Total
Ag	8%	13%	26%	54%	100%
Other	43%	9%	16%	33%	100%
Equity	33%	7%	17%	44%	100%
FX	18%	5%	39%	38%	100%
Interest	27%	4%	12%	57%	100%
NP Metal	9%	18%	27%	45%	100%
Energy	27%	4%	20%	49%	100%
Prec Metal	21%	14%	28%	37%	100%

revenue generated by the average new contract was $2.1 million (Table 7). Innovations did about 30% better than the average contract and imitations did only half as well. Similar to the case of lifetime volume, the first mover contract generated about 2.5 times the revenue as the imitation contracts. Note that the single best performing innovation, Eurodollars, generated a present value of $300 million in revenue on a lifetime volume of 5 billion contracts traded (Table 7).

In order to remove the bias involved in lifetime volume and present value of lifetime earnings, we also calculated the present value of revenues generated in the first five years and the first 10 years of a contract's life. While these numbers will be shared later in the paper (in Table 11) when we compare six different measures of contract success, we will say here that taking a shorter term view makes product extensions look almost as attractive over 10 years and 50% more attractive than innovations over a five-year period. In fact, over a five year period, both product extensions and imitations generate more revenue than do innovations.

4. Volume in the Fifth Year

Some of the earlier research judged success by how actively a new contract traded in the third year of life. Because of our larger time span, we are giving new contracts five years to show whether they have traction or not. So for every new contract we capture how much trading took place in its fifth year. For example, we would measure 1984 volume for a contract launched in 1980. Because we use annual data, we do not know whether the contract started in January or December of 1980, meaning by the end of 1984 it could have had either a full five years or only a bit over four years to develop. This variance becomes less important the further out we go and is another reason why the fifth year is a better choice than the third year.

Prior research looked at a single number that divided successful from unsuccessful contracts, with various authors using 1,000, 10,000, 120,000, and 250,000 contracts per year as the threshold for success. Rather than use a single threshold, we create four categories of success based on volume in the fifth year of trading:

Highly successful – greater than 1 million contracts.

Successful – between 100,000 and 1 million contracts.

Moderately successful – between 0 and 100,000 contracts.

Dead – zero contracts.

There is a bit of arbitrariness in choosing any specific definition, but multiple tiers allow us to recognize that there are levels of success in most endeavors, as manifested by gold, silver, and bronze in the Olympics.

We notice first that a bit more than half of all new contracts have zero volume in their fifth year (Table 8). We also notice that a visible share of new contracts is highly successful and that imitations (30% highly successful) do considerably better than innovations (19% highly successful).

Are some products noticeably more successful than others? We can see from Table 10 that about half of all new interest rate, agricultural, and energy contracts have gone to zero volume on or before the fifth year of trading. The fact that agricultural products die more frequently and are least likely to become highly successful is consistent with the low hanging fruit theory. Because agricultural futures contracts have been around since the 1860s, all of the most obvious agricultural products have already been converted into futures contracts, leaving only the least likely to succeed. One would generally expect the success rate in any product category to decline over time.

Not all products fit neatly into this theory, but the product categories with the smallest percentage of highly successful contracts are also the oldest — agricultural, metals, and foreign exchange.

5. Consistency of Product Success Measures

We have examined six measures of success in launching new futures contracts. Do we find that the six measures point in the same direction regarding the best performing innovation types, exchanges, commodity categories, and time periods? While we never find perfect uniformity across all these measures, we do find strong tendencies in the same direction.

Regarding levels of innovation (Table 11), the three most comprehensive measures of success, lifetime volume, the PV of lifetime revenue, and the PV of 10-year revenue all suggest that innovations are the most profitable new contracts to launch. Extensions last a few months longer and have the highest PV of five-year revenue than do innovations. Also, imitations have the highest fifth year volume.

When we examine success by exchange (Table 12), the CME wins by almost all measures. The NYMEX's contracts lasted one month longer on average. It is well known that from 1955 till 2000, the CBOT had substantially higher volumes than all other exchanges, so the fact that the CME gradually closed the gap and then pulled ahead was due in part to the fact that its new contracts performed better than the CBOT's.

Is there consistency among the success measures when applied to commodity categories? By measures of lifetime volume and revenue, interest rates absolutely dominated (Table 13). However, by the shorter term benchmarks, equities did better. This is explained partly by the fact that the first interest rate futures contracts began in 1975 and had a seven-year lead on the 1982 launch of stock index contracts. Also, stock index contracts appear to build volume more rapidly on average than do interest rate contracts. While we have made clear that we do not put much stock in the lifespan as a measure of success, we note that precious metals last over twice as long as equity and interest rate contracts. This is due to these contract's early starts. Platinum was listed in 1956, silver in 1963, and palladium in 1968.

We finally apply these six success measures to see which time periods have generated the most successful contracts (Table 14). By almost every measure, the 1980s was the golden decade for successful launches. The average lifetime volume of contracts born in the 1980s was 76.3 million, more than twice any other decade. There is a natural bias here in that contracts launched in earlier decades have more time to build lifetime volume. Note however, that the average volume for 1980 new listings is over twice that of the 1970s and 65 times that of the 1960s. The 1960s saw launches exclusively in physical commodities and the 1970s mainly in physical commodities. The 1980s was the first decade to be dominated by financial launches, and financial contracts attracted much more trading than trading in physical commodities ever did. Note also that one of the few success measures that the 1980s did not win in was volume in the fifth year of trading. The average contract in the 1990s had built up a volume of one million in the fifth year, compared to 707,200 for 1980s contracts. Part of this was due to the spectacular performance of the 1997 E-mini S&P 500, which reached 39 million by the fifth year.

III. PRODUCT INNOVATION AND COMPETITION

In contrast to some other countries with a single futures exchange, the U.S. futures market has been long characterized by a number of exchanges aggressively competing for market share. The direct competition over products often involved the top two exchanges, the CBOT and CME, but there were many cases in which multiple exchanges would list identical or very similar products about the same time. Sometimes such multiple listings are driven by events. For example, when the law prohibiting Americans from owning gold was eliminated in 1974, there were seven gold futures contracts listed at five different exchanges within a very short period of time.

Given the tendency of product competition to be winner-take-all, and the belief that the winner will generally be the first exchange to build up significant market liquidity in a new product, a common exchange strategy is to attempt to be first in launching new markets. If one exchange learns that another exchange is developing a new product, it will attempt to come to market with the same or similar product as quickly as possible in order to minimize the time advantage of its competitor.

Table 11. Success Measure by Innovation Types.

SUCCESS MEASURE	Innovations	Imitations	Extensions	All contracts
Life Span (yrs.)	5.8	4.9	6.0	5.7
Lifetime Vol	31,330,000	11,450,000	21,630,000	23,830,000
PV lifetime revenue	2,091,000	832,700	1,478,000	1,617,000
PV 10-yr revenue	865,400	536,100	688,600	738,600
PV 5-yr Revenue	200,700	88,910	296,000	209,800
5th Year Volume	558,000	691,400	614,000	605,200

Table 12. Success Measure by Exchanges

SUCCESS MEASURE	CME	CBOT	NYMEX	All Other Current Exchanges	All contracts
Life Span (yrs.)	6.3	4.1	6.4	5.3	5.7
Lifetime Vol	45,190,000	997,800	24,840,000	1,441,000	23,830,000
PV Lifetime revenue	2,807,000	52,780	1,795,000	1,096,400	1,617,000
PV 10-Yr revenue	1,577,600	47,140	634,500	445,500	738,600
PV 5-Yr Revenue	377,600	29,110	262,800	128,300	209,800
5th Year Volume	1,261,000	60,910	1,033,000	243,400	605,200

Table 13. Success Measure by Categories.

SUCCESS MEASURE	Ag	Other	Equity	Foreign	Interest	NP Metals	Energy	Precious Metals	All contracts
Life Span Yrs	6.7	3.8	4.5	5.9	4.7	8. 1	4.9	10.6	5.7
Lifetime vol	4,729,000	1,627,000	39,920,000	6,137,000	87,320,000	9,183,000	26,330,000	16,050,000	23,830,000
PV Lifetime Revenue $	581,300	113,000	2,176,000	439,200	5,714,000	1,016,000	1,834,000	1,834,000	1,617,000
PV 10-yr revenue $	262,100	115,300	3,322,000	190,000	1,399,000	387,100	874,300	780,300	738,600
PV 5-yr revenue $	117,900	164,000	623,500	40,540	289,900	120,900	285,900	190,200	209,800
5th year volume	101,100	71,330	1,839,000	114,300	1,250,000	200,200	1,118,000	271,000	605,200

Table 14. Success by Decade Listed.

SUCCESS MEASURE	1950-1960	1960-1970	1970-1980	1980-1990	1990-2000	2000-2010	All Decades
Life Span (yrs.)	8.1	6.3	9.5	8.7	5.7	3.7	5.7
Lifetime vol	1,922,000	1,145,000	31,780,000	76,320,000	37,630,000	4,611,000	23,800,000
PV lifetime revenue ($)	497,700	291,300	3,399,000	4,997,000	1,961,000	220,100	1,243,000
PV 10-yr revenue ($)	228,500	228,400	830,400	955,700	836,700	273,100	403,900
PV 5_yr revenue ($)	160,500	87,880	218,500	355,800	225,800	146,400	150,200
5th year volume	36,000	71,570	304,300	707,200	1,010,000	606,400	604,600

Each exchange in the United States tends to hold a portfolio of monopoly products. On the day that the CME and the CBOT merged there was no overlap in their actively traded products. Futures markets tend to be liquidity-driven monopolies, a variant of the concept of network effects in economics. The reason is that the more buyers and sellers are present in a market, the more valuable that market is to all involved because bid-ask spreads narrow, market depth increases, and the market becomes both less costly and safer (in the sense of being able to easily find a counterparty) to trade in. Since this liquidity is extremely important to traders, they will always be attracted to markets with greater liquidity, other things being equal. If one exchange has developed substantial liquidity in a product, it is very difficult for another exchange to list that same product and attract traders to its market. Even when several exchanges start the same product at about the same time, at some point one market starts to move ahead in volume and gradually traders leave the less liquid market to trade in the more liquid market, typically leaving one exchange with all the business.

For example, in 1981 three exchanges listed negotiable certificates of deposit (CD) futures. The CME had an advantage over its two competitors, the CBOT and the New York Futures Exchange (NYFE), a subsidiary of the New York Stock Exchange, in that its market makers could hedge their CD risk in a liquid 90-day T-bill futures market on the CME floor. In the first year the CME had more than twice the volume of the other two contracts, and within two years volume in the other two markets had dropped to zero and the CME had 100% market share.

Anecdotes are helpful, but we would like to more rigorously explore this tendency toward liquidity-driven monopoly by utilizing our half century of new contract data to test a few propositions.

A. Clustering of New Products around Major Innovations

Is the liquidity driven monopoly principle and the first mover advantage sufficient to cause competing exchanges to react to major new innovations with their own related products in such a fashion that all activity clusters in a very short period of time? Figures 3–6 say no. Or more accurately, there is often an initial clustering, followed by a competitive battle that often continues over decades. Because the agricultural innovation occurred in the 1860s, long before our data begin, we focus on four major innovations: energy, interest rates, foreign exchange, and stock indexes.

1. Energy Clustering

The first energy contract, propane, was launched in 1967, followed by heating oil in 1974, gasoline in 1981, crude oil in 1983, and then by natural gas in 1990 (Figure 3). Most of the energy contracts during the first 23 years, except for crude oil and natural gas, died quickly or were lightly traded. NYMEX was pumping out most of the new products with no competition until 1982 to 1984 when the CBOT and CME launched a series of crude oil, gasoline, and heating oil products, all of which died within a year. So the energy innovation was a slowly evolving idea, and there was not a clustering of competing exchanges around the first energy contract.

2. Interest Rate Clustering

Interest rate contracts experienced a bit more initial clustering (Figure 4). In 1975, the CBOT listed the first of 12 unsuccessful mortgage-backed securities contracts. The CME followed the next year with a highly successful 90-day T-bill contract. The CBOT came back in 1977 with two contracts, an unsuccessful commercial paper contract and another that became the most actively traded contract in the world for many years — the U.S.Treasury bond contract. Then 1978 brought interest rate contracts from the CBOT, CME, and the now defunct American Commodity Exchange (ACE).[6] This cluster crested with seven contracts in 1979, with one from the CME and two each from the CBOT, COMEX and ACE. While the number of interest rate launches fell back, 1981 was notable because one of the five contracts was CME's three-month Eurodollar contract. This is the kind of competitive clustering we had in mind.

But the broad category of interest rate contracts continued to be fertile and competitive ground long after this initial cluster. In fact from 1975 through the end of this study in 2010, there was not a single year without a new interest rate futures contract. Not only did the exchanges already mentioned stay active, but a series of three exchanges were created for the express purpose of trying to capture interest rate market share from the CBOT and sometimes the CME. In 2001, Broker Tec (BTEC) launched three Treasury bond and note contracts. They were dead by 2003. In 2004 and 2005, a new Chicago subsidiary of Eurex (officially registered as USFE and doing business as Eurex US), listed six Treasury bond and note contracts. They also were dead within a couple of years. Finally, in 2009 and 2010, ELX listed four Treasury bond and note contracts and one Eurodollar contract. In 2010, all of these contracts traded over one million contracts, and three of them traded over three million contracts.

3. Foreign Exchange Clustering

Foreign exchange contracts also had a small initial bunching (Figure 5). It began with a currency index listed by the International Currency Exchanged in 1970. It was premature as the Bretton Woods fixed exchange rate system was still in place. The CME got things rolling with seven major currencies in 1972 (the German mark, British pound, Italian lira, Japanese yen, Swiss franc, Canadian dollar and Mexican peso). They started slow and took about seven years to really start taking off. All survived, except the lira. The following year there were another seven contracts: The CME listed the Dutch Guilder, and six imitations were launched by NYMEX and the New York Cotton Exchange, which later merged into NYBOT and then was purchased by ICE Futures US. In 1974, the CME listed the French franc and NYMEX added four more FX contracts. Activity then died down for a while, until the newly created NYSE subsidiary, the New York Futures Exchange (NYFE) decided to enter the fray with five CME imitations in 1980. These all died

6. The American Commodity Exchange (ACE) was a short-lived market (1978–1981) that listed only three products: GNMA mortgage-backed securities, T-bills, and T-bonds.

Figure 3. New Energy Contracts.

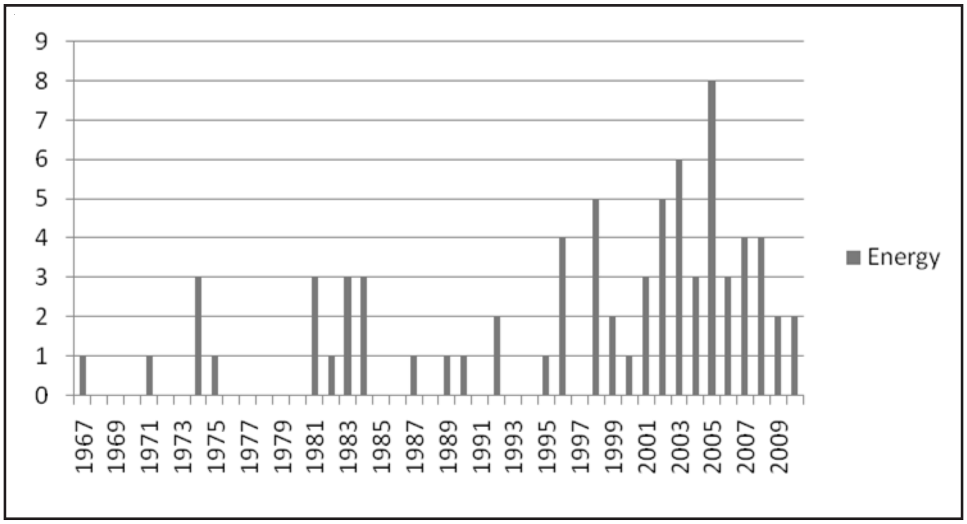


Figure 4. New Interest Rate Contracts.

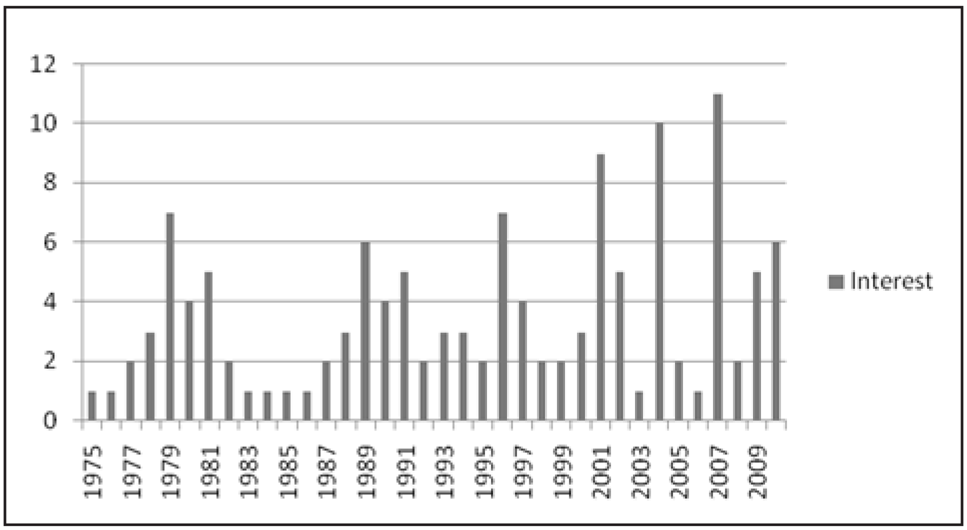


Figure 5. New Currency Contracts.

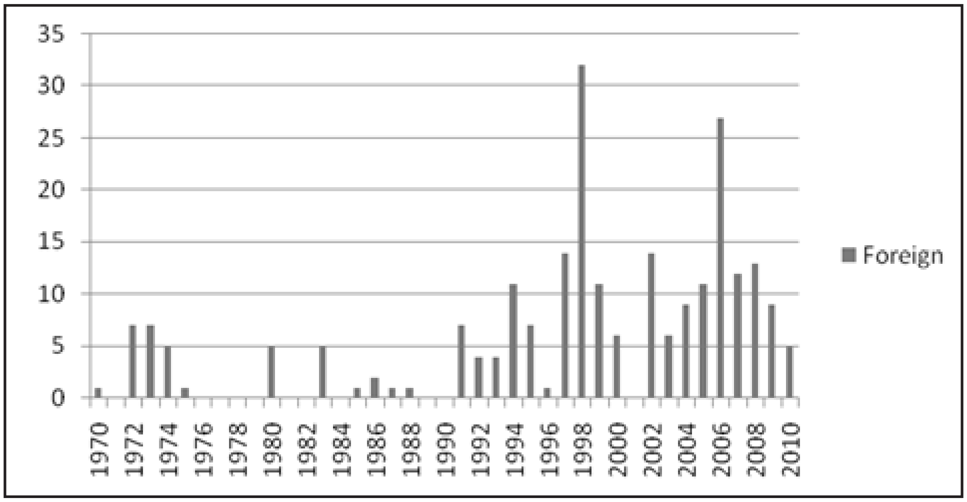
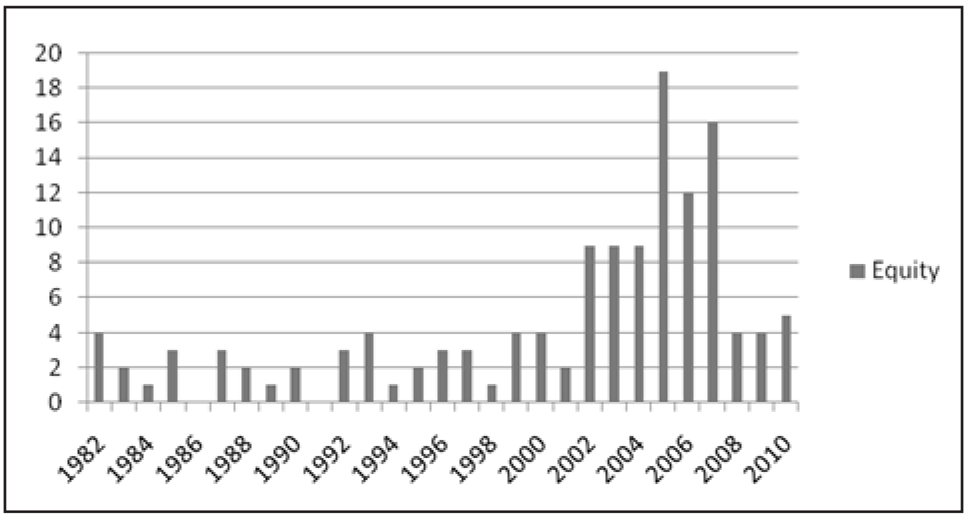


Figure 6. New Equity Contracts.



the next year. In 1983, the MIDAM came into the arena with five of its signature mini versions of full commercial-sized contracts successfully listed elsewhere. These contracts lasted for almost two decades, until the CME began listing its own mini versions.

In 1991, the Philadelphia Board of Trade (PBOT) began building up its own arsenal of CME look-alike currencies, which never captured any significant market share, but did last almost a decade. The period from 1991 to 2010 was characterized by much more listing activity than occurred around the CME's original 1972 launch. There were two significant peak listing years. In 1998, there were 32 FX contracts listed, 31 of them by NYBOT, which was trying to become a second anchor in the foreign exchange business, by focusing on cross rates (exchange rate pairs that do not include the dollar), which the market leader, the CME, had largely ignored. The other spike, 27 FX listings in 2006, was 100% ICE.

So foreign exchange listings also show some initial clustering, but most currency futures contracts were listed during a two-decade period beginning 20 years after the initial innovation was made.

4. *Equity Clustering*

The chart of new equity listings (Figure 6) looks remarkably like that of currencies — some initial competitive clustering, followed two decades later by much more innovation and competitive activity. In 1982, after an SEC-CFTC jurisdictional dispute was settled with the Shad-Johnson Accord, four stock index futures were listed by three exchanges. The KCBT was first with the Value Line, because it had submitted its application long before the others. It was not an institutionally important index and never traded very much, but it did last 22 years before it died in 2004. Two months later the CME listed its S&P 500, which went on to become the most actively traded stock index futures contract in the world. And the newly created NYFE listed the NYSE Composite along with a Financial Sector index. The Financial Sector died the next year, but the NYSE Composite hung on for 21 years. Remarkably, the CFTC approved nine stock indexes in that first year, though only four were listed. This was because both COMEX and the CBOT created what were essentially imitations of the S&P 500 and the DJIA, respectively, and both were blocked in court from listing.

Those first four years saw only 10 equity index contracts listed by four exchanges — the three 1982 pioneers plus the CBOT, which launched two contracts the next year, neither of which lasted very long. One of the constraints on listing more products was that, unlike corn, cattle, or crude oil, stock indexes were protected intellectual property and could only be traded by an exchange if a licensing agreement were put in place. In the early years, futures were viewed as borderline inappropriate by the securities industry and Dow Jones, for one, absolutely refused to license its index for such activity. Fifteen years later, Dow Jones saw how hugely successful and respectable stock index futures had become, and in need of money it leased its index to the highest bidder, which happened to be the CBOT and which finally got the CBOT back into the stock index business. The thing responsible for creating a new much larger cluster of listings beginning in 2002 was the fact that index companies began creating a lot more indexes and new players, like the CBOE Futures Exchange (CFE), began listing index products. The CFE alone listed nine stock index contracts in 2005. They all died before the year was out.

B. Is the Principle of Liquidity Driven Monopoly Supported by the Data?

To what extent do exchanges have monopoly positions in specific product listings? To test this, we search for product prototypes, such as silver or corn or soybeans or Treasury bills, and then organize all contracts into groups around each of these prototypes. The contracts in a prototype group might be identical or may differ from one another by size, grade, delivery location, or maturity but are largely substitutable for one another in trading. If it differs sufficiently, it becomes a different prototype. So soybeans, soybean oil, and soybean meal are three different prototypes; they have different uses and values. For example, during our 55-year period there have been six silver contracts listed at five exchanges, each of them in the prototype group we call silver. In any given year, there were never more than three silver contracts actively traded, often only two and occasionally one. Silver coins were a separate prototype because coins can have a significant and varying numismatic value when compared to silver bars.

1. Is There Only One Active Contract for Each Group of Essentially Identical Contracts?

For each product prototype in each year, we calculate the number of actively traded contracts associated with that prototype and then take the average number of contracts per prototype group for that year. In its pure form, liquidity-driven monopoly would suggest that each group should have only one actively traded product in each prototype group and that the average for all groups for each year should be one, except for those cases where the battle for the winning contract has not yet resolved itself. In those unresolved cases where a number of contracts still have volume, the number could be two, three, four, or even five.

As can be seen from Figure 7, the number of directly competing contracts has on average ranged from 1.5 to 2.25 and shown a general decline, bottoming out in 2004 and then risen steadily to about 3.75 in 2010. While we expected this number to be closer to 1.0, the fact that we have had an average of almost 2.0 suggests that, despite the expected outcome, we continue to have vigorous competition in U.S. futures markets. This six-year increase in competition may have an explanation. It was beginning in late 2003 and early 2004 that competition from an electronic Chicago subsidiary of Eurex pushed the CBOT and CME to shift their members and customers away from the floor and onto the screen. It may be that as futures trading has become more completely electronic, exchanges have found that it is

Figure 7. Average Number of Essentially Identical Contracts per Competition.

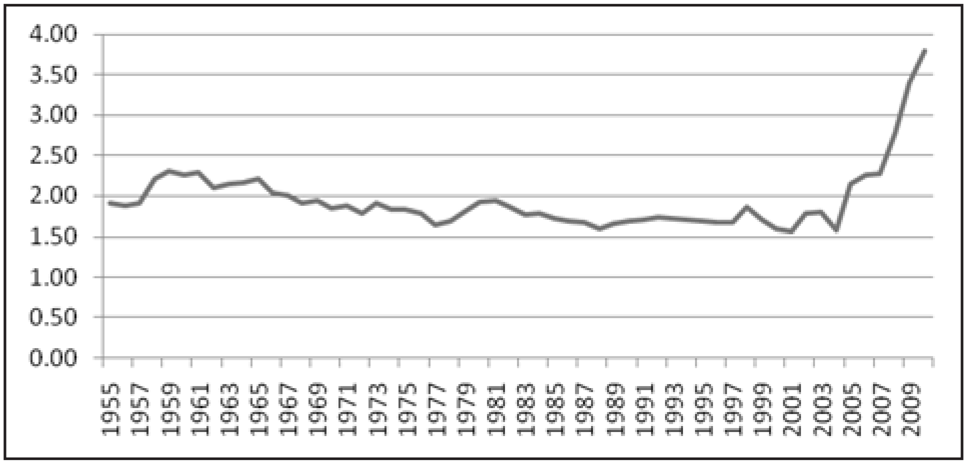


Figure 8. Dominant Contract's Average Share per Competition.

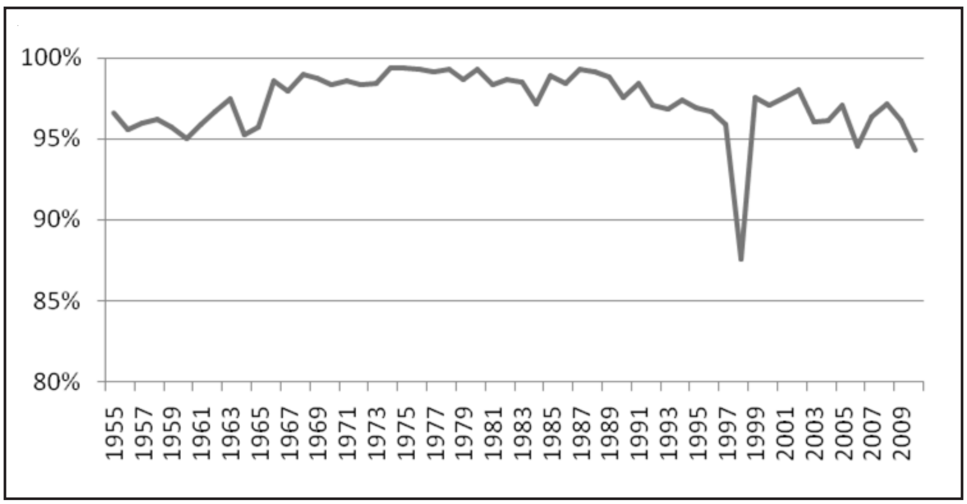


Figure 9. Percent of Cases Dominant Contract is an Innovation, Imitation, Extension, or pre-1956 Contract.

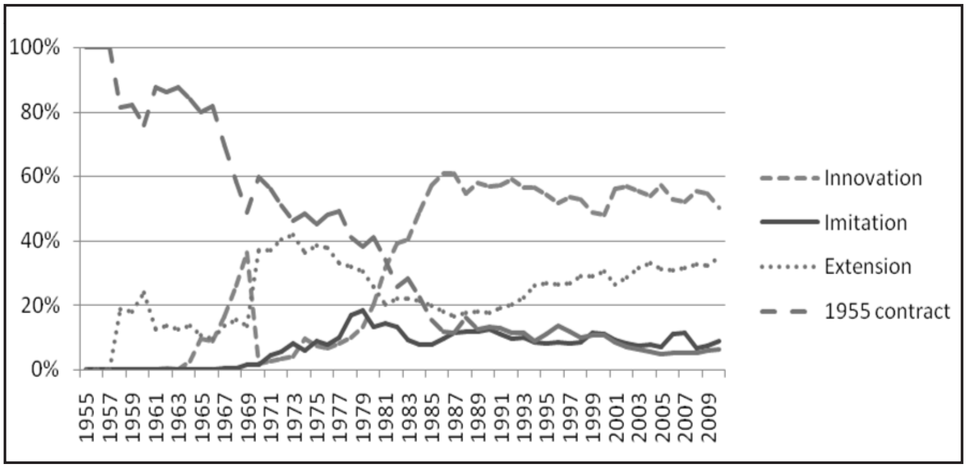
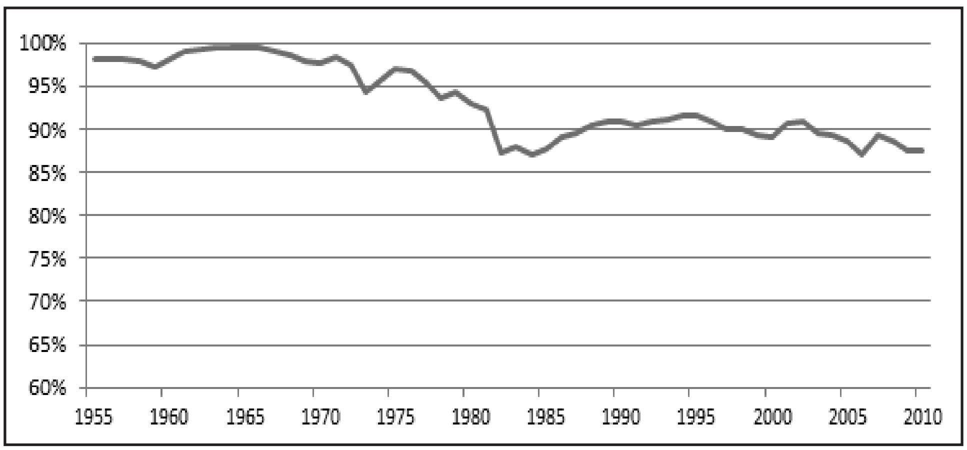


Figure 10. Market Share of Top 20 Contracts.



increasingly cheap and easy to list new competitive products, and therefore we have seen this increase in the number of competing contracts from 1.5 to almost 3.75.

2. Is the Market Share of the Dominant Contract in Each Prototype Group Almost 100%?

Even if there is still a competitive battle going on, the share of the dominant contract in each contested prototype group should be moving toward 100%. To test this, we calculate the market share of the dominant product in each prototype group and then take the average of these market shares across all groups for each year. As can be seen from Figure 8, the market share of the dominant contract has averaged between 95 and 100% in all but three years, 1998, 2006, and 2010. This may well be consistent with a world of liquidity-driven monopolies and the 1 to 5% share captured by competitors is the average share captured by contenders as the battles for monopoly are gradually resolved, The huge drop to an 88% share in 1998 is a mystery, and we cannot easily explain the rise in dominant product share from 1960 to 1974, nor the drop from 1974 to 2010.

3. Is There a First Mover Advantage?

By definition, the innovator is the first mover. And by definition an imitation or product extension is a contract that is listed no sooner than the year following the innovation. So if it is true that first movers are much more likely to win battles over contested contracts, then we should find that the innovation should always, or at least mostly, be the dominant contract when multiple similar contracts are contending for market share. Figure 9 tells us, for each year, the percentage of cases where the dominant contract is an innovation, an imitation, a product extension, or a contract that was listed before 1956 (in which case we do not know which of these types it is).

In 1956, virtually all competitions were among contracts that had been created before 1956, so the dominant contract would virtually always be a pre-1956 contract. In fact it was not until 1981 that the dominant contracts ceased being the old pre-1956 contracts. Ignoring the role of these legacy contracts and focusing on contracts listed in 1956 and later years, which means focusing on the contracts we know to be innovations, imitations, and product extensions, we find only weak support for the first mover theory. In fact, until 1981, the dominant contract in competitions was much more likely to be a product extension than an innovation. And even after 1981, while innovations were more likely than either extensions or imitations to be the dominant contract, they were the dominant contract in only 40 to 60% of the cases. The finding that would fully support the first mover theory would be if dominance by imitations and product extensions were always close to zero and innovations combined with the legacy contracts had close to 100% market share. That is not the case here.

4. Has Increased New Product Listings Reduced the Market Share of the Top Contracts?

If all the new products are solving problems for risk managers and traders, we might expect to see an increased diffusion of volume among more contracts. That would suggest a decline in the volume share of the top 20 contracts. We find that from 1981 to 2010, the market share of the top 20 products fell from 98% to 94%, not a huge diffusion but a visible one.

IV. CONCLUSIONS

In this paper we examined the 916 new futures contracts listed by 39 exchanges over the period 1956 to 2010. Of these, 44% were innovations, 35% were product extensions, and 21% were imitations. This analysis led to the following findings:

- The average lifespan of a new futures product is just under six years.
- Contract innovations tend to be more successful than extensions and imitations.
- The CME, which over the past 55 years has fought its way from being in the CBOT's shadow to being the top U.S. exchange, has more aggressively created new contracts (5.1 per year vs. 2.9 for the CBOT), and those contracts have on average been more successful.
- The 1980s was the golden decade of new contract success by almost every measure.
- Interest rate contracts generated the highest lifetime volumes and revenues, while agricultural and exotic contracts generated the least, on average.
- There is a strong tendency toward liquidity-driven monopoly (or winner take all) in U.S. futures markets. When there is product competition, there is an average of only two exchanges competing and the dominant contract tends to have over a 95% market share.
- However, the widely held view that the first mover always wins, is not supported by our findings. Even though innovations dominated product competition about 50% of the time, product extensions dominated over 30% of the time.

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TRANSACTION TAX AND MARKET QUALITY OF U.S. FUTURES EXCHANGES: AN EX-ANTE ANALYSIS

C. Johan Bjursell, George H. K. Wang, and Jot Yau*

In this paper, we analyze the impact of a transaction tax on the market quality of U.S. futures markets by estimating the elasticity of trading volume and of price volatility with respect to bid-ask spread in a three-equation model framework for 11 financial, agricultural, metals, and energy futures for the period 2005–2010. We find that (1) Trading volume has a negative relationship with bid-ask spread and a positive relationship with price volatility after controlling for other factors; (2) bid-ask spread has a negative relationship with trading volume and a positive relationship with price volatility; and (3) price volatility has a positive relationship with bid-ask spread and with trading volume after controlling for other variables. We demonstrate that a transaction tax, which is analogous to a bigger bid-ask spread, will drastically reduce trading volume if the tax constitutes a significant increase in the total fixed trading cost, and/or the elasticity of trading volume with respect to transaction cost is high enough. Thus, a transaction tax may not raise substantial revenue for the government as suggested in other studies.

In reaction to the recent financial crisis and government budget deficit, there has been considerable interest in imposing taxes on financial transactions, including futures trading.[1] Legislative proposals on financial transaction taxes are not new to the United States as they have been sent to Congress for consideration from time to time for the purpose of either raising revenue for financing government

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1. In the wake of the 2007–2008 global financial crisis, Korea urged the G-20 countries to consider an international levy on bank transactions at the G-20 meeting in 2010, while the IMF had presented its own bank-tax proposal at the same meeting (*The Wall Street Journa*l, June 4, 2010, A14). The European Commission had also considered various financial transaction taxes, and a detailed plan of a financial transaction tax would be ready for approval by November 2011 (Zweig 2011).

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JEL Classification: G10

budget deficit or for funding regulatory agencies, such as the CFTC and/or SEC. For example, during the 1990 budget negotiation, the Bush administration proposed a broad-based 0.5% tax on transactions in stocks, bonds, and derivatives. In 1993 the Clinton administration proposed a fixed 14 cent tax on transactions in futures and options on futures. Recently, the Obama administration has proposed a user fee in the 2012 federal budget on all futures trading to fund the CFTC.[2] This has rekindled the debate on the potential costs and benefits of a financial transaction tax in the United States, and their potential impact on the futures markets.

In general, proponents of financial transaction taxes (FTTs)[3] argue that it would increase government revenue and curb excessive market volatility by reducing noise trading, a significant source of price fluctuations. Opponents of FTTs argue that transaction tax does not necessarily reduce excessive price volatility. Instead, it would adversely affect market liquidity in terms of wider bid-ask spread and lower trading volume, and increase the cost of hedging and cost of capital. The lack of or reduction in market liquidity might drive some or all securities trading to overseas markets not burdened by taxation, a major concern for the U.S. financial services industry, particularly the futures industry. Previous studies, theoretical and empirical, seem not to be able to offer a definitive conclusion about the desirability of such a tax. Most studies recognize that different assumptions used in theoretical models would lead to different conclusions. Thus, before one can make an informed judgment on the desirability of a transaction tax on U.S. futures, one should be able to estimate ex ante the potential impact of a transaction tax on the market quality (i.e., trading volume, bid-ask spread, and price volatility) of U.S. futures markets and on its contribution to government revenue.

The purpose of this paper is threefold. First, we apply a three-equation structural model to empirically estimate the relations among trading volume, bid-ask spread, and price volatility. Based on the empirical modeling, we are able to evaluate the relations among trading volume, bid-ask spread and price volatility for different types of futures, including financial, agricultural, metals, and energy. These relationships are important for understanding the impact of changes in transaction cost (via bid-ask spread) on trading volume and price volatility and their interaction and feedback dynamics. Second, we provide updated reliable elasticity estimates of trading volume with respect to trading costs, which are the major inputs for estimating realistic post-tax trading volume and tax revenue. Unlike previous studies, elasticity estimates are based on the more recent period (2005–2010) that covers episodes of volatile market conditions during the 2007–2008 financial crisis and the electronic trading regime.[4] This update is important because significant changes in

2. Twenty-eight members of the U.S. House of Representatives had co-sponsored a legislation that would impose a transaction tax on regulated futures transactions. The proposed tax is 0.02% of the notional amount of each futures transaction to be charged on each party of the transaction, projecting a forecast revenue of hundreds of billions of dollars per year (Cronin 2010; Noll 2010).

3. Financial transaction taxes (FTTs) can be classified into (1) securities transaction tax (STT); (2) currency transaction tax (CTT or Tobin tax); (3) capital levy or registration tax; (4) bank transaction tax (BTT); and (5) real estate transaction tax (Matheson 2011).

4. Transaction data for all 11 futures, except one, are from the electronic trading platform.

trading technology, market structure, and globalization of futures exchanges have taken place since the 1990s. Third, we provide estimates of the potential revenue that can be collected from a transaction tax in the selected U.S. futures markets using the more reliable estimates of elasticity of trading volume from our model.

The rest of the paper is organized as follows. Section I presents a literature review. Section II describes the data and variable measurement. Empirical models and the methodology for model estimation are presented in Section III. Empirical results are presented in Section IV. Section V applies the estimated elasticities of demand for futures trading to estimate the potential tax revenue under alternative tax rates. Section VI concludes the paper.

I. LITERATURE REVIEW

The extant literature has extensive theoretical treatises on the pros and cons of a financial transaction tax as well as empirical evidence and analyses of issues relating to a financial transaction tax.[5] We will briefly review the literature on the debate and analysis on the major issues related to the imposition of a transaction tax on financial markets: (1) theoretical studies on the pros and cons of imposing a transaction tax; (2) empirical studies on the verification of theoretical arguments for and against a financial transaction tax; (3) the impact of a transaction tax on the migration of trading and relative competitiveness of the futures industry; and (4) the estimation of the amount of potential tax revenue that can be raised from futures trading.

A. Theoretical Studies

First, on the impact of a transaction tax on market quality in terms of curbing excessive market volatility, one can make reference to the arguments originally put forward by Keynes (1936), and elaborated by Tobin (1978), Stiglitz (1989), and Summers and Summers (1989). Keynes (1936) argues that a transaction tax that makes speculative trading less profitable could reduce excess market volatility and stabilize the financial markets because he believes short-term speculative trading is the source of excess volatility. Friedman (1953), however, argues that speculation cannot in general be destabilizing since, if it were, the participants involved would lose money. Moreover, advocates of the Efficient Market Hypothesis argue that speculators, by rationally arbitraging the unexploited profit opportunities when market becomes inefficient, help clear markets, stabilize prices, and bring the assets and securities back to their fundamental values (Fama 1965). However, Tobin (1978) argues that a transaction tax that lowers excess volatility will promote a price formation mechanism more strongly focused on long-term fundamentals because corporate managers will focus more on long-term strategies, instead of implementing myopic policies to fulfill the wishes of short-term investors. He argues that markets

5. For example, see reviews in Schwert and Seguin (1993); Pollin, Baker, and Schaberg (2003); McCulloch and Pacillo (2010); Matheson (2011); and others.

are "fundamental valuation efficient" if prices reflect fundamental valuation without excess volatility. Stiglitz (1989) and Summers and Summers (1989) argue that a securities transactions tax could raise the efficiency of financial markets by crowding out market participants that behave irrationally or waste too many resources for this speculative zero-sum game. Summers and Summers (1989) further believe that the efficiency benefits derived from curbing speculation are likely to outweigh any costs of reduced liquidity or increased costs of capital that come from a financial transaction tax. In contrast, opponents argue that the benefits of transaction tax are likely to be outweighed by its potential costs, because it would increase the cost of capital and securities' values (e.g., Amihud and Mendelson 1993, 2003), and reduce market liquidity (i.e., decrease in trading volume and increase in bid-ask spreads).

Some advocates point out that, if differentiated across trading vehicles, the transaction tax could boost stability by creating incentives for financial market participants to move over-the-counter transactions to transparent and well regulated venues (Färm and Ludvigsson 2011).

Formal theoretical models have been developed to help demonstrate the impact of a transaction tax in a more complete equilibrium setting. For example, Kupiec (1996) demonstrates that, although a transaction tax can discourage noise traders from trading and thus reducing short-term destabilizing trading volume and price volatility, it will also depress asset prices to the extent that this drop in equilibrium prices results in higher return volatility. Since the initial decrease in price volatility will be overwhelmed by the unambiguous increase in return volatility due to the tax, a transaction tax may not reduce but actually increase the volatility of asset returns in a simple general equilibrium model. The implication is that we cannot simply separate and interpret the impact of a transaction tax on each of the relevant variables in a partial equilibrium setting.[6] Likewise, in a general equilibrium model, Song and Zhang (2005) show that a transaction tax may discourage not only the destabilizing trading activities of noise traders but also those of the rational and stabilizing value investors. The net effect of a transaction tax on volatility depends on the change of trader composition from the implementation of the tax. Furthermore, a transaction tax may decrease trading volume and increase bid-ask spread. Thus, short-term price volatility may increase due to the larger price impact of a given trade, while the net impact of a transaction tax on market price volatility could be decreasing or increasing. The final result depends on the relative magnitude and interaction of the change in trader composition and liquidity.

Pellizzari and Westerhoff (2009) show the effectiveness of transaction taxes depends on the types of trading markets where market liquidity is determined either endogenously or exogenously. They show that in a continuous double auction market, the imposition of a transaction tax is not likely to reduce market volatility, whereas in a dealership market, a transaction tax may reduce market volatility. Lo, Mamaysky,

6. This lends support to our empirical modeling in this paper that market quality variables (trading volume, bid-ask spread, and price volatility) must be taken into consideration together simultaneously in the estimation procedure.

and Wang (2004), using a dynamic theoretical model of asset prices and trading volume, show that even small fixed trading costs will generate relatively large premium in asset prices and reduce trading volume significantly.

In addition to traditional models that assume agent rationality in the model and rational expectations about future events, other theoretical models also incorporate characteristics that are observed in the real financial markets, such as excess liquidity, excess price volatility, fat-tailed distribution of returns, volatility clustering, incomplete information, and not fully rational agents.[7]

In sum, extant theoretical models suggest mixed effects of a transaction tax on price volatility and trading volume. Impacts of transaction taxes on price volatility and trading volume depend very much on the assumptions of the theoretical model and the assumed channels through which the effect of a transaction tax passes.

B. Empirical Studies

Theoretical models reviewed above include models that are purely theoretical and models that incorporate some stylized facts observed in the real markets. The review of the extant literature on theory demonstrates that different conclusions and implications can be obtained from different models depending on the assumptions used. Thus, theoretical models cannot resolve the debate about the appropriateness of a transaction tax. We now proceed to review the empirical evidence related to the impact of transaction tax on trading cost, trading volume and price volatility in different countries.

Mulherin (1990) examines the relationship between trading costs in the NYSE and the daily volatility of the DJIA returns from 1897 to 1987, and concludes that the imposition of a transaction tax may not necessarily reduce volatility. Despite evidence of increased volatility after the introduction of a 1% transaction tax in 1986, Umlauf (1993) does not find a systematic relationship between transaction taxes and price volatility across tax regimes in Sweden. Likewise, Jones and Seguin (1997) find that volatility fell in the year after the abolishment of the minimum commission rates in NYSE and AMEX markets, but the decline in volatility was also observed in the NASDAQ market. Roll (1989) uses the cross-section data of 23 countries for the period 1987–1989 to examine whether there are systematic differences in price volatility that can be explained by margin requirements, transaction taxes, and price limits. He does not find evidence that volatility is negatively related to transaction taxes. Hu (1998) examines the effect of 14 transaction tax changes that occurred in Hong Kong, Japan, Korea, and Taiwan during the period 1975 to 1994, and finds that on average an increase in tax rate has no effect on market volatility. Chou and Wang (2006) find no significant changes in the daily price volatility of the Taiwan index futures after the tax reduction. In contrast, Liu and Zhu (2009) find evidence that reduction in transaction costs significantly increase price volatility in the Japanese equity market.

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7. For a review of the literature on alternative theoretical models, see Wang and Yau (2012).

Other studies document that there is a positive relationship between price volatility and transaction costs in equity markets. Bessembinder (2000) documents that larger tick sizes are associated with higher transaction costs and also with higher volatility, while Hau (2006) finds similar evidence in the French equity market. Bessembinder and Rath (2002) find that stocks that had moved from NASDAQ to NYSE where trading costs were lower experienced a reduction in volatility. Baltigi, Li, and Li (2006) find that an increase in transaction tax leads to greater price volatility in the Chinese stock markets.

There is limited empirical evidence on the impact of a transaction tax on the U.S. futures markets. Wang and Yau (2000) propose a three-equation structural model to estimate the elasticity of trading volume with respect to bid-ask spread and price volatility in the U.S. futures markets. They find a negative relationship between bid-ask spread and trading volume, and a positive relationship between bid-ask spread and price volatility. Inferring that a transaction tax would have the same effect as a bid-ask spread, they conclude that such a tax will reduce trading volume but may not reduce price volatility.[8] Aliber, Chowdhry, and Yan (2003) study the impact of a small transaction cost on the trading volume and price volatility of four currency futures traded on CME for the period 1977–1999. They find that an increase of 0.02% in the transaction cost leads to an increase of volatility by 0.5% points on these currency futures, coupled with a decline in asset prices due to the decline in demand because of higher transaction costs.

C. Migration of Trading and Relative Competitiveness

Previous literature on transaction tax also sheds light on the potential adverse effects of a financial transaction tax on the international competitiveness of the U.S. financial services industry. While Summers and Summers (1989) did not believe a transaction tax would cripple the U.S. equities trading in the United States back then in 1989, they admitted that for derivatives and commodities trading a transaction tax could have damaging impacts on the industry as evidenced in the demise of the Sweden Options and Futures Exchange due to an options transaction tax. Edwards (1992) believes even a very small transaction tax would be sufficient to drive all U.S. futures trading to overseas untaxed markets.[9] Umlauf (1993) and Campbell and Froot (1994) document evidence of a significant migration in trading volume from the actively traded Swedish stocks to London after the Swedish transaction tax was increased from 1% to 2% in May 1986. Chou and Wang (2006) document evidence that migration of significant trading volume of Taiwan stock index futures

8. Sahoo and Kumar (2011) applied the three-equation structural model proposed by Wang and Yau (2000) to examine the relations among trading volume, bid ask spread, and price volatility for five actively traded futures in India. They obtained similar empirical results as Wang and Yau (2000) did for the U.S. futures that there is a negative relationship between bid-ask spread and trading volume, and a positive relationship between bid-ask spread and price volatility.

9. Countries have indicated their concern for a transaction tax that is not global, and are aware that relative competitiveness may be changed by the burden of a non-global transaction tax. See *The Wall Street Journal* (June 4, 2010, A14) and Zweig (2011), in which he discusses the proposal on a global transaction tax on flash trading.

contracts from the Singapore Exchange (SGX) to TAIFEX occurred after the tax cut from 5 to 2.5 basis points on May 1, 2000.

D. Potential Tax Revenue

Proponents of a transaction tax suggest that the revenue potential of a transaction tax is formidable. Congressional Budget Office (CBO) estimates the revenue from a broadly based 0.5% securities transaction tax to be about $12 billion per year based on a five-year average. Based on the same tax rate used by the CBO, Summers and Summers (1989) suggest a similar figure (at least $10 billion a year). Pollin, Baker, and Schaberg (2003) suggest that revenue from a securities transaction tax could be as large as $70–$100 billion per year.[10] Outside the United States, Roll (1989) estimates that a securities transaction tax in Japan would bring in $12 billion a year. The European Commission in a June 2011 budget proposal expects a financial transaction tax to contribute €50 billion per year to the European budget, or €350 billion over a seven-year period (Uppal 2011).

Edwards (1992) doubts that a transaction tax on futures transactions will potentially generate significant tax revenue. He argues that the elasticity of trading volume in futures markets is much more elastic than that of equities because close substitutes are easily available in international futures markets with the advent in trading and information technologies.[11] In other words, competition from international futures exchanges is keen. Thus, he believes the potential revenue from a transaction tax estimated by the CBO was overstated because the elasticity of demand (-0.26) used in the estimate was based on U.S. equities assuming no good substitutes. Edwards (1992) argues that given a more elastic trading volume in futures, a transaction tax of the magnitude of 0.5% would probably eliminate all futures trading in the United States and drive all futures transactions overseas. In such a case, no revenue would be collected. According to his conservative estimate, not much revenue (only $287 million) could be raised from futures trading even if the lowest tax rate (0.0001%) and a low demand elasticity (-0.26) were assumed.[12] He concludes that a transaction tax on futures trading will not generate substantial revenue.

Chou and Wang (2006) find that the reduction in the transaction tax in the Taiwan index futures market did reduce tax revenue, and the proportional decrease in the tax revenue was less than the 50% reduction in the tax rate. Further, tax revenue increased in the second and third year after the tax reduction as compared

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10. The estimate was based on 1997 levels of market activity for stocks, bonds, and swaps, and the March 1999 level of market activity for futures and options.

11. Wang, Yau, and Baptiste (1997) provide the first empirical estimates of the elasticity of trading volume for several U.S. futures contracts. They documented that estimates of the elasticity of trading volume with respect to trading costs were in the range of −0.116 to −2.72, which were less than those elasticities (−5 to −20) used by Edwards (1992), but higher than the elasticity of −0.26 used in CBO (1990).

12. −0.26 was the elasticity used in CBO (1990). Edwards (1992) also used elasticities ranging from −1 to −20 in estimating the potential tax revenue.

to the year before the tax reduction. This suggests that tax reduction has no permanent negative impact on tax revenue.

The contributions of our paper to futures market literature are as follows:

(1) We estimate the parameters of bid-ask spread, trading volume, and price volatility structural equations for 11 futures contracts with recent daily and intraday data from 2005 to 2010. This update is important because the futures trading face huge market volatility during this sample period and the environment and international competitions among futures exchanges in the past decades are significantly different than those in the 1990s. Thus, our results provide new empirical evidence to validate the pros and cons of the imposition of transaction tax on U.S. futures markets.

(2) We provide new estimates of the elasticity of trading volume with respect to trading cost for 11 futures contracts. These estimates are the required input to estimate potential tax revenue based on different proposed transaction tax rate schedules.

II. DATA AND VARIABLE MEASUREMENT

Data for this study include the following 11 futures contracts:

Futures	Trading Platform	Time periods
1. Financial Futures		
(a) S&P 500 (CME)	Pit floor	Jan 2005- Dec 2010
(b) E-mini S&P500 (CME)	Electronic	Jan 2005- Dec 2010
(c) 30-Year T-bond (CBOT)	Electronic	Jan 2005- Dec 2010
(d) 10-Year T-Note (CBOT)	Electronic	Jan 2009- Dec 2010
(e) British Pound (CME)	Electronic	Jan 2008- Dec 2010
2. Agricultural Futures		
(a) Wheat (CBOT)	Electronic	Jan 2007- Dec 2010
(b) Soybean (CBOT)	Electronic	Jan 2007- Dec 2010
3. Metals Futures		
(a) Copper (COMEX)	Electronic	Jan 2008- Dec 2010
(b) Gold (COMEX)	Electronic	Jan 2008- Dec 2010
4. Energy Futures		
(a) Crude Oil (NYMEX)	Electronic	Jan 2008- Dec 2010
(b) Heating Oil (NYMEX)	Electronic	Jan 2008- Dec 2010

These futures are chosen because they cover several categories, including financial, agricultural, metals, and energy futures. They are actively traded futures in their own categories, hence mitigating the problem of infrequent trading. Furthermore, since the majority of futures contracts are now executed on the electronic platform, futures trading on the electronic platform are selected to mitigate the potential problems arising from insufficient liquidity.

We use the first position contract of each month as the nearby contract, and the next contract following the nearby contract the first deferred contract.[13] The inclusion of two contracts with differing maturities ensures a representative cross-sectional sample of the futures market with maximum variations in the bid-ask spread and price volatility, which allow reliable estimation of the relative importance of each explanatory variable in determining the trading volume in different futures markets.

The time and sales intraday data from the Institute for Financial Markets are used to estimate the daily mean of the effective bid-ask spreads, intraday price volatility, average daily price level, and trading volume for contracts traded on the electronic platform. The trading volume of the S&P 500 index futures and open interest of all contracts are obtained from Bloomberg for the time period under study.

We use the price reversal methodology to calculate the daily effective bid-ask spread (see Wang, Yau, and Baptiste 1997). The effective bid-ask spread is estimated as follows: (1) an empirical joint price distribution of ΔP_t and ΔP_{t-1} during a daily interval is created; (2) the subset of price changes that exhibit price continuity (i.e., a positive (negative) change followed by another positive (negative) change) is discarded; (3) the absolute values of price changes that are price reversals are taken; (4) the mean of absolute values obtained in the step (3) is computed as the average daily effective bid-ask spread.

Two daily unconditional volatility measures are derived from the intraday time and sales data and used in this study. Based on Anderson et al. (2001), our first daily realized volatility is defined as:

$$\hat{\sigma} = \sqrt{\sum_{t=1}^{n} r_t^2}\, x100 \tag{1}$$

where n is the number of intraday five-minute returns, and $r_t = (\ln(P_t) - \ln(P_{t-1}))$ is the five-minute intraday return at each five-minute interval. The second volatility estimator is the high-low estimator proposed by Parkinson (1980), which is defined as:

$$\hat{\sigma} = (\sqrt{\frac{(1\mathrm{n}(H_t - \ln(L_t))^2}{4\ln(2)}})x100 \tag{2}$$

where H_t and L_t are the daily high and low prices, respectively.[14]

13. During the delivery month period, we use trading volume as an indicator of contract rollover to determine the timing of contract roll-over that takes place when the current open position in the nearby contract is being rolled over to the next contract with a new expiration. For example, when the trading volume of the first deferred futures is greater than that of the current nearby futures, we make the first deferred contract to become the nearby contract and the second deferred contract the first deferred contract for the next contract month period.

14. For further discussion on estimating the daily volatility from intraday data, see Bollen and Inder (2002).

III. EMPIRICAL MODELS AND ESTIMATION METHODOLOGY

To estimate the potential impact of a transaction tax on market quality (i.e., in terms of liquidity as measured by the magnitude of trading volume, bid-ask spread, and price volatility and their subsequent changes after the tax) of a futures market,

$$TV_{it} = \beta_{10} + \beta_{11}BAS_{it} + \beta_{12}IV_{it} + \beta_{13}3TB_{it} + \beta_{14}OI_{it-1} + \beta_{15}TV_{it-1} + D_1 + e_{1it} \quad (3)$$

$$BAS_{it} = \alpha_{20} + \alpha_{21}TV_{it} + \alpha_{22}IV_{it} + \alpha_{23}MP_{it} + \alpha_{24}BAS_{it-1} + D_1 + e_{2it} \quad (4)$$

$$IV_{it} = \delta_{30} + \delta_{31}TV_{it} + \delta_{32}BAS_{it} + \delta_{33}OI_{it-1} + \sum_{j=1}^{k}\delta_{3j}IV_{it-j} + D_1 + e_{3it} \quad (5)$$

we use a three-equation structural model framework.[15] The empirical model is specified as follows:

Equation (3) is the trading volume equation, where TV_{it} is the trading volume of the futures contract at i^{th} maturity time on the t^{th} day. Trading volume is specified as a function of the effective bid-ask spread (BAS_{it}), price volatility (IV_{it}), three-month T-bill ($3TB_{it}$), one-period lagged open interest (OI_{it-1}) and one-period lagged trading volume ($TV_{i\,t-1}$).

BAS_{it} is the mean of intraday effective bid-ask spreads of a futures contract at i^{th} maturity time on the t^{th} day. Bid-ask spread is a major component of the transaction cost. Higher transaction costs would decrease the opportunity for market participants, leading them to search for alternative trading vehicles with lower transaction costs. Hence, trading volume is expected to be negatively related to the size of the bid-ask spread.

IV_{it} is the intraday price volatility of a futures market on the t^{th} day. Based on the mixture distributions hypothesis, price volatility is expected to be positively related to trading volume.[16] The three-month T-bill ($3TB_{it}$) is used as a surrogate for the information variable that affects changes in the expected physical position of hedgers. A change in the expected physical position is another determinant of trading volume. The three-month T-bill rate is expected to be inversely related to trading volume, reflecting the opportunity cost of holding inventory.

OI_{it-1} represents the one-period lagged open interest of the i^{th} futures contract. Open interest is the total number of outstanding, unsettled contracts. It is expected to have a positive impact on trading volume because higher open interest will generate

15. The three-equation structural model of trading volume, bid-ask spread, and price volatility was first proposed and used by Wang and Yau (2000).

16. The mixture distributions hypothesis (e.g., Clark 1973 and Tauchen and Pitts 1983) is a theoretical model that explains the positive relation between trading volume and price volatility induced by a third latent variable, that is, new information arrivals.

greater trading volume when market participants close out their unsettled positions.

Equation (4) is the bid-ask spread equation, where bid-ask spread is a function of the price risk (measured by price volatility, IV_{it}), trading volume (TV_{it}), daily mean price (MP_{it}), and one-period lagged bid-ask spread (BAS_{it-1}). These variables are included here because they were found to be significant in previous studies (e.g., Wang and Yau 2000).

Trading volume is a simple measure of market liquidity. As trading volume increases, we expect that there is greater opportunity for market participants to offset the undesirable position of their inventories, which reduces their price risk. This in turn makes market participants lower their bid-ask spreads. Accordingly, we expect a negative relationship between the bid-ask spread and trading volume in equation (4).

Transaction price changes (i.e., the price risk) imply two types of risk for market makers. First, market makers may bear nonsystematic risk due to the under-diversification in assets they hold. Second, large price changes may correlate with the presence of information traders, and market makers must increase the bid-ask spread to compensate for the expected trading losses against informed traders. Hence, intraday price volatility, a proxy for the price risk in equation (4), is expected to have a positive relationship with bid-ask spreads. The daily average price (MP_{it}) of the futures contracts is used to control for the effect of differing measurement scale on the same futures with different price levels due to different expiration dates (the nearby and first deferred contracts).

Equation (5) is the price volatility equation. We specify the intraday price volatility (IV_{it}) as a function of trading volume (TV_{it}), bid-ask spread (BAS_{it}), one-period lagged trading volume (TV_{it-1}) and several lagged price volatility ($IV_{i,t-j}$) j = 1,…, 6. The greater the trading volume is, the greater the possibility that prices fluctuate, thus creating greater price volatility. In addition, the change in volume may be due to information arrivals, which will increase volatility according to the mixture distributions hypothesis. Another source of intraday price volatility is due to bounces in the bid-ask spread. Market makers demand wider bid-ask spreads when they trade with informed traders or when they take the opposite position of a large trade (i.e., they demand a larger liquidity premium facing such trades). Thus, greater transaction price movements may also be attributed to large variations in the bid-ask spread.

At this juncture, a note on the one-period lagged explanatory variables in equations (3) through (5) is warranted. These one-period lagged explanatory variables are specified as partial adjustments to our model to take account of the distributed lag effect in the dependent variables. In addition, for the price volatility equation, a few more lag terms of price volatility are included in the equation to take into account of the persistence effect of price volatility.

In all three equations, we use a dummy variable as a fixed model effect in pooling the nearby and first deferred contracts. The dummy variable, D1, is equal to one for observations for the first deferred contract and zero otherwise. Finally, e_{1it} , e_{2it} , and e_{3it} are the error terms of equations (3), (4), and (5), respectively.

We proceed with our empirical estimation in three steps. First, all variables in equations (3) through (5) are transformed into natural log, enabling us to stabilize the variance of the error terms toward a symmetric distribution. In addition, estimated coefficients from the equations can be readily interpreted as the elasticity of trading volume, effective bid-ask spread, and price volatility with respect to their explanatory variables.

Second, the augmented Dickey-Fuller (ADF) test (Fuller 1996) is applied to each time series to test for a unit root in the time series sample. Results from the ADF test will provide guidance as to whether the model should be estimated in the level or first-difference form. Table 1 presents results of the ADF tests on the log transformed variables. Results indicate that trading volume, bid-ask spread, price volatility, and open interest are free of the unit root problem, whereas three-month T-bill and the daily mean futures price have a unit root.[17] After taking the first difference, three-month T-bill and the daily mean futures price are reduced to stationary time series. Based on these results, the three-equation model is estimated in level form for all variables, except for three-month T-bill and the daily mean futures prices where first differences are used.

Third, the generalized method of moments (GMM) procedure (Hansen 1982) with the optimal weighted matrix proposed by Newey and West (1987) is used to estimate the parameters of the three-equation model.

IV. EMPIRICAL RESULTS

Tables 2 through 12 present the empirical results of the trading volume, bid-ask spread, and price volatility equations for the selected futures. Table 13 reports the point and interval estimates of the elasticity of trading volume with respect to transaction cost for these futures.

A. Trading Volume Equation

In the trading volume equation, the coefficients of bid-ask spread (ln(BAS)) are negatively related to trading volume and are statistically significant at the 1% level for all eleven futures. These negative coefficients can be interpreted as estimates of the elasticity of trading volume (TV) with respect to BAS for the futures contracts examined in this paper (4th row and 2nd column, Tables 2 through 12).

Table 13 reports the point and 95% interval estimates of the elasticity of trading volume with respect to transaction cost (bid-ask spread) in the second and third column respectively for the futures contracts studied. The point elasticity ranges from –2.6 (E-mini S&P 500 index futures) to –0.81 (Heating Oil). In other words, trading volume and transaction cost (bid-ask spread) are negatively related for all

17. We also applied Maddala and Wu's (1999) simple unit root test to our panel data. The results are qualitatively the same as those of the separate unit root tests for the nearby and first deferred samples. To save space, we do not report these results here.

futures contracts in this study. For example, the elasticity of –2.6 for the E-mini S&P500 index futures indicates that trading volume for this futures will decrease 2.6% for each 1% increase in the bid-ask spread. The lower-end of the corresponding interval estimates with a 95% confidence level are all greater than one, except for 30-year T-bond (–0.972) and Heating Oil (–0.923). These results suggest that the elasticity of trading volume with respect to transaction cost (such as the bid-ask spread) had been very high during the period 2005–2010 for most futures examined. The important implication is that an increase in the bid-ask spread due to, say, a new transaction tax on futures trading, could substantially reduce trading volume and decrease liquidity for the U.S. futures exchanges.

The coefficients of price volatility (ln(IV)) in the trading volume equation are all positive and statistically significant at the 1% level for all 11 futures (Tables 2–12). This result is as expected as theory suggests that an increase in price volatility changes the reservation price of speculators and increase the demand for risk transfer by hedgers. Both effects should lead to a higher trading volume (Martell and Wolf 1987). This empirical result is also consistent with those of previous studies, such as Tauchen and Pitts (1983), Wang, Yau, and Baptiste (1997), and Wang and Yau (2000).

In general, higher short-term interest rate increases the cost of carry in the cash or spot assets or commodities, reduces hedging needs in the futures market, and reduces speculative trading by making alternative investments more attractive. Thus, a reduction in speculative and hedging activities in the futures markets would lower trading volume. Thus, it is expected that there is a negative relationship between trading volume and short term risk-free rate (measured by the three-month T-bill). However, the coefficients of three-month T-bill in the trading volume equations are mixed for the 11 futures. For example, the coefficient of three-month T-bill in the E-mini S&P 500's (Copper's) trading volume equation is negative (positive) and significant at the 10% level. The coefficients of three-month T-bill in the trading volume equation for other futures in the sample are either negative or positive, but none of them are significant at the 10% level.

The coefficients of open interest lagged one period (OI_{t-1}) in the trading volume equation of Crude Oil, and all five financial futures are positive and significant at least at the 5% level, whereas the coefficients for Soybean and Gold futures are also positive but not significant. The coefficients of lagged open interest for Wheat, Copper, and Heating Oil futures are negative, although only the coefficient for Copper futures is significant at the 1% level. It is generally agreed that higher open interest indicates more trades are likely in the future.

All coefficients of one period lagged trading volume ($\ln(TV_{t-1})$) are significantly positive at the 1% level. They range from 0.72 for the 30-Year T-bond futures to 0.37 for Gold futures. Significance in the coefficients of lagged trading volume for all 11 futures in our sample lends strong support to our partial adjustment model specification, affirming persistence in trading volume.

Thus far, two interesting empirical results are noteworthy. First, the elasticities of trading volume with respect to transaction cost (proxied by the bid-ask spread)

Table 1. Empirical Results of Augmented Dickey-Fuller (ADF) Tests on the Stationary of Time Series Data.

Contract	Ln (TV_i)	Ln(IV_i)	Ln(BAS_i)	Ln (OI_i)	Ln ($3TB_i$)	Ln (MP_i)
S&P500 futures						
Nearby	-8.88**	-4.20**	-2.92	-8.62**	-0.74	-1.39
First deferred	-9.10**	-3.80**	-9.97*	-19.38**	-1.21	-1.29
E-mini S&P 500						
Nearby	-3.81**	-4.36**	-4.66**	-4.99**	-0.39	-1.35
First deferred	-10.52**	-4.70**	-10.04**	-9.97**	-0.99	-1.21
30-Year T-bond						
Nearby	-4.99**	-3.24*	-2.93*	-8.98**	-0.83	-2.24
First deferred	-9.42**	-4.07**	-8.76**	-6.99**	-1.37	-2.60
10-Year T-Note						
Nearby	-4.41**	-3.88**	-22.56**	-6.23**	-2.16	-2.06
First deferred	-7.20**	-7.58**	-7.72**	-6.44**	-1.85	-2.33
British Pound						
Nearby	-5.87**	-3.33*	-2.78	-6.47**	-2.11	-1.74
First deferred	-8.29**	-5.19**	-6.13**	-7.23**	-1.80	-1.59
Wheat						
Nearby	-8.48**	-7.37**	-2.78	-8.66**	-0.87	-1.67
First deferred	-7.01**	-7.68**	-5.15**	-4.98**	-1.11	-1.72

Table 1, continued. Empirical Results of Augmented Dickey-Fuller (ADF) Tests on the Stationary of Time Series Data.

Contract	Ln (TV_i)	Ln(IV_i)	Ln(BAS_i)	Ln (OI_i)	Ln ($3TB_i$)	Ln (MP_i)
S&P500 futures						
Soybean						
Nearby	-4.78**	-3.10*	-3.81**	-9.72**	-1.34	-2.43
First deferred	-7.00**	-3.52**	-6.18**	-5.33**	-0.92	-1.94
Copper						
Nearby	-4.97**	-3.7**	-5.78**	-9.17**	-2.17	-0.57
First deferred	-5.96**	-3.46**	-6.46**	-5.23**	-1.98	-1.23
Gold						
Nearby	-4.03**	-3.43**	-4.03**	-6.66**	-1.92	-0.66
First deferred	-5.65**	-4.16**	-6.10**	-4.75**	-1.69	-1.92
Crude Oil						
Nearby	-6.6**	-2.94*	-2.74	-15.29**	1.87	-1.37
First deferred	-12.0**	-3.45*	-5.92**	-10.96**	-1.74	-1.29
Heating oil						
Nearby	-9.33**	-3.20*	-1.34	-14.25**	-2.08	-1.21
First deferred	-12.56**	-3.31*	-5.45**	-7.00**	-1.83	-1.31

Note: The critical values of the ADF unit root test are -3.425, -2.864, and -2.56 for the 1%, 5%, and 10% level of significance, respectively. ** and * denote significance at the 1% and 5%, respectively.

Table 2. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of S&P 500 Index Futures (Chicago Mercantile Exchange), January 2005 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	-0.27	0.36**	-0.61**
	(-0.32)	(4.14)	(-4.85)
D_1	0.66**	0.64**	-0.20**
	(5.21)	(10.63)	(-6.45)
$\ln(TV_t)$	---	-0.12**	0.04**
	---	(-14.09)	(5.70)
$\ln(BAS_t)$	-0.81**	---	0.27**
	(-6.98)	---	(11.53)
$\ln(IV_t)$	0.52**	0.35**	---
	(7.32)	(16.86)	---
ΔMP_t	---	-1.13	---
	---	(-1.52)	---
$\ln(OI_{t-1})$	0.37**	---	0.05**
	(4.46)	---	(3.76)
$\ln(TV_{t-1})$	0.45**	---	---
	(14.66)	---	---
$\ln(BAS_{t-1})$	---	0.42**	---
	---	(14.56)	---
$\ln(IV_{t-1})$	---	---	0.28**
	---	---	(12.31)
$\ln(IV_{t-2})$	---	---	0.13**
	---	---	(5.62)
$\ln(IV_{t-3})$	---	---	0.10**
	---	---	(4.25)
$\ln(IV_{t-4})$	---	---	0.12**
	---	---	(5.26)
$\ln(IV_{t-5})$	---	---	0.09**
	---	---	(4.13)
$\ln(IV_{t-6})$	---	---	0.06**
	---	---	(2.88)
$\Delta(\ln(3TB_t))$	-0.13	---	---
	(-0.65)	---	---
R^2 Adj	0.78	0.88	0.71
F Stat	1,601.48**	3,773.06**	655.33**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 3. Empirical Results on Trading Volume, Bid-Ask Spread and Price Volatility Equations of E-mini S&P 500 Index Futures (Chicago Mercantile Exchange), January 2005 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	3.21**	0.66**	-0.49**
	(7.75)	(15.94)	(-6.04)
D_1	-0.97**	-0.10**	0.14**
	(-6.45)	(-5.90)	(4.91)
$\ln(TV_t)$	---	-0.11**	0.11**
	---	(-20.96)	(12.41)
$\ln(BAS_t)$	-2.60**	---	0.51**
	(-12.76)	---	(17.01)
$\ln(IV_t)$	0.76**	0.17**	---
	(12.33)	(12.63)	---
ΔMP_t	---	-0.95**	---
	---	(-3.81)	---
$\ln(OI_{t-1})$	0.10**	---	-0.02**
	(3.20)	---	(-2.42)
$\ln(TV_{t-1})$	0.43**	---	---
	(13.71)	---	---
$\ln(BAS_{t-1})$	---	0.32**	---
	---	(9.53)	---
$\ln(IV_{t-1})$	---	---	0.43**
	---	---	(22.62)
$\ln(IV_{t-2})$	---	---	0.15**
	---	---	(7.82)
$\ln(IV_{t-3})$	---	---	0.06**
	---	---	(3.30)
$\ln(IV_{t-4})$	---	---	0.07**
	---	---	(3.80)
$\ln(IV_{t-5})$	---	---	0.09**
	---	---	(4.74)
$\ln(IV_{t-6})$	---	---	0.03*
	---	---	(1.69)
$\Delta(\ln(3TB_t))$	-0.32*	---	---
	(-1.74)	---	---
R^2 Adj	0.96	0.92	0.81
F Stat	11,204.78**	6,368.82**	1,211.31**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 4. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of U.S. Treasury Bond Futures (Chicago Mercantile Exchange), January 2005 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	0.14	-1.03**	0.14*
	(0.61)	(-10.70)	(2.05)
D_1	-0.87**	-0.04	0.09**
	(-6.42)	(-0.84)	(4.32)
$\ln(TV_t)$	---	-0.10**	0.04**
	---	(-11.96)	(7.59)
$\ln(BAS_t)$	-0.87**	---	0.19**
	(-8.31)	---	(9.83)
$\ln(IV_t)$	0.28**	0.15**	---
	(3.77)	(3.90)	---
ΔMP_t	---	-1.60	---
	---	(-1.12)	---
$\ln(OI_{t-1})$	0.03**	---	-0.00
	(2.33)	---	(-0.71)
$\ln(TV_{t-1})$	0.72**	---	---
	(26.79)	---	---
$\ln(BAS_{t-1})$	---	0.36**	---
	---	(7.75)	---
$\ln(IV_{t-1})$	---	---	0.18**
	---	---	(8.42)
$\ln(IV_{t-2})$	---	---	0.12**
	---	---	(5.81)
$\ln(IV_{t-3})$	---	---	0.13**
	---	---	(5.58)
$\ln(IV_{t-4})$	---	---	0.13**
	---	---	(6.07)
$\ln(IV_{t-5})$	---	---	0.17**
	---	---	(8.06)
$\ln(IV_{t-6})$	---	---	0.13**
	---	---	(6.16)
$\Delta(\ln(3TB_t))$	-0.19	---	---
	(-0.86)	---	---
R^2 Adj	0.92	0.68	0.43
F Stat	5,201.18**	1,179.07**	215.02**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t -statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 5. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of 10-Year U.S. Treasury Note Futures (Chicago Board of Trade), January 2009 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	-1.62**	-1.50**	0.24
	(-3.61)	(-9.46)	(1.59)
D_1	-0.64**	-0.08*	0.10**
	(-3.87)	(-2.15)	(2.93)
$\ln(TV_t)$	---	-0.14**	0.05**
	---	(-16.44)	(3.75)
$\ln(BAS_t)$	-1.36**	---	0.30**
	(-6.49)	---	(5.46)
$\ln(IV_t)$	0.49**	0.31**	---
	(3.63)	(6.63)	---
ΔMP_t	---	-3.12	---
	---	(-1.03)	---
$\ln(OI_{t-1})$	0.08**	---	-0.00
	(3.09)	---	(-0.13)
$\ln(TV_{t-1})$	0.66**	---	---
	(14.51)	---	---
$\ln(BAS_{t-1})$	---	0.10*	---
	---	(2.04)	---
$\ln(IV_{t-1})$	---	---	0.10**
	---	---	(2.42)
$\ln(IV_{t-2})$	---	---	0.12**
	---	---	(2.75)
$\ln(IV_{t-3})$	---	---	0.15**
	---	---	(3.50)
$\ln(IV_{t-4})$	---	---	0.09**
	---	---	(2.56)
$\ln(IV_{t-5})$	---	---	0.10**
	---	---	(2.52)
$\ln(IV_{t-6})$	---	---	0.10**
	---	---	(3.41)
$\Delta(\ln(3TB_t))$	-0.16	---	---
	(-1.01)	---	---
R^2 Adj	0.94	0.78	0.29
F Stat	2,773.93**	781.57**	48.70**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 6. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of British Pound Futures (Chicago Mercantile Exchange) from January 2008 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	-5.14**	-4.73**	1.22**
	(-8.82)	(-15.75)	(5.65)
D_1	-0.83**	0.01	0.00
	(-4.18)	(0.22)	(0.04)
$\ln(TV_t)$	---	-0.25**	0.07**
	---	(-20.38)	(3.74)
$\ln(BAS_t)$	-0.97**	---	0.22**
	(-8.44)	---	(6.69)
$\ln(IV_t)$	0.34**	0.35**	---
	(4.44)	(10.76)	---
ΔMP_t	---	-0.14	---
	---	(-0.09)	---
$\ln(OI_{t-1})$	0.27**	---	-0.02
	(6.32)	---	(-1.00)
$\ln(TV_{t-1})$	0.41**	---	---
	(8.94)	---	---
$\ln(BAS_{t-1})$	---	0.14**	---
	---	(3.47)	---
$\ln(IV_{t-1})$	---	---	0.14**
	---	---	(3.71)
$\ln(IV_{t-2})$	---	---	0.08**
	---	---	(2.67)
$\ln(IV_{t-3})$	---	---	0.17**
	---	---	(5.27)
$\ln(IV_{t-4})$	---	---	0.10**
	---	---	(3.75)
$\ln(IV_{t-5})$	---	---	0.11**
	---	---	(3.96)
$\ln(IV_{t-6})$	---	---	0.11**
	---	---	(3.64)
$\Delta(\ln(3TB_t))$	-0.14	---	---
	(-1.21)	---	---
R^2 Adj	0.94	0.86	0.46
F Stat	3,846.58**	1,704.93**	115.36**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 7. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of Wheat Futures (Chicago Board of Trade) from January 2007 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	2.01**	0.29**	-0.85**
	(11.53)	(5.45)	(-8.42)
D_1	-0.25**	-0.01	0.09**
	(-7.70)	(-0.79)	(4.43)
$\ln(TV_t)$	---	-0.08**	0.19**
	---	(-9.82)	(15.03)
$\ln(BAS_t)$	-0.98**	---	0.68**
	(-11.53)	---	(13.96)
$\ln(IV_t)$	0.74**	0.22**	---
	(18.36)	(10.86)	---
ΔMP_t	---	0.21	---
	---	(1.00)	---
$\ln(OI_{t-1})$	-0.00	---	0.00
	(-0.44)	---	(0.03)
$\ln(TV_{t-1})$	0.66**	---	---
	(27.86)	---	---
$\ln(BAS_{t-1})$	---	0.63**	---
	---	(20.97)	---
$\ln(IV_{t-1})$	---	---	0.20**
	---	---	(10.23)
$\ln(IV_{t-2})$	---	---	0.02
	---	---	(1.12)
$\ln(IV_{t-3})$	---	---	0.05**
	---	---	(2.72)
$\ln(IV_{t-4})$	---	---	0.08**
	---	---	(3.82)
$\ln(IV_{t-5})$	---	---	0.01
	---	---	(0.40)
$\ln(IV_{t-6})$	---	---	0.01
	---	---	(0.61)
$\Delta(\ln(3TB_t))$	-0.07	---	---
	(-1.05)	---	---
R^2 Adj	0.89	0.84	0.52
F Stat	2,690.28**	2,039.94**	216.34**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 8. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of Soybean Futures (Chicago Board of Trade), January 2007 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	2.14**	0.43**	-0.83**
	(11.15)	(8.43)	(-9.68)
D_1	-0.12**	-0.01*	0.05**
	(-3.96)	(-1.94)	(2.85)
$\ln(TV_t)$	---	-0.09**	0.19**
	---	(-10.97)	(16.80)
$\ln(BAS_t)$	-1.66**	---	0.86**
	(-11.42)	---	(13.28)
$\ln(IV_t)$	0.77**	0.17**	---
	(13.97)	(9.56)	---
Δ MP_t	---	-0.18	---
	---	(-1.20)	---
$\ln(OI_{t-1})$	0.00	---	-0.01*
	(0.20)	---	(-2.10)
$\ln(TV_{t-1})$	0.60**	---	---
	(20.03)	---	---
$\ln(BAS_{t-1})$	---	0.56**	---
	---	(15.37)	---
$\ln(IV_{t-1})$	---	---	0.18**
	---	---	(7.56)
$\ln(IV_{t-2})$	---	---	0.15**
	---	---	(4.72)
$\ln(IV_{t-3})$	---	---	0.03
	---	---	(1.38)
$\ln(IV_{t-4})$	---	---	0.03
	---	---	(1.13)
$\ln(IV_{t-5})$	---	---	0.07**
	---	---	(2.33)
$\ln(IV_{t-6})$	---	---	0.00
	---	---	(0.16)
$\Delta(\ln(3TB_t))$	-0.07	---	---
	(-0.87)	---	---
R^2 Adj	0.90	0.88	0.58
F Stat	2,883.11**	2,760.88**	270.49**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 9. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of Copper Futures (Commodity Exchange) from January 2008 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	1.92**	0.38**	-0.07
	(8.13)	(8.46)	(-0.88)
D_1	0.21**	0.01	-0.01
	(3.44)	(0.36)	(-0.36)
$\ln(TV_t)$	---	-0.27**	0.08**
	---	(-29.38)	(5.66)
$\ln(BAS_t)$	-1.44**	---	0.26**
	(-13.09)	---	(6.59)
$\ln(IV_t)$	0.43**	0.24**	---
	(6.81)	(8.92)	---
ΔMP_t	---	-0.17	---
	---	(-0.50)	---
$\ln(OI_{t-1})$	-0.10**	---	0.00
	(-4.03)	---	(0.32)
$\ln(TV_{t-1})$	0.45**	---	---
	(11.33)	---	---
$\ln(BAS_{t-1})$	---	0.19**	---
	---	(6.89)	---
$\ln(IV_{t-1})$	---	---	0.15**
	---	---	(4.87)
$\ln(IV_{t-2})$	---	---	0.15**
	---	---	(4.84)
$\ln(IV_{t-3})$	---	---	0.14**
	---	---	(4.11)
$\ln(IV_{t-4})$	---	---	0.21**
	---	---	(7.14)
$\ln(IV_{t-5})$	---	---	0.08**
	---	---	(2.68)
$\ln(IV_{t-6})$	---	---	0.10**
	---	---	(3.54)
$\Delta(\ln(3TB_t))$	0.19*	---	---
	(1.66)	---	---
R^2 Adj	0.89	0.84	0.51
F Stat	1,982.57**	1,576.17**	152.28**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 10. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of Gold Futures (Commodity Exchange) from January 2008 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	2.77**	0.90**	-0.86**
	(13.69)	(12.39)	(-11.37)
D_1	0.06	0.06**	-0.01
	(1.39)	(3.23)	(-0.73)
$\ln(TV_t)$	---	-0.21**	0.19**
	---	(-15.41)	(14.19)
$\ln(BAS_t)$	-2.02**	---	0.63**
	(-16.59)	---	(13.71)
$\ln(IV_t)$	0.93**	0.33**	---
	(18.67)	(14.43)	---
ΔMP_t	---	-0.25	---
	---	(-0.76)	---
$\ln(OI_{t-1})$	0.01	---	-0.00
	(1.56)	---	(-1.20)
$\ln(TV_{t-1})$	0.37**	---	---
	(10.41)	---	---
$\ln(BAS_{t-1})$	---	0.29**	---
	---	(6.32)	---
$\ln(IV_{t-1})$	---	---	0.20**
	---	---	(7.37)
$\ln(IV_{t-2})$	---	---	0.15**
	---	---	(6.54)
$\ln(IV_{t-3})$	---	---	0.06**
	---	---	(2.56)
$\ln(IV_{t-4})$	---	---	0.05**
	---	---	(2.38)
$\ln(IV_{t-5})$	---	---	0.13**
	---	---	(5.63)
$\ln(IV_{t-6})$	---	---	0.04*
	---	---	(2.06)
$\Delta(\ln(3TB_t))$	0.01	---	---
	(0.14)	---	---
R^2 Adj	0.94	0.94	0.68
F Stat	4,070.27**	4,427.94**	310.38**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 11. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of Crude Oil Futures (New York Mercantile Exchange) from January 2008 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	0.69*	-0.24**	0.10
	(1.68)	(-3.85)	(0.57)
D_1	-0.54**	-0.04**	0.18**
	(-10.43)	(-6.13)	(7.26)
$\ln(TV_t)$	---	-0.07**	0.18**
	---	(-11.03)	(13.70)
$\ln(BAS_t)$	-1.00**	---	0.41**
	(-9.65)	---	(10.59)
$\ln(IV_t)$	0.38**	0.08**	---
	(9.39)	(11.40)	---
$\Delta\ MP_t$	---	0.01	---
	---	(0.07)	---
$\ln(OI_{t-1})$	0.06**	---	-0.03**
	(4.14)	---	(-4.70)
$\ln(TV_{t-1})$	0.50**	---	---
	(18.76)	---	---
$\ln(BAS_{t-1})$	---	0.77**	---
	---	(37.96)	---
$\ln(IV_{t-1})$	---	---	0.24**
	---	---	(8.34)
$\ln(IV_{t-2})$	---	---	0.13**
	---	---	(5.46)
$\ln(IV_{t-3})$	---	---	0.14**
	---	---	(5.84)
$\ln(IV_{t-4})$	---	---	0.12**
	---	---	(4.55)
$\ln(IV_{t-5})$	---	---	0.13**
	---	---	(5.78)
$\ln(IV_{t-6})$	---	---	0.10**
	---	---	(4.17)
$\Delta(\ln(3TB_t))$	0.01	---	---
	(0.21)	---	---
R^2 Adj	0.86	0.89	0.79
F Stat	1,444.42**	2,492.48**	539.30**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 12. Empirical Results on the Trading Volume, Bid-Ask Spread and Price Volatility Equations of Heating Oil Futures (New York Mercantile Exchange) from January 2008 to December 2010.

	$\ln(TV_t)$	$\ln(BAS_t)$	$\ln(IV_t)$
Intercept	-1.35**	-0.95**	0.97**
	(-3.74)	(-7.62)	(5.13)
D_1	-0.20**	-0.04**	0.06**
	(-5.53)	(-3.57)	(3.82)
$\ln(TV_t)$	---	-0.16**	0.17**
	---	(-12.08)	(11.45)
$\ln(BAS_t)$	-0.80**	---	0.31**
	(-13.78)	---	(11.87)
$\ln(IV_t)$	0.48**	0.19**	---
	(12.18)	(11.25)	---
$\Delta\ MP_t$	---	0.08	---
	---	(0.35)	---
$\ln(OI_{t-1})$	-0.00	---	-0.02
	(-0.24)	---	(-1.48)
$\ln(TV_{t-1})$	0.48**	---	---
	(16.56)	---	---
$\ln(BAS_{t-1})$	---	0.69**	---
	---	(28.02)	---
$\ln(IV_{t-1})$	---	---	0.23**
	---	---	(8.09)
$\ln(IV_{t-2})$	---	---	0.15**
	---	---	(5.98)
$\ln(IV_{t-3})$	---	---	0.11**
	---	---	(4.34)
$\ln(IV_{t-4})$	---	---	0.08**
	---	---	(3.34)
$\ln(IV_{t-5})$	---	---	0.11**
	---	---	(4.31)
$\ln(IV_{t-6})$	---	---	0.11**
	---	---	(4.40)
$\Delta(\ln(3TB_t))$	-0.03	---	---
	(-0.91)	---	---
R^2 Adj	0.76	0.89	0.75
F Stat	755.85**	2,264.19**	439.43**

The table reports the parameter estimates of the trading volume, effective bid-ask spread, and price volatility in the three equation model specified in Section III, equations (3) to (5). All variables are in log form. The definition of each variable is as follows: TV=trading volume; BAS=effective bid-ask spread; IV=realized volatility; OI=open interest. 3TB=Three-month T-bill; D_1=1 if it is the first deferred contract and zero otherwise; and subscript t-j, j=1…6, denotes the number of lagged periods. Numbers in parentheses denote t-statistics. ** and * denote significance at the 1% and 5% levels, respectively.

Table 13. Elasticity of Trading Volume with Respect to Transaction Costs in Selected U.S. Futures Markets.

Contract	Point Estimates[1]	Interval Estimates[2]
1. Financial futures		
S&P500	-0.81 (0.12)	(-1.043, -0.577)
E-mini S&P500	-2.60 (0.06)	(-2.723, -2.477)
30-Year T-Bond	-0.87 (0.10)	(-0.972, -0.671)
10-Year T-Note	-1.36 (0.22)	(-1.794, -0.925)
British Pond	-0.97 (0.13)	(-1.214, -0.726)
2. Agricultural futures		
Wheat	-0.98 (0.09)	(-1.171, -0.789)
Soybean	-1.66 (0.15)	(-1.960, -1.360)
3. Metals futures		
Copper	-1.44 (0.10)	(-1.640, -1.240)
Gold	-2.02 (0.13)	(-2.275, -1.765)
4. Energy futures		
Crude Oil	-1.00 (0.11)	(-1.216, -0.784)
Heating Oil	-0.80 (0.06)	(-0.923, -0.677)

Notes: 1. Numbers in parentheses denote standard errors for the corresponding point estimates. 2. Interval estimates are given for a 95% confidence level.

for most of the 11 futures in our sample have become very elastic. This empirical result corroborates the significant progress in the globalization of international futures trading made during the period of 2005–2010, enabling cross-border trading easier. Thus, any regulation that leads to an increase in the futures trading cost would significantly reduce trading volume and weaken the relative competitiveness of the U.S. futures industry. Second, given our results, the elasticity used in the CBO's 1990 report, which is the –0.26 elasticity estimated by Epps (1976) based on U.S. stock data, seriously understates the current elasticities in the futures markets. Hence, the CBO's study overestimates the potential revenue of a transaction tax in futures markets.

B. Bid-Ask Spread Equation

The third column in Tables 2–12 presents the coefficient estimates of the explanatory variables in the bid-ask spread equation. The coefficients of trading volume are negative and statistically significant at the 1% level for all 11 futures. They range from –0.27 (Copper) to –0.07 (Crude Oil). For example, a 10% decrease in the Copper futures' trading volume will result in a 2.7% increase in the bid-ask spread. These results affirm that a decrease in trading volume would increase the bid-ask spread (transaction or trading cost), reducing market liquidity. These results are consistent with those of Wang, Yau, and Baptiste (1997), Wang and Yau (2000), Chou and Wang (2006), and Sahoo and Kumar (2011).

The coefficients of price volatility (IV) are significantly positive for all 11 contracts. This result is expected because an increase in price volatility implies market-makers face inventory risk and risk of trading with informed traders. Therefore, they will increase the bid-ask spread to minimize their potential loss. The magnitude of the elasticity of bid-ask spread with respect to price volatility falls in the range of 0.35 (S&P 500 and British Pound) to 0.07 (Crude Oil).

Changes in daily mean price (ΔMP) are used to control for the measurement scale effect of differing price levels of futures contracts with different maturities. Most of the coefficients for the changes in daily mean price are negative but not significant, except for the E-mini S&P 500 index futures.

The coefficients of one-period lagged bid-ask spread (BAS_{t-1}) are positive and statistically significant for all 11 futures. This indicates that the dynamic adjustment of BAS is not usually complete within a one-day period for these eleven futures.

C. Price Volatility Equation

The fourth column in Tables 2–12 presents the empirical results on the price volatility equation. The coefficients of trading volume (TV) and bid-ask spread (BAS) are significantly positive at the 1% level for all 11 futures. This can be interpreted that trading volume increases because of arrival of new information. Likewise, our finding that a positive relationship exists between BAS and price volatility is also consistent with the theory that bounces in the bid-ask spread have a positive impact on price volatility in the futures literature (e.g., Wang, Yau, and Baptiste 1997; Wang and Yau 2000; Chou and Wang 2006; Sahoo and Kumar 2011). This result is also consistent with Hau's (2006) result that an increase in minimum tick size led to an increase in price volatility in the French equity market.

Since the relations between price volatility and trading volume, and between price volatility and bid-ask spread (proxy for a transaction tax), are both positive, our findings suggest that the impact of a transaction tax on price volatility depends on the net effect of the decreasing trading volume and widening bid-ask spread on price volatility. However, we observe that the coefficient of bid-ask spread is relatively larger than the coefficient of trading volume in the price volatility equation for all the futures we studied. For example, in Table 2, the coefficient of trading volume is 0.04, whereas the coefficient of bid-ask spread is 0.27 for the S&P 500 index futures. Thus, the positive impact of an increase in the bid-ask spread on price volatility will offset the negative impact on price volatility from a declining trading volume, which has a smaller positive coefficient with price volatility than with bid-ask spread. That is, an increase in bid-ask spread due to an increase in transaction tax may not reduce price volatility; it depends on the net effects of an increase in bid-ask spread and a decline in trading volume.

The coefficient of one-period lagged open interest is expected to be negative

Table 14. Estimates of Transaction Costs in Selected U.S. Futures Markets.

(1) Contract	(2) Exchange	(3) Minimum Tick	(4) No-member Clearing[a]	(5) Exchange Fee[a]	(6) NFA[b] Fee[a]	(7) Brokerage Fee	(8) Total Fixed Transaction Cost[c]
S&P500	CME	$12.50	$0.78	$0.00	$0.02	$1.50	$14.80
E-mini S&P500	CME	$12.50	$0.39	$0.75	$0.02	$1.14	$14.80
30-Year T-Bond	CBOT	$31.25	$0.06	$0.50	$0.02	$1.37	$33.20
10-Year T-Note	CBOT	$15.62	$0.06	$0.50	$0.02	$1.37	$17.57
British Pound	CME	$6.25	$0.60	$1.00	$0.02	$0.33	$8.20
Wheat	CBOT	$12.50	$0.06	$1.75	$0.02	$1.68	$16.01
Soybean	CBOT	$12.50	$0.06	$1.75	$0.02	$1.62	$15.95
Copper	COMEX	$10.00	$1.45	$0.00	$0.02	$1.48	$12.95
Gold	COMEX	$12.50	$1.45	$0.00	$0.02	$1.48	$15.45
Crude Oil	NYMEX	$10.00	$1.45	$0.00	$0.02	$1.48	$12.95
Heating Oil	NYMEX	$4.20	$1.45	$0.00	$0.02	$1.48	$7.15

Notes: [a] Per side. These fees charges to a non-exchange member. [b] National Futures Association. [c] Total fixed transaction cost (column (8)) is the sum of columns (3)-(7).

Table 15. Estimates of Post-Tax Trading Volume in Selected U.S. Futures Markets.

(1) Contract	(2) Total Trading Volume (2010)[a]	(3) Average Yearly Price (2010)	(4) Total Fixed Transaction Cost	(5) Current Elasticity[b]
S&P500	7,689,961	$283,981	$14.80	-0.81
E-mini S&P 500	555,328,670	$56,776	$14.80	-2.60
30-Year T-Bond	83,509,754	$124,069	$33.20	-0.87
10-Year T-Note	293,718,907	$121,174	$17.57	-1.36
British Pound	30,220,239	$96,522	$8.20	-0.97
Wheat	23,090,255	$29,512	$16.01	-0.98
Soybean	36,993,960	$52,434	$15.95	-1.66
Copper	10,305,670	$8,572	$12.95	-1.44
Gold	44,730,345	$122,616	$15.45	-2.02
Crude Oil	168,652,141	$79,621	$12.95	-1.00
Heating Oil	26,970,106	$9,033	$7.15	-0.80

because it is used as a measure of the overall liquidity lagged one period. We find that the coefficients of lagged open interest are negative and significant in the price volatility equations for three futures (E-mini S&P500 index, Soybean and Copper), whereas those for the rest of the sample are mixed in sign and statistically insignificant.

The coefficients of six lagged intraday volatility ((TV_{t-j}) j = 1,…, 6) are all significantly positive for all 11 futures. Magnitudes of these coefficients are monotonically declining. These results suggest that price volatility has a persistence effect, and the recent lagged volatility has a larger influence on the current volatility.

Finally, the F-statistics for all equations are significant at the 1% level with high values of R-squared, suggesting that our models adequately explain the daily variations of trading volume, bid-ask spread, and price volatility in all selected futures markets.

V. ESTIMATION OF POTENTIAL TAX REVENUE

One of the major issues being debated on a transaction tax proposal is whether a transaction tax could generate substantial tax revenue. In this section, we estimate the potential tax revenue that could be raised from futures transactions given our estimates of elasticity of trading volume as presented above.

Transaction cost is one of the major factors in determining the profitability in trading in a given financial market. Any increase in the transaction cost of undertaking a futures transaction will cause participants to re-evaluate the benefits associated with that instrument. Depending on the magnitude of a transaction tax relative to

Table 15, continued. Estimates of Post-Tax Trading Volume in Selected U.S. Futures Markets.

Tax Rate: 0.02%			Tax Rate: 0.002%		
(6) Transaction Tax as % of Total Fixed Transaction Cost[c]	(7) Change in Volume[d]	(8) Post-Tax Volume[e]	(9) Transaction Tax as % of Total Fixed Transaction Cost[f]	(10) Change in Volume[g]	(11) Post-Tax Volume[h]
383.76%	-23,903,786	- 100%	38.38%	-2,390,379	5,299,582
76.72%	-1,107,792,715	-100%	7.67%	-110,779,271	444,549,399
74.74%	-53,301,299	29,208,455	7.47%	-5,430,130	78,079,624
137.93%	-550,983,687	-100%	13.79%	-55,098,369	238,620,538
235.42%	-69,010,009	-100%	23.54%	-6,901,001	23,319,238
36.87%	-8,342,529	14,747,726	3.69%	-834,253	22,256,002
65.75%	-40,309,945	-100%	6.58%	-4,030,994	32,902,966
13.24%	-1,964,737	8,340,933	1.32%	-196,474	10,109,196
158.73%	-143,418,044	-100%	15.87%	-14,341,804	30,388,541
122.93%	-26,089,467	-100%	12.29%	-20,727,348	147,924,793
25.27%	-5,451,749	21,518,357	2.53%	-545,175	26,424,931

[a]Total trading volume for each contract in year 2010 is obtained from FIA volume statistics. [b]Coefficients of ln(BAS) on the TV equation from column 2, row 4 of Tables 2-12. [c]Transaction tax as % of total fixed transaction cost (column (6)) = [Average yearly price (column (3)) x 0.02%] / Total fixed transaction (column (4)) [d]Change in trading volume (column (7)) = Post-tax volume (column (8)) - Trading volume (column (2)) [e]Post-tax volume (column (8)) = Total trading volume (column (2)) x (1+[current elasticity (column (5)) x Transaction tax as % of total fixed transaction cost (column (6))]; if <0, column (8) is indicated by - 100% [f]Transaction tax as % of total fixed transaction cost (column (9)) = [Average yearly price (column (3)) x 0.002%] / Total fixed transaction (column (4)) [g]Change in trading volume (column (10)) = Post-tax volume (column (10)) - Trading volume (column (2)) [h]Post-tax volume (column (11)) = Total trading volume (column (2)) x (1+[current elasticity (column (5)) x Transaction tax as % of total fixed transaction cost (column (9))]; if <0, column (11) is indicated by - 100%

the total transaction cost, a customer may elect to use alternative hedging and speculative strategies. Thus, a decline in trading volume induced by a transaction tax could have an adverse impact on the businesses of futures exchanges.

In order to estimate a transaction tax as a percentage of the total fixed transaction cost, we collect various fixed fees for the 11 futures contracts in our samples from associated futures exchanges and on-line brokerage firms for non-clearing members.[18] Table 14 presents the total fixed transaction cost (column 8), which is the sum of two major components: (1) the bid-ask spread approximated by the minimum tick size (column 3); and (2) various transaction fees, including the

18. Exchange and NFA fees for futures are obtained from Ira Epstein Division of Linn Group, Inc. Recent changes in exchange fees are obtained from the website of CME.

Table 16. Estimates of Post-Tax Revenue in Selected U.S. Futures Markets.

			Tax Rate: 0.02%			Tax Rate: 0.002%		
(1) Contract	(2) Average Yearly Price (2010)	(3) Current Elasticity	(4) Naïve Method[a]	(5) Elasticity Adjusted[b]	(6) % Change to the Naïve Method[c]	(7) Naïve Method[a]	(8) Elasticity Adjusted[b]	(9) % Change to the Naïve Method[c]
S&P 500	$283,981	-0.81	$436,760,532	$0.00	-100%	$43,676,053	$30,099,612	-31.08%
E-mini S&P 500	$56,776	-2.60	$6,305,896,991	$0.00	-100%	$630,589,699	$504,797,045	-19.95%
30-Year T-Bond	$124,069	-0.87	$2,072,187,486	$724,770,376	-65.02%	$207,218,749	$193,845,281	-6.45%
10-Year T-Note	$121,174	-1.36	$7,118,223,079	$0.00	-100%	$711,822,308	$578,292,436	-18.76%
British Pound	$96,522	-0.97	$583,383,582	$0.00	-100%	$58,338,358	$45,016,390	-22.84%
Wheat	$29,512	-0.98	$136,289,676	$87,0481,01	-36.13%	$13,628,968	$13,136,552	-3.61%
Soybean	$52,434	-1.66	$387,315,432	$0.00	-100%	$38,731,543	$34,504,359	-10.91%
Copper	$8,572	-1.44	$17,668,989	$14,300,463	-19.06%	$1,766,899	$1,733,214	-1.91%
Gold	$122,616	-2.02	$1,096,935,043	$0.00	-100%	$109,693,504	$74,522,687	-32.06%
Crude Oil	$79,621	-1.00	$2,685,649,749	$0.00	-100%	$268,564,975	$235,496,271	-12.31%
Heating Oil	$9,033	-0.80	$48,725,003	$38,875,710	-20.21%	$4,872,500	$4,774,007	-2.02%

Notes: [a] Estimated potential revenue under this method is computed as: Trading volume 2010 (column 2, Table 15) x Average Yearly Price (2010) (column 2, Table 16) x Tax rate [b] Estimated potential revenue under this method is computed as: Post-tax trading volume (column 8 for 0.02% tax rate, column 11 for 0.002% tax rate, Table 15) x Average Yearly Price (2010) (column 2, Table 16) x Tax rate non-member clearing fee, exchange fee, National Futures Association (NFA) fee, and brokerage fee (columns 4–7, respectively). Table 14 does not include any variable cost associated with each futures transaction, firm-specific overhead fixed costs, or the market impact cost associated with large trades. Thus, the total fixed transaction cost presented in Table 14 is actually the minimum trading cost for a futures transaction.[19] As indicated, trading in the Crude Oil futures costs the most and the British Pound futures the least.

Table l5 presents our estimates of the post-tax trading volume under assumed tax rates of 0.02% and 0.002% for the eleven futures.[20] We first calculate the 0.02% tax on a futures transaction based on the notional value of the futures contract, as approximated by the average yearly price (column 3) in this study. We then express the transaction tax as a percentage of the total fixed transaction cost (column 4) in column 6. Second, we compute the post-tax volume (column 8), that is, the estimated trading volume after a transaction tax is imposed, based on one plus the product of the transaction tax as a percentage of the total fixed cost (column 6), current elasticity (column 5), and total trading volume (column 2). Third, we compute the change in trading volume (column 7), which is equal to the post-tax volume (column 8) minus the total trading volume (2010) (column 2). We compute the same for 0.002% tax rate as well.

Results from Table 15 show that with a transaction tax of 0.02%, trading in seven out of the eleven futures would be totally eliminated from local trading or simply be migrated to overseas exchanges (column 8). These seven futures contracts are (1) S&P 500 index; (2) E-mini S&P 500 index; (3) 10-year T-Note; (4) British Pound; (5) Soybean; (6) Gold; and (7) Crude Oil. This result suggests that the impact of a transaction tax on trading costs and trading volume varies significantly with different types of futures.

Table 16 presents estimates of the potential post-tax revenue (columns 5 and 8 for 0.02% and 0.002% tax rates, respectively) for the 11 futures using the estimated post-tax trading volume (columns 8 and 11, Table 15) based on the estimated elasticity of trading volume from our models. For comparison purposes, we also estimate the post-tax revenue calculated by the naïve method (columns 4 and 7), which simply calculates the tax revenue from multiplying the trading volume (2010, column 2, Table 15) and the notional contract value (average yearly price, 2010, column 2), by the two assumed tax rates. The tax revenue generated by the naïve method (column 4) is often used by proponents of transaction tax as the basis for arguing that transaction tax would generate substantial tax revenue.[21] For the 0.02% tax rate, seven futures (S&P 500, E-mini S&P 500, 10-Year T-Note, British Pound, Soybean,

19. The estimated total fixed transaction cost in Table 14 might be lower than the actual transaction cost because the effective bid-ask spread is often greater than the minimum tick size that we used in Table 14.

20. We used a tax rate of 0.02% of the notional value of each futures contact because the House of Representatives had proposed to impose a 0.02% tax on futures transactions (see Cronin 2010 and Noll 2010).

21. CBO's (1990) study also used an elasticity of −0.26 as the input to calculate the post-tax volume and potential tax revenue.

Gold, and Crude Oil) with zero post-tax volume would therefore generate zero tax revenue (column 5), which is 100% less than the corresponding tax revenue calculated by the naïve method. The other four futures (30-Year T-Bond, Wheat, Copper, and Heating Oil) generate tax revenues that are less than the corresponding estimated tax revenues from the naïve method in the range of –19.06% to –65.02% (column 6).

There are three noteworthy findings. First, the magnitude of the decline in the post-tax volume depends on the relative importance of the transaction tax to the total fixed cost and/or the elasticity of trading volume with respect to transaction costs for each futures. For example, the post-tax trading volume of the S&P 500 index futures is reduced to zero when the transaction tax is 383.76% of the total fixed transaction cost with an elasticity equals to –0.81. In the Soybean case, the elasticity is high (i.e., –1.66) but the post-tax volume still drops to zero even if the transaction tax is only 65.75% of the total fixed transaction cost. Second, the impact of a transaction tax on the transaction cost and trading volume varies significantly with different types of futures. Third, the transaction tax revenue estimated by the pre-tax volume or with an unrealistically low elasticity can seriously over-estimate the post- tax revenue.

VI. CONCLUSION

This paper examines the potential impact of a transaction tax on the market quality (i.e. trading volume, bid-ask spread and price volatility) of the U.S. futures markets. To this end, we estimate the empirical relations among trading volume, bid-ask spread, and price volatility within a three-equation structural model for 11 active U.S. futures, including financial, agricultural, metals, and energy futures. Our results indicate that (1) trading volume is negatively related to bid-ask spread, and positively related to price volatility after controlling for other factors; (2) bid-ask spread is negatively related to trading volume and positively related to price volatility; and (3) price volatility has a positive relationship with bid-ask spread and with trading volume after controlling for other variables. These results confirm that a transaction tax, which is analogous to a greater bid-ask spread, will reduce trading volume, increase bid-ask spread, and may not reduce market price volatility in the futures markets studied. Furthermore, the impact of a transaction tax on transaction cost and trading volume varies significantly with the type of futures contracts.

We also estimate the potential post-tax trading volume and tax revenue with the update estimates of the elasticity of trading volume with respect to trading costs under alternative tax rates. For a 0.02% tax rate of the notional value of the contract, we find that the trading volume for seven futures (S&P 500, E-mini S&P 500, 10-Year T-Note, British Pound, Soybean, Gold, and Crude Oil) would be totally eliminated, resulting in a zero post-tax revenue from these seven futures. Thus, a transaction tax of 0.02% on futures trading hardly seems like a promising avenue for raising tax revenue.

In summary, an increase in transaction cost due to a sizable transaction tax could have significant adverse impacts on market quality. A transaction tax will likely not raise substantial revenue for the government as suggested in other studies, but it may hurt the international competitiveness of the U.S. futures markets.

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MARGIN BACKTESTING

Christophe Hurlin and Christophe Pérignon*

This paper presents a validation framework for collateral requirements or margins on a derivatives exchange. It can be used by investors, risk managers, and regulators to check the accuracy of a margining system. The statistical tests presented in this study are based either on the number, frequency, magnitude, and timing of margin exceedances, which are defined as situations in which the trading loss of a market participant exceeds his or her margin. We show that these validation tests can be implemented at the individual level or at the global exchange level.

What makes derivatives exchanges so special is the extremely low default risk that market participants are exposed to. Collateral requirements or margins are the major tools to protect derivatives users against the default of their counterparties. The challenge faced by derivative exchanges is to set margins high enough to mitigate default risk but not so high as to shy traders away and damage liquidity. The goal of this paper is to design a methodological framework allowing risk managers and regulators to check the validity of the margins charged to derivatives users. It consists of a series of diagnostic tools allowing one to detect misspecified models that lead to margins that are either excessively conservative or lenient. Checking the validity of a margining system is particularly important nowadays as more and more over-the counter (OTC) derivatives products are migrating to clearing platforms (Duffie and Zhu 2010).[1]

There are two types of margining systems used in practice: the Standard Portfolio Analysis of Risk (hereafter SPAN) system and the Value-at-Risk (hereafter VaR) model. Both margining systems consider a series of scenarios representing potential one-day ahead changes in the underlying assets' price and volatility and

1. The clearing activity consists in confirming, matching, and settling all trades on an exchange. In order to reduce the risk of non-performance, exchange-traded derivatives are guaranteed against counterparty failure by a central counterparty clearing house. On most derivatives exchanges, only a subset of market participants (i.e., the clearing members) can directly trade with the clearing house whereas all non-clearing member participants have to trade through a designated clearing member.

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generate simulated distributions of potential profit-and-loss (hereafter P&L) for derivatives users. Under SPAN, the system selects for each position the largest loss across all considered scenarios, combines financial instruments within the same underlying asset, and total margin is given by the sum of the risk of all underlying assets less some diversification adjustments (CFTC 2001; Chicago Mercantile Exchange 2009). Differently, VaR margins are set such that the probability of the loss on the entire derivatives portfolio exceeding the margin is equal to a pre-specified level, such as 1% (Knott and Mills 2002; Cruz Lopez, Harris, and Pérignon 2011).

On a regular basis, the risk-management department of the clearing-house and the regulatory agencies check the validity of the margining system. In particular, they make sure that the hypothetical shocks used in the scenarios are extreme enough and that the estimation of the derivative prices is reliable. Of particular concern is a situation in which margins are set at too low a level. In this case, a default by a clearing member following a big trading loss would lead to a massive shortfall, which may propagate default within the clearing system (Jones and Pérignon 2012).

While the performance of the SPAN system has been investigated in a number of papers (Kupiec 1994; Kupiec and White 1996; Eldor, Hauser, and Yaari 2011), VaR margins have not to our knowledge been investigated in the academic literature. This increasingly-popular modeling approach offers several advantages though. First, as it is based on a quantile, it allows derivatives exchanges to pick the level of tail risk that best fits with their risk tolerance. A second advantage is that quantile-based margins are less sensitive to simulation design than maximum-based margins, such as SPAN margins. Most importantly for this study, quantile-based margins can be validated ex-post using formal backtesting methodologies. For instance, as an α% quantile is by definition exceeded α% of the time, one can check whether in reality α% VaR margins are indeed exceeded α% of the time.

Compared to market risk VaR (Jorion 2007; Christoffersen 2009a), which is used by banks to monitor their trading risk and compute capital requirements, the estimation of VaR margin is much simpler. In general, the quantile of the return at time t cannot be estimated without making some strong assumptions about the underlying distribution. Specifically, since there is only one return observation on each date, it is usually assumed that the returns are independently and identically distributed over time. Under these assumptions, VaR can be estimated from the historical path of past returns. In the context of VaR margin; however, the situation is quite different because P&L observations are simulated at time t. This is an ideal situation from an econometric point of view because the quantile of the P&L distribution can be directly estimated without making any assumptions regarding its behavior over time.

Our main contribution to the literature on derivatives margins is to present a backtesting framework for derivatives margins. It consists of a series of hypotheses that must be validated by a well-functioning margin model. Then, we propose a series of statistical tests that aim to test these hypotheses in order to detect misspecified margining models. We show that these validation tests can be implemented either at the indivual investor level or at the global exchange level. In this framework, not only can we find out whether a model is misspecified but we can also unmask the reasons of rejection of a misspecified model. Finally, in order to ease the implementation of the backtesting methodologies presented in this paper, we created a website on which users can freely upload their margins and P&L data and run the associated computer codes (www.RunMyCode.org).

The outline of the paper is the following. In Section I, we discuss how to estimate VaR margins and present the main testable hypotheses. In Section II, we show how to test these hypotheses in order to validate or invalidate a given margining model. We present in Section III some statistical test that aim to validate the margining model at the exchange level. Section IV summarizes and concludes our paper.

I. MARGIN ESTIMATION AND TESTABLE HYPOTHESES

A. Margin Estimation

For retail investors, margins are typically set at the contract level (e.g., $1,000 for any long or short position in a given futures contract). Depending on the expected volatility, the derivatives exchange can adjust the level of the margin, as shown by Brunnermeier and Pedersen (2009, Figure 1) for the S&P 500 futures. Differently, for large market participants such as clearing members, margins are computed at the portfolio level in order to account for diversification effects and are adjusted daily. The VaR margin B_i is set such that there is a probability α that the loss on the derivative position exceeds the margin:

$$\Pr\left[V_{i,t} < -B_{i,t|t-1}(\alpha)\right] = \alpha \tag{1}$$

where V_i denotes the P&L of investor i, and α is called the coverage rate. Let $\omega_{i,t-1}$ be the vector of positions of clearing member i at the end of day t–1:

$$\omega_{i,t-1} = \begin{bmatrix} \omega_{i,1,t-1} \\ \vdots \\ \omega_{i,D,t-1} \end{bmatrix} \tag{2}$$

where D is the number of derivatives contracts (futures and options) traded on this exchange and $i = 1, ..., N$. To arrive at a margin for this portfolio, the clearing house considers a series of S scenarios representing potential one-day ahead changes in the level and volatility of the underlying assets. For each scenario, the value of the portfolio is recomputed, or marked-to-model, using futures and option pricing formulas, and the associated hypothetical P&L is computed:

$$v_{i,t} = \begin{bmatrix} v_{i,t}^{1} \\ \vdots \\ v_{i,t}^{S} \end{bmatrix}. \tag{3}$$

Given the simulated path $\{v_{i,t}^{s}\}_{s=1}^{S}$, the VaR margin for clearing member i is given by:

$$\widehat{B}_{i,t} = \text{percentile}\left(\{v_{i,t}^{s}\}_{s=1}^{S}, 100\alpha\right). \tag{4}$$

The clearing house will proceed in the same way for the $N-1$ other clearing members and only those who will be able to pile up this amount of collateral on their margin accounts will be allowed to trade on the next day.

B. Backtesting VaR Margin

Traditionally the quality of the forecast of an economic variable is assessed by comparing its *ex-post* realization with the *ex-ante* forecast value. The comparison of the various forecast models is thus generally made by using a criterion such as the Mean Squared Error criterion or standard information criteria (AIC and BIC). However, this approach is not suitable for VaR margin forecasts because the true quantile of the P&L distribution is not observable. That is why VaR assessment is generally based on the concept of margin exceedance (also called hit, violation, or exception).

For a given clearing member i, a margin exceedance is said to occur if the *ex-post* realization of the P&L at time t, $V_{i,t}$, is more negative than the *ex-ante* VaR margin forecast. Let $I_t(\alpha)$ be a binary variable associated with an α% VaR margin at time t (we omit the index i for simplicity):

$$I_t(\alpha) = \begin{cases} 1 & \text{if } V_{i,t} < -B_{i,t|t-1}(\alpha) \\ 0 & \text{otherwise} \end{cases}. \tag{5}$$

As stressed by by Christoffersen (1998, 2009b), VaR forecasts are valid if and only if the violation process $I_t(\alpha)$ satisfies the following two hypotheses:

- The Unconditional Coverage (hereafter UC) hypothesis: The probability of an *ex-post* return exceeding the VaR forecast must be equal to the α coverage rate:

$$\Pr[I_t(\alpha) = 1] = \mathbb{E}[I_t(\alpha)] = \alpha. \tag{6}$$

- The Independence (hereafter IND) hypothesis: VaR margin violations observed at two different dates for the same coverage rate must be distributed independently. Formally, the variable $I_t(\alpha)$ associated with a margin exceedance at time t for an α% coverage rate should be independent of the variables $I_{t-k}(\alpha)$, $\forall\, k \neq 0$. In other words, past VaR violations should not be informative about current and future violations.

The UC hypothesis is quite intuitive. Indeed, if the frequency of violations observed over T days is significantly lower (respectively higher) than the coverage rate α, then risk is overestimated (respectively underestimated). However, the UC hypothesis sheds no light on the possible dependence of margin exceedances. Therefore, the independence property of violations is an essential one, because it is related to the ability of a VaR margin model to accurately model the higher-order dynamics of the P&L. In fact, a model that does not satisfy the independence property can lead to clusterings of margin exceedances even if it has the correct average number of violations. Consequently, there must be no dependence in the violations variable, whatever the coverage rate considered.

When the UC and IND hypotheses are simultaneously valid, VaR forecasts are said to have a correct Conditional Coverage (hereafter CC), and the VaR violation process is a martingale difference with:

$$\mathbb{E}\left[I_t(\alpha) - \alpha \,|\, \Omega_{t-1}\right] = 0. \tag{7}$$

This last property is at the core of most of the validation tests for VaR models (Christoffersen 1998; Engle and Manganelli 2004; Berkowitz, Christoffersen, and Pelletier 2011). It is worth noting that equation (CC) implies that the violation $I_t(\alpha)$ has Bernoulli distribution with a success probability equal to α:

$$\{I_t(\alpha)\} \text{ are } i.i.d. \text{ Bernoulli}(\alpha). \tag{8}$$

II. TESTS OF MARGIN ACCURACY

A. Frequency of Margin Exceedances

A first way of testing margin accuracy is to test the number or the frequency of margin exceedances. Thus the null hypothesis corresponds to equation (6):

$$H_{0,UC} : \mathbb{E}[I_t(\alpha)] = \alpha. \tag{9}$$

A first statistical test, called the *Z*-test, is based on a normal approximation and the assumption of independence. Consider a sequence $\{I_t(\alpha)\}_{t=1}^{T}$ of T margin exceedances associated to VaR (α%) margins and denote by H the total number of exeedances or hits, $H = \sum_{t=1}^{T} I_t(\alpha)$. If we assume that the variables $I_t(\alpha)$ are *i.i.d.*, then under the null of UC, the total number of hits has a Binomial distribution:

$$H \sim B(T, \alpha) \tag{10}$$

with $\mathbb{E}(H) = \alpha T$ and $\mathbf{V}(H) = \alpha(1-\alpha)T$. For a large T sample the Binomial distribution can be approximated by a normal distributon and a simple Z-test statistic can be defined as:

$$Z = \frac{H - \alpha T}{\sqrt{\alpha(1-\alpha)T}} \approx N(0,1). \tag{11}$$

Alternatively, Kupiec (1995) and Christoffersen (1998) propose a Likelihood Ratio (hereafter LR) test based on the process of *VaR* margin exceedances $I_t(\alpha)$. Under H_0, the LR statistic is defined as:

$$LR_{UC} = -2\ln\left[(1-\alpha)^{T-H}\alpha^{H}\right] + 2\ln\left[\left(1-\frac{H}{T}\right)^{T-H}\left(\frac{H}{T}\right)^{H}\right] \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(1). \tag{12}$$

Under the null (9), the LR_{UC} statistic converges to a chi-square distribution with two degrees of freedom. The intuition for the LR test is the same as for the Z statistics. The null of UC is not rejected if the empirical frequency of VaR margin exceedances H/T is close enough to the coverage rate α. Jorion (2007) reports some non-rejection regions for the LR_{UC} test. For a 5% nominal size and sample size $T = 250$, the UC assumption is not rejected if the total number of VaR(1%) violations is strictly smaller than 7. If the sample size is equal to 500, the total number of exceedances must strictly range between 1 and 11.

B. Frequency and Severity of Margin Exceedances

A key limitation of the previous approach is that it is unable to distinguish between a situation in which losses are below but close to the margin and a situation in which losses are considerably below the margin. Colletaz, Hurlin, and Pérignon (2012) propose a backtesting methodology that is based on the number and the severity of VaR exceptions. Their approach exploits the concept of *super exception*, which is defined as a loss greater than a super VaR margin $B_{i,t|t-1}(\alpha')$ whereas the coverage probability α' is much smaller than α (e.g., $\alpha = 1\%$ and $\alpha' = 0.2\%$). As in Section I.B, we define a hit variable associated with $B_{i,t|t-1}(\alpha')$:

$$I_t(\alpha') = \begin{cases} 1 & \text{if } V_{i,t} < -\beta_{i,t|t-1}(\alpha') \\ 0 & \text{otherwise} \end{cases} \quad \text{with } \alpha' < \alpha \tag{13}$$

The defining feature of their approach is to account for both the frequency and the magnitude of VaR margin exceedances. The intuition is the following. If the frequency of super exceptions is abnormally high, this means that the magnitude of the losses with respect to $B_{i,t|t-1}(\alpha)$ is too large. For both VaR margin exceptions and super exceptions, they propose to use a standard backtesting procedure. Consider a time series of T VaR margin forecasts for an α (respectively α') coverage rate and let H (respectively H') be the number of associated VaR margin violations:

$$H = \sum_{t=1}^{T} I_t(\alpha) \qquad H' = \sum_{t=1}^{T} I_t(\alpha'). \tag{14}$$

Colletaz, Hurlin and Pérignon (2012) propose a new tool, called the *Risk Map*, which graphically summarizes all information about the performance of a VaR model. It is based on a joint test of the number of VaR exceptions and VaR super exceptions:

$$H_{0,MUC} : \mathbb{E}[I_t(\alpha)] = \alpha \text{ and } \mathbb{E}[I_t(\alpha')] = \alpha'. \tag{15}$$

The corresponding test statistic consists in a multivariate unconditional coverage test. This test is based on three indicator variables:

$$J_{0,t} = 1 - J_{1,t} - J_{2,t} = 1 - I_t(\alpha) \tag{16}$$

$$J_{1,t} = I_t(\alpha) - I_t(\alpha') = \begin{cases} 1 & \text{if } -B_{i,t|t-1}(\alpha') < V_{i,t} < -B_{i,t|t-1}(\alpha) \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

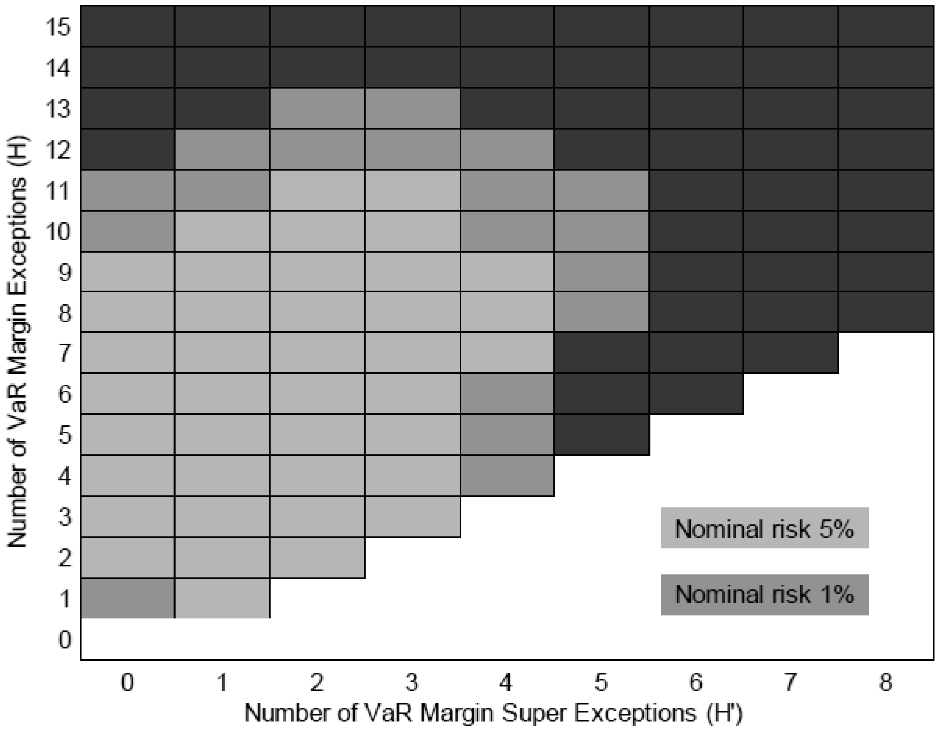
$$J_{2,t} = I_t(\alpha') = \begin{cases} 1 & \text{if } V_{i,t} < -B_{i,t|t-1}(\alpha') \\ 0 & \text{otherwise} \end{cases}. \tag{18}$$

The $\{J_{i,t}\}_{i=0}^{2}$ are Bernoulli random variables equal to one with probability $1-\alpha$, $\alpha - \alpha'$, and α', respectively. Given these definitions, we can test the joint hypothesis (15) using a LR test. Let us denote $H_i = \sum_{t=1}^{T} J_{it}$, for $i = 0, 1, 2$, the count variable associated with each of the Bernoulli variables. The multivariate unconditional coverage test is an LR test that the empirical exception frequencies significantly deviate from the theoretical ones. Formally, it is given by:

$$\begin{aligned} LR_{MUC}(\alpha,\alpha') = & -2\ln\left[(1-\alpha)^{H_0}(\alpha-\alpha')^{H_1}(\alpha')^{H_2}\right] \\ & + 2\ln\left[\left(1-\frac{H_0}{T}\right)^{H_0}\left(\frac{H_0}{T}-\frac{H_1}{T}\right)^{H_1}\left(\frac{H_2}{T}\right)^{H_2}\right] \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(2). \end{aligned} \tag{19}$$

A Risk Map can be constructed based on the rejection zones for different confidence levels (Figure 1). Note that the cells below the diagonal are not colored as they correspond to situations in which the number of super exceptions exceeds the number of exceptions, which is of course impossible. If the (H, H′) pair corresponds to a light gray cell, we conclude that we cannot reject the null hypothesis $\mathbb{E}[I_t(\alpha)] = \alpha$ and $\mathbb{E}[I_t(\alpha')] = \alpha'$ at the 95% confidence level. If (H, H') falls in the gray zone, we can reject the null at the 95% but not at the 99% confidence level.

Figure 1. Backtesting VaR Margins with the Risk Map.



Notes: This figure displays a Risk Map based on the *p*-value of a multivariate unconditional coverage tests, $LR_{MUC}(\alpha, \alpha')$ for different numbers of VaR margin exceptions (H) and VaR margin super exceptions (H'). Parameter values are α=%, α'=0.2%, and T=500.

Finally, a dark gray cell implies that we can reject the null hypothesis at the 99% confidence level.

C. Independence of Margin Exceedances

The UC property does not give any information about the temporal independence of VaR margin exceedances. However, generating margin exceedances that are temporally independent is an important property for a margining system to have since it suggests that the margin immediately reflects new information. A margining system that violates this property leads to clusters of margin exceedances.[2]

It is important to note that these two VaR margin properties are independent one from the other. At this point, if a VaR margin does not satisfy either one of these two hypotheses, it must be considered as not valid. For example, satisfying the hypothesis of unconditional coverage does not compensate for the possible existence of violations clusters nor the noncompliance with the independence

2. Berkowitz and O'Brien (2002) show that the VaR models used by six large U.S. commercial banks (1) tend to be very conservative, at least when financial markets are not under stress and (2) lead to clusters of VaR exceedances. This second result indicates that risk models fail to forecast volatility changes.

hypothesis. On the contrary, there is CC when the VaR margin satisfies both the UC and IND hypotheses.

1. LR Approach

Christoffersen (1998) proposes an LR test based on the assumption that the process of *VaR* margin exceedances $I_t(\alpha)$ is modeled with the following matrix of transition probabilities:

$$\Pi = \begin{pmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{pmatrix} \tag{20}$$

where $\pi_{ij} = \Pr[I_t(\alpha) = j \mid I_{t-1}(\alpha) = i]$, that is, probability of being in state j at time t conditioning on being in state i at time $t-1$. Under the null of independence, we have $\pi_{01} = \pi_{11} = \beta$ and:

$$H_{0,IND} : \Pi_\beta = \begin{pmatrix} 1-\beta & \beta \\ 1-\beta & \beta \end{pmatrix} \tag{21}$$

where β denotes a denotes a margin exceedance probability, which can be different from the coverage rate α. What these transition probabilities imply is that the probability of experiencing a margin exceedance in the current period depends on the occurrence or not of a margin exceedance in the previous period. The estimated VaR margin exceedance probability is the empirical frequency of violations, *H/T*. Under the alternative, no restriction is imposed on the Π matrix. The corresponding LR statistic, denoted LR_{IND} is defined by:

$$\begin{aligned} LR_{IND} &= -2\ln\left[\left(1-\frac{H}{T}\right)^{T-H}\left(\frac{H}{T}\right)^{H}\right] \\ &\quad + 2\ln\left[(1-\hat{\pi}_{01})^{n_{00}}\hat{\pi}_{01}^{n_{01}}(1-\hat{\pi}_{11})^{n_{10}}\hat{\pi}_{11}^{n_{11}}\right] \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(1) \end{aligned} \tag{22}$$

where n_{ij} denotes the number of times we have $I_t(\alpha) = j$ and $I_{t-1}(\alpha) = i$, and:

$$\hat{\pi}_{01} = \frac{n_{01}}{n_{00}+n_{01}} \qquad \hat{\pi}_{11} = \frac{n_{11}}{n_{10}+n_{11}}. \tag{23}$$

Finally, it is also possible to test the CC assumption for VaR margins. Under CC:

$$H_{0,CC} : \Pi_\alpha = \begin{pmatrix} 1-\alpha & \alpha \\ 1-\alpha & \alpha \end{pmatrix} \tag{24}$$

and then:

$$LR_{CC} = -2\ln\left[(1-\alpha)^{T-H}(\alpha)^{H}\right] + 2\ln[(1-\widehat{\pi}_{01})^{n_{00}}\widehat{\pi}_{01}^{n_{01}}(1-\widehat{\pi}_{11})^{n_{10}}\widehat{\pi}_{11}^{n_{11}}] \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(2) \tag{25}$$

The corresponding *LR* statistic, denoted LR_{CC}, is defined by the sum of the LR_{UC} and LR_{IND} statistics. Under the null of CC, it satisfies:

$$LR_{CC} = LR_{UC} + LR_{IND} \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(2). \tag{26}$$

2. Regression-based Tests

Engle and Manganelli (2004) suggest another approach based on a linear regression model. This model links current margin exceedances to past exceedances and/or past information. Let $Hit(\alpha) = I_t(\alpha) - \alpha$ be the demeaned process associated with $I_t(\alpha)$:

$$Hit_t(\alpha) = \begin{cases} 1-\alpha & \text{if } V_{i,t} < -B_{i,t|t-1}(\alpha) \\ -\alpha & \text{otherwise} \end{cases}. \tag{27}$$

Consider the following linear regression model:

$$Hit_t(\alpha) = \delta + \sum_{k=1}^{K} \beta_k Hit_{t-k}(\alpha) + \sum_{k=1}^{K} \gamma_k z_{t-k} + \varepsilon_t \tag{28}$$

where the z_{t-k} variables belong to the information set Ω_{t-1}. For example, one can use lagged P&L, squared past P&L, past margins, and so on. Whatever the chosen specification, the null hypothesis test of conditional efficiency corresponds to testing the joint nullity of all the regression coefficients:

$$H_{0,CC} : \delta = \beta_k = \gamma_k = 0, \qquad \forall k = 1,..,K. \tag{29}$$

The independence hypothesis implies that β_k and γ_k coefficients are equal to zero whereas the unconditional coverage hypothesis is verified when δ is null. Indeed, under the null hypothesis, $\mathbb{E}\,[Hit_t(\alpha)] = \mathbb{E}\,(\varepsilon_t) = 0$, which implies by definition that $\Pr\,[I_t(\alpha) = 1] = E\,[I_t(\alpha)] = \alpha$.

Denote the vector $\Psi = (\delta \;\; \beta_1 ... \beta_K \; \gamma_1 \; ...\gamma_K)'$ of the $2K + 1$ parameters in this model and Z the matrix of explanatory variables of model (28), the Wald statistic, denoted DQ_{CC}, in association with the test of CC hypothesis then verifies:

$$DQ_{CC} = \frac{\widehat{\Psi}' Z' Z \widehat{\Psi}}{\alpha(1-\alpha)} \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(2K+1) \tag{30}$$

where $\hat{\Psi}$ is the OLS estimate of Ψ. Notice that one can also test the UC hypothesis by testing $H_{0,UC}: \delta = 0$ or test the IND hypothesis with $H_{0,\,\text{IND}}: \beta_k = \gamma_k = 0$. A natural extension of the test of Engle and Manganelli (2004) consists in considering a (probit or logit) binary model linking current violations to past ones (Patton 2002; Dumitrescu, Hurlin, and Pham 2012).

3. Autocorrelation Test

Rather than using a regression model, Berkowitz, Christoffersen, and Pelletier (2011) test directly the martingale difference assumption. As under CC, the VaR margin exceedance process $Hit_t(\alpha)$ is a martingale difference; it should be uncorrelated. A natural test is the univariate Ljung-Box test of $H_{0,\,CC}: r_1 = ... = r_K = 0$ where r_k denotes the k^{th} autocorrelation:

$$LB(K) = T(T+2)\sum_{k=1}^{K} \frac{\hat{r}_k^2}{T-k} \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(K) \tag{31}$$

where $\hat{r}_k$ is the empirical autocorrelation of order k of the $Hit(\alpha)$ process.

D. Duration between Margin Exceedances

The UC, IND, and CC hypotheses also have some implications on the time between two consecutive VaR margin exceedances. Following Christoffersen and Pelletier (2004), we denote by d_v the duration between two consecutive VaR margin violations:

$$d_v = t_v - t_{v-1} \tag{32}$$

where t_v denotes the date of the v^{th} exceedance. Under CC hypothesis, the duration process d_i has a probability density function given by:

$$f(d_v;\alpha) = \alpha(1-\alpha)^{d_v-1} \quad d_v \in \mathbb{N}^*. \tag{33}$$

This distribution characterizes the memory-free property of the VaR margin violation process $I_t(\alpha)$, which means that the probability of observing a violation today does not depend on the number of days that have elapsed since the last violation. Note that $\mathbb{E}(d_v) = 1/\alpha$ since the CC hypothesis implies an average duration between two margin exceedances equals to $1/\alpha$. The general idea of the test consists in specifying a distribution that nests equation (33), so that the memoryless property can be tested through parameter restriction. In this line, Christoffersen and Pelletier (2004) use under the null hypothesis the exponential distribution, which is the continuous analogue of the probability density function in equation (33):

$$g(d_v;\alpha) = \alpha \exp(-\alpha d_v). \tag{34}$$

Under the alternative hypothesis, Christoffersen and Pelletier (2004) postulate a Weibull distribution for the duration variable:

$$h(d_v; a, b) = a^b b d_v^{b-1} \exp\left[-(a d_v)^b\right]. \tag{35}$$

As the exponential distribution corresponds to a Weibull distribution with $b = 1$, the test for IND is:

$$H_{0,IND} : b = 1 \tag{36}$$

and for CC is:

$$H_{0,CC} : b = 1,\ a = \alpha \tag{37}$$

Christoffersen and Pelletier (2004) propose the corresponding LR test (see also Haas 2005), and Candelon et al. (2011) derive a GMM duration-based test.

III. TESTS OF GLOBAL VALIDITY

To the best of our knowledge, all empirical studies on VaR backtesting considers individual banks in isolation (Berkowitz and O'Brien 2002; Pérignon and Smith 2010; Berkowitz et al. 2011). The reason for doing so is that financial institutions use different proprietary risk models, which needs to be tested separately. Differently on a derivatives exchange, the margins of all market participants are computed using the same model developed by the clearing house. Hence, this model can be tested globally using information from all market participants, which helps in detecting misspecified models.

A. Definitions

Let us denote $I_{i,t}(\alpha)$ the VaR margin exceedance for clearing member i at time t. We define the Global Unconditional Coverage (hereafter GUC) hypothesis as a situation where the probability of an *ex-post* loss exceeds the VaR margin forecast is equal to the α coverage rate for all clearing members:

$$H_{0,GUC} : \mathbb{E}[I_{i,t}(\alpha)] = \alpha \quad \forall i = 1,..,N. \tag{38}$$

The GUC means that the frequency of VaR margin exceedances is accurate for all clearing members. Note that it is important not to pool the N margin exceedance processes. Indeed, an under-estimation of the margin for member i could be offset by an over-estimation of the margin for another member j. Thus, the GUC hypothesis requires the UC hypothesis to be valid for all clearing members.

We proceed in a similar way for the Global Independence (hereafter GIND) hypothesis. Under GIND, the VaR margin exceedances observed for all the members at two different dates are independent; that is, $I_{i,t}(\alpha)$ is independent from $I_{i,t-k}(\alpha)$,

$\forall k \neq 0$. Furthermore, $I_{i,t}(\alpha)$ is also independent from past (and future) VaR margin exceedances of other members $I_{j,t-k}(\alpha)$, $\forall k \neq 0$ and $j \neq i$. Notice that we allow for contemporaneous dependencies between VaR margin exceedances of different members.

Finally, the global conditional coverage (GCC) hypothesis corresponds to a case where the N margin exceedance processes are a martingale difference:

$$H_{0,GCC} : \mathbb{E}\left[I_{i,t}(\alpha) | \Omega_{t-1} \right] = \alpha \quad \forall i = 1,..,N \tag{39}$$

where Ω_{t-1} denotes the information set available at time t – 1 for all the members, including past values of VaR margin and VaR margin exceedances of other members j.

A natural test for the GUC hypothesis consists in testing the null (38) against the following alternative:

$$H_{1,GUC} : \mathbb{E}[I_{i,t}(\alpha)] \neq \alpha \quad \text{for } i \in S \tag{40}$$

$$\mathbb{E}[I_{i,t}(\alpha)] = \alpha \quad \text{for } i \in \overline{S} \tag{41}$$

where $dim(S) = N_1$ satisfies $1 < N_1 \leq N$ and $dim(\overline{S}) = N_2$ with $N_1 + N_2 = \mathrm{N}$. Under this alternative, the margin of at least one member does not satisfy the UC hypothesis. Similarly, a natural test of GCC is based on the null (GCC) against the alternative:

$$H_{1,GCC} : \mathbb{E}\left[I_{i,t}(\alpha) | \Omega_{t-1} \right] \neq \alpha \quad \text{for } i \in S \tag{42}$$

$$\mathbb{E}\left[I_{i,t}(\alpha) | \Omega_{t-1} \right] = \alpha \quad \text{for } i \in \overline{S}. \tag{43}$$

B. Testing Strategies

Let us consider an individual test statistic of the UC (or CC) hypothesis, denoted X_i specific to clearing member *i*. For instance, for the *UC* test, this statistic corresponds to the LR_{UC} statistic or the duration-based LR_{UC} statistic. For the CC test, this statistic corresponds to the LR_{CC} statistic, DQ statistic, or duration-based statistic LR_{CC}. Whatever the chosen test, the individual statistic for member *i* can be expressed as a non-linear function of the sequence of the margin exceedances of this member, that is, $X_i = g\,(I_{i,1}(\alpha), ..., I_{i,T}(\alpha))$. To test the GUC or GCC null hypothesis, we follow Im, Pesaran, and Shin (2003) and use the average of the individual statistics:

$$\overline{X}_N = \frac{1}{N} \sum_{i=1}^{N} X_i = \frac{1}{N} \sum_{i=1}^{N} g(I_{i,1}(\alpha),..,I_{i,T}(\alpha)). \tag{44}$$

If we assume margin exceedances are cross-sectionally independent, that is, $I_{i,t}$ are independent of $I_{j,s}$ for $i \neq j$ and all (t,s), the $\overline{X}_N$ statistic converges to a normal distribution when T and N grow large. The intuition is as follows. When T tends to infinity, each individual statistic X_i converges to the same distribution. For instance, the LR_{UC} statistic converges to a chi-square distribution. Under the cross-sectional independence assumption, the individual statistics $X_i = g(I_{i,1}(\alpha), ..., I_{i,T}(\alpha))$ are also independent. Thus, the individual statistics X_i are independently and identically distributed. The central limit theorem is then sufficient to show that the cross-sectional average mean $\bar{X}_N$ converges to a normal distribution when N tends to infinity:[3]

$$\bar{X}_N \underset{N,T\to\infty}{\overset{d}{\longrightarrow}} N(0,1). \tag{45}$$

An alternative testing strategy consists in combining the p-values associated with the N individual tests. A Fisher type test is then defined by:

$$P_{X_N} = -2\sum_{i=1}^{N}\log(p_i) \underset{T\to\infty}{\overset{d}{\longrightarrow}} \chi^2(2N). \tag{46}$$

For any statistic X_i, such as LR_{UC}, LR_{CC}, or DQ_{CC}, its p-value is uniformly distributed over [0, 1]. Under the assumption of cross-sectional independence, P_{X_N} has a chi-square distribution with $2N$ degrees of freedom. For large N samples, we can use a standardized statistic:

$$Z_{X_N} = -\frac{\sum_{i=1}^{N}\log(p_i) + N}{\sqrt{N}} \underset{N,T\to\infty}{\overset{d}{\longrightarrow}} N(0,1). \tag{47}$$

IV. CONCLUSION

Having a well-functioning margining system is a prerequisite for any derivatives exchange. It allows the exchange to closely monitor tail risk and make the system resilient. In this paper, we have provided a backtesting framework allowing investors, risk managers and regulators to validate margin models. The statistical tests we have presented capture different facets of the margin model performance including frequency, timing, and magnitude of margin exceedances. Rather than being substitutes, the different statistical tests appear to complement each other and can be used to identify the source(s) of model misspecification.

The quest for the ideal margining system is still ongoing. Market participants and regulators want collateral requirements to be less procyclical in order to prevent liquidity spiral (Brunnermeier and Pedersen 2009). What we show in this paper is a

3. When the contemporaneous exceedances $I_{i,t}$ and $I_{j,t}$ are correlated, the distribution of the average statistic $\bar{X}_N$ can be estimated by bootstrap.

second property that ideal margins should have: Their accuracy should be testable ex-post. Indeed, even the most advanced risk measures are of little help if they cannot be systematically validated.

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