Accuracy, Timeliness, and Managers' Discretion of Fair Value Pricing: Evidence From the Banking Industry

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Abstract

Combining qualitative field research and quantitative empirical research methods, this paper attempts to "open up the black box" of fair value practices of US banks and identify constraints on bank managers' discretion imposed by new institutional changes after the 2008 financial crisis. Field research provides evidence that since 2010, there have been many significant institutional changes, particularly TRACE and third-party vendors, which have established significant constrains on managers' discretion over fair values. Specifically, banks predominately apply third-party vendors' feeds to generate financial statements. Most of the banks that I interviewed passively (near 100%) pass through vendor's feeds with (at most) occasional adjustments. External auditors also predominately rely on (different) vendors' prices to verify and challenge banks' inputs. Empirical evidence shows that third-party vendors and TRACE can generate accurate and timely pricing feeds, which dominate the historical costs in all performance measures. In addition, the ubiquitous availability of vendors' daily fair value prices at individual security level has subsequently restrained managers' discretion from the portfolio level to the security level. Even at the security level, TRACE and vendors' prices have put an upper bound on managers' discretion, sometimes to only 15% of the original level. Finally, my findings highlight the possibility that fair values, particularly after 2010, might be less subjective, less costly to implement, and more convenient for auditors to verify and challenge, than the literature previously reported.

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Accuracy, Timeliness, and Managers' Discretion of Fair Value Pricing: Evidence from the Banking Industry

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Abstract

ABSTRACT: This paper investigates how recent institutional developments impact the potential channels, and thus available discretion, by which managers can manipulate reported fair values. First, I use extensive field research to document the mechanisms used by banks to procure and report fair values—particularly incorporating the impact of the 2011 FINRA's Trade Reporting and Compliance Engine (TRACE), and concurrent increase in independent third-party vendors. Key insights include that (i) banks predominantly apply third-party vendors' feeds to generate financial statements (with nearly 100% of vendors' feeds passing *automatically* to reported financial statements, with only rare adjustments); and (ii) external auditors predominantly relying on different vendors' prices to verify and challenge banks' inputs. Second, I employ three proprietary datasets of daily financial-instrument level pricing—capturing both TRACE and third-party vendors—to document the following insights. I find that vendors' evaluated prices dominate historical costs in all performance metrics, confirming they provide a more accurate, objective, and reliable proxy for fair value than historical cost. I also find that vendors' fair values are value-relevant and account for 90% of the trade-to-trade price variance, creating an upper bound on managerial discretion (of only 15% of the original level). Finally, I find that bank managers respond to these newly imposed constraints by alternatively engaging in more spoofing-transaction based fair value manipulations: suggesting this is a likely (even primary) channel by which manipulation can be attained. Overall, the evidence suggests that fair values, particularly after the above institutional developments, appear less subjective, less costly to implement, and more convenient for auditors to verify and challenge, than the literature has previously reported.

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1. Introduction

1.1. Background and Motivation

Prior research provides strong evidence of managerial manipulation in the reporting of fair value estimates (Benson and Teclezion 2007; Benston 2008). The evidence appears particularly compelling in the context of fair value estimates based on inputs not directly observed from the markets: so-called Level 2 and 3 fair value estimates. Benston (2008) summarizes this view: "fair values other than those taken from quoted prices could be readily manipulated by opportunistic and overoptimistic managers, would be costly to make, and very difficult for auditors to verify and challenge." The related and on-going debate between fair value and historical cost reflects an implicit yet crucial assumption: *no accurate, objective, and reliable alternative approaches are available to estimate fair value other than historical cost*.

Much of the prior research relies on quarterly Level 2 and 3 aggregated data prior to 2011. Critically, this research does not reflect recently enacted institutional changes surrounding the daily security-level pricing and reporting process itself: i.e., how individual daily fair values are generated, validated, aggregated to the general ledger, and ultimately reported in the financial statements. This paper fills this gap in two ways. First, I use field research to extensively document the mechanisms used by banks to procure and report fair values, incorporating two key recent institutional developments intended to improve the fair value reporting process: independent third-party vendors and FINRA's Trade Reporting and Compliance Engine (TRACE). Second, I use three proprietary datasets of daily financial instrument-level—capturing both TRACE and vendor pricing—to evaluate how these new developments affect managerial discretion and the potential channels by which to manipulate fair values. Thus, this study reexamines prior literature's general conclusions on discretion in banks' reporting of fair values, including the novel and undocumented impact of TRACE and third-party vendor pricing.

The US banking industry is an ideal setting for this research, as banks hold large numbers of financial instruments subject to fair value accounting. To maximize instruments *ex ante* likely subject to greater managerial discretion, I focus on the infrequently traded structured credit products (SCP), which includes: asset-backed securities (ABS); collateralized mortgage obligations (CMO); mortgage-backed securities (MBS); and to-be-announced (TBA) securities.[1] SCPs are one of the largest but least-studied segments of the financial market, with valuation process that are poorly understood, in part owing to their complexity and low trading activity.[2]

For my qualitative field research, I interview 100+ professionals from banks, third-party vendors, external auditors, FINRA, broker-dealers, and BWIC firms.[3] I also shadow fair value professionals for one complete financial statement generating cycle, including attendance at a quarterly valuation oversight committee meeting. My quantitative research consists of empirical tests using three proprietary datasets acquired from the vendors and TRACE, with data spanning 2011-2015. Descriptively, I find that the average number of trades per security over the 4.5-year sample period is 5.17, averaging 107 days between adjacent trade dates. Critically, during the past 10 years,

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[1] A to-be-announced (TBA) is a forward contract for a homogeneous pool of MBS pass-throughs.

[2] At 2016, there are $8.9 trillion outstanding in MBS; this compares to $13 ($8.9) [$3.8] trillion in the Treasury (corporate bond) [municipal bond] markets. Data are from www.sifma.org/research/statistics.aspx.

[3] Bid Wanted in Competition (BWIC) is a system, in which an institutional investor submits its bid list to various dealers. Dealers make bids on the listed securities, with those having the highest bids then contacted.

independent third-party vendors have begun to fill in the price gaps between adjacent trades, by supplying daily security-level evaluated prices.

Through my field research, three key insights emerged. First, banks principally "outsource" their pricing functions to independent third-party vendors. In particular, banks predominantly pass through vendors' pricing feeds *directly* to their reported financial statements, with (at most) occasional adjustments: almost all banks that I interviewed pass nearly 100% of vendors' feeds automatically to their general ledger. Second, external auditors also predominantly rely on different vendors' pricing feeds and expertise to verify and challenge banks' reported fair values; this includes directly contacting their *clients*' vendors for further information and validation. Third, these recent institutional developments allow me to characterize the three potential channels by which managers can manipulate fair values: strategic vendor selection or cherry picking among vendors (Channel One); manipulating general ledger's numbers and/or strategically timing the recognition of unrealized gains/losses (Channel Two); and spoofing the vendors—that is, manipulating vendors' prices through purposefully "spoofed" transactions that are subsequently cancelled (Channel Three).

My quantitative research then supplements the above field research observations by providing three pieces of supporting evidence that managerial discretion over fair values is constrained by TRACE and vendor pricing in Channels One and Two, with Channel Three appearing to be the only mechanism through which any viable managerial manipulation can occur. First, I find that the evaluated prices from different vendors are quite similar and show little systemic biases. In particular, pricing differences between two vendors' feeds have thin-tailed distributions, indicating that extreme pricing differences are less likely to occur compared to corresponding normal distributions. This evidence suggests that managerial discretion via strategic vendor selection (Channel One) is likely quite limited.

Second, I assess vendor performance by comparing its pricing feeds to both the historical costs and the next trade prices. I find that vendors' evaluated prices dominate historical costs in all performance metrics, including variance reduction, model bias, forecast error, mean error, and directional correctness. In particular, vendors' fair values are value-relevant, accounting for 85% of the price movements subsequent to the initially reported historical costs, and also explain 90% of the inter-trade price variance. This evidence suggests that vendors' prices provide effective valuation reference points for the next trades; and thus appear to be a more accurate, objective, and reliable proxy for fair value than historical cost. Furthermore, the ubiquitous availability of vendors' prices to all market participants (auditors, investors, and regulators) suggests an upper bound on managerial discretion through Channel Two, only 15% of the original level.

Third, focusing on a particular type of "Cancelled-Single" trades, I investigate whether bank managers purposefully use cancellations to spoof vendors' prices. I find that vendors' prices react promptly and significantly to the initial posted trades, yet only gradually and less markedly to the later cancellations. This asymmetric response gives bank managers a potential means to artificially inflate/deflate vendors' prices and then enjoy the ensuing favorable temporarily-mispriced fair values. I also find that both the scope and extent of the Cancelled-Single trades are limited. Together, with corroborating evidence from additional tests, vendors' asymmetric response to the original trades and later cancellations provides evidence that bank managers engage in limited spoofing-transaction-based fair value manipulations through Channel Three.

The qualitative field research section of this study consists five parts. First, I focused on the largest 40 US banks (in terms of total assets) and interviewed more than 50 fair value pricing experts and professionals from 11 banks. These professionals include CFOs, controllers, front desk traders, fair value committee members, model validation specialists, and internal auditors, and IPV team. The US banking industry is dominated by big banks, with the top 40 banks consisting about 91.1% of the total assets of the entire industry. The average of total assets of the 11 banks combined would rank about 20 within the top 40 top banks.[4] In this part of the qualitative research, I try to identify the various components of the black box, and the dynamics among these components.

Second, I shadowed fair value professionals for one complete financial statement generating cycles at one of these 11 banks. This bank is the largest of the 11 banks.[5] I also attended one quarterly fair value oversight committee meeting. In this part of the qualitative research, I try to follow a complete cycle of the generation of banks' quarterly financial statements and gain insights of the details of the internal control systems within the bank.

Third, I conducted field research and interviewed more than 20 professionals at two major third-party pricing vendors. Now I switched my focus from within the banks to external mechanisms impacting banks' daily fair value practices. In this part, I try to gain

[4] Due to confidentiality agreements, I cannot disclose the precise numbers and specifics.
[5] Due to confidentiality agreements, I cannot disclose the precise numbers and specifics.

insights of the daily operations of these vendors. Most importantly, I want to learn the dynamics and interactions between these vendors and the banks.

Forth, I conducted field research and interviewed more than 10 professionals at Financial Industry Regulatory Authority (FINRA)'s Trade Reporting and Compliance Engine (TRACE). Simply put, TRACE is a centralized platform for over-the-counter (OTC) market transactions. For SCPs, since May 16, 2011, virtually *all* trades in the securitized credit product (ABS, CMO, MBS) market have been required to be reported to TRACE by broker/dealers. TRACE also disseminates the transaction data to the market participants during the day. In this part, I try to gain insights of the daily operations of TRACE system. Most importantly, I want to learn the impacts of TRACE on the pre-trading transparency of the thinly-traded SCP securities and the impacts on the price identification process of the dealers and third-party vendors.

Fifth, I interviewed auditors of valuation services at big four auditing firms and professionals from various broker/dealer firms and specialists from Bid Wanted in Competition (BWIC) firms.

In addition, I have obtained three unique data sets from the two independent third-party pricing vendors and from TRACE. I conduct further empirical tests on the accuracy and timeliness of their pricing feeds and on market transparency and bank managers' discretion.

1.2.Contribution

This study makes five contributions. First, the field research provides a rich descriptive analysis surrounding banks' daily fair value pricing practices as well as the undocumented impact of TRACE and vendors' pricing on managerial discretion. Thus, it builds on prior research examining earnings management of banks, including fair value measurements (Beatty and Harris 1999; Beatty et al. 2002; Ettredge et al. 2010; Fiechter and Meyer 2010; Liao et al. 2010; and Song et al. 2010). I contribute to the literature by being among the first papers to try to "open up the black-box" around banks' daily fair value pricing practices. By combining qualitative and quantitative methodologies, this study contribute to the fair value literature by shedding lights on the intricate internal control systems within banks and external constraints set by the recent institutional changes.

Second, the proprietary TRACE and vendor datasets allow investigation of daily fair values for individual securities; this improves previous research relying on quarterly financial statement data at an aggregate portfolio level (Level 2 and 3) (Beatty et al. 2002; Thomas and Zhang 2002; Bens et al. 2002, 2003; Kanagaretnam et al. 2004; and Roychowdhury 2006). I also contribute to the literature by being among the first papers that study the role of the role of third-party vendors and TRACE on pre-trade transparency and improve post-trade reporting, as well as banks' price identification process. Prior studies on third-party vendors are practically non-existent; researches on TRACE are scarce and mainly from finance microstructure field.[6]To my best knowledge, this study would be the first one investigating the role of third-party vendors and TRACE on fair values in accounting literature. In addition, the three unique data sets I acquired

[6] Please refer to the literature review session for more details.

from vendors and TRACE allow me to investigate the intricate specifics and details of banks' *daily* fair value pricing operations, a significant improvement over the *quarterly* financial statement data used by current literature.

Third, it is the first to suggest that vendors' evaluated prices dominate historical costs in all performance metrics, as well as to identify the related point estimate (85%) reduction in bank managers' discretion.

Forth, it provides a framework of three channels by which managers can potentially manipulate fair values, with empirical evidence that Channel Three (spoofing the vendors) appears the most viable for feasible managerial manipulation.

Finally, I also contribute to the accounting literature by being among the first papers that study complex securities such as SCPs. The unique datasets allow me to further breakdown the portfolios of level 2 and level 3 assets into more detailed sub-categories at individual security level. At the same time, SCPs are more complex than corporate and municipal bonds, which are the exclusive focus of the current literature. First, each corporate bond has a unique issuer that promises to make the contractual payments, whereas an SCP typically includes the payment obligations of numerous borrowers. Second, every owner of a bond issue is promised identical payments, whereas an SCP can include multiple tranches that differ in terms of payment priority in case of default. Third, SCPs are typically created by investment banks or their affiliates from credit contracts, whereas corporate bonds are issued directly to investors. Finally, the size of the asset pool underlying an SCP changes randomly over time as the underlying loans are paid

The rest of this paper is organized as follows. Section 2 reviews prior research. Section 3 provides some institutional details necessary for the following discussions. Section 4 discusses the qualitative field research methodology and results. Section 5 discusses the hypothesis development and research design. Section 6 presents and discusses the empirical results from the quantitative archival research. Section 7 concludes.

2. Literature Review

This study follows three streams of research: 1) research on fair value accounting; 2) research on third-party vendors, TRACE, and SCPs; and 3) institutional changes. In this section, I briefly review the three streams of research.

2.1.Fair Value Accounting

The debate over fair value accounting (fair value vs. historical cost) has been long-lived and inconclusive. The core concept of fair value accounting is that all assets and liabilities on the balance sheet should be measured and carried at "fair" market-prices or model-determined values instead of carrying at the historical costs. In addition, any change in the fair value of an asset or a liability flows through or reported either directly in net income or through equity of the current period.

The SFAS 157 Fair Value Measurements provides practical guidelines on the consistent measurement of fair values. In addition, SFAS 157 requires firms to classify fair value assets and liabilities into three broad hierarchies or levels.[7]

Proponents of fair value accounting argue that fair value measures can better reflect the "true" or "fair" value of a company's assets and liabilities and can provide more value-relevant information to the broader market, investors, analysts, and regulators. They further argue that more accurate and timely information can be reflected by fair value prices to investors than other alternative accounting approaches. In addition,

[7] SFAS157 (Fair Value Measurement) specifies three fair value classification hierarchies or levels based on the inputs used to evaluate the underlying financial assets or liabilities Level 1 fair value inputs are observable, quoted prices for identical assets and liabilities directly in active markets. Level 2 fair value inputs can be from three different sources: active market quoted prices for similar assets or liabilities; non-active market quoted prices for identical or similar assets; or indirect inputs such as yield curves or implied interest rates, default rates, etc. Level 3 fair value inputs are unobservable, and should be based on the best and all reasonably available information. Clearly Level 3 fair value involves managers' subjective judgements.

if banks' risk can be better described by fair values, then fair value accounting might potentially reduce the opportunities of financial crises (Financial Crisis Advisory Group 2009; Bleck and Liu 2007).

Opponents, on the contrary, argue that historical cost is more objective and reliable than fair value, which might provide managers discretions and room to choose the inputs to the valuation models and thus manipulate earnings. Furthermore, they think fair value accounting requires more subjective judgments in the process of preparing accounting information, which may bring inaccuracy and uncertainty and lead to increased stock volatility.

Early fair value research has principally focused on the fair values' value-relevance and whether they can provide incremental explaining power in equity returns (Barth 1994; Barth et al. 1995; Nelson 1996; Barth et al. 1996; Liang and Riedl 2011). Recent studies have switched their focus from value relevance to the requirements of fair value disclosure (Liao et al. 2010; Song et al. 2010; Riedl and Serafeim 2011).

At the same time, some studies have investigated whether fair values are biased, costly to verify, and allow managers to manipulate to their advantages (Benston 2008; Ryan 2008; Martin et al. 2006).

Finally, others research focuses on managerial discretion over fair values (particularly Level 2 and Level 3) on earnings management and whether fair values increase audit fees (Chen et al. 2010; Ettredge et al. 2010; Fiechter and Meyer 2010; Heflin and Valencia 2012).

2.2.Research on third-party vendors, TRACE, and SCPs

To my best knowledge, there have been no research papers on third-party vendors and on TRACE in the accounting literature.

Most previous research papers on TRACE have mostly come from finance field and almost exclusively focused on corporate bonds. Early stages include Bessembinder et al. (2006), Harris and Piwowar (2006), Edwards et al. (2007), Goldstein et al. (2007), and Green et al. (2007b). These papers focus on estimating and quantifying transaction costs, in particular, on the potential impacts of transaction costs on trading activity and credit risk.

More recent papers have switched their focuses by relying on different sets of liquidity measures and examining different sample periods to quantify liquidity and transaction costs. See, for example, Mahanti et al. (2008), Bao et al. (2011), Jankowitsch et al. (2011), Lin et al. (2011), Nashikkar et al. (2011), Dick-Nielsen et al. (2012), Feldhutter (2012), Friewald et al. (2012), and Ronen and Zhou (2013).

In summary, these studies focusing on the effects of FINRA's TRACE has found the following (for corporate bonds only) main conclusions: bid/ask spreads for corporate bonds has been effectively narrowed after the implementation of TRACE; transaction costs for corporate bond have also been effectively reduced; some studies estimate that TRACE accounts for a savings of more than $1.0 billion for the overall corporate bond market; improved valuation precision for mutual funds can be attributed to TRACE, in addition, TRACE has reduced the valuation dispersion between various mutual funds holding the same bond instrument; and finally, corporate bond market liquidity has not been verifiably reduced since the introduction of TRACE.

Prior finance and economics research studying SCPs using TRACE data, to my best knowledge, are very rare. For example, Atanasov and Merrick (2012) focuses on a segmented market of TBA (to be announced, a particular sub category of SCPs) transactions and estimate that the execution costs for TBA trades for the segmented market are generally quite small (under 10 bps).

Hollifield, Neklyudov, and Spatt (2012) examines the dealer networks architecture for asset-backed securities (ABS) and commercial mortgage-backed securities (CMBS). Their analysis of the topology of the interdealer market has shown that there are two different types of dealers: the well-connected centralized dealers and less-connected peripheral dealers. In addition, they find that the bid–ask spreads charged by the more interconnected central dealers tend to be lower than those charged by the peripheral dealers.

Friewald, Jankowitsch, and Subrahmanyam (2012) investigates various commonly used liquidity measures and proxies in the academic literature for US fixed-income securitized product market. The authors estimate that round-trip SCP transactions incur an average of 66 bp transaction cost for the entire SCP market. They also found that SCP liquidity varies with bond characteristics, for example SCP traded by major institutions, issued by a federal authority ("agencies", such as GSEs), or with relative low credit risk are more liquid than other SCP securities.

2.3.Institutional Changes

Social scientist use institutional theory to explain the organizational homogeneity (DiMaggio 1983; Powell 1983) and understand institutional changes (Thelen and Steinmo 1992). Here I mainly review the institutional change literature most relevant to this study.

Thelen (2003) argues that most significant forms of institutional change occur mainly due to the endogenous (internal) mechanisms of change, rather than from exogenous shocks. Thelen (2003)' argument suggests that social scientists should pay more attention to the more influential internal structural changes than external ones. Along this same line of research, Streeck and Thelen (2005) further classify the processes of change according to two change dimensions (result of change and process of change) into four distinctive categories: reproduction by adaptation, gradual transformation, survival and return, and breakdown and replacement. The last two processes (survival and return, and breakdown and replacement) represent *abrupt* institutional change dynamics, which have been adequately researched by previous scholars. The fundamental contribution of Streeck and Thelen (2005) comes from the first two processes (reproduction by adaptation, gradual transformation), which represent *incremental* institutional change dynamics. In particular, the first process (incremental and discontinuity) represents "gradual transformation" and incremental internal changes through institutions' own *intentions* of change and *actions* of change. In fact, Streeck and Thelen (2005)'s gradual transformation (incremental and discontinuity) is fundamentally linked to the concept of gradual transformation proposed by Thelen (2003), which suggests that institutions can and do achieve these gradual transformations through periodical and internal renegotiation without drastic or abrupt changes.

Based on the findings of Thelen (2003) and Streeck and Thelen (2005), Mahoney and Thelen (2010) further proposes an analytical model to explain these different processes of institutional changes:

$$\begin{bmatrix} \boxed{\begin{matrix} Characteristics\ of \\ Political\ Context \end{matrix}} \\ \boxed{\begin{matrix} Characteristics\ of \\ Institutions \end{matrix}} \end{bmatrix} \rightarrow \boxed{\begin{matrix} Type\ of\ Dominant \\ Change - Agent \end{matrix}} \rightarrow \boxed{\begin{matrix} \text{Type of Institutional} \\ \text{Change} \end{matrix}}$$

Specifically, Characteristics of Political Context and Characteristics of Institutions can both influence Type of Dominant Change-Agent, which in turn can impact Type of Institutional Change. In addition, Characteristics of Political Context and Characteristics of Institutions can both directly impact Type of Institutional Change. Similar to Streeck and Thelen (2005), Mahoney and Thelen (2010)'s contribution is to propose a theory of gradual institutional change and endogenous incremental development, while the majority of previous research has focused on the consequences of exogenous shocks and associated abrupt institutional changes. A direct outcome of Mahoney and Thelen (2010)'s proposed theoretical framework is that there exist four possible types of gradual institutional change: displacement, layering, drift, and conversion.

Another contribution of Mahoney and Thelen (2010) is that the authors propose that specific institutional settings might as well shape different change strategies for various change agents within the institutions. Mahoney and Thelen (2010) highlights four such change strategies: insurrectionaries, symbionts, subversives, and opportunists. The authors also provide some details of each of the four agent types. Insurrectionaries intentionally attempt to remove institutions or associated rules, in order to achieve internal prominence. Symbionts are agents who require support from their "host" institutions, they can either facilitate (mutualistic) or compromise (parasitic) the efficiency of the rules of the host institution.

Subversives are agents who have their own agenda to replace the institutions, but they achieve their goals replacing the institutions in a concealed way. They first work within the current institutional system and follow the expected rules. Then they wait for the "right moment" and pursue their desired institutional changes. Finally, opportunists are agents without explicit or well-defined predisposition for the continuity of the institutions. The following table summarizes different behavior of each type of agents (Mahoney and Thelen 2010, page 23).

	Seeks to Preserve Institution	**Follows Rules of Institution**
Insurrectionaries	No	No
Symbionts	Yes	No
Subversives	No	Yes
Opportunists	Yes/No	Yes/No

(Source: Mahoney and Thelen 2010, page 23)

3. Background Information Necessary for the Ensuing Discussions Results

Before starting the discussion on qualitative and quantitative result sections, I feel the need to provide some detailed background information, because this topic (particularly on complex security such as SCPs) is rarely discussed in previous literature and the information and discussions here are essential for the following discussions.

Table 0-1 shows the average fair value assets and liabilities breakdown by fair value hierarchy for the 10 largest U.S. bank holding companies. All the percentages reported in the table are based on total fair value assets (as 100%). From Table 0-1, we can draw some preliminary conclusions:

- Compared with fair value *liabilities* (8%), fair value *assets* (100%) are by far the largest component of the entire fair-valued financial instruments;
- The majority of the fair value assets/liabilities are level 2 (93% and 22%);
- Available-for-Sale (AFS) assets are the largest component of fair value assets (70%), and majority of AFS are of level 2 (60%).
- Derivatives are the second largest component of the financial instruments, (18% for level 2 assets and 19% of level 2 liabilities)

Prior studies have documented significant differences between Level 2 and Level 3 fair values. For example, (Song et al. 2010) shows that compared with corresponding Level 2 fair values, Level 3 fair values are less value relevant; (Riedl and Serafeim 2011) shows that Level 3 fair values are associated with a higher cost of capital; in addition, (Ettredge et al. 2010) shows that Level 3 fair values are associated with higher audit fees. Furthermore, Fiechter and Meyer (2010) find that during the 2008 financial crisis, banks take advantage of Level 3 fair value unrealized gains and losses to take a big bath.

Results from Table 0-1, however, show that Level 3 fair value *assets*, surprisingly, only account for 7% of the entire fair value assets; and level 3 *liabilities* are practically negligible (~0%).

In addition, Figures 0-2 to 0-5 provide time trend charts for the percentages of Level 2 and Level 3 fair values. Figures 0-2 to 0-5 suggest that there is a clear decreasing trend of Level 3 fair value assets, suggesting that *many banks choose to classify more financial instruments under level 2 rather than level 3*. Another observation from my field research is that from vendors' perspective, there are no distinctions between level 2 and level 3 fair values. They are just the same products from the same information assembly line. A security, classified as level 3 by a client, does not necessarily incur more time and efforts for the vendor to evaluate, nor does it necessarily imply a less accurate evaluated price. If this is indeed the case, then *the distinction between level 2 and level 3 fair values might not be as evident as the literature has previously reported* (Ettredge et al. 2010; Fiechter and Meyer 2010; Song et al. 2010).

Table 0-2 shows US bank holding company fair value assets breakdown by fair value hierarchy and by security type. One interesting quick observation is that almost all the fair value *liabilities* are carried at historical cost or amortized cost. This implies that bank managers have little discretion over the fair value pricings for these liabilities. Thus, in the remainder of the study, I will focus only on fair value *assets*. Another interesting observation from Table 0-2 is that *majority of fair value assets are evaluated by third-party vendors*.

For the remainder of this paper, I will focus SCP securities only and ignore derivatives, corporate and municipal bonds, and banks' private equity investments.

Firstly, although banks' derivative exposure[8,9] is significant and derivatives are a big part of banks fair value assets (18% of level 2 assets and liabilities), I will not include derivatives in this study, because banks managers' discretions over the valuations of derivatives are very limited due to the so-called daily "*collateral margining*" mechanism. Every morning, banks' collaterals, the majority of which are derivative contracts (credit default swap, currency swap, interest rate swap, etc.) are settled between banks and counter-parties. Collateral / derivative valuations are negotiated daily between the two parties. Obviously, banks and the counter-parties have opposite valuation incentives, that is, banks' gain from high derivative valuations mean the instant loss for the counter-party. Unless there are some kind of systemic collusions between banks and counter-parties, it can be safely assumed that derivative price identification process is reasonable and fair. At the same time, it can be safely assumed that banks' managers' discretion over fair value pricing of derivatives is very limited, if not at all negligible.[10]

Secondly, in addition to derivatives, I will further ignore corporate bonds and municipal bonds (munis) in this study, although banks' exposure to them is also significant (Tables 0-1 and 0-2). The reason is straightforward: compared to highly illiquid SCPs, the majority of the corporate bonds and munis are traded more frequently with higher liquidity and more transparency. Bank fair value groups' responsibility to identify the prices for corporate bonds and munis is to "build the bridge" between the last trade to 4:00PM bond market close. This "bridge-building" process is relatively mechanical (by applying *observable* and *verifiable* inputs such as yield curve / interest

[8] Table 0-1 shows that derivatives are 20% of total Level 2 FV assets; AFS is 64% of total Level 2 FV assets, 87% of total Level 2 liabilities, second most important items of FV assets/liabilities, next to AFS.
[9] Derivatives include interest rate futures/options, Interest rate swaps, foreign currency swaps, commodity swaps, and certain option and forward contracts, and other complex and highly structured derivatives, certain CDS, interest rate lock commitments.
[10] Almost all of the practitioners that I interviewed agreed this conclusion.

rate movements between last trade and 4:00PM) and well understood by all the parties involved (trader, internal control, third-party vendors, external auditors, investors, and regulators, etc.).[11] This same "bridge-building" process can be applied to other securities, including international equities and small domestic equities, although these securities are normally classified as level 1 of the fair value hierarchy. Appendix A presents the schematic illustration of this bridge-building fair value practices. More interestingly, most banks just simply outsource the daily pricings for corporate bonds and munis to the third-party vendors with little intervention. Therefore, it can be safely assumed that banks' managers' discretions over fair value pricing of corporate bonds and munis are somewhat limited.[12]

Thirdly, in this study, I will mainly focus on the so-called structured credit products (SCPs), including ABS, MBS, CMO, and TBA. Banks managers have relatively large discretions over the fair value pricing of these complex securities, mainly due to two main reasons. First, most of these SCPs have low liquidity and trading activities; and second, SCPs' valuation process, before the recent institutional changes, was ill-understood and there was no consensus among the parties involved. Most importantly, according to the current literature, the inputs for the valuation process might be quite subjective and not easily *observable* and *verifiable*. Bessembinder, Maxwell, and Venkataraman (2013) reports that during their 21-month period (05/16/2011 – 01/31/2013), only 17.8% of the MBS issues were traded at all, with an average of only 4.1 trades in each MBS security; only 30% of the ABS issues were traded at all, with an

[11] Investment-grade corporate and municipal as well as government bond prices generally are calculated through use of a computer model with little or no manual intervention. These models are affected by macroeconomic-, sector- and issuer-level data as well as the specific terms and conditions of the individual bonds in the model.
[12] Almost all of the practitioners that I interviewed agreed this conclusion.

average of only 4.97 trades in each ABS security; only 27.8% of the CMO issues were traded at all, with an average of only 4.64 trades in each CMO security. This paper documents similar very low SCP trading activity. Table 1 shows that the average number of trades per security over the 4.5-year sample period (05/16/2011 – 12/31/2015) is only 5.2, averaging more than 100 days between adjacent trades. In particular, the average numbers of trade per security for ABS, CMO, MBS, and TBA are 12.85, 7.64, 4.44, and 9.11, respectively. The average number of days between adjacent trades for ABS, CMO, MBS, and TBA are 79.76, 106.54, 108.17, and 107.65, respectively. Descriptive statistics reported in Table 1 suggest that ABS is the most liquid security type, while CMO is most illiquid type.

Fourthly, I will also ignore Federal Reserve Bank and Federal Home Loan Bank (FHLB) stock and private equity investments (Table 0-2). Federal Reserve Bank and Federal Home Loan Bank (FHLB) stocks are so-called "nonmarketable equity investments", which are not publicly traded and are acquired by the banks *only* to meet regulatory requirements. Banks typically elect the fair value option for *some* of these investments with the remainder of these investments accounted for under the cost or equity method. In addition, banks typically review at least quarterly for possible OTTI. For the private equity investments, third-party vendors generally have ad-hoc valuation services if customer banks have such request. But for most major US banks, the exposure to private equity investments is quite limited.

In summary, contrary to the beliefs from previous literature that managers have discretion over ***entire*** portfolio of level 2 and level 3 fair values, real world mechanism and constraints put significant limits on managers' discretions: they have limited discretion for derivatives, corporate bonds, and munis. Most importantly, *for most "regular" mid-sized or small-sized US banks, these three asset classes (derivatives, corporate bonds, and munis) add up to almost 100% of the fair value instruments*.

All this considered, for most banks, managers' discretions are quite limited. Only managers at big Wall Street banks with significant exposure to SCPs are likely to have discretions over the price identifications. For the remainder of the study, I will only focus on the price identifications and fair value pricing of SCPs.

4. Qualitative Field Research Results

In this section, I discuss qualitative field research methodology and results. The qualitative field research section of this study consists six parts: car-dealership analogy, third-party vendors, FINRA's TRACE, US banks, financial statement generating cycle and fair value committee meeting, and external auditors.

4.1.Car-Dealership Analogy

I would like to start with an analogy. The picture painted by the current literature for fair value pricing is very much like the valuation of an "art gallery" (thus art gallery model), where the entire portfolio of level 2 and level 3 fair values are treated as two separate pieces of art. The art gallery managers have unchecked discretions over the pricings and can easily manipulate the prices to their advantages. In the following sections, I would argue that, with many recent institutional changes, the current fair value practice is more like a "car dealership" (thus car dealership model), where each car is analogous to each individual security; the dealership's parking lot is analogous to banks' balance sheet; pricing companies such as Edmonds.com, Kelley Blue Book, and Autobytel Inc. are analogous to independent third-party vendors; a hypothetical nation-wide centralized car transaction system is analogous to FIRNA's TRACE; online car discussion groups and bulletin boards are analogous to BWIC.

In the following sessions, I would like to show that just like cars, almost all financial securities are quite standardized and well parameterized; just like car dealerships, most banks' balance sheets are consist of uncomplicated and straightforward financial instruments with reasonable liquidly; just like pricing companies such as

Edmonds.com, third-party vendors make security-level price quotes widely available to buyers, auditors, and regulators, thus significantly decrease the information asymmetry; a nation-wide centralized transaction system, FIRNA's TRACE gather and disseminate timely transaction information, thus significantly increase the market transparency; just like on line discussion groups and bulletin boards, BWIC firms gather and disseminate both binding and non-binding price bids. Therefore, all these new institutional changes and mechanism have lowered managers' discretion from portfolio level to individual security level and have limited their discretion only to SCPs (analogous to specialized vintage cars). Another interesting conclusion from this analogy is that historical cost might not be a good reference point for the fair value price identification.

4.2.Third-party Vendors

Independent third-party vendors, also called evaluated pricing services (EPS)[13], have been one of the fastest growing financial intermediaries since the 2008 financial crisis. EPS executives[14] estimated that the entire evaluated pricing service industry in 2017 is a one-billion-dollar business. Third party vendors' primary business is to provide *daily security-level* computer-driven or manually calculated evaluated prices for illiquid and OTC securities. In addition vendors have been in the market-data business for nearly 30 years.[15] However, their pricing feeds for SCPs have become more widely available *only* after the 2008 financial crisis, due to more market demands and due to availability of necessary IT infrastructure and computing powers. Nowadays, major third-party vendors provide pricing services covering almost the entire universe of financial securities. A key

[13] In this study, I will use the following two terms interchangeably: evaluated pricing services and third-party vendors.
[14] Executives from the three largest EPS gave me the same estimate in separate occasions.
[15] IDC and S&P were the dominant pricing vendors before the 2008 financial crisis.

driver behind vendors' booming business is regulation. Regulations since the financial crisis, such as Sarbanes-Oxley and Dodd-Frank, put a higher degree of importance on information transparency and data accountability.

"Post-crisis changes to fair value measurement and disclosures have seen a shift in price discovery via the *broker/client* relationship to pricing *vendor/client* relationship," said Jayme Fagas at Thomson Reuters. "This further highlights the demand for independent, third-party evaluated pricing."

Before I start detailed discussions on vendors, I should stress that vendors' main business responsibilities are *neither* to "seek the intrinsic theoretical true values" of the underlying security, *nor* to detect fraud transactions and associated prices. Rather, vendors are "*just a messenger*" to incorporate all available information and market color, as *quickly* as they can, as *objectively* as they can, from all market participants, and then pass on these *timely* and *accurate* market information/sentiments to all clients in the form of a single price, which "the next transaction is mostly likely to trade at for the this particular moment". Thus if there is a fire sale, vendors will mark down the price accordingly and promptly. Again, it is an irrelevant question whether this marked-down price represents the true "intrinsic value" of the security. If someone later on realizes that the marked-down price is too low and is willing to purchase the security at a higher price through real transactions, vendors will mark up the price accordingly and promptly, just as before.

Providing *daily* evaluated security-level prices is vendors' main business function, which can be broken into two major distinctive parts by the liquidity of the underlying security. First, for securities with high liquidity, vendors' pricing feeds are mainly to address the so-called “stale price” problem. For illustrative purposes, I will use US–domiciled mutual fund (i.e., Fidelity Japan Fund FJPNX or DFA Japanese Small Company Portfolio DFJSX)’s fair valuation of their Japanese equity holdings as an example. Fair valuation of similar securities, including international equity, domestic small cap equity, corporate bond, municipal bond, etc., follows the same methodology. Appendix A gives detailed timeline and performance measurements for liquid Japanese equity fair valuation. If we ignore all day-light saving time changes, Japanese markets closes at 1:00AM EST time (time point 0 in the Figure), while US industry standard required that mutual funds’ net asset value (NAV) should be calculated as the portfolio value at 4:00PM EST time (time point 2 in the figure). Therefore, there is a 13-hours gap between time point 0 and 2. Clearly, most recent US market movements between time point 0 and 2 are not incorporated in the 13 hour old “stale” Japan close prices, thus giving NAV predictability and “market-timing” opportunities. Incorporating the market information within this 13-hour gap, vendors provide daily fair value evaluation, an estimate of the price that would prevail in a liquid market given public information available at 4:00PM EST time. One of the most common practices is that to use the price movement of CME Nikkei 225 future (4:00PM EST) and Japan Nikkei 225 future (1:00AM EST), which is actively traded during this 13 hour gap, as a broader market movement index and adjust each portfolio holding stock x_i according to the historical regression coefficients ($x_i \sim \alpha_0 + \alpha_1 \cdot \Delta Nikkei\ 225$) for each stock.

$$\Delta Nikkei\ 225 = \frac{CME\ Nikkei\ 225\ future\ (4{:}00PM\ EST) - Japan\ Nikkei\ 225\ future\ (1{:}00AM\ EST)}{Japan\ Nikkei\ 225\ future\ (1{:}00AM\ EST)}$$

Then for each portfolio holding stock x_i, we can run the following regression:

$$Each\ portfolio\ holding\ stock\ x_i \ \sim \ \alpha_0 + \alpha_1 \cdot \Delta Nikkei\ 225$$

And adjust the Japan closing price (1:00AM EST) according to the regression coefficient α_0 and α_1.This time-bridge building process is relatively straightforward (even quite mechanical) and well understood by the literature (i.e., Zitzewitz, 2003; 2004), practitioners, external auditors, and regulators.

Second, for securities with low liquidity (i.e., CMO: the two adjacent observed CMO trades might be 4 month apart), vendors, since the financial crisis, have begun to "fill-in" the gap between two trades, by providing *daily security-level* evaluated estimates. This valuation process hasn't been well-examined by the literature. For the remainder of this study, I will focus my discussions on this second part, more specifically, vendors' evaluated pricing of illiquid SCPs, including ABS, CMO, MBS, and TBA.

For thinly traded complex securities such as SCPs, vendors typically reply on both computer and algorithm based valuation models (called "bucketing" pricing[16] methodology) and manual pricing. In the bucketing pricing models, vendors often estimate the value of non-traded securities by incorporating characteristics and observed prices for similar traded securities. Third-party vendors compile transaction prices from various sources (either directly from broker/dealers or indirectly from FINRA's TRACE) and a pricing matrix or a system of pricing buckets are constructed using these recent transaction data, from which key valuation parameters such as credit spreads to specific benchmarks and prepayment assumptions are created and updated as new data become available. Securities are further segregated into different buckets of similar securities by

[16] "bucketing" pricing is a 2.0 upgraded version of the well-known "matrix pricing".

characteristics such as term, vintage, waterfall structure, rating, size, and so on. Once spread levels have been stratified, similar securities can be priced relative to a benchmark using the bucket. Normally each SCP bucket contains 10 to 15 securities per bucket, with risk-weighted bands and buckets. And these buckets are dynamic and constantly changing to reflect the most recent market conditions.[17] Bucketing methodology can either makes sector-wide adjustments, or security-level adjustments. In addition, third party pricing service utilizes observable inputs including: pool specific characteristics such as loan age, loan size, and credit quality of borrowers; yields for Treasury securities of various maturities; a range of spread and discount margin assumptions; floating rate indices such as LIBOR; structural and waterfall features of each bond; and recent trading and bidding activity for bonds with similar collateral characteristics. As a final step of quality control, bucketing pricing algorithms check prices against recent trading and BWIC indications on each SCP security and then make adjustments according to these trading indications that it considers appropriate. All the inputs and the associated model assumptions used to make a pricing decision are stored and well-documented, allowing for clients' timely price challenge and auditors' request.

In addition to these "robot-like" algorithm based models, vendors also have a large group of evaluators (also called independent analysts), who are mostly former traders from major banks or broker/dealers. Evaluators are almost in constant contact with the desks of broker-dealers (ideally the primary dealer) that make a market in the security to get a current valuation. Evaluators have similar skills and market knowledge as bank traders/dealers. However, they are generally more informed than traders at a

[17] "bucketing" pricing methodology is different from "matrix pricing", in that the buckets are dynamic, rather than static as in the matrix pricing, which has fixed "buckets".

particular bank, because they can view almost *all* the prices and quotes for all similar transactions on the current markets, while traders at a particular bank only see the relevant ones to their bank. Interestingly, all the evaluators that I have interviewed are former traders from leading wall-street banks,[18] who are "not easily fooled by tricks of other traders and dealers". These evaluators have a wider array of access to the quoting universe and thus have a more robust ability to collect, analyze, evaluate, construct, and disseminate pricing feeds than any individual investor. With their fingers on the pulse of both *actual* trades and *intention* to trade, the evaluators are information gatherers and are most sensitive to the market sentiments and movements. Vendors then typically will combine evaluators' inputs with the models and/or adjust the model prices to remain in line with any visible trades in the market. One major vendor that I interviewed has 16 total experienced SCP evaluators, covering a universe of total 1.3 million SCP securities. Among these 1.3 million SCP securities, about 1.1 million are pools, whose prices need less human interventions. Each evaluator, therefore, covers between one thousand to ten thousand active SCP securities.

Major clients of the third-party vendors include buy-side asset managers, hedge funds, insurance companies, government agencies, auditors, regulators, and banks. Mutual funds/asset managers are, by far, the most important clients, and are *the* driving forces behind the vendor's business, because of their needs to calculate NAV every day. Banks, however, are quite low in the pecking order. Banks can and most often do outsource the valuation to third party valuation vendors, because most banks also have their buy-side asset management arms and vendors' subscriptions generally have already

[18] However, evaluators can come from any backgrounds.

been paid for by the asset-management branches. Since this "coleslaw" option[19] requires no upfront investment or ongoing maintenance of a system, *it is cost effective to the banks*. Another important reason banks use third party vendor pricing is *convenience*. Daily batch files of the pricing feeds sent from secure FTP channels from the vendors are easily incorporated into banks' data automation interfaces and back-office leger platforms. In fact, the entire batch FTP system is so automated, mechanical, and without human intervention, that it is very hard for any person to manually override the prices. Thus, contrary to the current view of literature, *vendors' pricing services are cost-saving and operationally easy to implement*.

Third-party vendors generally have two delivery channels to their clients (including banks). First channel is the fixed time batch delivery to the middle office pricing group. Most vendors have four fixed time deliveries: 10AM NY time, London Close (specific NY time depends on daylight saving time), 3:00PM NY time, and 4:00PM NY time. And the clients can choose which batch file(s) they want to subscribe to. The second delivery channel is vendors' intra-day time sensitive channel to banks' trading desks, which allows clients to assess to third-party evaluated prices and associated pricing models in real time. One major third-party vendor has a continuously evaluated pricing (CEP) model with good performances. According to the vendor's internal document, for big trade (transaction dollar value over $1 million), the CEP prices provided by the vendor do not vary from TRACE posted real trade price by more than 0.5 bp for approximately 80% of all trades covered by CEP. For most banks, their OTC

[19] One bank manager I interviewed joked that "bank's subscription to vendors' services is only the coleslaw of a meal, asset managers are the real steak".

derivative traders (CDS and interest rate swaps) do subscribe and use vendors' real-time pricing feeds.

For the delivered pricing files, in addition to the evaluated prices, vendors also deliver *all* the associated valuation assumptions and inputs to the pricing models, at the *security* level. For some SCPs, the delivered pricing files have around 100 field columns, including bid, mid, ask, spread, pre-payment speed, liquidity, spread to swaps, discount margin, Z spread, transaction information from previous trades, etc. Therefore, the clients virtually have access to the "whole story and history" of the security and the *relational networks* to similar securities via implied assumptions and inputs. When clients issue challenges to vendors' pricing feeds, they will normally provide new information or evidence *targeting specific valuation assumptions or inputs*, rather than a general challenge of the final price.

There have been some major recent mergers and acquisitions for the evaluated pricing services industry. Before 2015, the largest third-party vendor firm was Interactive Data Corporation (IDC), followed by S&P's Securities Evaluations (SPSE), Markit, and Thomson Reuters. In October 2015, Intercontinental Exchange (ICE) acquired IDC for $5.2 billion.[20] On October 04, 2016, ICE also completed acquisition of SPSE. On March 21, 2016, Markit merged with IHS Inc. to form IHS Markit. Now [21] the remaining "big four" evaluated pricing services are ICE, Markit, Thomson Reuters, and Bloomberg. ICE's acquisitions of IDC and SPSE (the top two EPS before the acquisitions) have created a huge market vacuum to other EPSs. For example, when external auditors use one vendor's pricing feeds to verify and challenge bank's inputs, they must choose/use a

[20] The transaction closed on December 14, 2015.
[21] As of May 2018.

different (from the current bank's vendor) vendor's pricing feeds in order to maintain independent. With the former top two SPSs acquired by ICE, auditors must find a different SPS with similar coverage, customer services, and valuation expertise.

Both vendors and their clients pay close attentions to the performance of the pricing feeds. The competitions among vendors for better performance are fierce, because clients' valuation committee will normally base on vendors' relative performances to award business to these vendors accordingly.

The most relevant institutional mechanisms for the third-party vendors are challenge mechanism and "law of single price" principle. First, the so-called "law of single price" principle put significant constraints on bank managers' discretion over fair value pricing. All the third-party vendors embrace the same "law of single price" principle, where for one particular point of time, the same security must be identified with the same price to *all* clients. Generally, one security is held by more than one financial institutions, may it be hedge fund, mutual fund, insurance company, etc. At the same time, this security can be held on both the asset and the liability side; it can be taken by the long position or by the short position, with opposite valuation incentives to different firms. Most importantly, as we discussed before, mutual funds are by far the most important clients and *the* driving forces behind vendors. Because mutual funds must face buyers' addition and sellers' redemption at the same time, it can be safely assumed that mutual funds don't have systemically biased valuation incentives for their NAVs. In addition, when the evaluated price for one particular security is "produced" either by vendor's automated algorithm or evaluators, these evaluated price "producers" are "client-blind", that is, they have no a priori information of the clients who will be using this evaluated price because the production of evaluated price happens before the delivery of the price. Therefore, it is very hard (if not totally impossible) for the evaluators to deliver an artificially inflated or deflated price to one favorite client, and not to all the other clients. Using the previously mentioned car-dealership analogy, when the pricing companies such as Edmonds.com or Kelley Blue Book (analogous to the vendors) posting the car reference prices on line, they have no a priori information of the clients who will be using this evaluated price. Their potential clients could be either buyers or sellers with opposite valuation incentives; could be auditors or regulators; could be other competing pricing companies, etc.

Moreover, bank managers' discretion over fair value pricing is significantly limited due to their low positions in the pecking order, due to small leverage in the power balances between vendors and their clients, and due to competition among vendors. The discussion above suggests that third-party vendors don't have systemically biased valuation incentives on their own pricing feeds. In the following quantitative test sessions, I will conduct further empirical tests on this hypothesis.

Second, the vendors' challenge process is the key mechanism for the dynamics and interactions between vendors and banks. All the third-party vendors have established similar process for their clients to submit inquirers regarding specific evaluated prices. If clients do not agree with some of vendors' prices, they may "challenge" the evaluation, by presenting a disagreement with vendors' evaluated price in regard to a specific security on a particular date. In the challenge process, clients provide market information or new evidence they think that the vendors have failed to consider. For most of the time, this new piece of information is in a form of a trade in the same or a similar security, trader's marks, or dealer's bid, etc. Upon receipt of the challenge and associated new trade information, vendor evaluators review and verify the market information presented by the client. Then evaluators may either *affirm* the current evaluation (deny client's challenge), or *update* the evaluation (accept client's challenge). Most importantly, evaluators update the current evaluated price on a *going-forward* basis, that is, the current issued evaluated price stay the same, and vendors will incorporate the new market data for *only* the *future* prices to *all* clients (not only to the one who has issued the challenges). This "no back-fill" mechanism also put a limit on bank managers' discretions. If a bank challenges and wins, current day prices stay the same; rather vendors will incorporate updated information on the *next day* prices to *all* their clients.

Generally challenges from the clients are of two types: tolerance-triggered automatic challenges and data-driven / evidence-driven challenges. Most of the clients have pre-set tolerance or triggering levels for price variances, if the vendors' prices are out of this tolerance level, an automatic challenge will be issued to the vendor through the data delivery interface or data port. These challenges will receive less attention from the vendors. Data-driven / evidence-driven challenges, however, are forwarded to vendors' special teams which will handle these challenges that demand more special attention and treatment. All challenges, relevant evidence or new market information presented, adjustment results, and correspondences between vendors and clients, are fully documented to keep an audit trail for future verification. In general, most challenges are responded within 24 hours by vendors.

One vendor that I interviewed informed me that on average, it receive 5-25 challenges (each challenge per security) from each of their client. The vendor wins about

70% of all the challenges.[22, 23] But note that these challenge numbers come from *all* the clients, mostly from mutual funds. This vendor also mentioned that challenges from banks are concentrated near month end, quarter end, or year end, when bank mangers pay attention to prices. Normally, a few days before banks close their accounting books at month/quarter/year end, banks start the challenge "dry-run" to pre-release month/quarter/year end pressure. Through these near month/quarter/year end challenge "dry-runs" bank managers hope that they can win at least some of these challenges before they close their accounting books. In the case that banks issue the challenge on or after month/quarter/year and the books are closed, if vendor has a new price, it will be reflected in the *following* month's books. Through my field research, one interesting insight has emerged: for SCPs, vendors generally receive 2,000~3,000 total challenges each month with a spike of number of challenges within 1.5 weeks *after* month end, mainly due to the fact that most hedge funds don't close their books until 1-2 weeks after month end. [24] These challenges are mainly concentrated at the middle (40~60 cents on a dollar) priced bonds. Another vendor that I interviewed informed me that on average, it only make forward adjustments on 10-15% of all the challenges it receives.

Vendors also have their own internal control mechanisms against potential bias and lack of independence. Most vendors also allow their clients to have customer score-card system to give feedbacks to the vendors. Vendors normally have monthly committee meetings to review all the price challenges, the corresponding adjustment results, and the

[22] Due to confidentiality agreements, I cannot disclose the precise numbers and specifics.
[23] On successful challenge case is that one student loan backed securities were prices around 80% by the vendor, but the vendor missed the guarantees from the federal government, so the bank challenged and won. The final prices were set at 97%.
[24] Through my field research, I have learned that hedge fund managers have even less discretions over fair values than bank traders. Due to their small sizes and less resources, hedge funds generally directly apply vendors' pricing feeds. In addition, some funds require having more than 3 external independent pricing sources for one security.

feedback score-cards. It is quite hard for a particular evaluator or a group of evaluators to systematically issue biased pricing feeds or adjustments.

In addition to the main business function of providing daily evaluated prices, third-party vendors have other channels to increase market transparency, including message parsing, sector level time series reports, transparency metrics, and market summary statistics. One of the most important such channels is the market indices of securitized products owned and administered by vendors. For example, according to Markit's securitized index manual, Markit provides synthetic tradable indices for different securitized product collateral types, including ABX (index name) for non-agency RMBS (collateral type), MBX (index name) for agency RMBS (collateral type), CMBX (index name) for non-agency CMBS (collateral type), etc. These synthetic tradable securitized product indices allow investors to gain insights into the overall-market level performance of the specific SCP product types. Because these synthetic tradable securitized product indices are based on the most liquid products and standard transactions, their liquidity and standardization allow market participants to accurately measure aggregate market sentiments, which further give investors opportunities to express their own opinion on the overall market color by taking long or short index positions accordingly. Furthermore, these sector-specific SCP indices allow investors to gauge specific interest / credit spreads for each risk class and closely mirror the current credit conditions of one specific underlying sector (non-agency RMBS, agency RMBS, or non-agency CMBS). Most importantly, because average peripheral investors (valuation consumers) cannot directly participate in the indices trading, the liquidity, transparency, and standardization of these synthetic tradable securitized product indices have given more benefits to these peripheral investors. Because now these peripheral investors can view and access the current index spreads for a specific risk class and the implied market sentiments of major investment banks and innermost "core" dealers (valuation producers).

The ubiquitous availability of vendors' pricing feeds and increased market transparency through vendors' tradable indices have caused novel and significant changes to banks' operations and business models. One major insight through my field research is that banks predominately apply third-party vendors' feeds to generate financial statements, due to regulatory pressure and fiduciary oversight, and most importantly due to operational convenience, cost reduction, and efficiency. Most of the banks that I interviewed 100% passively pass through vendor's feeds without any adjustments.[25] From third-party vendors' perspective, many major wall-street banks use the pricing feeds as default inputs to their ledge books and ultimately to their financial statements. Only when the pricing feeds trigger the pre-set variance tolerances, then banks will issue challenges.

In addition to the banks' operations and business models, wide-spread availability of third-party vendors' pricing feeds has had far-reaching impacts on banks' broker-client relationship. "Post-crisis changes to fair value measurement and disclosures have seen a shift in price discovery via the broker/client relationship to pricing vendor/client relationship," said Jayme Fagas at Thomson Reuters. Traditionally before the 2008 financial crisis, dealers were the most important player in the securitized and structured finance OTC markets. Dealers played a key role in the price identification process mainly because their market making function facilitated market liquidity creation

[25] I will elaborate more on this topic from banks' perspectives in sections 5.3 and 5.4.

and because dealers' ability and willingness to commit their own capital to finance and maintain positions in particular SCP securities. Therefore, dealers' fundamentally contribute to the ultimate price discovery, derivation, and verification through two vital functions: dealers' market making function and dealers' liquidity providing function.

However, dealers' vital role in SCP price identification was seriously undermined by the financial crisis, in that the 2008 financial crisis either put many traditional dealers out of business, or many major banks who were dominant players in the dealer market, chose to get out of the dealer business altogether. Filling in the vacuum left, evaluated pricing services, since then, have been replacing most of the traditional dealer's responsibilities and business functions, particularly SCP's price identification and verification. One of the biggest advantages of evaluated pricing services over traditional dealers is that evaluated pricing services are considered *independent* and *neutral*, without systemic incentives for biased prices. The reason behind vendors' independence and neutrality is that vendors, unlike dealers, do not invest or commit their own capital in the underlying securities. While dealers' market making and liquidity providing functions can be (and for most of the time, are) both biased by dealers' self-interests, vendors' function is to provide evaluated prices to their clients. Using the previously mentioned car-dealership analogy, most people would trust prices provided by pricing companies such as Edmonds.com or Kelley Blue Book (analogous to the vendors) more than the prices provided by the car-dealership (analogous to the dealers), who are either selling car to you or buying car from you. One executive from a major vendor told me in the interview: "third-party vendors have taken away the arrogance from traders and dealers, whose jobs are more mundane and mechanical nowadays".

Furthermore, one of the biggest vendors' impacts, which might have profound rippling effects across the entire financial system, is that the *search costs* for both relevant transactions and price discovery has been significantly reduced by vendors' pricing feeds after the crisis. And the much lower search costs are currently enjoyed by all the parties involved, including investors, auditors, regulators, and other stakeholders.

In summary, there are some very interesting dynamics and interactions between third-party vendors and their clients through challenge mechanism. In addition, contrary to the current view of accounting literature, vendors' pricing services are cost-saving and operationally easy to implement. Finally, the recent institutional mechanisms such as "law of one price" and "no back-fill" principles have put significant limits on bank managers' discretion over fair value pricing. Meanwhile, financial intermediaries, such as third-party vendors, have been reducing information asymmetry between bank managers and other parties (by "leveling the playgrounds/battle fields"), bring more standardizations to the market, lowering the entry barriers for more checks and balances due to the much lower search costs, holding bank managers more accountable, and switching the power balance away from the bank managers.

4.3.FINRA's TRACE

Financial Industry Regulatory Authority (FINRA) is a self-regulatory organization (SRO). More specifically, FINRA is a non-governmental private organization that self-regulates its member trading exchange markets and financial security brokerage firms. In the United States, the principal federal regulatory authority for regulating security industry and enforcing the federal securities laws is the Securities and Exchange Commission (SEC), which established by the Federal Securities Exchange Act of 1934. Originally, SEC delegated the authority to enforce industry standards and rules to national stock exchanges (e.g., the NYSE and NASDAQ) and Financial Industry Regulatory Authority (FINRA). The SEC, on July 26, 2007, approved a merger of the member regulation, enforcement and arbitration operations of the New York Stock Exchange (NYSE) and the National Association of Securities Dealers (NASD). As the result of this merger, a new SRO, the Financial Industry Regulatory Authority (FINRA), was formed.

According to FINRA's website, FINRA is the largest independent self-regulatory organization (SRO) for *all* securities firms and brokerage firms in the U.S. *Every* firm and broker that sells securities to the public in the United States must be first licensed and then registered by FINRA.[26] As of 2017, FINRA oversees 3,726 brokerage firms, 153,143 branch offices and 629,677 registered securities representatives.[27] In addition to offering regulatory oversight over *all* securities firms broker and brokerage firms that do business with the public in the US, FINRA also offer "professional training, testing, and licensing of registered persons, arbitration and mediation, market regulation by contract for the NYSE, the NASDAQ Stock Market, Inc., the American Stock Exchange LLC, and the International Securities Exchange, LLC; and industry utilities, such as Trade Reporting Facilities and other OTC operations".[28] As of 2017, FINRA's total enforcement fines and penalties totaled $64.9 million, with total restitution $66.8 million,

[26] http://www.finra.org/about.
[27] http://www.finra.org/newsroom/statistics.
[28] http://www.finra.org/newsroom.

individuals barred 492 individuals suspended 733; security firms expelled 21, brokerage firms suspended 29, and fraud and insider trading cases referred for prosecution 855.[29]

One of the main business functions of FINRA is to provide market transparency services, particularly for the less liquid OTC markets, by facilitating investors and market participants to "have access to trade information so they can more effectively assess securities prices and valuations".[30] Currently, FINRA offers five transparency facilities: Trade Reporting and Compliance Engine (TRACE), Alternative Display Facility (ADF), Trade Reporting Facilities (TRF), OTC Reporting Facility (ORF), and OTC Bulletin Board.[31]

The most important and commonly used FINRA transparency facilities and services is FINRA's Trade Reporting and Compliance Engine (TRACE). According to FINRA's regulations, TRACE is the "FINRA-developed vehicle that facilitates the *mandatory* reporting of OTC secondary market transactions in eligible fixed income securities. *All* broker/dealers who are FINRA member firms have an obligation to report transactions in TRACE-Eligible Securities to TRACE under an SEC approved set of rules".[32] I need to emphasize two points here. First, TRACE-Eligible Security does not include all U.S. treasury securities, all money market instruments, or any debt securities issued by foreign sovereign entities. In this paper, I will focus my discussions on SCP securities only. Second, FINRA's definitions of SCPs (ABS, CMO, MBS, and TBA) are slightly different from the terminologies used by Wall Street practitioners or academics. This might cause much confusion to the readers and new TRACE users. For example,

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[29] http://www.finra.org/newsroom/statistics.
[30] http://www.finra.org/industry/transparency-services.
[31] http://www.finra.org/industry/transparency-services.
[32] http://www.finra.org/industry/trace.

FINRA’s definition of ABS can both refer to the narrowly defined conventional “asset backed securities”; or it can also refer to the entire asset class including ABS, MBS, TBA, and CMO. Bessembinder, Maxwell, and Venkataraman (2013) provides excellent, concise, and clear definitions for each SCP security subtypes. For the convenience of the reader, I quote Bessembinder, Maxwell, and Venkataraman (2013)’s definitions in Appendix. Please refer to Appendix B for more specified definitions used in this paper.

According to FINRA’s rules and regulations, all SCP securities (ABS, CMO, MBS, and TBA) are TRACE-eligible. As of June 2017, TRACE consolidates all transaction data for each SCP sub types. As a result, investors and market professionals can get timely access to transaction information of *almost all* SCP transactions in the US. The only notable hypothetical exception is the OTC trades of SCPs *among insurance companies*, without any brokers/dealers involved. In the US, the insurance companies are overseen by National Association of Insurance Commissioners (NAIC), not by FINRA. Through my field research, I interviewed both FINRA and NAIC professionals. Both sides gave me very similar estimate that TRACE covers at least 99.9%, if not 100%, of the entire universe of SCP transactions. The reason is that SCP transactions (contracting and settlement) are quite complex in nature. The scenario in which two insurance companies, bypassing any brokers/dealers, trade SCPs directly with each other is highly unlikely, if not entirely nonexistent. So it is safe to assume that essentially *all* trading activities of SCPs are reported to TRACE.

Another important FINRA’s regulation essential to the ensuing discussion and quantitative hypothesis testing is that according to FINRA’s rules, in a trade between two dealers, both dealers need to report to TRACE, thus, TRACE can see both the buy- and sell- sides of the same trade. However, in a trade between a dealer and a customer, who is not a FINRA member, only the dealer-side of the trade needs to report to TRACE; FINRA does not require the customer-side of the trade to be reported to TRACE. Most importantly, FINRA does not check if the customer-side of the trade is spurious or totally “made-up” by the dealer. Therefore, price manipulation in inter-dealer trades requires a higher level of collusion. In the ensuing quantitative hypothesis testing section, empirical tests have documented a disproportionally high percentage of the dealer-customer trades in the potentially spoofing trades.

TRACE also has rules on the reporting timeframes for different types of securities (effective December 01, 2015):

Type of Security	Other Transactions - Reporting Times
Corporate Bond	Within 15 minutes of time of execution
Agency Debt Security	Within 15 minutes of time of execution
Agency Pass-Through MBS Traded TBA for Good Delivery	Within 15 minutes of time of execution
Agency Pass-Through MBS Traded TBA not for Good Delivery	Within 60 minutes of time of execution
Specified Pool Transactions & SBA Backed ABS Transactions	Within 60 minutes of time of execution
Asset-Backed Securities	Within 15 minutes of time of execution
All other Securitized Products a/k/a ABSX (CDO, CLO, CBO and private label CMBS)	Same day during TRACE business hours
CMOs/REMICs	Same day during TRACE system hours

(Source: FINRA’s website)

Since May 16, 2011, virtually *all* trades in SCP markets have been required to be *reported* to TRACE by broker/dealers. Though TRACE has been collecting all transaction data since May 16, 2011, FINRA has been disseminating this information to the market in different phases (staged dissemination): on November 12, 2012, FINRA started to release TBA transaction information; on July 22, 2013, FINRA started to release information for MBS specified pool transactions; on June 1, 2015. FINRA started to release information of ABS transactions; on March 20, 2017, FINRA started to release CMO transaction information. (Source: FINRA's website)

For the staged dissemination, investors can access this information on the FINRA's website or by subscription through third-party vendors, including "Bloomberg, MarketAxess, Reuters, and Moneyline Telerate" (Source: FINRA's website). This following table shows a sample of FINRA's disseminated trade data:

Trade Status	CUSIP	Sub Product	Quantity	Price	Report Date	Report Time	BuySell	Buyer Capacity	Seller Capacity	Contra Party
T	21H******	TBA	5000000	100.109	20110516	84740	S		A	D
T	01F******	MBS	90000	104.000	20110516	84848	B	P		C
T	313******	TBA	4377298	105.563	20110516	84849	S		P	C
X	059******	ABS	560000000	104.867	20110516	84854	B	P		D
T	314******	TBA	1000000	103.203	20110516	91226	B	A		D
X	126******	CMO	50000	99.000	20110516	91310	B	P		D
T	173******	MBS	49000	104.750	20110516	91421	S		P	C
R	02R******	ABS	25000000	103.234	20110516	92710	B	P		D
C	02R******	TBA	25000000	103.234	20110516	92710	B	P		D
T	064******	TBA	2361387	107.969	20110516	92716	B	P		D

TradeStatus

T = Trade Report
X = Trade Cancel
C = Cancelled Correction
R = New Correction
Y = Reversal (a transaction that has been reverse more than 20 days)

Buyer/Seller Capacity

P = Principal
A = Agency

Contra-Party

D = Inter-dealer trades
C = Customer-dealer trades

For each trade, dealers need to report the following transaction information to TRACE: the CUSIP of the underlying security being traded, its subtypes (ABS, CMO, MBS, or TBA), size of the trade, trade price, report date and time. For trade status, there are five applicable values: T=Trade Report, X=Trade Cancel, C=Cancelled Correction, R=New Correction, Y=Reversal. This paper will mainly focus on two trade types: regular trade (T) and cancelled trade (X). Buy/Sell Indicator is to identify whether the reported trade is a buy or sell (B=Buy, S=Sell). Buyer/Seller Capacity fields represent whether this trade is an agency-trade or principal trade reported by the corresponding buyer/seller (A=Agency, P=Principal). Simply put, agency trade is dealers' trading for a client. In an agency trade, dealers cannot charge spread to the client, rather they earn trade commission from the trade. Principal trade, on the other hand, is dealers' trading for themselves or money for their firms. In general, in a principal trade dealers execute a trade for a client from the inventory held by their firms. Contra Party Indicator identifies the type of trade based on the contra party reported (C=Customer trade, D=inter-Dealer trade). According to FINRA's rules, "Inter-Dealer Buys (Contra Party Indicator=D, Buy/Sell Indicator=B) and Inter-Dealer Sells (Contra Party Indicator=D, Buy/Sell Indicator=S) reflect two sides of the same trade, reported from each member firm's perspective".[33]

4.4. US Banks

Figure 0-1 shows the market shares of top US commercial banks in terms of total assets. For the second quarter of 2017, there are totally 300 BHCs. From 06/30/2009 to 06/30/2017, the total number of BHCs has the following descriptive statistics:

[33] FINRA's TRACE user's manual.

Mean	Min	25% Percentile	Median	75% Percentile	Max	Std
376.4	295.0	303.25	391.5	418.25	460.0	56.8

Figure 0-1 shows that the US banking industry is dominated by big banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) consisting about 69.9%, 82.3%, 88.5%, 91.8%, and 93.4% of the total assets of the entire industry, respectively. In addition, market shares for top 10, 20, and 30 banks show a decreasing trend from 2009 to 2017, while market shares for top 40 and 50 banks are quite stable over time. In the following discussion, it is assumed that the top 50 banks can sufficiently represent the entire US banking industry.

In order to open up the black box of how much discretion bank managers have over fair values and how banks' financial statements are generated, through field research I interviewed more than 60 bank managers from 15 of the top 40 US banks (more than 100 in total including professionals from auditors, vendors, FINRA, and other firms). My field research has two major findings: first, most banks that I interviewed predominately use third-vendors' pricing feeds as direct input to their general ledger and ultimately to their financial statements. In fact, most of these 15 banks that I interviewed nearly 100 percent passively pass-through vendor's feeds with little manual changes and adjustments. Among major Wall Street banks, Wells Fargo is the only one publicly disclosing the percentage of *unadjusted* vendors' inputs (in terms of dollar value) on its financial statements. The December 31, 2015 Wells Fargo's total fair values consist of 99.99926% *unadjusted* fair values by pricing feeds directly from brokers or third-party vendors. Only 0.00074% of the total fair values are manually *adjusted* by bank managers. In addition, Table III shows that in 2016, out of the total 265 public bank holding companies (BHC), 188 banks publicly disclosed in their 10K that they at least “predominately” rely on vendors’ feeds with “occasional adjustments”.[34] These 188 banks’ total level II AFS (AFS2) represents 83% of the total AFS2 of the entire population; their total level III AFS (AFS3) represents 96% of the total AFS2 of the entire population. Second, banks have many internal control, governance, and oversight mechanisms to curb managers’ discretion over fair values. I will elaborate the details of the internal mechanisms of the bank black box. Figure I depicts many of the internal and external control mechanisms, and Figure II depicts organizational structure of relevant committees and groups within a typical bank.

All the banks that I interviewed have centralized electronic automatic accounting platforms with various names at different banks. These platforms all have IT infrastructures/interfaces/ports that take in FTP batch files of pricing feeds from third-party vendors. After a necessary yet very brief quality control check, vendors’ prices automatically flow to the general ledger, on which bank’s financial statements and FR Y-9C reports are based. The entire process is generally overseen by a Valuation Oversight Committee.[35] The specific daily valuation process is generally managed by an independent price verification team (IPV team).

Two very important aspects I want to emphasize here is that first, most banks have internal separation of responsibilities and checks and balances. For example, IPV team is completely separated from the front-office trading desks. At most banks, IPV teams reports directly to the valuation committee and CFOs. Second, for most banks, managers don’t have direct inputs to the general ledger. They can observe these inputs,

[34] These 188 banks either “100% all pass-through without any adjustments”, or “almost all 100% pass-through”, or use the following words to describe their use of third-party vendors’ feeds: most of, majority, primarily, predominately, occasionally adjust, substantial.

[35] Different banks might have different organization structure and different committee names, including pricing committee, risk management, pricing oversight, etc.

but they don’t have control over it. If a manager really asserts that a vendor price is not reflective of market value, she must provide justifications including other traders’ price, recent sales of similar securities to the IPV team and the valuation committee. If approved by the committee, the IPV team will issue challenges back to the vendors through vendors’ automatic interface or simply via E-mail. IPV teams also work closely with other involved parties, including external auditors, internal auditors, risk management, controller, and finance group. In addition to the IPV teams, banks generally also have a separate and independent model validation team, whose responsibilities include validation of IPV’s conceptual design of the valuation models, data validation and quality assessment, and process validation. Please refer to Figure II for more detailed organizational structure of relevant committees and groups within a typical bank.

It is the IPV team (through the approval from valuation committee), not bank managers, who decide the price and control process, which vendor to use, who is the primary/secondary vendor, and ultimately which numbers should be used as inputs to the general ledger. Therefore, IPV teams have the final say on the fair values. IPV team answers for its own committee and managers, who are different from bank managers. Normally, the IPV team will run series of back-tests, analysis, and horse-races to decide which vendors to uses and who will be the primary/default pricing source, who will be the secondary source. Primary pricing feeds will be used as default inputs to the general ledger. If the primary prices trigger pre-determined variance tolerances, different banks have different pre-determined processes: some will use the secondary sources’ prices; some will use the average of the primary and secondary sources, etc.

"In the past it used to come down to who was more thick-skinned– the traders or the IPV team," comments one IPV team head at one of the largest Wall Street banks. "But due to organizational changes, the P&L, product control and risk sections are now working together. It is now our say at the end of the day."

For the IPV team, there are some significant institutional changes after the financial crisis. Most banks have given IPV teams (and valuation committees) more political power within the banks, allocated more budget to IPV teams, made IPV team more visible and accountable. Most IPV valuation specialists are former trader, or "quants" from the front office trading desks. In addition, most of the IPV team members have advanced degrees in the quantitative fields, such as math, economics, physics, or engineering.

In addition, banks have many different ways to put more controls over the challenge mechanism and the overall fair valuation process.

- In order to limit the potential biased influences, when they issue challenges back to the vendors, some banks that I interviewed only issue challenges without a "suggested price" or not even with the direction of the challenges. They only provide vendors with new information and new evidence.
- One major leading bank has a policy that if bank traders or bank managers are not satisfied with vendors' prices, they must sell a small portion (5% for example) of the portfolio and make a real transaction. Then the IPV team will use the realized market price to evaluate the portfolio.
- On a monthly basis, the Valuation Committee receives the tolerance challenges by managers. The Valuation Committee then formally submits the challenge

to the vendor. The results of the challenge process are reviewed by the Valuation Committee. Upon receipt of the challenge, vendor may *affirm* the current evaluation, or *update* the evaluation on a *going forward* basis incorporating the new market data. If a challenge is not accepted and the price differential is determined by the Valuation Committee to be significant, Committee will override the valuation received from the primary third party pricing vendor and utilize a valuation received from the back up pricing vendor. An override is effective for *one day*, at which point the Valuation Committee will convene and reexamine (and, if necessary, revise) prospectively the methodology used to value the security.

- All challenges and associated audit trails are well documented. Many banks have incorporated evaluation challenges into their workflow, tracking communications and recording response and completion time.

- All pricing vendors are subject to an annual on-site due diligence review that includes a detailed discussion about the methodologies used, particularly for evaluated prices, and any changes to the methodologies.

For bank managers, they cannot cherry pick among vendor's feeds, because the pricing policy and primary/secondary vendors are set by the IPV team. There are only two possible ways for bank managers to manipulate book ledger numbers to their advantages: convince the committee and IPV team to issue challenges or manipulate prices through *real* transactions. My previous discussions have clearly shown that bank mangers' discretion is significantly limited in the challenge mechanism. But can they manipulate prices through real transactions? First of all, it is illegal for traders to manipulate prices through fraud transactions. In addition, most of banks that I interviewed have policy / mechanisms against this:

- "Best Execution", in which traders must have at least 3 price quotes from at least 3 different dealers in order to make the transaction. Traders must choose the best prices among the 3 price quotes.[36]

- Mechanism against "short-term round-trip" transactions. Many banks have set up policies/rules against "short-term round-trip" transactions, such as repo 105 (no de-recognition of security on bank's book). In addition, banks also have "Wash sale" rules, which specify that the span of round-trip transactions has to be larger than 60 days.

In summary, banks have set up many new policies/internal control mechanism since the financial crisis, which put significant constraints on banks managers' discretion over fair values. This can be summarized by comments from a former "star" and "big-short-caliber" trader[37] that I interviewed in my field research: "Bank managers and traders used to have tremendous says over pricing, especially before the crisis. However, this is not true anymore.

Figure I to III and Table 0-1 to 0-3 provide details of the relevant institutional details, including various components of the black box, quarterly valuation committee meeting, banks' fair value methodologies, etc.

In addition, Figures 0-2 to 0-5 provide time trend charts for the percentages of Level 2 and Level 3 fair values. Figure 0-2 presents the percentage of level 2 fair value assets over total assets for top US commercial banks. $y-axis$ represents the ratio of

[36] In my field research, I personally witnessed a case in which one manager did not like a huge mark-down from the vendor. The trader got a favorite price quote from his "buddy" from another bank, and then issued a challenge request to the IPV team. But the IPV team denied the challenge request.
[37] Interestingly, he currently works for a major third-party vendor.

(Level 2 Fair Value Assets) / (Banks' Total Assets). Figure 0-2 shows that in general, bigger banks hold higher percentage of Level 2 Fair Value Assets than smaller banks, , with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 24.2%, 23.1%, 20.9%, 18.5%, 18.6%, and 18.3% of their total assets as Level 2 Fair Value assets, respectively. Figure 0-2 also shows that Level 2 Fair Value assets are a significant part of banks' total assets for top banks. Top 10 banks classify around one quarter (24.2%) of their total assets as Level 2 Fair Value Assets. One important observation is that there is a very prominent decreasing trend of the percentage of Level 2 fair value assets over total assets since 2011.

Figure 0-4 presents the percentage of Level 2 fair value assets over total fair value assets for top USs commercial banks. $y-axis$ represents the ratio of (Level 2 Fair Value Assets) / (Total Fair Value Assets). Figure 0-4 shows that in general, bigger banks hold lower percentage of Level 2 Fair Value Assets than smaller banks, , with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 68.8%, 75.8%, 78.9%, 78.6%, 80.1%, and 87.7% of their total fair value assets as Level 2 Fair Value assets, respectively. One notable observation is that Level 2 Fair Value assets are a significant part of banks' total fair value assets for top banks. Top 10 banks classify around 70% (68.8%) of their total fair value assets as Level 2 Fair Value Assets. The most interesting observation here is that *the percentages of Level 2 fair value assets over total fair value assets have been quite stable since 2011*.

Figure 0-3 presents the percentage of level 3 fair value assets over total assets for top us commercial banks. $y-axis$ represents the ratio of (Level 3 Fair Value Assets) / (Banks' Total Assets). Figure 0-3 shows that in general, bigger banks hold higher percentage of Level 3 Fair Value Assets than smaller banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 2.7%, 2.1%, 1.6%, 1.4%, 1.5%, and 1.5% of their total assets as Level 3 Fair Value assets, respectively. One notable observation is that top banks classify significantly less assets as Level 3 Fair Value Assets than Level 3. For example, this percentage for top 10 banks is only 2.7% for Level 3, compared with 24.2% for Level 2. The most interesting observation here is that *there is a more prominent decreasing trend for the percentage of Level 3 Fair Value Assets over Banks' Total Assets since 2011*.

Figure 0-5 presents the percentage of level 3 fair value assets over total fair value assets for top us commercial banks $y - axis$ represents the ratio of (Level 3 Fair Value Assets) / (Total Fair Value Assets). Figure 0-5 shows that in general, bigger banks hold higher percentage of Level 3 Fair Value Assets than smaller banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 8.0%, 6.8%, 6.0%, 6.8%, 6.8%, and 5.6% of their total fair value assets as Level 3 Fair Value assets, respectively. One notable observation is that top banks classify significantly less assets as Level 3 Fair Value Assets than Level 3. For example, this percentage for top 10 banks is only 8.0% for Level 3, compared with 68.8% for Level 2. Compared to Figure 0-3, Figure 0-5 shows *an even more prominent decreasing trend for the percentage of Level 3 Fair Value Assets over Total Fair Value Assets since 2011*.

In summary, Figures 0-2 to 0-5 suggest that there is a clear decreasing trend of Level 3 fair value assets, suggesting that *many banks choose to classify more financial instruments under level 2 rather than level 3*. Another observation from my field research is that from vendors' perspective, there are no distinctions between level 2 and level 3 fair values. They are just the same products from the same information assembly line. A security, classified as level 3 by a client, does not necessarily incur more time and efforts for the vendor to evaluate, nor does it necessarily imply a less accurate evaluated price. If this is indeed the case, then the distinction between level 2 and level 3 fair values might not be as evident as the literature has previously reported (Ettredge et al. 2010; Fiechter and Meyer 2010; Song et al. 2010).

4.5.Financial Statement Generating Cycle and Fair Value Committee Meeting

In addition to "opening up the black box" around bank's daily fair value practice, I also want to follow the complete trail and full production cycle of a fair value number from its origination to its final destination on banks' financial statements. Thus, I shadow fair value professionals for one complete financial statement generating cycle at one major Wall Street bank and attended its quarterly fair value committee meeting. From my interactions with Wall Street practitioners, I have learned that fair value operations vary by banks; sometime these differences can be very significant. Thus my findings here might not be generalizable to other banks. However, they do provide some valuable insights deep into bank's fair value operations.

In general, a bank's 10-K filing is not due until 90 days after the end of the fiscal year and a 10-Q filing is not due until 45 days after the end of a fiscal quarter. The full financial statement production cycle that I have shadowed is for a 10-Q. Again, I will focus my discussion only on the fair value pricing of SCP securities.

At 4:00PM on the day of quarter end (day 0), bank takes in the batch FTP file from vendors. At this time, vendors' pricing feeds 100% pass-through and land on bank's general ledger. When the day ends, bank's accounting books are closed. On this particular day, bank managers have access to (can view) vendors' inputs to the general ledger; however they can do nothing to influence these inputs.

Bank managers generally only pay *real* attention to fair value prices several days before month end/quarter end/year end. Because of this "book closing" policy and "no back fill" from the vendors, bank managers choose to issue challenges (via bank's IPV team) of securities with potential uncertainties and material implications a few days *before* the quarter end (day -3 for example). If managers win these "dry run" challenges, vendors will incorporate new information and evidence in on-going prices, thus the new prices can enter bank's general ledger before it is closed. While some bank managers do "abuse" the challenge privileges, the IPV team adds an extra layer of control: they first check if the new evidence is substantial, then they will assess if the potential impact is material, not to the bank manager, but to the entire bank portfolio. IPV team will only forward the challenges with substantial evidence support and material impacts to the vendors. For this particular bank that I have shadowed, challenges are normally concentrated at month end, with 5-25 challenges per month. And vendors win about 75% of all challenges.

The most important event for the fair value production cycle is the quarterly valuation oversight committee meeting.[38] For this bank, the committee meeting is scheduled on the 15th day of the first month (day 15). Between day 0 and day 15, IPV team work very hard to do quality control and compile the vendors' feeds; at the same time, internal auditors and external auditors work closely with the IPV team to check the

[38] Different banks have (some time very) different names for the committee meeting.

security prices. 10-Qs are generally unaudited, but this bank invites external auditors to the entire fair value pricing process for both 10-K and 10-Q.

On day 15, valuation oversight committee meeting is attend by all parties involved, including CFO, controller, finance group, audit committee, risk management, compliance, product control, model validation, and IPV team. All the challenges are reviewed and related information (including challenge results, assumption/input challenged, new evidence provided, manager name, portfolio, etc.) are documented. It is the committee who decides on the final prices used to generate the financial statements. However, in reality, it is the IPV team who has done all the "dirty work"; the committee will generally issue approvals to IPV team's recommendations. But one point is quite clear from my field research, that is, only prices with *material* impacts and *substantial* evidences are adjusted. If necessary, the committee will ask relevant managers to explain certain challenges and transactions. Another interesting finding is that one bank manager told me that sometimes it is relatively easier for him to use a lower mark (manipulate the fair values *downward*) because the IPV teams and auditors put so much scrutiny on the potentially inflated prices. For this particular committee meeting, roughly about more than 99% (in terms of dollar values) of the fair values were un-adjusted and enter the financial statement; less than 1% were adjusted.

Another important function for the committee meeting is to review price verification procedures / standards and independent control framework. It also discussion the classification the financial instruments as Level 1, Level 2 or Level 3 of the fair value hierarchy. At some committee meetings, model validation group and risk management will discuss issues including internal valuation models' theoretical soundness, calibration techniques where needed, and the appropriateness of the model for a specific product in a defined market. Generally, fair value price verification is done monthly and models are independently reviewed annually.

In summary, through my field research, one key insight has emerged. Banks' entire financial statement generating process is highly automated. All the non-automated manual parts are well-documented based on IT platforms. It is very hard (if not impossible) for any person (even the CEO, CFO, valuation committee member, IPV team member, or accountant) to arbitrarily and manually override any one of the prices flowing to the financial statements.

4.6.External Auditors

Through my field research, I have interviewed both the third-party vendors and auditors. From the vendors' perspective, audit firms (particular their valuation teams and Wall Street bank auditors) are among the most important subscribers and users of vendors' pricing services. In addition, responding to inquiries from audit firms are one of the largest components of third-party vendors' daily work, particularly around quarter end and year end. One executive from a major vendor that I interviewed told me that "auditors are among our largest clients."

From the auditors' perspective, due to the strict confidentiality agreement, I cannot report in this study most of what I have learned from my interviews and field research. But one message is quite clear and unmissable, that is, Audit firms *predominantly* use third-party vendors' evaluated prices and rely on these pricing feeds to verify and challenge banks' inputs to their financial statements. One big four auditor that I interviewed in my field research told me that "audit firms overwhelmingly use third-party vendors for their pricing feeds. Also the auditors can directly contact clients' third-party vendors for further information."

If this is indeed the case, we need to revisit and rethink the conclusions on the interactions between auditors and banks from prior literature. We need to incorporate the recent institutional changes, particularly auditors' easy access to vendors' daily pricing feeds. We have a large body of literature studying the interactions between auditors and managers. On the surface, it seems to be the interaction between auditors and managers. However, beneath the surface, it might be nothing, but a fight between two sets of vendor prices: one used by banks, and the other used by auditors. In the following empirical analysis sessions, I will further compare fair value prices from two different vendors to see if there are systemic differences between these two sets of pricing feeds (Hypothesis 1).

In addition, large auditing firms such as the "Big Four" generally have their own centralized security valuation & modeling teams, through which an auditor can access not only to multiple vendors' pricing feeds on one particular security, but also to all other auditing teams' valuation opinions on similar securities – the auditing teams could be from different continents; and the securities could be held by many different institutions.

Another important message quite clear and unmissable from my interviews and field research is that auditors' easy access to vendors' pricing feeds at individual *security level* and to the associated valuation expertise at *security* level from vendors' client services has significantly lowered: not only the information asymmetry but also the valuation expertise asymmetry between auditors and bank managers. Almost every trader that I interviewed in my field research was contemptuous of both internal and external auditors. Now equipped with security level details of valuation assumptions used, input parameter specifics, and prices of similar securities from the third-party vendors, auditors are not so easily fobbed off by the traders any more. Although external and internal auditors might still be not as technically adept as the traders or bank managers on the complex security valuation models, they can now get vendors' direct support and clarification from evaluators / specialists who process similar levels of security-specific valuation expertise as the traders.

In my field research, one managing director from one Big Four valuation team told me that all major auditing firms have similar internal valuation teams, with about 40% of their business supporting internal auditors and 60% serving outside clients (hedge funds, insurance companies, etc.). Interestingly, he thinks auditors' internal valuation teams are more technically sophisticated than the third-party vendors because of the following two reasons. First, auditors' internal valuation teams are more focused, in that they only cover 500 to 1,000 securities requested from their internal auditors, and they can do in-depth analysis (cash flow, prepayment scenarios, simulations, etc.) for each individual security.[39] Second, auditors' internal valuation teams also have subscriptions to *all* major third-party vendors and thus can access to *all* their pricing feeds, while vendors don't typically see their competitors' feeds. In summary, although external and internal auditors themselves might still be not as technically shrewd as bank managers, they now can get direct support from vendors' evaluators / their own specialists, who collectively process at least similar levels of security-specific valuation expertise as the bank managers. One vendor executive comments: "third-party vendors have taken away

[39] He also thinks auditors' internal valuation teams are doing the real *evaluation*, while third-party vendors are merely doing *pricing*.

the arrogance from traders. Traders' job has become more mundane and mechanical nowadays".

The third clear message from my interviews is that the recent institutional changes, particularly the *security-specific* pricings from third-party vendors and *security level* transaction information from TRACE have significantly lowered bank managers' discretion over fair values from *portfolio* level to each individual *security* level. All the interactions between bank managers and auditors / vendors are well documented and most importantly this audit trail is at each individual security level. It is getting more and more difficult for the bank managers to systemically and consistently manipulate fair values upward or downward to their advantages. While bank manages used to have clouts over the valuation of the entire portfolio of fair values, with these new institutional changes and associated constraints, they have to fight harder and harder on the "battleground" of each individual security to gain some advantages. Although bank managers might still have some discretion over the fair value pricings at the security level, new institutional changes have gradually shifted the power balance away from the bank managers.

In summary, the recent institutional changes, particularly the *security-specific* pricings from third-party vendors and *security level* transaction information from TRACE have significantly lowered bank managers' discretion over fair values from *portfolio* level to each individual *security* level. While bank manages used to have clouts over the valuation of the entire portfolio of fair values, with these new institutional changes and associated constraints, they have to fight harder and harder on the "battleground" of each individual security to gain some advantages. In the quantitative archival session, I will present more detailed empirical test results on the convergence or divergence of pricing feeds from two different vendors across various asset classes.

5. Hypothesis Development and Research Design

After previous discussions, it is very natural to ask this intuitive and fundamental question: what are the specific impacts of TRACE and vendor pricing on managerial discretion through these three channels? I will empirically test these three channels one-by-one.

5.1. Channel One: Managerial Strategic Vendor Selection

Channel One is managerial strategic selection of vendors by cherry-picking favorable vendor prices. My field research shows that most banks do have internal control mechanisms against managerial cherry-picking. For example, all the banks that I interviewed have pre-determined order of primary and secondary pricing sources. This order is decided annually or semi-annually by the valuation committee, not by bank managers.[40] At the same time, frequent vendor-switching is also costly and operationally inconvenient because it requires making changes of the automatic routines at IT infrastructure level. However, despite these internal control mechanisms, if the evaluated prices from different vendors are indeed empirically convergent, then the constraints on managerial discretion arise not at the downstream banks' consumption level, but at the upstream vendors' production level.

H1 (Channel One): *There are no systemic differences between different vendors' prices.*

[40] Normally, the IPV team, under the supervision of the valuation committee, conducts annual or semi-annual back-testing and analysis to determine the relative performance among different vendors, and decide the order of primary/secondary sources accordingly.

In order to empirically test H1, I regress pricing feeds from one vendor on the prices from a second vendor:

$$FirstVendorPrice_{i,t} = \alpha_0 + \alpha_1 \cdot SecondVendorPrice_{i,t} + \epsilon_{i,t} \ (1)$$

High coefficients of $\alpha_1 \approx 1$ indicates that the two vendors' pricing feeds are highly correlated; high adjusted R-square $R^2 \approx 1$ indicate that the simple model (1) fits the data well. In addition, I also conduct joint tests on $\alpha_0 = 0 \ and \ \alpha_1 = 1$ to test whether the two prices are similar to each other. If the F-test results for the joint tests of $\alpha_0 = 0 \ and \ \alpha_1 = 1$ are significant, it can be safely concluded that the two vendors' prices are similar to each other.

I also calculate price differences:

$$PriceDifferences_{it} = FirstVendorPrice_{i,t} - SecondVendorPrice_{i,t}$$

and compare the kernel density curves of the price differences to normal distributions. Symmetric kernel density curves around zero indicates that $PriceDifferences_{it}$ is not systematic biased so that bank managers cannot cherry pick favorable prices among vendors. In the meantime, if the kernel density curves are much narrower than the normal curves, that is the distribution of $PriceDifferences_{it}$ is not "fat-tailed", then extreme pricing differences between two vendors are unlikely to occur compared to normal distributions.

5.2.Channel Two: Vendors' Effective Performance

Channel Two has two distinct but principally connected pathways: 1) managerial strategic timing of real transactions to recognize selected unrealized gains/losses; and 2) managerial manipulating general ledger accounting numbers through the challenge mechanism.

The first pathway is fundamentally linked to the real earnings management literature. Prior literature shows that managers engage in real transactions to manipulate earnings (Healy and Wahlen 1999; Beatty et al. 2002; Thomas and Zhang 2002; Bens et al. 2002, 2003; Kanagaretnam et al. 2004; Graham et al. 2005; Roychowdhury 2006; Dechow et al. 2010). In addition, prior research reports that managers exploit historical cost to achieve earnings management (Herrmann et al. 2001; Barlev and Haddad 2003; Ramesh et al. 2004; Laux & Leuz 2009). For example, Barth et al. (2017) reports that historical cost-based accounting provides bank managers with the opportunity and discretion to engage in earnings management by timely realizing selected gains and losses.[41]

Managerial discretion in *both* pathways is rooted in the *same* fact that historical cost, as a pricing reference point, is "stale" and fixed, and thus can deviate significantly from the dynamic current market value. In the event that vendors' fair values could account for a significant portion of the ensuing price movements since the historical costs, thus providing reliable and accurate up-to-date valuation reference points for the next trades, then management's discretion in the first pathway (strategic timing) will be significantly constrained. At the same time, vendors' fair values are widely available to

[41] The unrealized gains and losses are recognized in other comprehensive income (OCI) on the income statement. They are not recognized in earnings until they are realized through real transactions. Section 6.3 provides more details discussion.

all market participants (IPV team, valuation committee, auditors, and regulators, etc.). As long as vendors' prices provide reliable and accurate up-to-date valuation reference points, it would be quite difficult for the managers to systemically and consistently win the challenges. Thus management's discretion in the second pathway (manipulating general ledger numbers through challenges) will also be significantly constrained. In summary, managerial discretion in *both* pathways is based on one common factor, that is, vendors' effective performance:

H2 (Channel Two): *Vendors' fair values have information content and are value-relevant, in that they can account for significant price movements since historical costs and can provide reliable and accurate up-to-date pricing reference points for the next trades.*

In order to empirically test H2 (Channel Two), I employ a difference-in-difference approach in which I compare vendors' performance to historical costs, before and after FINRA's dissemination. Specifically, I first examine whether vendors' prices could bring significant improvements over historical costs and then examine whether these improvements could be augmented by FINRA's dissemination. For H2, the basic research design entails estimating the following equation, using two different models[42]:

$$Y = \alpha_0 + \alpha_1 \cdot X + \alpha_2 \cdot Post_{i,t} + \alpha_3 \cdot X \times Post_{i,t} + Controls + \epsilon_{i,t} \qquad (2)$$

$$Model1\text{:} \begin{cases} Y_1 = TRACE_{i,(n+1)} \\ X_1 = Vendor_{i,n} \end{cases} \; and \;\; Model2\text{:} \begin{cases} Y_2 = \Delta TRACE = TRACE_{i,(n+1)} - TRACE_{i,0} \\ X_2 = \Delta Vendor = Vendor_{i,n} - Vendor_{i,0} \end{cases}$$

42 Detailed definitions, calculations, and illustrations of the commonly used performance metrics can be found in Table 3.

5.3.Channel Three: Spoofing the Vendors

Channel Three is managerial manipulation of vendors' prices through spoofing ill-intentioned cancellation trades. According to FINRA, spoofing is a type of market manipulation that "involves placing certain non-bona fide orders with the intention of triggering other market participants to place orders, followed by canceling the non-bona fide order, and entering an order on the opposite side of the market." For simplicity, in the following sections, I use the word "spoofing" to denote "managers' submitting orders they intended to cancel". Spoofing has been popular in algorithmic high frequency trading, where "spoofers" bid or offer with intent to cancel before the orders are filled.[43] For example, they can manipulate prices through creating false pessimism when they cancel many previously placed orders, or through creating false optimism when they place many offers in bad faith. Spoofing in high frequency trading has been in existence for a least a decade and are well-known in the traders' world.[44] It would be a surprise that SCP traders are *not* familiar with the essentials of spoofing tricks. A more detailed illustration of the "Canceled-Single" trades can be found in Table 5.

H3 (Channel Three): *In response to the new institutional developments and many associated internal and external constraints in Channel One and Two, bank managers engage in spoofing-transaction based fair value manipulations through Channel Three.*

In order to empirically test H3 (Channel Three), I focus on a very particular type of "Cancelled-Single" trades. Simply put, a "Cancelled-Single" trade is a trade initially posted on Day_0, but is subsequently cancelled on Day_{Cancel}. More specifically,

43 Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.

44 Key examples of lawsuits against spoofing include Panther Energy Trading ("Panther"), Biremis Corporation ("Biremis"), and Hold Brothers On-line Investment Services, LLC ("Hold Brothers").

- The average timespan between $[Day_0, Day_{Cancel}]$ is 4.5 days (Table 5);
- The initial legal *agreement* of the trade itself is cancelled. Because the average timespan between $[Day_0, Day_{Cancel}]$ is 4.5 days and it normally takes much longer to settle a complex SCP transaction, no money has been transferred; the ownership of the security has not changed hands. No real transaction has ever happened;
- The cancelled transaction is the *only* trade for this particular security on Day_0, that is, there are no parallel, concurrent, or side trades for this security on Day_0;
- There are no other trades between $[Day_0, Day_{Cancel}]$ for this particular security, thus there are no contamination and no interference from trades between $[Day_0, Day_{Cancel}]$;

This "Cancelled-Single" trade provides a "vacuum-like" setting to test how intermediaries (and agents in general) react to and process new information.[45] It also provides a robust setting to further test the efficient-market hypothesis. If the efficient-market hypothesis holds here, on Day_0 vendors should promptly and fully adjust their fair values in response to the initial posted transactions; on Day_{Cancel} vendors should reverse back to the original price levels in a symmetric, unbiased, and prompt fashion. However, if the efficiency-market hypothesis does not hold, on Day_{Cancel} vendors might be less sensitive to the cancellation and adjust their fair values only gradually and less markedly. This asymmetric response pattern might give bank managers a potential way to manipulate vendors' fair values. For example, 1) on Day_0, a bank manager posts an initial trade with a favorable price and a larger than normal trading volume to make the

[45] Please refer to Table 5 Panel A1 for schematic and detailed illustration of the Canceled-Single trade.

trade more "sensational"; 2) on Day_{Cancel}, bank manager *quietly* cancels the original trade. The cancellation order, buried in thousands of other trades, can be easily neglected by vendors; 3) in the following days Day_n after Day_{Cancel}, vendors might continue issuing favorable prices.

The research design to test H3 (Channel Three) entails estimating the following equation:

$$y_{it} = \alpha_0 + \alpha_1 \cdot Event1_{it} + \alpha_2 \cdot Event2_{i,t} + \cdots + Controls + \epsilon_{i,t} \ (3)$$

where y_{it} refers to the vendors' pricing feeds. $IndicatorEvent1_{it}$, $IndicatorEvent2_{it}$,... refer to the dummy variable specifying Day_0, Day_{Cancel}, Day_1 ..., and so on. Regression (3) is run separately for the "positive jumps" and "negative jumps", where a positive / negative jump specifies an upward / downward adjustment on Day_0 for vendors' prices in response to the posted initial trades.[46]

I also compare trading volumes of the "Canceled-Single" trades to those of the controls (normal non-cancelled trades for the same security but at different times). Suppose bank managers do manipulate fair values by "spoofing" using Cancelled-Single trades, in order to augment the spoofing effects, they have to post an artificially and significantly higher volume to make the spoofing trade more "sensational", thus attracting attentions from the vendors and other market participants. Therefore, I expect to see higher trading volumes in Cancelled-Single trades.

[46] The details and specifics for the definitions for dummy variables for the initial report, later cancellation, reversion on day 5, day 10, day 15, and day 20 can be found in Table 5.

Moreover, I compare the percentage of dealer-customer trades for the "Canceled-Single" trades to that for the entire sample. According to FINRA rules, in a trade between a dealer and a customer, only the dealer needs to report to TRACE. In an inter-dealer trade, both dealers need to report to TRACE as two separate buy and sell orders. Thus, price manipulation in inter-dealer trades requires a higher level of collusion than in dealer-customer trades. Thus, I expect to see a disproportionally high percentage of the dealer-customer trades in the Canceled-Single trades.

6. Empirical Results

I acquire three unique datasets of daily financial instrument-level pricing feeds from TRACE and vendors. Table 1 provides summary statistics. Following (Nick-Nielsen 2014) and (Rossi 2014), my cleaning procedure filters out 36.39% erroneous and duplicate transactions. The final dataset consists of 16,020,744 transactions from 525,174 unique securities. It is worth noting that the trading activity for SCP is very thin. The average number of trades per security is 5.17 during the 4.5-year sample period; these 5.17 trades take place on 3.49 distinct trading days, implying that SCPs are generally traded more than once in a particular day. Notably, the average timespan between adjacent transactions $[TRACE_0, TRACE_{n+1}]$ is 107.6 days.

6.1. Channel One: Managerial Strategic Vendor Selection

Table 2 presents the results for the test of H1 (Channel One). The two key results from Panel A are the significant and close to 1 coefficients on $Vendor2$ ($\alpha_1 \approx 1$); and the very high adjusted R-squares ($R^2 \approx 1$). In addition, the joint F-tests for $\alpha_0 = 0 \; and \; \alpha_1 = 1$ are all significant at the $p < 0.01$ levels. Results from Panel A imply that the pricing feeds from two different vendors are very similar to each other.

Because the nature of linear regression is to study the *average* linear relationship and thus might average out the effects of extreme observation, Panel B presents the histograms of the pricing differences between two vendors. The red and blue lines represent kernel density curves and normal curves, respectively. A key observation is that the kernel density curves are symmetrical around zero, showing no signs of systematic biases. In the meantime, the kernel density curves are much narrower than the normal curves, implying that the pricing differences are "thin-tailed" and with higher kurtosis than normal distribution (any kurtosis higher than 3 means thin-tailed distribution).

Panel C presents the results for formal normality test. It is clear that the distributions for the differences are not normal, primarily due to the low variance and high kurtosis. This implies once again that the pricing differences are thin-tailed and that extreme pricing differences between two vendors are unlikely to occur compared to normal distributions.

Consistent with H1, findings in Table 2 collectively suggest that the pricing feeds from two different vendors are very similar; that there are no systemic biases for the differences; and that the extreme differences are much less likely to occur than corresponding normal distributions. Thus, it is difficulty for bank managers to strategically and systemically cherry pick favorable fair values among different vendors through Channel One.

6.2.Channel Two: Vendors' Effective Performance

Table 3 presents the results for the test of H2 (Channel Two). Previously, Table 1 shows that the average time span between adjacent trades $TRACE_0$ and $TRACE_{n+1}$ is 107.6 days. Therefore, we can treat $TRACE_0$ as *historical cost*. Table 3 Panels B1-B3 show that comparing to historical cost $TRACE_0$, vendors' fair values $Vendor_n$ have performed quite effectively, in that, on average, vendors' last price $Vendor_n$ are 83% of the times closer to the next trade $TRACE_{n+1}$; they are 89.4% directionally correct; they have very high (close to 1) Rho; they have small forecast errors and mean errors; there are no systemic patterns for bias and error. Notably, vendors' last price $Vendor_n$ can bring 91.6% of variance reduction, compared to the historical cost $TRACE_0$. From Panel

C1 indicates that vendors' last price $Vendor_n$ (red line) has significantly reduced the inter-trade variances of historical cost (blue line) and there are no signs of systemic biases. One unexpected result, though, from Table 3 is that there are no significant improvements post- vs. pre- FINRA's dissemination (Panel B2 and B3). This result is somewhat surprising, because it is expected that FINRA's timely dissemination of transaction data to the public will remarkably reduce information asymmetry and increase pre-trade transparency. One possible explanation is that market insiders such as the vendors rely on alternative more expeditious / efficient information channels. As discussed before, vendors have direct access to all the major trading desks; in addition, they also have access to the traders' *intention* to trade from BWIC. For most trades, dealers have to report to TRACE within 15-60 minutes of the time of the execution. At the same time, TRACE generally disseminates trade information within 15 minutes after it receives the reported trade. So, the conservative estimate for the total timespan between the execution and TRACE's dissemination is 15-60 minutes. Although FINRA dissemination might reduce the information asymmetry for the *general public*, it is most likely that during this 15-60 minute window, market professionals including vendors, might have already been informed through other timelier information channels.

Table 4 presents the formal regression results for the test of H2 (Channel Two). Two different regression models are used to test H2:

$$Y = \alpha_0 + \alpha_1 \cdot X + \alpha_2 \cdot Post_{i,t} + \alpha_3 \cdot X \times Post_{i,t} + Controls + \epsilon_{i,t} \qquad (2)$$

$$Model1\text{:} \begin{cases} Y_1 = TRACE_{i,(n+1)} \\ X_1 = Vendor_{i,n} \end{cases} \; and \;\; Model2\text{:} \begin{cases} Y_2 = \Delta TRACE = TRACE_{i,(n+1)} - TRACE_{i,0} \\ X_2 = \Delta Vendor = Vendor_{i,n} - Vendor_{i,0} \end{cases}$$

Model 1 and Model 2 have yielded identical regression coefficients and standard errors, except for the estimates for the constant α_0. Only Model 2 results are reported in Panel A. A key result from Panel A is the positive, significant, and close to 1 coefficients on $X = \Delta Vendor$. Detailed calculations from Panel C indicate that $Vendor_n$ can predict / account for around 85% of the next trade price $TRACE_{n+1}$, a significant improvement over the historical cost $TRACE_0$. Once again, there are no significant performance improvements after TRACE dissemination (the interaction terms are not significant), suggesting that vendors had other timelier channels to acquire information. Another interesting observation worth noting is that for the entire sample, CMO, and MBS, coefficients for $Gap\ btw\ [T_0, T_{n+1}]$ are both negative and significant, suggesting that vendors' accuracy forecasting the next trade price $TRACE_{n+1}$ decreases with the timespan between $TRACE_0$ and $TRACE_{n+1}$. This result makes intuitive sense: the longer the timespan between $[TRACE_0, TRACE_{n+1}]$, the less efficient and accurate the forecast.

Another important implication from Table 4 is that we can have a point estimate of the percentage reduction of managerial discretion. Here I define managerial discretion as the difference between managers' reported value and the reference value (the most recent widely available price):

$$Discretion \equiv Managers' Reported\ Value - Reference\ Value$$

First, suppose we lived in the pre-crisis world, where there were no institutional infrastructures such as TRACE and vendors. If a bank manager wanted to give a fair value estimate $Manager_n$ for one particular security on day n, the only price available to her and *everyone else* is the last observed price $TRACE_0$, therefore we have $Reference\,Value_{pre} = TRACE_0$. In addition, $Manager_n$ should be on average centered on the next real transaction price $TRACE_{n+1}$, because if manager's estimate $Manager_n$ is consistently far off from $TRACE_{n+1}$, the manager would look either incompetent or ill-intentioned in the eyes of other market participants (her peers, IPV team, and auditors). Therefore, I can further assume that the expected value of $Manager_n$ is the next observed transaction price $TRACE_{n+1}$, that is:

$$E[Manager_n] = TRACE_{n+1}$$

Then the expected value for bank manager's discretion is:

$$\begin{aligned} E\left[Discretion_{pre}\right] &= E\left[Manager_n - ReferenceValue_{pre}\right] \\ &= E[Manager_n - TRACE_0] = E[Managers_n] - E[TRACE_0] \\ &= TRACE_{n+1} - TRACE_0 \end{aligned}$$

Second, back to the current post-crisis world, where vendors' price $Vendor_n$ is *ubiquitously available* to all the major parties as a pricing reference point, thus we have $Reference\,Value_{post} = Vendor_n$. Then at this particular moment (day n) bank managers discretion is expected to be:

$$E[Discretion_{post}] = E[Manager_n - ReferenceValue_{post}]$$
$$= E[Manager_n - Vendor_n] = E[Managers_n] - E[Vendor_n]$$
$$= TRACE_{n+1} - Vendor_n$$

Comparing $E[Discretion_{pre}]$ and $E[Discretion_{post}]$, we can see that vendors' contribution to reducing managerial discretion is essentially moving the $ReferenceValue$ from $TRACE_0$ to $Vendor_n$. This means that the expected value of managerial discretion has decreased from the original $(TRACE_{n+1} - TRACE_o)$ to $(TRACE_{n+1} - Vendor_n)$:

$$\Delta Discretion = E[Discretion_{pre}] - E[Discretion_{post}] = Vendor_n - TRACE_0$$

This value $\Delta Discretion$ can be precisely estimated from the regression results of Model 2. Please refer to Table 4 Panel C for detailed calculations. Therefore, we have:

$$Percentage\ Decrease\ in\ Descretion = \frac{Discretion_{pre} - Discretion_{post}}{Discretion_{pre}} \approx 85\%$$

This means that the ubiquitously available TRACE and vendors' prices have decreased managerial discretion by 85%.

In summary, results reported in Tables 3 and 4 have provided strong evidence supporting H2. These results suggest that vendors' prices have information content and are value-relevant, in that they *dominate the historical costs in all performance metrics*.

For example they can reduce around 90% of the original trade-to-trade variance, while having minimal bias, forecast error, and mean error. Furthermore, compared to historical costs, vendors' prices significantly reduce managerial discretion through Channel Two, by as much as 85%.

6.3. Channel Three: Spoofing the Vendors

Table 5 presents the results for the test of H3 (Channel Three). The average time span between the initial reported trade Day_0 and later cancellation Day_{Cancel} is 4.49 days. The key results from Panels B1 and B2 are that vendors do react promptly and significantly to the initial reports on Day_0, with positive/negative and significant coefficients ($Initial\ Report$) for the positive/negative "jumps". Vendors, however, don't fully respond to the later cancellation on Day_{Cancel} with non-significant coefficients ($Later\ Cancellation$).[47]

Given the results from Panel B1 and B2, I further test whether vendor prices would eventually revert back to their original levels. Results of regressions of vendors' prices on four dummy variables (5 days, 10 days, 15 days, and 20 days *after the cancellation*) are shown in Panels B3-4. The coefficients for $Day5$ are slightly significant at $p = 0.1$ level; they are positive/negative for the positive/negative jumps. The coefficients for $Day10$ and $Day15$ are non-significant at all; but they are still positive/negative for the positive/negative jumps. The coefficients for $Day20$, however, don't even have the consistent signs for either positive or negative jumps at all. These

[47] A positive / negative jump specifies an upward / downward adjustment on Day_0 for vendors' prices in response to the posted initial trades. And Initial Report and Later Cancellation are two dummy variables specifying these two event dates.

results indicate that vendors' prices, on average, revert back quickly to the original level within 10-15 days.

These results from Panel B1-B4 indicate a possibility that even the weak-form of efficient-market hypothesis does not hold in this particular setting. Although financial intermediaries, such as vendors, react expeditiously to the initial posted transactions, their response to the later cancellation is asymmetrically slow and gradual. It takes more than 10 days for the vendors to fully absorb and digest the cancellation information; and for the prices to fully revert back to their original levels. This asymmetric reaction on Day_0 and Day_{Cancel}, thus, provides a short-term (around 10 days) predictability of the future price movements. These results also suggest that financial intermediaries might react differently and asymmetrically to the *advent* of *new* economic information from the *disappearance* of the same *old* information.

One potential mechanism behind this asymmetric response might be the "crowding out effect", in that the impact of the later cancellation is driven down or even eliminated by the swarm of other concurrent buy- and sell- orders. Another potential mechanism might have a much deeper root in human behavior or even in physiological asymmetric response to novel stimuli. For example, Matthews (2011) reported that human subjects have considerably shorter subjective duration from repeated stimuli than from novel items, perhaps because repeated presentations of the same object cause a reduction in the neural response. Therefore a fruitful avenue for future research would be applying behavioral economics methods to test peoples' asymmetric response to the *advent* and *disappearance* of the same economic information, in a more controlled setting. Another fruitful avenue for future research would be to document whether bank managers strategically use high volume concurrent buy- and sell- orders to "crowd out" the market impacts of the ill-intentioned spoofing cancellation trades.

Finally, Table 6 presents results from additional tests of H3. Here I compare trading volumes of the Cancelled-Single trades to those of the controls (normal non-cancelled trades from the same security but at different times). Panel A shows that Cancelled-Single trades have significantly higher proportion of dealer-customer trades (89%) than the entire sample (36.7%), this proportion is even higher (88.8% vs. 23.5%) for TBA. Panel B shows that trading volumes for the Cancelled-Single trades are notably higher than those for the normal controls, consistently at almost all levels of mean, 5th percentile, 25th percentile, median, 95th percentile, and 95th percentile. Panel C presents the formal regression results. The independent variable $CanceledSingleIndicator$ is an indicator variable where $CanceledSingleIndicator = 1$ for Canceled-Single trades and 0 for normal non-cancelled trades. The coefficients for this $CanceledSingleIndicator$ variable are all positive and significant, indicating that trading volumes are indeed significantly higher for the Cancelled-Single trades compared to their normal non-cancelled controls.

In summary, Cancelled-Single trades have significantly higher trading volumes and consist of pre-dominantly dealer-customer trades. These two pieces of evidence collectively indicate a possibility that these Cancelled-Single trades might *not* be the result of simple input errors, in that random errors would have caused equally higher or lower erroneous trading volume; they would also have happened equally in dealer-customer or inter-dealer trades. Instead, this evidence suggests another possibility: bank managers might use these spoofing Cancelled-Single trades to manipulate vendors' fair values. As discussed before, FINRA mandates that in dealer-customer trades, only the dealer need to report to TRACE, while in an inter-dealer trade, both dealers need to report to TRACE. Therefore, manipulation in inter-dealer trades requires a significantly higher level of collusion. In the meantime, higher than usual trading volumes are more sensational and could have a more notable impact on vendors' prices.

I have to emphasize three points here. First, there is no definitive proof that bank managers use Cancelled-Single trades to spoof the market and manipulate fair value prices. The definitive proof would need to substantiate that the *intent* for the initial posted trades is not to execute, but to cancel.[48] Though specific *intent* is exceedingly difficult to establish,[49] Tables 5 and 6 do provide solid evidence that financial intermediaries respond asymmetrically to the *advent* and later *disappearance* of the same economic information; and that trading volumes and dealer-customer proportion are significantly and consistently higher in Cancelled-Single trades. This evidence indicates that Cancelled-Single trade might be one of the potential channels that bank managers could use to spoof vendors' fair value prices. This lack of definitive proof naturally leads to unresolved issues and directions for future research. For example, a fruitful avenue for future research would be to provide further evidence on the dynamics between banks managers and vendors. For example, do Cancelled-Single trades occur more frequently during stress times due to credit shock, interest shock, high volatility, etc.? Another fruitful avenue for future research would be to incorporate commercially available BWIC or Bloomberg messages posted by traders to further test whether they strategically use these messages to artificially spoof market sentiment and manipulate market expectations.

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[48] For example, the Swedish Financial Supervisory Authority defined spoofing as "a strategy of placing orders that is *intended* to manipulate the price of an instrument, for example through a combination of buy and sell orders."

[49] Manipulation of Commodity Futures Prices—The Unprosecutable Crime, YALE J. ON REG. 281, 356–57 (1991)).

Second, the scope of the Cancelled-Single trades is very limited. Table 5 Panel A2 shows that out of the 16,020,744 total transactions, there are only 4,144 Cancelled-Single trades, with 50 from ABS, 535 from CMO, 3,399 from MBS, and 160 from TBA. These Cancelled-Single trades are quite rare, and account for only 0.02% of the total trading volume of the entire sample and 0.28% of the daily trading volume. Therefore, the impact of Cancelled-Single trade on the overall market is immaterial, if not totally negligible. In addition, the timespan for potential Cancelled-Single trades is also very limited. The artificially inflated (deflated) fair value prices and associated market sentiment of over-optimism (over-pessimism) from spoofing trades are short-lived. Results from Table 5 Panel B indicate that market sentiments represented by vendors' prices are only slightly higher than the original level on the 5th day, and completely revert back to the original level within 10-15 days. Furthermore, the bank manager who initiated the original Cancelled-Single trade is fully aware that other traders may also recognize the over-optimism (over-pessimism) through access to vendors' pricing feeds. Therefore, the real window to take advantage of the Cancelled-Single trades is most likely even shorter.

Third, although the Cancelled-Single trades might seem to be immaterial to the overall market, they might have consequential impacts on individual bank trader' performance. This spoofing is at the very micro individual trader or portfolio manager level, not at the firm level. The unrealized gains and losses through potential spoofing are recognized in other comprehensive income (OCI). The unrealized gains and losses are recognized in earnings only when they are realized through real transactions (Barth et al. 2014). Thus, the spoofing and fair value manipulation will have no direct impacts on a *firm's earnings* or a *CEO's performance* per se. However, unrealized gains and losses are still relevant to this study due to three reasons. First, prior studies find that other comprehensive income is value relevant, particularly the unrealized securities gains and losses component (Dhaliwal et al. 1999; Biddle and Choi 2006; Chambers et al. 2007; Bamber et al. 2010). Second, the unrealized gains and losses through potential spoofing will definitely have an effect on an individual trader or portfolio manager's portfolio valuation and associate performances/bonus. In fact, portfolio managers' manipulation of vendors' fair value prices to their advantages is not uncommon. The most well-known case is PIMCO's odd-lot discount manipulation.[50] Third, although the unrealized gains or losses themselves might not affect firm's earning, banks (at firm level) might still use subsequent real transactions to reap the benefits of the artificially created over-pessimism or over-optimism from spoofing.[51] Therefore, another fruitful avenue for future research would be to document whether banks, following the initial Cancelled-Single trades, use subsequent separate real transactions to cash in (and recognize in earnings) these unrealized gains and losses induced by spoofing.

In summary, results reported in Tables 5 and 6 have provided strong evidence supporting H3. Prior evidence supporting H1 and H2 suggests that the new institutional developments have put significant constraints on managerial discretion in Channels One

[50] For example, see SEC's lawsuit against PIMCO at https://www.sec.gov/litigation/admin/2016/ia-4577.pdf; or SEC's press release of the settlement at: https://www.sec.gov/news/pressrelease/2016-252.html. For more detailed information, please refer to the following articles: https://www.assetmanagementadvocate.com/2016/12/odd-lots-and-valuation-deja-vu-part-1/ and https://www.assetmanagementadvocate.com/2016/12/odd-lots-and-valuation-deja-vu-part-2/.

[51] According to the July 2013 CFTC's milestone case against Panther Energy Trading and Michael Coscia, a high-frequency trader, spoofers placed a "relatively small order to sell futures that they did want to execute, which they quickly followed with several large buy orders at successively higher prices that they intended to cancel". By placing the large buy orders, spoofers "sought to give the market the impression that there was significant buying interest, which suggested that prices would soon rise, raising the likelihood that other market participants would buy from the small order" spoofers were then offering to sell. (Source: McLeod, Andrew Saks (July 22, 2013), "CFTC Fines Algorithmic Trader $2.8 Million For Spoofing In The First Market Abuse Case Brought By Dodd-Frank Act, And Imposes Ban", Finance Magnates, retrieved April 25, 2015 and https://en.wikipedia.org/wiki/Spoofing_(finance))

and Two. Therefore, bank managers must find an alternative channel to manipulate fair values. Results from Tables 5 and 6 suggest that bank managers could engage in more spoofing-transaction based fair value manipulation through Channel Three.

7. Conclusion

In this study, I find that banks predominantly apply vendors' feeds to generate financial statements. In addition, external auditors also predominantly rely on (different) vendors' pricing feeds and expertise to verify and challenge banks' fair values. I also find that vendors' evaluated prices dominate the historical costs in all performance metrics and can be a more accurate, objective, and reliable proxy for fair value than historical cost. In addition, vendors' prices are value-relevant in that they can account for 90% of the price variances between trades and put an upper bound on managerial discretion, sometimes to only 15% of the original level. Lastly, there are only limited channels through which managers can manipulate fair values. Recent institutional developments have put significant constraints on managerial discretion through Channel One and Two. However, there are signs that bank managers could manipulate fair values through Channel Three. Taken together, my research suggests that recent institutional changes after 2010 have established permanent constraints on managerial discretion over fair values, which might be more objective (or less subjective), less costly to implement, and more convenient for auditors to verify and challenge, than the literature previously reported.

Moreover, I emphasize the following. First, the purpose of this study is not to take sides in the fair value debate; rather I strive to document the recent institutional changes and novel infrastructure developments essential to *both* sides of the debate. Second, the main focus of this study is not to compare managerial discretion in the pre- and post-TRACE/vendors periods, which would be an effective approach only in the absence of the understanding of the underlying causal mechanism. Rather I try to assess vendor performance by comparing vendor prices directly to the historical costs in the post-period. This choice is, firstly, due to data availability (i.e. TRACE only started collecting SCP transaction data on May 16, 2011). Secondly, prior discussions on field research and causal inference suggest that the first order effects and the *causal mechanism* come directly from vendors' effective performance (i.e. vendors' prices can reliably and accurately predict next trade prices). Therefore, once the field research has pinpointed the underlying *causal mechanism*, comparing the pre- and post- periods, a joint test for macro-level aggregated association itself, can only provide *corroborating* and *additional* evidence (Gow et. al. 2016). At the same time, some recent studies try to provide this corroborating evidence by investigating the effect of vendors' prices on management's real transaction based earning and capital management, for example (Liu 2017).

Finally, I wish to remark on vendors' role and fair value accounting from a broader perspective. A common thread that I weave throughout this study is how vendors' prices affect managerial discretion and the potential ways they can manipulate fair values. From a narrower and shorter-term perspective, vendors' evaluated prices do seem to put significant constraints on managerial discretion. However, I should also discuss several critical caveats / *negative* consequences and guard against falling into a false sense of security and invulnerability from vendors' prices. It is far too early to celebrate the triumph of fair value accounting for the following four reasons.

First of all, the next trade price $TRACE_{n+1}$ might not be entirely exogenous to vendors' prices at all. Due to vendors' increasing clout and ubiquitous availability of their evaluated prices, both the buy- and sell- side traders might use vendors' last price $Vendor_n$ as a reference point when they negotiate the next trade. Therefore, it might not be a total surprise after all that vendors' price $Vendor_n$ can *passively* account for 85% of the inter-trade price movement, because they can, in fact, *actively* induce or even "produce" the next trade price $TRACE_{n+1}$. Second, as discussed previously, the vendors' job is not to find securities' intrinsic values; rather their primary concern is to pass on all relevant information in the form of a single price, at which "the next transaction is mostly likely to occur for this particular moment." Therefore, vendors will keep efficiently passing on irrationally exuberant market orders even if the security is evidently overvalued. Third, vendors' price identification for a non-traded security mainly relies on cross-references to transactions of similar securities through a relational network of implied valuation inputs. In addition to this relational network, the ubiquitous availability of vendors' prices has made the entire financial system more tightly connected. While increased interdependence and cross-reference might decrease the *idiosyncratic* valuation risks for individual securities, they can significantly increase the *systematic* risks for the entire financial system, because the *very foundation* of the entire relational network might be dubious and shaky. Finally, recent institutional changes, together with the rapid development of information technology, have made vendors' fair value "production" an automatic, standardized, and even mechanical process built on an information assembly line. This hard-wired and mechanical process has made localized news and sentiments proliferate more efficiently and ubiquitously through the financial system. More importantly, it might create self-reinforcing feedback loops that amplify originally localized optimistic/pessimistic sentiments and opinions, thus exacerbating system instability. For instance, vendors' prompt markdown in response to a random fire sale at a reginal bank might reverberate throughout the entire financial system and ultimately trigger systemic collapse.

Appendix A. Schematic Illustration of Fair Value Process of International Equities

For illustrative purposes, I will use US–domiciled mutual fund (i.e., Fidelity Japan Fund FJPNX or DFA Japanese Small Company Portfolio DFJSX)'s fair valuation of their Japanese equity holdings as an example. Fair valuation of similar securities, including international equity, domestic small cap equity, corporate bond, municipal bond, etc., follows the same methodology.

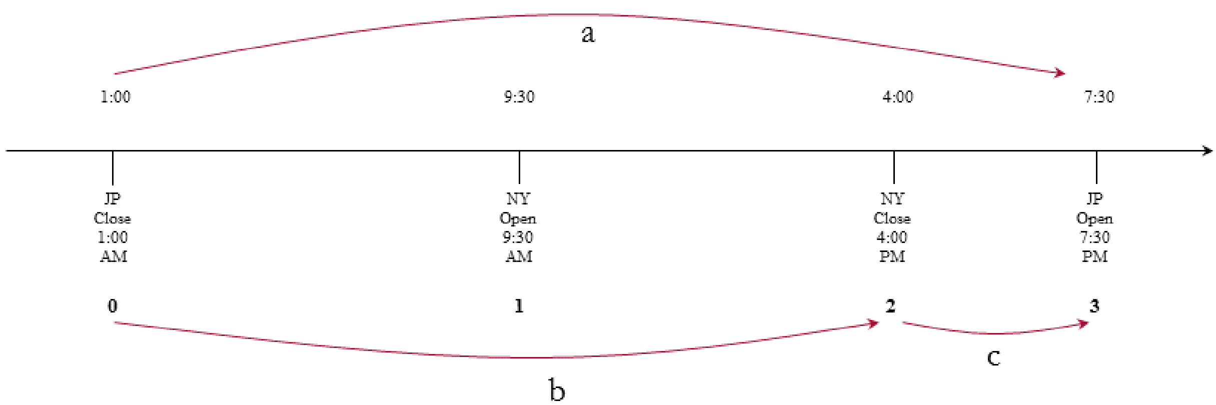

Figure above gives detailed timeline and performance measurements for liquid Japanese equity fair valuation. If we ignore all day-light saving time changes, Japanese markets closes at 1:00AM EST time (time point 0 in the Figure), while US industry standard required that mutual funds' net asset value (NAV) should be calculated as the portfolio value at 4:00PM EST time (time point 2 in the figure). Therefore, there is a 13-hours gap between time point 0 and 2. Clearly, most recent US market movements between time point 0 and 2 are not incorporated in the 13 hour old "stale" Japan close prices, thus giving NAV predictability and "market-timing" opportunities. Incorporating the market information within this 13-hour gap, vendors provide daily fair value evaluation, an estimate of the price that would prevail in a liquid market given public information available at 4:00PM EST time. One of the most common practices is that to use the price movement of CME Nikkei 225 future (4:00PM EST) and Japan Nikkei 225 future (1:00AM EST), which is actively traded during this 13 hour gap, as a broader market movement index and adjust each portfolio holding stock x_i according to the historical regression coefficients ($x_i \sim \alpha_0 + \alpha_1 \cdot \Delta Nikkei\ 225$) for each stock.

$$\Delta Nikkei\ 225 = \frac{CME\ Nikkei\ 225\ future\ (4{:}00PM\ EST) - Japan\ Nikkei\ 225\ future\ (1{:}00AM\ EST)}{Japan\ Nikkei\ 225\ future\ (1{:}00AM\ EST)}$$

Then for each portfolio holding stock x_i, we can run the following regression:

$$Each\ portfolio\ holding\ stock\ x_i \ \sim\ \alpha_0 + \alpha_1 \cdot \Delta Nikkei\ 225$$

And adjust the Japan closing price (1:00AM EST) according to the regression coefficient α_0 and α_1.

This time-bridge building process is relatively straightforward (even quite mechanical) and well understood by the literature (i.e., Zitzewitz, 2003; 2004), practitioners, external auditors, and regulators.

Very similar to the definitions in Table 3 Panel A, commonly used performance metrics are defined here (ignore any daylight saving changes):

	Definition
Time Point	
0: $JapanClose$	Japanese markets close at 1AM EST
1: $NYOpen$	Major US markets open at 9:30AM EST
2: $NYClose$	NAV is calculated as prices at 4:00PM EST
3: $JapanOpen$	Japanese markets open at 7:30PM EST (next day)

	Calculation Formula	Regression Analogy
Variable Definition		
$a = return(3,0)$,	$JapanOpen\ /\ JapanClose - 1$	Dependent Variable
$b = return(2,0)$,	$NYClose\ /JapanClose - 1$	Independent Variable
$c = return(3,2)$,	$JapanOpen\ /NYCloase - 1$	Residual

	Calculation Formula
Performance Metrics	
Rho(ρ):	$correlation(a, b), \rho = regression\ coefficient\ \kappa \times \sigma_a/\sigma_b$,
Days_Closer:	$How\ many\ times\ \lvert c\rvert < \lvert a\rvert$,
Directional_Correct:	$How\ many\ times\ sign(a)\ =\ sign(b)$,
Forecast_Error:	$mean(\lvert c\rvert)/mean(\lvert a\rvert)$,
Model Bias:	$correlation(b, c), a\ measure\ of\ arbitrage\ opportunities$,
Variance_Reduction:	$1 - variance(c)/variance(a), regression\ R\ sqare$,
Mean_Error:	$mean(c)$.

Appendix B. Description of SCP Subtypes

Bessembinder, Maxwell, and Venkataraman (2013) provides excellent, concise, and clear definitions for SCP security subtypes. For the convenience of the readers, I put the direct quotations of their basic SCP definitions here.

To be announced (TBA): A TBA trade is a forward contract between the buyer and the seller for a pool of mortgage-backed securities. On the trade execution date, the buyer and the seller set a delivery price for a homogeneous pool of assets (typically, government-backed mortgages). The agreement specifies six criteria that the pool shall meet, which include issuer (e.g., Fannie Mae), maturity (typically a 30- or 15-year pool), coupon (e.g., 4%), face value ($100 million), price, and settlement month.

Thus, the TBA market provides the secondary liquidity for mortgage underwriters to sell off loans that conform to pre-specified lending criteria and offset the risk of locking mortgage rates.

Source: Bessembinder, Maxwell, and Venkataraman (2013)

Specified pool: In a specified pool trade, the identity of the security (i.e., CUSIP) to be delivered at settlement is specified on the date of trade execution. Many securities in this category are not considered homogeneous and include nonstandard contract terms, such as ARMs, interest only, and so on.

Source: Bessembinder, Maxwell, and Venkataraman (2013)

Mortgage-backed security (MBS): An MBS or pass-through bond is a structured bond that represents a claim on the cash flows from mortgage loans. Commercial mortgage-backed securities (CMBSs) are secured by commercial real estate (e.g., shopping malls, offices, multifamily, industrial), whereas residential mortgage-backed securities (RMBSs) are secured by single-family or two to four-family real estate.

Source: Bessembinder, Maxwell, and Venkataraman (2013)

<u>Agency vs. private label securities</u>: Agency securities are issued by government-sponsored enterprises (GSEs), which enjoy an implicit government guarantee of timely payment of obligations (Freddie Mac, Fannie Mae, Ginnie Mae, and the Small Business Administration, or SBA). Private label securities are issued by private institutions (typically, special purpose vehicles associated with banks) and incorporate some form of credit enhancement from bond insurers.

Source: Bessembinder, Maxwell, and Venkataraman (2013)

<u>Asset-backed security (ABS)</u>: An ABS is a pass-through bond that represents a claim on reference consumer assets, such as credit card receivables (CARD), student loans (STUDENT), auto loans and leases (AUTO), equipment loans (EQIP), and so on. Mortgage loans (HOME), made to credit-impaired borrowers, and home equity loans (HEL), made to prime borrowers, do not conform to GSE standards and serve as ABS reference assets.

Source: Bessembinder, Maxwell, and Venkataraman (2013)

<u>Collateralized mortgage obligation (CMO)</u>: A CMO or pay-through structure is backed by a collateral pool of mortgages and allocates the cash flows of the underlying reference assets to a series of securities pursuant to a set of rules. The securities are divided into multiple tranches that have different maturities and different priorities for the receipt of principal and interest. The "senior" tranches are considered the safest securities. If the reference asset consists of high-yield bonds (leveraged loans), the

structured notes are called collateralized debt obligations (CDOs) or collateralized loan obligations (CLOs).

Source: Bessembinder, Maxwell, and Venkataraman (2013)

FIGURE 0-1 Market Shares of Top US Commercial Banks in terms of Total Assets

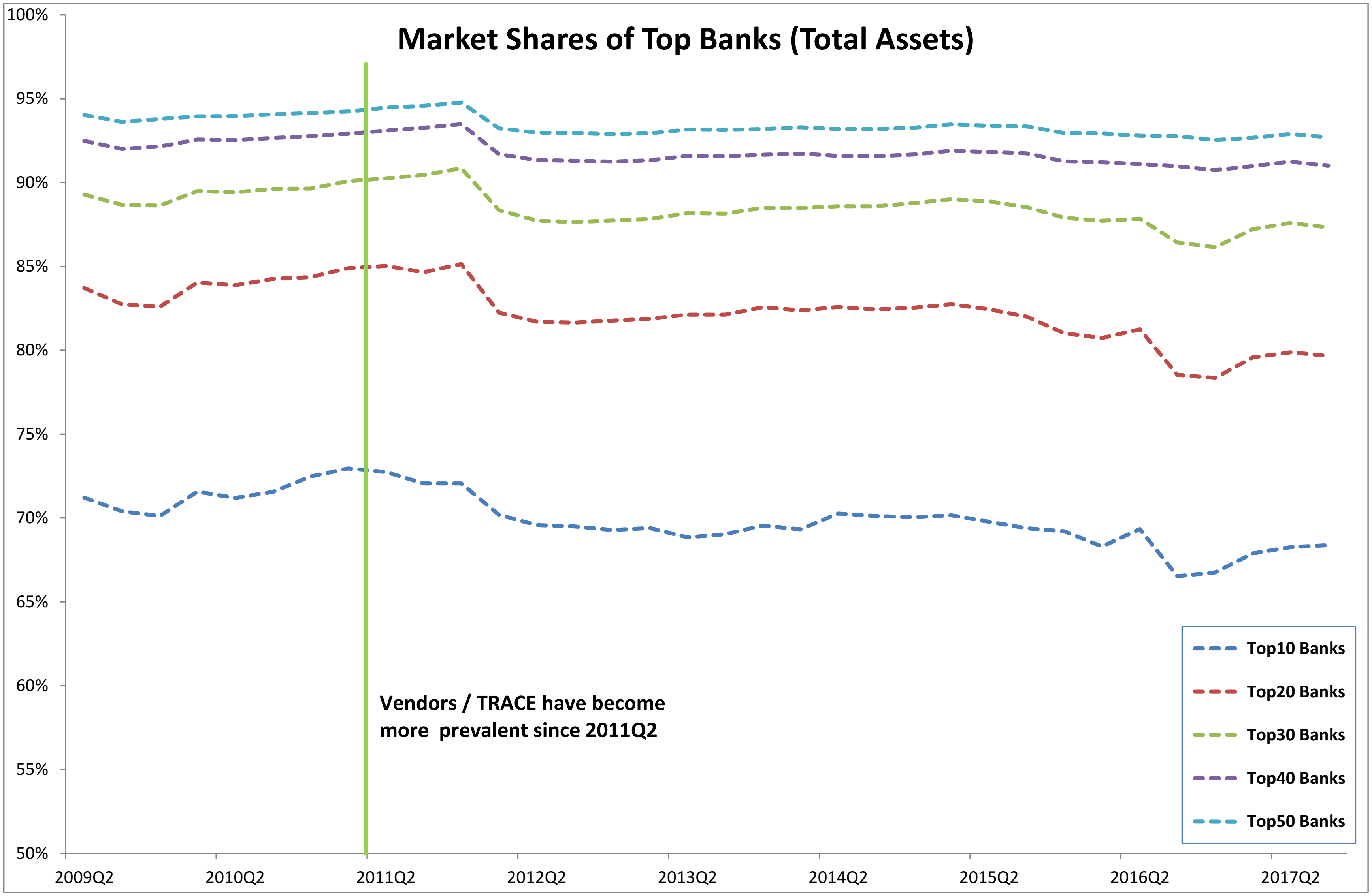

Figure 0-1 presents the overall market shares of top US commercial banks in terms of total assets.

- The US banking industry is dominated by big banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) consisting about 69.9%, 82.3%, 88.5%, 91.8%, and 93.4% of the total assets of the entire industry, respectively.

- For the second quarter of 2017, there are totally 300 BHCs. From 06/30/2009 to 06/30/2017, the total number of BHCs has the following descriptive statistics:

Mean	Min	25% Percentile	Median	75% Percentile	Max	Std
376.4	295.0	303.25	391.5	418.25	460.0	56.8

- In the following discussion, it is assumed that the top 50 banks can sufficiently represent the entire US banking industry.

- Market shares for top 10, 20, and 30 banks show a decreasing trend from 2009 to 2017, while market shares for top 40 and 50 banks are quite stable over time.

- Vendors and TRACE have become more prevalent since 2011.

    - FINRA and TRACE have been collecting all SCP transaction data since May 16, 2011.
    - On November 12, 2012, FINRA started to release TBA transaction information.
    - On July 22, 2013, FINRA started to release information on individual market segments for MBS specified pool transactions.
    - On June 1, 2015. FINRA started to release information of ABS transactions.
    - On March 20, 2017, FINRA started to release CMO transaction information.

- Data from Federal Reserve FR Y-9C Consolidated Financial Statements for Holding Companies, from 06/30/2009 to 06/30/2017.

FIGURE 0-2 Percentage of <u>Level 2</u> Fair Value Assets over <u>Total Assets</u> for Top US Commercial Banks

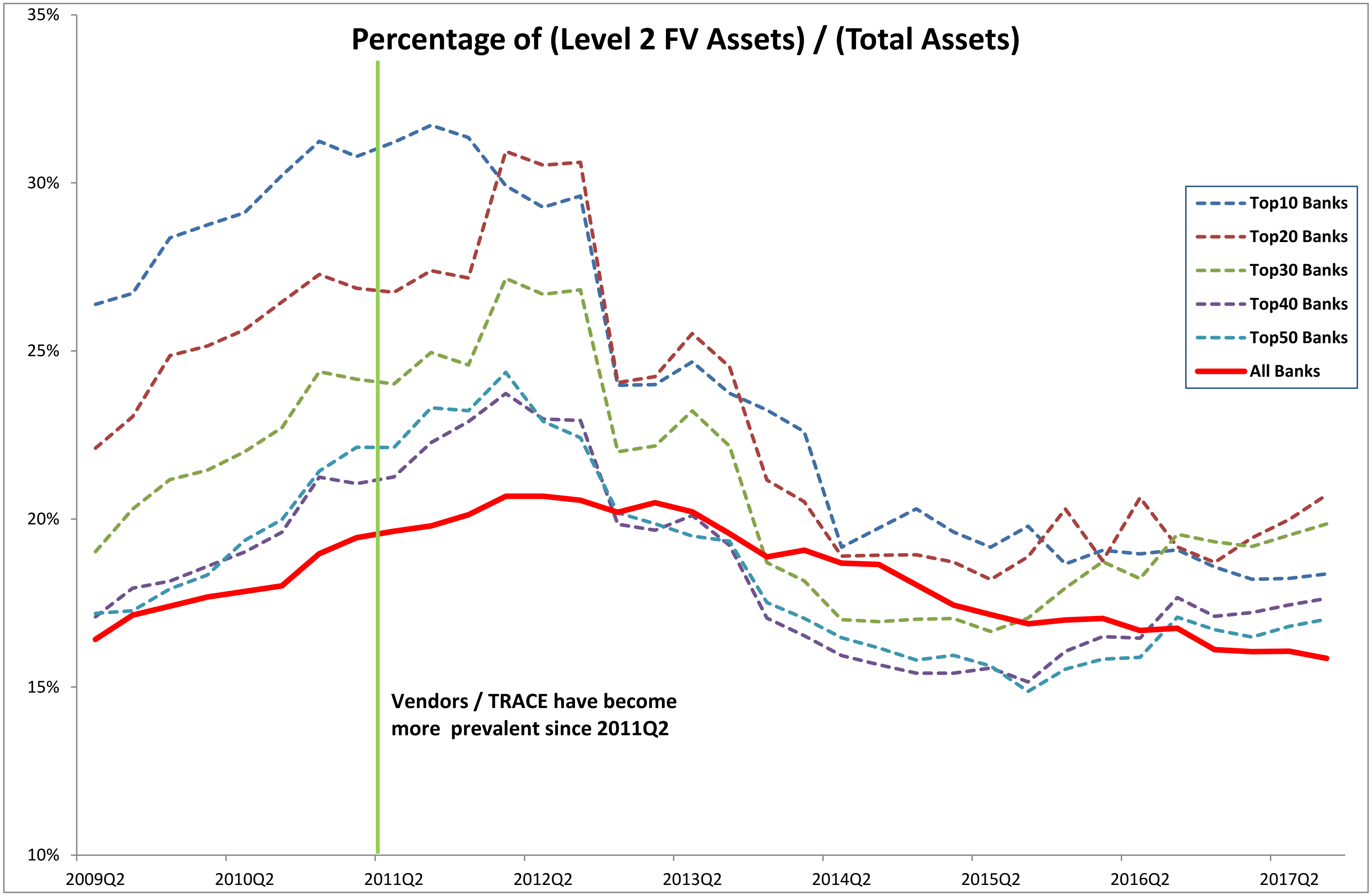

Figure 0-2 presents the percentage of level 2 fair value assets over total assets for top US commercial banks.

- $y - axis$ represents the ratio of:

$$\frac{Level\ \mathbf{2}\ Fair\ Value\ Assets}{Banks'Total\ Assets}$$

- In general, bigger banks hold higher percentage of Level 2 Fair Value Assets than smaller banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 24.2%, 23.1%, 20.9%, 18.5%, 18.6%, and 18.3% of their total assets as Level 2 Fair Value assets, respectively.

- One notable observation is that *Level 2 Fair Value assets are a significant part of banks' total assets for top banks*. Top 10 banks classify around *one quarter* (24.2%) of their total assets as Level 2 Fair Value Assets.

- There is a very prominent <u>decreasing</u> trend since 2011.

- Vendors and TRACE have become more prevalent since 2011.

  - FINRA and TRACE have been collecting all SCP transaction data since May 16, 2011.
  - On November 12, 2012, FINRA started to release TBA transaction information.
  - On July 22, 2013, FINRA started to release information on individual market segments for MBS specified pool transactions.
  - On June 1, 2015. FINRA started to release information of ABS transactions.
  - On March 20, 2017, FINRA started to release CMO transaction information.

- Data from Federal Reserve FR Y-9C Consolidated Financial Statements for Holding Companies, from 06/30/2009 to 06/30/2017.

FIGURE 0-3 Percentage of Level 3 Fair Value Assets over Total Assets for Top US Commercial Banks

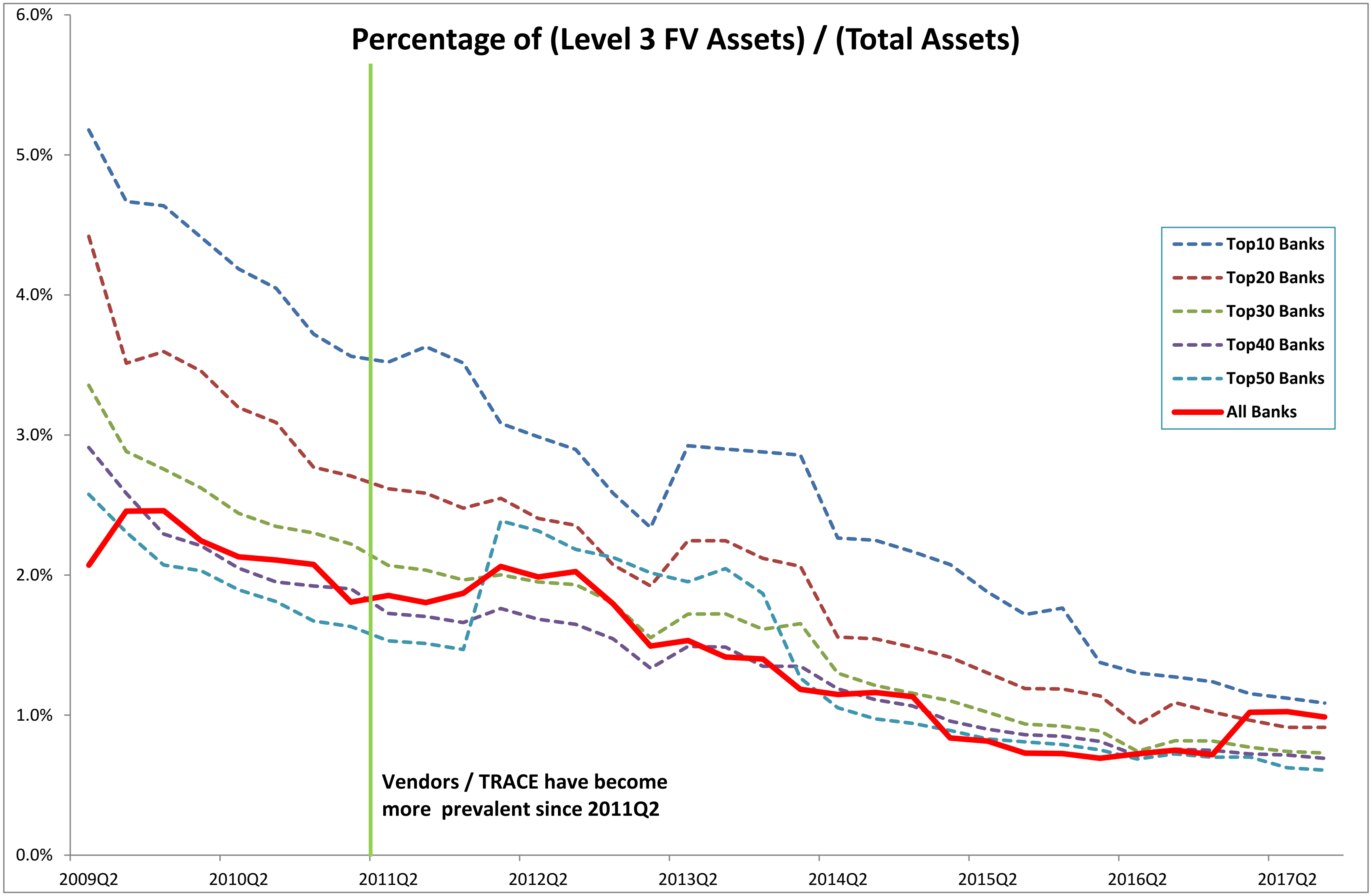

Figure 0-3 presents the percentage of level 3 fair value assets over total assets for top US commercial banks.

- $y - axis$ represents the ratio of:

$$\frac{Level\ \mathbf{3}\ Fair\ Value\ Assets}{Banks'Total\ Assets}$$

- In general, bigger banks hold higher percentage of Level 3 Fair Value Assets than smaller banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 2.7%, 2.1%, 1.6%, 1.4%, 1.5%, and 1.5% of their total assets as Level 3 Fair Value assets, respectively.

- One notable observation is that top banks classify significantly less assets as Level 3 Fair Value Assets than Level 3. For example, this percentage for top 10 banks is only 2.7% for Level 3, compared with 24.2% for Level 2.

- Another observation from my field research is that from vendors' perspective, there are no distinctions between level 2 and level 3 fair values. They are just the same products from the same information assembly line. A security, classified as level 3 by a client,

    - does not necessarily incur more time and efforts for the vendor to evaluate,
    - nor does it necessarily imply a less accurate evaluated price.

  If this is indeed the case, then the distinction between level 2 and level 3 fair values might not be as evident as the literature has previously reported (Ettredge et al. 2010; Fiechter and Meyer 2010; Song et al. 2010).

- There is an even more prominent <u>decreasing</u> trend for Level 3 Fair Value Assets since 2011.

- Vendors and TRACE have become more prevalent since 2011.

    - FINRA and TRACE have been collecting all SCP transaction data since May 16, 2011.
    - On November 12, 2012, FINRA started to release TBA transaction information.
    - On July 22, 2013, FINRA started to release information on individual market segments for MBS specified pool transactions.
    - On June 1, 2015. FINRA started to release information of ABS transactions.
    - On March 20, 2017, FINRA started to release CMO transaction information.

- Data from Federal Reserve FR Y-9C Consolidated Financial Statements for Holding Companies, from 06/30/2009 to 06/30/2017.

FIGURE 0-4 Percentage of Level 2 Fair Value Assets over Total Fair Value Assets for Top US Commercial Banks

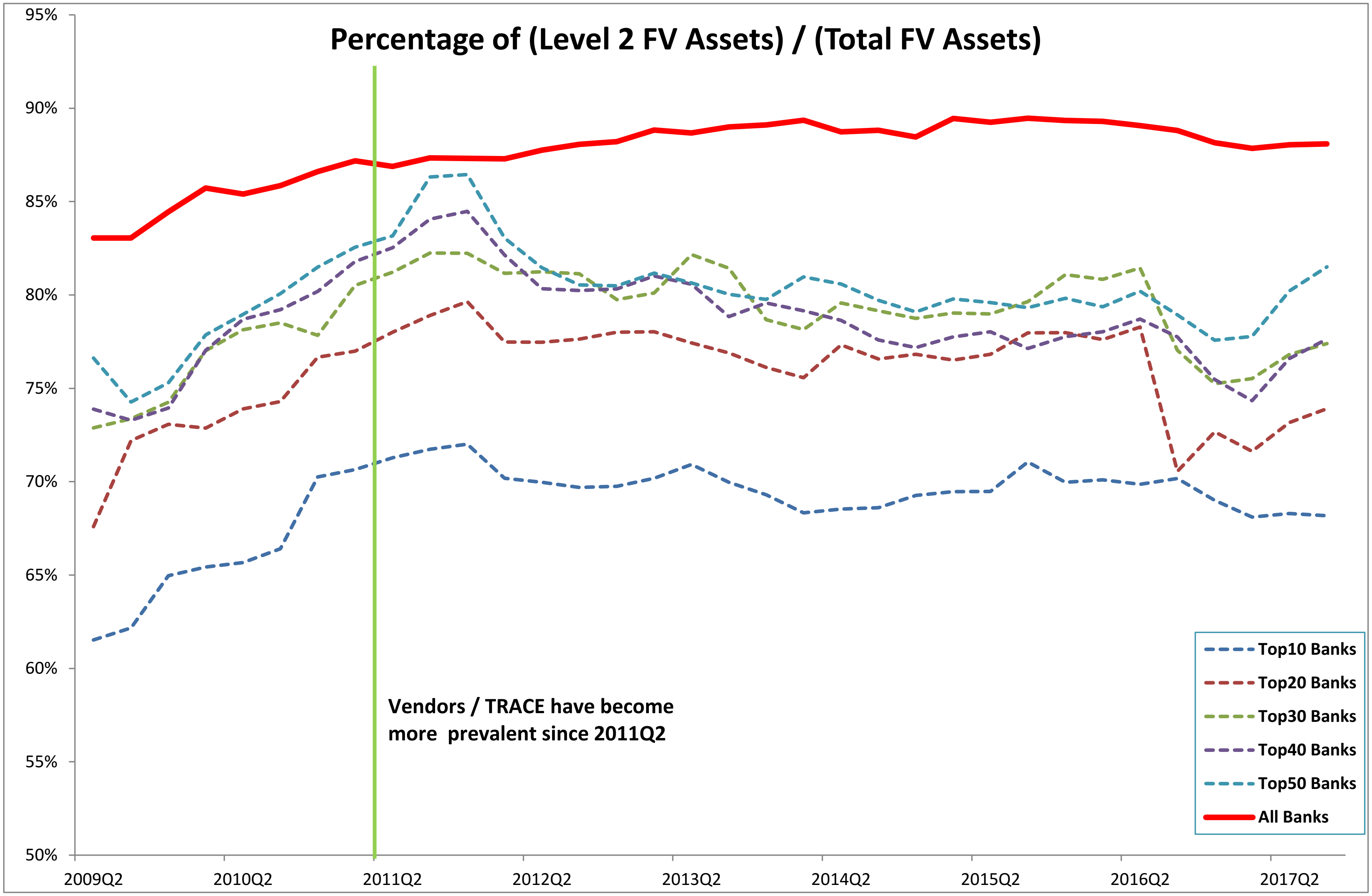

Figure 0-4 presents the percentage of level 2 fair value assets over total fair value assets for top US commercial banks.

- $y - axis$ represents the ratio of:

$$\frac{Level\ \mathbf{2}\ Fair\ Value\ Assets}{Total\ \boldsymbol{Fair\ Value}\ Assets}$$

- In general, bigger banks hold lower percentage of Level 2 Fair Value Assets than smaller banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 68.8%, 75.8%, 78.9%, 78.6%, 80.1%, and 87.7% of their total fair value assets as Level 2 Fair Value assets, respectively.

- One notable observation is that *Level 2 Fair Value assets are a significant part of banks' total fair value assets for top banks*. Top 10 banks classify around *70%* (68.8%) of their total fair value assets as Level 2 Fair Value Assets.

- The percentages of level 2 fair value assets over total fair value assets have been quite stable since 2011.

- Vendors and TRACE have become more prevalent since 2011.

    - FINRA and TRACE have been collecting all SCP transaction data since May 16, 2011.
    - On November 12, 2012, FINRA started to release TBA transaction information.
    - On July 22, 2013, FINRA started to release information on individual market segments for MBS specified pool transactions.
    - On June 1, 2015. FINRA started to release information of ABS transactions.
    - On March 20, 2017, FINRA started to release CMO transaction information.

- Data from Federal Reserve FR Y-9C Consolidated Financial Statements for Holding Companies, from 06/30/2009 to 06/30/2017.

FIGURE 0-5 Percentage of Level 3 Fair Value Assets over Total Fair Value Assets for Top US Commercial Banks

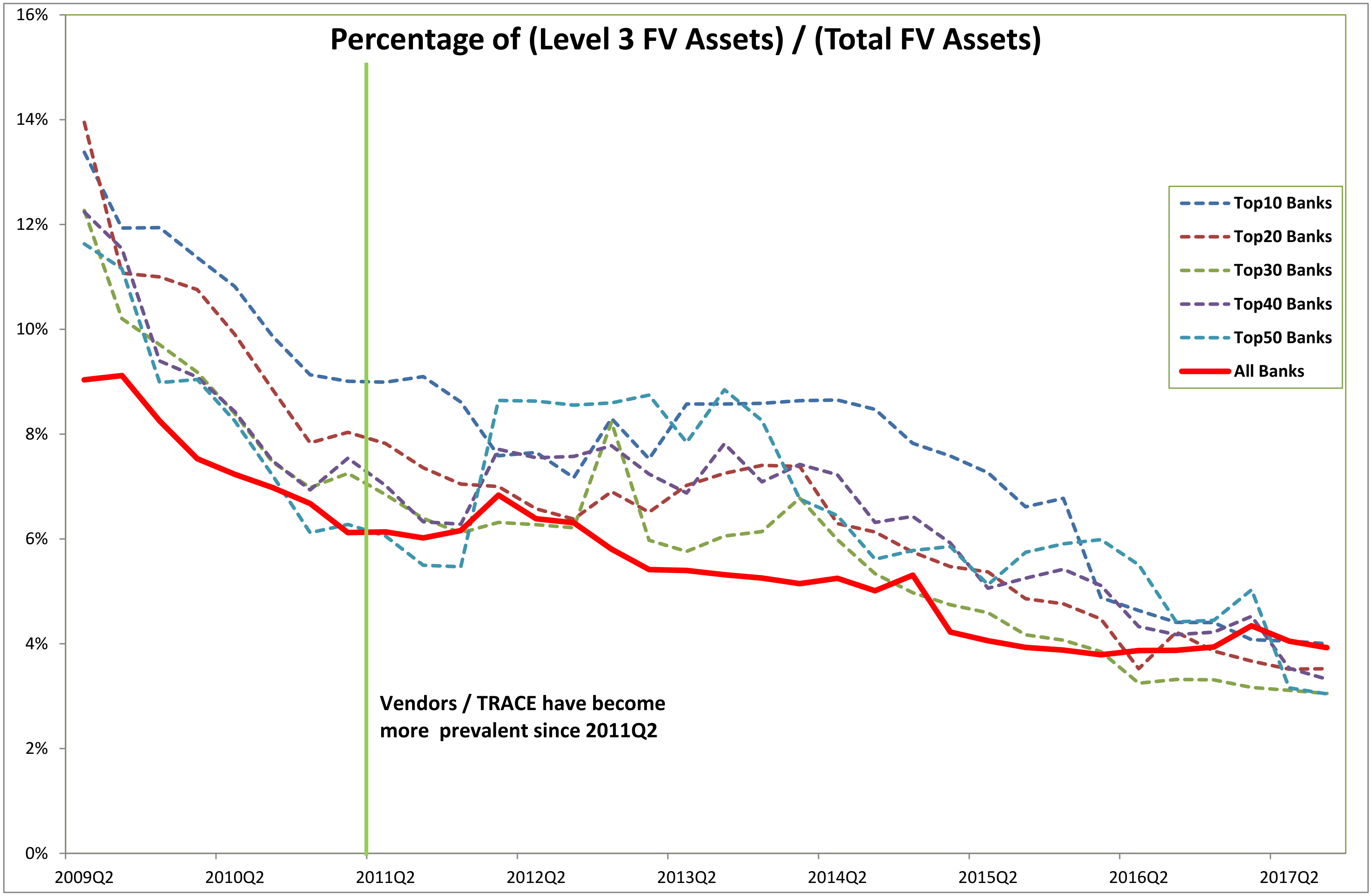

Figure 0-5 presents the percentage of level 3 fair value assets over total fair value assets for top US commercial banks.

- $y - axis$ represents the ratio of:

$$\frac{Level\ \mathbf{3}\ Fair\ Value\ Assets}{Total\ \boldsymbol{Fair\ Value}\ Assets}$$

- In general, bigger banks hold higher percentage of Level 3 Fair Value Assets than smaller banks, with the top 10, 20, 30, 40, and 50 bank holding companies (BHCs) holding about 8.0%, 6.8%, 6.0%, 6.8%, 6.8%, and 5.6% of their total fair value assets as Level 3 Fair Value assets, respectively.

- One notable observation is that top banks classify significantly less assets as Level 3 Fair Value Assets than Level 3. For example, this percentage for top 10 banks is only 8.0% for Level 3, compared with 68.8% for Level 2.

- Another observation from my field research is that from vendors' perspective, there are no distinctions between level 2 and level 3 fair values. They are just the same products from the same information assembly line. A security, classified as level 3 by a client,

  - does not necessarily incur more time and efforts for the vendor to evaluate,
  - nor does it necessarily imply a less accurate evaluated price.

  If this is indeed the case, then the distinction between level 2 and level 3 fair values might not be as evident as the literature has previously reported (Ettredge et al. 2010; Fiechter and Meyer 2010; Song et al. 2010).

- There is an even more prominent decreasing trend for Level 3 Fair Value Assets since 2011.

- Vendors and TRACE have become more prevalent since 2011.

  - FINRA and TRACE have been collecting all SCP transaction data since May 16, 2011.
  - On November 12, 2012, FINRA started to release TBA transaction information.
  - On July 22, 2013, FINRA started to release information on individual market segments for MBS specified pool transactions.
  - On June 1, 2015. FINRA started to release information of ABS transactions.
  - On March 20, 2017, FINRA started to release CMO transaction information.

- Data from Federal Reserve FR Y-9C Consolidated Financial Statements for Holding Companies, from 06/30/2009 to 06/30/2017.

FIGURE 1 Overall Picture of the Internal and External Control Mechanisms and Constraints of Bank Managers' Discretion

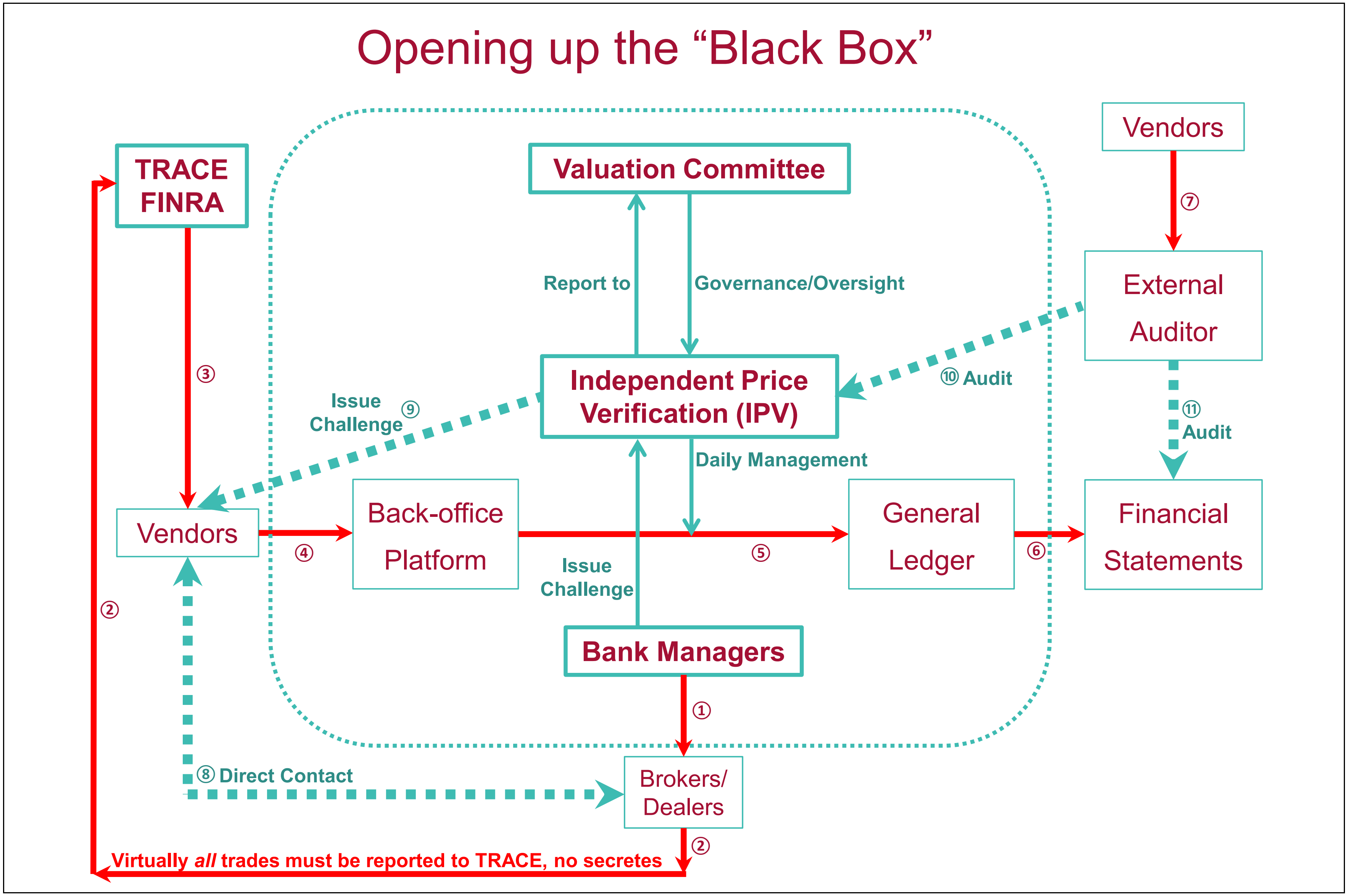

Figure 1 presents the schematic illustration of the components if I open up the black box. The dotted square represents bank's boundary. Red solid arrowed lines (① to ⑥) represent the information flow from bank managers ultimately to bank's financial statements. Green dotted lines (⑦ to ⑪) represent interactions (challenge, verification, etc.) between these components. Green solid lines represent the internal oversight and control within the bank (valuation committee, IPV team, and bank managers).

- We start with bank manager box in the middle. According to FINRA's rules, *virtually* all trades of SCPs between bank managers and broker/dealers (①) have to be reported (mostly within 15-60 minutes of execution) to TRACE (②). Bank managers can't engage in secrete trades.

- Third-party pricing vendors gather transaction information either directly from broker/dealer, or from TRACE (③), BWIC, and all other relevant channels (⑧). Vendors then generate daily fair value prices and deliver them through batch files to banks' back-office platform via secure FTP (④).

- After quality check, all the fair value prices are entered into banks general ledger (⑤), and ultimately flow to the financial statements (⑥). Bank managers don't have direct inputs to the general ledger. There are only three possible ways for bank managers to manipulate fair values: 1) cherry pick among vendors; 2) convince the committee and IPV team to issue challenges, thus change the general ledger accounting numbers; and 3) manipulating vendors' prices through spoofing transactions.

- External auditors also predominantly rely on different vendors' prices (⑦) to challenge bank managers' fair values (⑩) and audit their financial statements (⑪).

- Bank's Independent Price Verification (IPV) team manages the daily operation of the fair value process. It is also the IPV team (not the bank managers) who will decide whether to issue challenge back to the vendors (⑨).

- In addition, most of banks that I interviewed have policy / mechanisms against fraud transactions:

  - "Best Execution", in which traders must have at least 3 price quotes from at least 3 different dealers in order to make the transaction. Traders must choose the best prices among the 3 price quotes.[52]

  - Many banks have set up policies/rules against "short-term round-trip" transactions, such as repo 105. In addition, banks also have "Wash sale" rules, which specify that the span of round-trip transactions has to be longer than 60 days.

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[52] In my field research, I personally witnessed a case in which one manager did not like a huge mark-down from the vendor. The trader got a favorite price quote from his "buddy" from another bank, and then issued a challenge request to the IPV team. But the IPV team denied the challenge request.

FIGURE 2 Organizational Structure of Relevant Committees and Control Groups within a Typical US

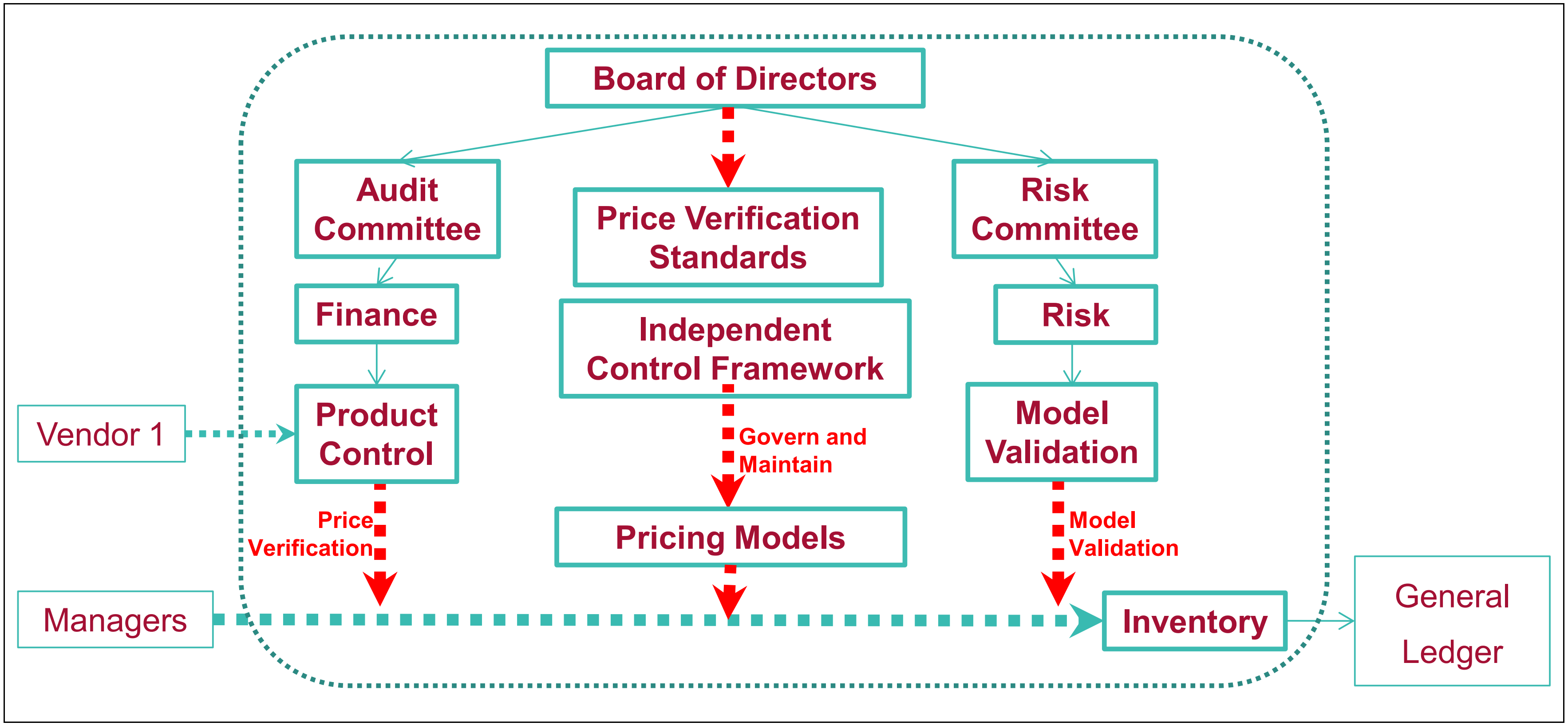


Figure 2 presents the schematic illustration of the Organizational Structure of Relevant Committees and Control Groups within a Typical US.

- The entire fair value pricing process is generally overseen by a Valuation Control Oversight Committee. [53] The specific daily valuation process is generally managed by an independent price verification team ("IPV").

- Most banks have internal separation of responsibilities and checks and balances. For example, IPV team is completely separated from the front-office trading desks.

- It is the IPV team (through the approval from valuation committee), not bank managers, who decide the price and control process, which vendor to use, who is the primary/secondary vendor, and ultimately which numbers should be used as inputs to the general ledger. Therefore, IPV teams have the final say on the fair values.

- In addition to the IPV teams, banks generally also have a separate model validation team, whose responsibilities include validation of IPV's conceptual design of the valuation models, data validation and quality assessment, and process validation.

- On a monthly basis, the Valuation Committee receives the tolerance challenges by managers. The Valuation Committee then formally submits the challenge to the vendor. The results of the challenge process are reviewed by the Valuation Committee. Upon receipt of the challenge, vendors seek to verify or corroborate the market information and then review the valuation.

- Vendor may affirm the current evaluation, or update the evaluation on a going forward basis incorporating the new market data. If a challenge is not accepted and the price differential is determined by the Valuation Committee to be significant, Committee will override the valuation received from the primary third party pricing vendor and utilize a valuation received from the back up pricing vendor. An override is effective for one day, at which point the Valuation Committee will convene and reexamine (and, if necessary, revise) prospectively the methodology used to value the security.

[53] Different banks might have different organization structure and different committee names, including pricing committee, risk management, pricing oversight, etc.

FIGURE 3 Valuation Oversight Committee Meeting at Quarter End at a Typical US Bank

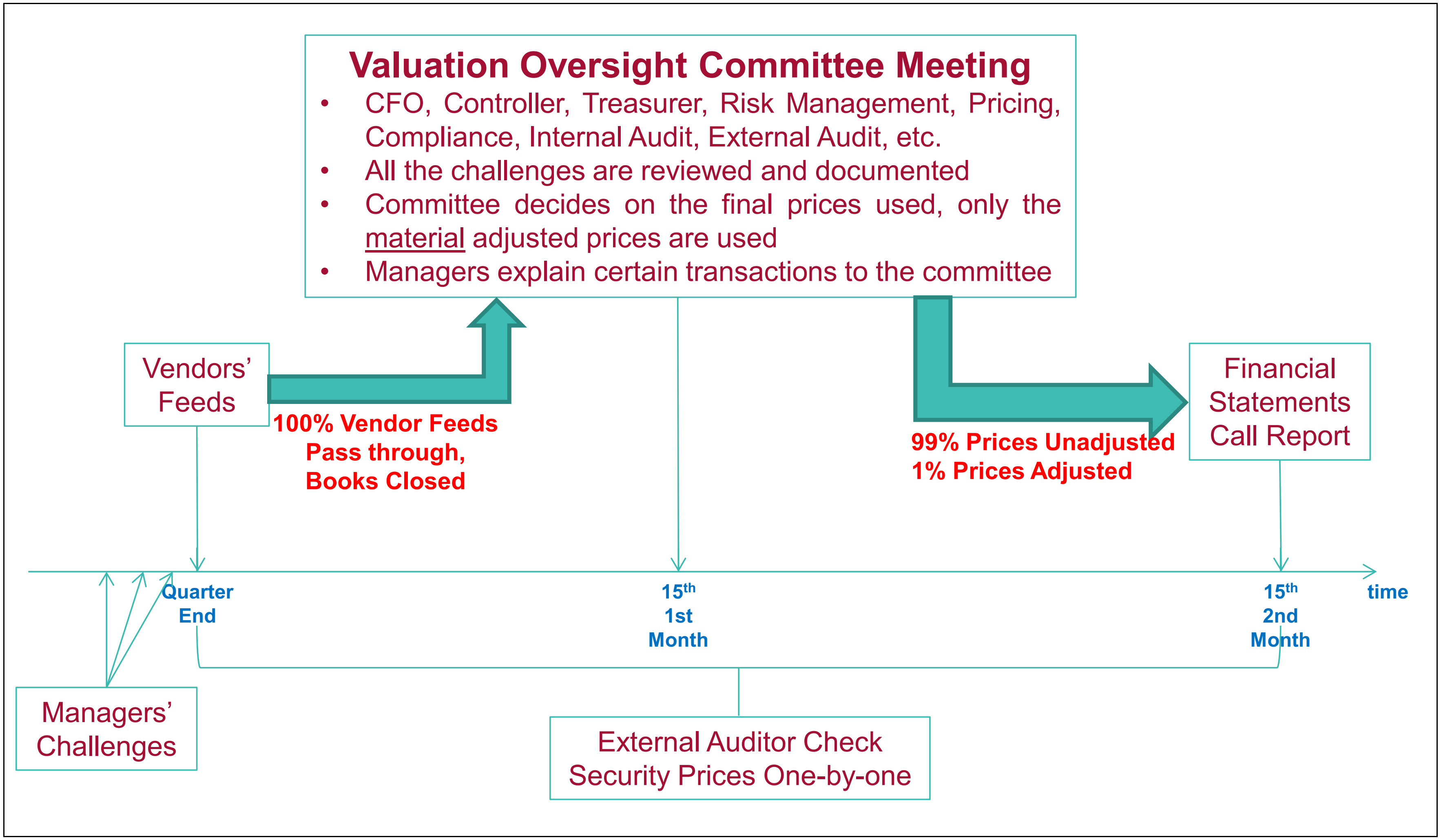


Figure 3 presents the schematic illustration of the financial statement generating cycle and fair value committee meeting.

- At 4:00PM of the day of quarter end (day 0), bank takes in the batch FTP file from vendors. At this time, vendors' pricing feeds 100% pass-through and land on bank's general ledger.

- The committee meeting is schedule on the 15th day of the first month (day 15). Between day 0 and day 15, IPV team work very hard to do quality control and compile the vendors' feeds.

- On day 15, valuation oversight committee meeting is attend by all parties involved, including CFO, controller, finance group, audit committee, risk management, compliance, product control, model validation, and IPV team.

- All the challenges are reviewed and related information (including challenge results, assumption/input challenged, new evidence provided, manager name, portfolio, etc.) are documented. It is the committee who decides on the final prices used to generate the financial statements.

- However, in reality, it is the IPV team who has done the "dirty work"; the committee will generally issue approvals to IPV team's recommendations. But one point is quite clear from my field research, that is, only prices with material impacts and substantial evidences are adjusted and used to generate financial statements. If necessary, the committee will ask relevant managers to explain certain challenges and transactions.

- Another important function for the committee meeting is to review price verification procedures / standards and independent control framework. It also discussion the classification the financial instruments as Level 1, Level 2 or Level 3 of the fair value hierarchy. At some committee meetings, model validation group and risk management will discuss issues including assess model risk arising from models' theoretical soundness, calibration techniques where needed, and the appropriateness of the model for a specific product in a defined market.

- Fair value price verification is done monthly; Models are independently reviewed annually

T A B L E 0-1

US Bank Holding Company (top 10) Fair Value Assets and Liabilities Breakdown by Fair Value Hierarchy

Top 10 Banks Assets	Total	Netted	Level 1	Level 2	Level 3
Available For Sale	69.6%	0.0%	9.0%	59.7%	1.0%
Loans & Leases Held	4.9%	0.0%	0.0%	3.2%	1.7%
Trading Assets					
Derivative	3.2%	16.4%	1.0%	18.4%	0.3%
Other Trading Assets	16.9%	0.0%	7.4%	9.4%	0.1%
All Other Assets	5.4%	1.0%	0.0%	2.2%	4.2%
Total Fair Value Asset	100.0%	17.4%	17.3%	92.9%	7.2%
Liabilities					
Trading Liabilities					
Derivatives	3.1%	16.3%	0.2%	18.8%	0.4%
Other Trading Liabilities	4.1%	0.0%	2.7%	1.4%	0.0%
Total Fair Value Liabilities	7.7%	17.2%	2.9%	21.6%	0.4%

Table 0-1 illustrates average fair value assets and liabilities breakdown by fair value hierarchy for the 10 largest U.S. bank holding companies.

- All percentages in the table are based on total FV assets (as 100%)
- Compared with fair value liabilities (7.7%), fair value assets (100%) are by far the largest component of banks' fair values
- Majority of fair value assets/liabilities are level 2 (92.9% and 21.6%, respectively);
- Available for sale (AFS) assets are largest component of fair value assets (69.9%), majority of AFS are of level 2 (59.7%).
- Derivatives are the second largest component, (18.4% for level 2 Asset, 18.8% of level 2 Liability, respectively)
- Largest fair value asset is level 2 AFS (59.7%). Largest fair value liability is level 2 derivatives (18.8%)

T A B L E 0-2

US Bank Holding Company Fair Value Assets Breakdown by Fair Value Hierarchy and by Security Types

Security Type	Level 1	Level 2	Level 3	Fair Value Method
Short-term Financial Asset	Cash and due from banks, federal funds			N.A.
Trading Assets	Equities, US Treasuries			N.A.
Investment Securities		RMBS, CMBS, ABS, munis, gov & agency MBS, corporate bonds	RMBS, CMBS, other ABS, CDOs, CLOs, mortgage loan securitizations	Vendors and Third Party
Mortgages Held For Sale (MHFS)		All		Vendors and Third Party
Loans Held For Sale (LHFS)		All		Vendors and Third Party
Loans (most not carried at FV)		Reverse Mortgages, commercial loans		Vendors and Third Party
Derivatives	Interest rate futures, options	Interest rate swaps, foreign currency swaps, commodity swaps, and certain option and forward contracts	Complex and highly structured derivatives, certain CDS, interest rate lock commitments	Vendors and Third Party
MSRs			MSRs & interest-only strips	Vendor
Foreclosed Assets		All		Ad hoc
Nonmarketable Equity Investments (FVO only)		Low income housing tax credit investments,	Federal Reserve Bank and Federal Home Loan Bank (FHLB) stock, and private equity investments	Ad hoc, OTTI

Table 0-2 illustrates US bank holding company fair value assets breakdown by fair value hierarchy and by security type.

- All Level 1 assets are unadjusted direct market prices
- All Level 2 and Level 3 assets are pricing feeds from vendors and third party providers
- Private equity investments: ad-hoc prices from third-party vendor valuation services. Most banks have limited exposure.

In summary, majority of fair value assets are evaluated by Third-party Vendors

T A B L E 0-3

2016 US Bank Holding Company (BHC)'s Disclosure of Use of Third-party Vendors' Pricing Feeds

Public Banks' Disclosure of Vendors' Usage	No. of Banks	AFS Level 2	AFS Level 3	Total Fair Value Level 2	Total Fair Value Level 3	Total Fair Value Assets	Total Asset
Banks that Use Vendors' Pricing Feeds	188	83%	96%	60%	67%	70%	75%
100% All Pass-through, No Adjustment	18	14%	11%	4%	2%	7%	8%
Almost All 100% Pass-through	10	17%	17%	6%	16%	11%	14%
Most of, majority, substantial, primarily, predominately, occasionally adjust, etc.	106	21%	44%	20%	25%	23%	22%
Others	54	32%	24%	30%	25%	30%	32%
Banks that Use Internal Valuation Models	6	13%	4%	38%	32%	28%	22%
Banks that Are Not Clear	62	4%	0%	1%	1%	2%	3%
Banks that No Information Is Available	9	0%	0%	0%	0%	0%	0%
Total	265	100%	100%	100%	100%	100%	100%

Table 0-3 illustrates 2016 US Bank Holding Company (BHC)'s disclosure of use of third-party vendors' pricing feeds.

In 2016, out of the total 265 public bank holding companies (BHC), 188 banks publicly disclosed in their 10K that they either "100% all pass-through without any adjustments", or "almost all 100% pass-through", or use the following words to describe their use of third-party vendors' feeds: most of, majority, primarily, predominately, occasionally adjust, substantial. These banks' total level II AFS (AFS2) represents 83% of the total AFS2 of the entire population; Their total level III AFS (AFS3) represents 96% of the total AFS2 of the entire population.

T A B L E 1

Summary and Descriptive Statistics

Panel A: TRACE Data Cleaning Procedure		
	No. of Transactions	Reduction Percentage
Original TRACE Data Delivery	25,185,925	
Delete Cancellations, Corrections, and Reversals	24,188,097	3.96%
Delete the NEW Cancellations	23,582,667	6.37%
Delete interdealer transactions (one of the sides BUY)	16,020,744	36.39%

Panel B: Descriptive Statistics of TRACE Data after the Cleaning Procedure							
	Sample Start	TRACE Dissemination	Sample End	Total No. of Transactions	Percentage of Transactions	Unique CUSIP	Percentage of CUSIP
Security Type							
ABS	5/16/2011	6/1/2015	12/31/2015	292,646	1.8%	4,709	0.9%
CMO	5/16/2011	3/20/2017	12/31/2015	2,824,963	17.6%	114,328	21.8%
MBS	5/16/2011	7/22/2013	12/31/2015	4,025,440	25.1%	401,931	76.5%
TBA	5/16/2011	11/12/2012	12/31/2015	8,877,695	55.4%	4,206	0.8%
Entire Sample				16,020,744	100.0%	525,174	100.0%

Panel C: Descriptive Statistics of Weighted-Average-Life, Liquidity, and Trading Activity)						
	WAL (year)	Liquidity Score (1-5)	No. of Trade per CUSIP	Unique Trading Days per	Timespan between Adjacent Trading Days	
	Mean	Mean	Mean	Mean	Mean	Median
Security Type						
ABS	4.34	2.91	12.85	6.94	79.76	51.42
CMO	4.87	3.33	7.64	4.38	106.54	79.47
MBS	4.19	3.75	4.44	3.21	108.17	75.00
TBA	.	4.31	9.11	5.75	107.65	78.85
Entire Sample	4.27	3.70	5.17	3.49	107.60	75.90

Panel D: TRACE Reporting Timeframes for different Security Types (Effective December 01, 2015)	
	Reporting Times
Security Type	
Corporate Bond	Within 15 minutes of time of execution
Agency Debt Security	Within 15 minutes of time of execution
Agency Pass-Through MBS Traded TBA for Good Delivery	Within 15 minutes of time of execution
Agency Pass-Through MBS Traded TBA not for Good Delivery	Within 60 minutes of time of execution
Specified Pool Transactions & SBA Backed ABS Transactions	Within 60 minutes of time of execution
Asset-Backed Securities	Within 15 minutes of time of execution
All other Securitized Products: CDO, CLO, CBO	Same day during TRACE business hours
CMOs/REMICs	Same day during TRACE system hours

The original TRACE dataset has 25,185,925 rows and 36 data fields (including CUSIP, price, trading volume, trade status, trade type, contra-party indicator, etc.). There are five possible trade status, regular trade (T), cancelled trade (X), cancelled correction (C), new correction (R), and reversal (Y). In this study, I mainly focus on the first two: regular trades (T) and cancelled trades (C).

There are two possible transaction types: principal and agency transactions. According to Section 206(3) of the Investment Advisers Act, a principal transaction is a situation where a registered investment advisor "acts as a principal for its own account and knowingly sells securities to, or buys securities from, a client"; while an agency transaction occurs when a registered investment advisor "arranges a trade between different advisory clients".

Contra-party indicator specifies two different types of trades in TRACE data: a dealer-customer trade is between a dealer and a customer ("Contra-Party" indicator = Customer); an inter-dealer trade is between two dealers ("Contra-Party" indicator = Dealer). According to FINRA's rule, in trades between a dealer and a customer, only the dealer need to report to TRACE, while in an inter-dealer trade, both dealers need to report to TRACE. Thus we expect to see significantly higher proportion of dealer-customer trades in the Cancelled-Single trade sample.

Panel A reports the TRACE data cleaning procedure. I follow the cleaning filter algorithms outlined in (Nick-Nielsen 2014) and (Rossi 2014), both of which drop around 35% of all the raw transactions. Panel A reports a similar total filtering rate of 36.39%.

Panel B reports the descriptive statistics of TRACE data after the cleaning procedure. Though TRACE has been collecting all transaction data since May 16, 2011, FINRA has been disseminating this information to the market in different phases (staged dissemination).

In Panel C, WAL stands for Weighted Average Life. The most interesting results are that the average number of trades for each security is 5.17; and the average number of days between adjacent observed transactions on TRACE is 107.6 calendar days (more than 3 months).

Panel D reports the TRACE reporting timeframes for different security types (effective December 01, 2015). Most of the SCP transactions have to be reported to TRACE within 60 minutes of the time of the execution.

T A B L E 2

Channel One – Strategic Vendor Selection

Panel A: Regression Results

	(1) Entire Sample	(2) ABS	(3) CMO	(4) MBS	(5) TBA
Vendor2	0.951***	0.965***	0.932***	0.952***	0.942***
	(3.91)	(5.94)	(3.62)	(4.93)	(4.18)
Observations	952,055	11,368	207,036	733,648	1,452
Adj R-squared	0.95802	0.97651	0.93183	0.92662	0.9242
CUSIP FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Joint F-test on α0=0 AND α1=1	5.84***	5.93***	4.37***	5.52***	5.24***

Clustered t-statistics by both date and CUSIP in parentheses *(continued)*

*** p<0.01, ** p<0.05, * p<0.1

Model:

$$FirstVendorPrice_{i,t} = \alpha_0 + \alpha_1 \cdot SecondVendorPrice_{i,t} + \epsilon_{i,t}$$

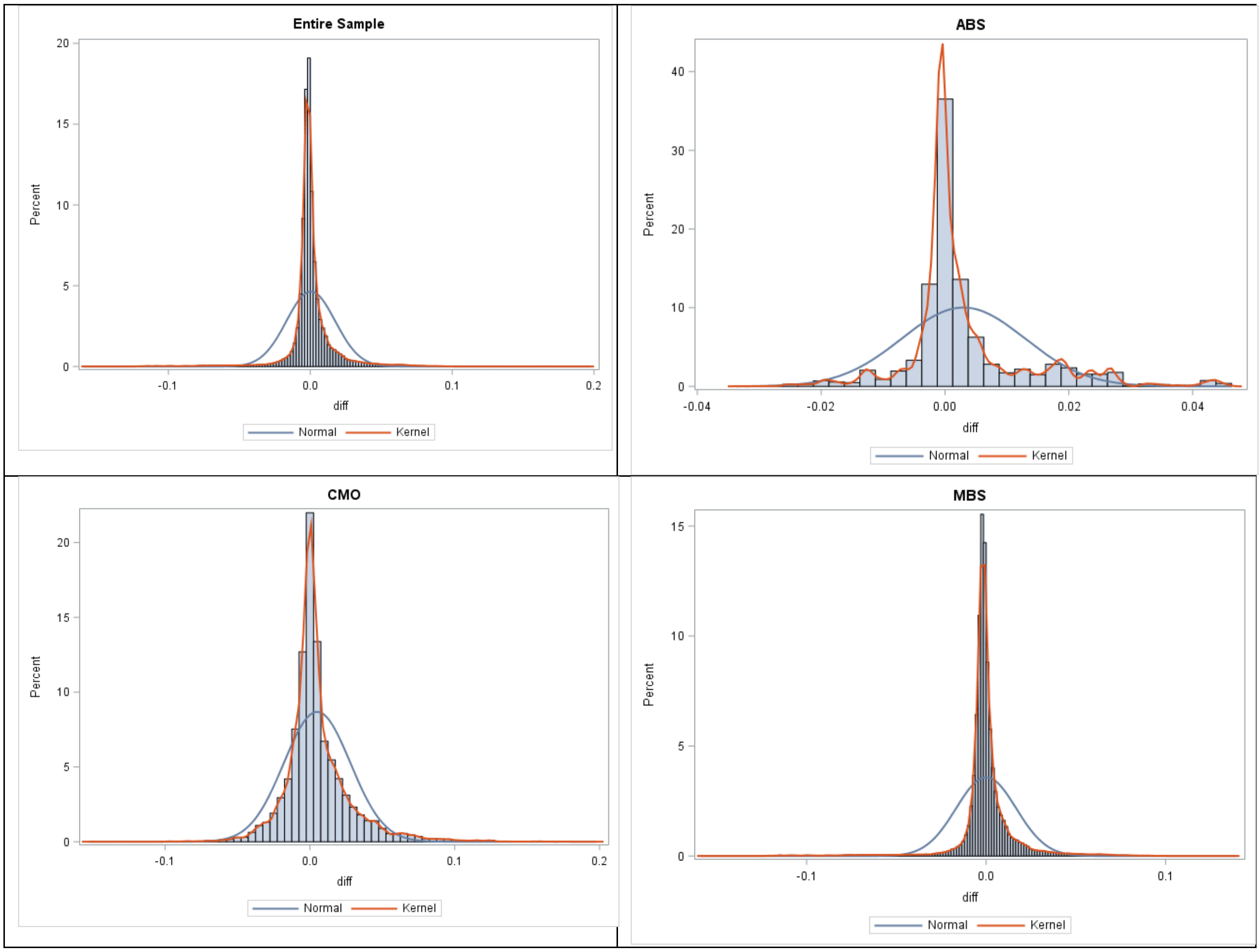
Panel A presents regression results comparing pricing feeds from two different vendors. $FirstVendorPrice$ denotes the pricing feed from Vendor 1, $SecondVendorPrice$ denotes the pricing feed from Vendor 2. Panel A indicates that the pricing feeds from two different vendors are quite similar on average, with high (close to 1) coefficient α_1 ($\alpha_1 \approx 1$) and high (close to 1) adjusted R-square ($R^2 \approx 1$). In addition, the joint F-tests for $\alpha_0 = 0$ and $\alpha_1 = 1$ are all significant at the $p < 0.01$ levels. Results from Panel A imply that the pricing feeds from two different vendors are *on average* very similar.

Panel B shows the histograms for the differences of two pricing feeds. The red and blue lines represent kernel density curves and normal curves, respectively. The kernel density curves are symmetrical and much narrower than the normal curves, showing no signs of systematic biases. More importantly, the kernel density curves are "thin-tailed", compared to corresponding normal curves.

Panel C presents the results for formal normality test. It is clear that the distributions for the differences are not normal, primarily due to the low variance and high kurtosis (any kurtosis higher than 3 means thin-tailed distribution). This implies once again that the pricing differences are thin-tailed and that extreme pricing differences between two vendors are unlikely to occur compared to normal distributions.

Panel B: Histograms of Price Differences of Pricing Feeds from Two Different Vendors

$$PriceDifferences_{it} = FirstVendorPrice_{i,t} - SecondVendorPrice_{i,t}$$



(*Continued*)

Panel C. Normality Test Results

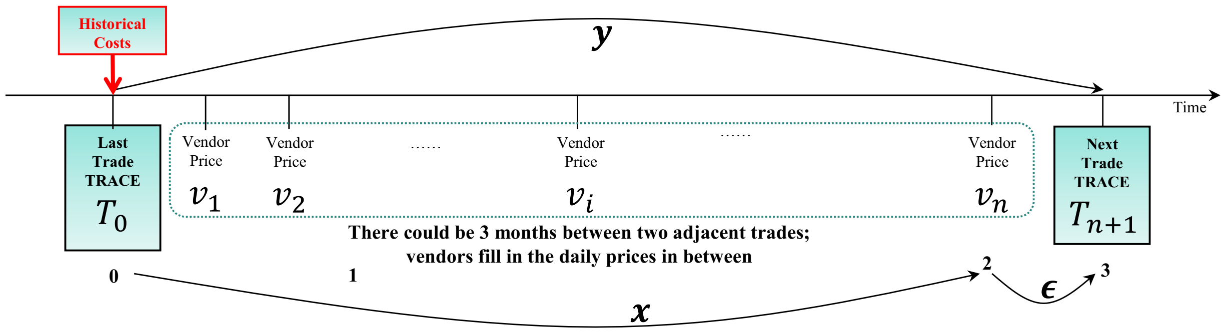
	Mean	Variance	Skewness	Kurtosis	Kolmogorov-Smirnov	Cramer-von Mises	Anderson-Darling
Security Type							
ABS	0.00	0.00	1.38	3.49	<0.010	<0.005	<0.005
CMO	0.00	0.00	1.39	6.47	<0.010	<0.005	<0.005
MBS	0.00	0.00	-0.85	15.22	<0.010	<0.005	<0.005
TBA	0.00	0.00	0.10	5.03	<0.010	<0.005	<0.005
Entire Sample	0.00	0.00	-0.46	14.38	<0.010	<0.005	<0.005
Standard Normal	0.00	1.00	0.00	3.00			

TABLE 3

Channel Two - Vendor Effective Performance

(Descriptive Results)

Panel A: Definitions and Illustration of Commonly Used Performance Metrics



	Definition
Time Point	
0: Day 0 -- Last Observed Trade on Day 0	Last TRACE Reported Transaction
1:Days between $[Day\ 0, Day\ n]$	Might be 3 months in between
2:$Day\ n$ -- Vendor's last price on Day n before Next Trade	Vendor Evaluated Daily Price on Day n
3: $Day\ (n+1)$ -- Next Observed Trade on Day $(n+1)$	Next TRACE Reported Transaction

Regression Analogy: $y = \kappa \cdot x + \epsilon$

	Calculation Formula	Regression Analogy
Variable Definition		
$y = return(3,0)$,	$NextTRACE\ /\ LastTRACE - 1 = T_{n+1}/T_0 - 1$	Dependent Variable
$x = return(2,0)$,	$VendorLastPrice\ /\ LastTRACE - 1 = v_n/T_0 - 1$	Independent Variable
$\epsilon = return(3,2)$,	$NextTRACE\ /VendorLastPrice - 1 = T_{n+1}/v_n - 1$	Residual

	Calculation Formula
Performance Metrics	
Rho(ρ):	$correlation(x, y), \rho = regression\ coefficient\ \kappa \times \sigma_x/\sigma_y,$
Days_Closer:	$How\ many\ times\ \vert\epsilon\vert < \vert y\vert,$
Directional_Correct:	$How\ many\ times\ sign(y) = sign(x),$
Forecast_Error:	$mean(\vert\epsilon\vert)/mean(\vert y\vert),$
Model Bias:	$correlation(x, \epsilon), a\ measure\ of\ arbitrage\ opportunities,$
Variance_Reduction:	$1 - variance(\epsilon)/variance(y), regression\ R\ sqare,$
Mean_Error:	$mean(\epsilon).$

Panel B1: Entire Sample Performance Metrics Vendors' Pricing vs. Historical Costs								
	TRACE Dissemination	Rho corr(x,y)	Days Closer	Direction Correct	Forecast Error	Bias corr(x,ε)	Variance Reduction	Mean Error
Security Type								
ABS	6/1/2015	95.2%	84.8%	87.4%	0.203	18.1%	90.6%	-0.00008
CMO	3/20/2017	90.8%	85.4%	89.7%	0.277	3.0%	82.4%	-0.00003
MBS	7/22/2013	96.3%	82.5%	89.4%	0.243	-5.6%	92.7%	0.00004
TBA	11/12/2012	97.2%	62.5%	81.3%	0.237	9.1%	94.4%	-0.00009
Entire Sample		95.7%	83.0%	89.4%	0.246	-4.9%	91.6%	0.00003

Panel B2: Before TRACE's Dissemination (Pre-Dissemination Sample) Performance Metrics								
	TRACE Dissemination	Rho corr(x,y)	Days Closer	Direction Correct	Forecast Error	Bias corr(x,ε)	Variance Reduction	Mean Error
Security Type								
ABS	6/1/2015	96.4%	85.1%	87.4%	0.185	-5.2%	93.0%	-0.00005
CMO	3/20/2017	90.8%	85.4%	89.7%	0.277	3.0%	82.4%	-0.00003
MBS	7/22/2013	95.8%	81.7%	89.0%	0.258	-5.5%	91.8%	0.00000
TBA	11/12/2012	95.1%	28.6%	71.4%	0.426	-10.7%	90.1%	-0.00006
Entire Sample		95.0%	82.7%	89.1%	0.261	-4.1%	90.2%	-0.00001

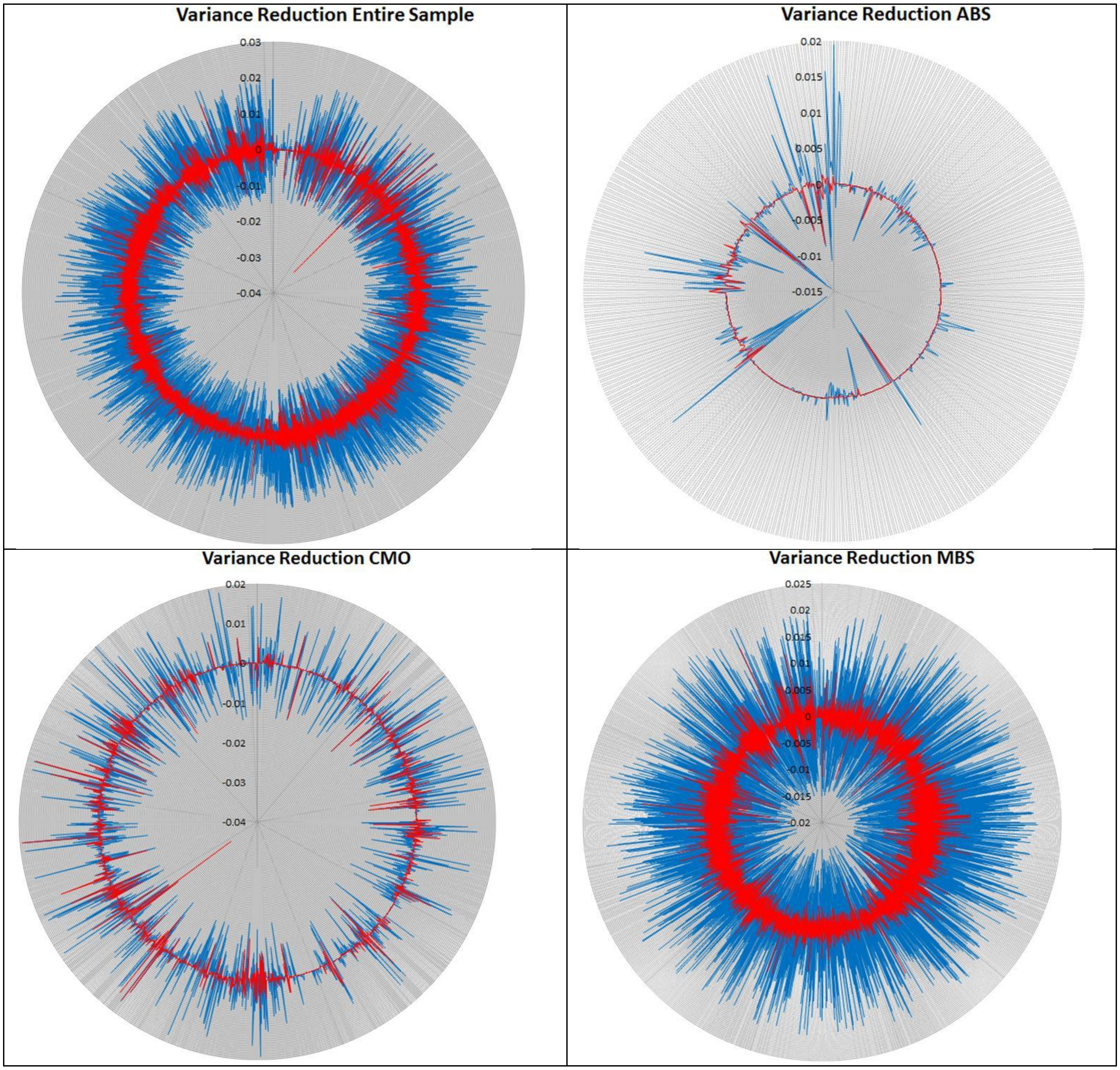
Panel B3: After TRACE's Dissemination (Post-Dissemination Sample) Performance Metrics								
	TRACE Dissemination	Rho corr(x,y)	Days Closer	Direction Correct	Forecast Error	Bias corr(x,ε)	Variance Reduction	Mean Error
Security Type								
ABS	6/1/2015	89.4%	78.6%	89.3%	0.328	7.5%	79.9%	-0.00083
CMO	3/20/2017							
MBS	7/22/2013	96.7%	83.4%	89.8%	0.227	-5.8%	93.5%	0.00008
TBA	11/12/2012	99.2%	88.9%	88.9%	0.117	-10.5%	98.4%	-0.00011
Entire Sample		96.7%	83.4%	89.8%	0.227	-5.9%	93.5%	0.00008

(continued)

Panel A reports the definitions of commonly used performance metrics, comparing vendor pricing to historical costs. Because the average number of days between adjacent trades on is 107 calendar days (Table 1 Panel C) and it would be the acquisition cost to the bank, the last observed TRACE price T_0 can be treated as *historical cost*.

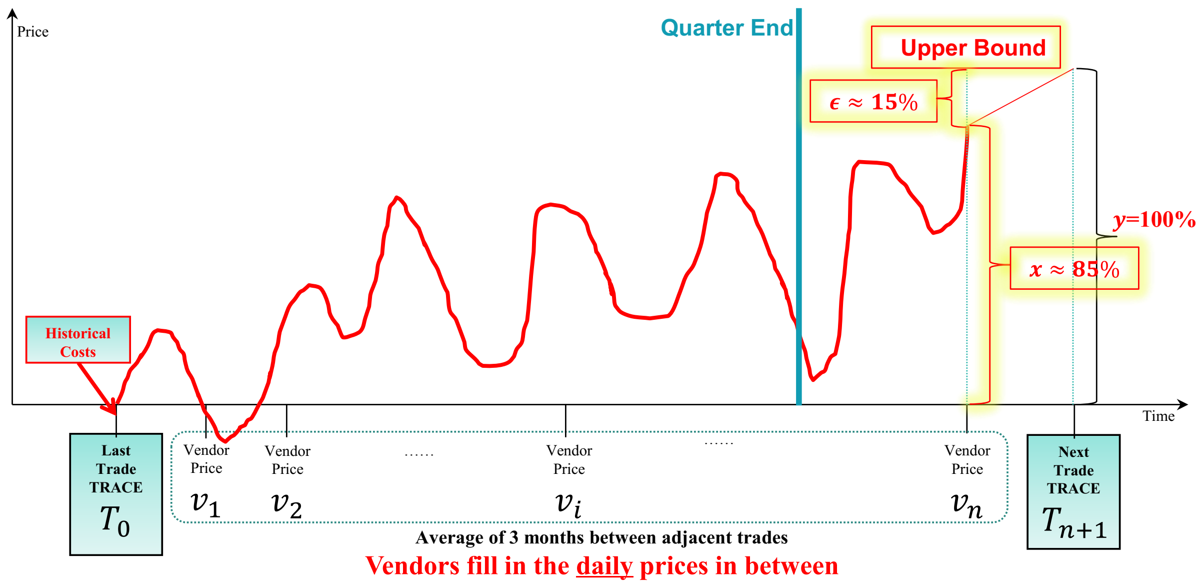
Panel B3 lacks CMO performance data due to data availability. Panels B1-3 show that vendors' prices *dominate the historical costs in every way*, in that, they on average reduce the variance by more than 90%; they are nearly 90% directionally correct; and they have low and unbiased errors, etc. Also, there are no significant differences in performance metrics in pre- and post- TRACE dissemination periods. This suggests that even before the official TRACE dissemination, vendors (and the market in general) have access to TRACE trade information through other timelier information channels.

Panel C1: Radar Chart Representations of Variance Reduction by Vendors' Pricing Feeds



(*Continued*)

Panel C2: Representations of Variance Reduction by Vendors' Pricing Feeds vs. Historical Costs



The intuition behind the definitions of $y, x, and\ \epsilon$ in Panel A and C2 is that we can treat the performance comparison between vendor prices and historical costs as a regression model:

$$y = \kappa \cdot x + \epsilon \quad (*)$$

- $y = T_{n+1}/T_0 - 1$ represents the original price change $[T_0, T_{n+1}]$ *without* vendor prices v_n;
- $x = v_n/T_0 - 1$ represents *vendor's contribution*, that is, the part of the price movement $[T_0, v_n]$ that can be explained or accounted for by vendor price v_n;
- $\epsilon = T_{n+1}/v_n - 1$ represents regression residual, which *cannot* be explained by vendor price v_n.

In this regression model, κ is the regression coefficient $\kappa = \rho \times \sigma_y/\sigma_x$, where $\rho = correlation(y, x)$; Variance_Reduction is nothing but the regression R-squared. In a perfect world, where vendors are doing a prefect job, their price v_n should be "spot-on", landing on the moving target of T_{n+1}, that is, $v_n = T_{n+1}$. Thus, we should have $\kappa = 1$ and $\epsilon = 0$. In a less perfect world, we should have $\kappa \neq 1$ and $\epsilon \neq 0$.

In Panel C1, blue lines represent the variance of $y = T_{n+1}/T_0 - 1$, that is, variance of the original regression dependent variable y, *without* the contribution from the independent variable x; red lines represent variance of $\epsilon = T_{n+1}/v_n - 1$, that is, variance of the regression residual, *with* the contribution from the independent variable x. The comparison of blue lines vs. red lines in Panel C1 can be interpreted as variance *without* vs. *with* the contribution of x from vendors.

Once again, Panel C1 shows that vendors' prices *dominate the historical costs in every way*, in that, they significantly reduce the variance between two observed TRACE prices. There are no obvious patterns or systemic biases of vendors' pricing feeds.

T A B L E 4

Channel Two - Vendor Effective Performance

(Regression Results)

Panel A: Regression Results

	(1) Entire Sample	(2) ABS	(3) CMO	(4) MBS	(5) TBA
X=ΔVendor	0.721***	0.682***	0.751*	0.788***	0.939
	(8.66)	(7.01)	(1.92)	(6.05)	(1.60)
Post		39.578		1.101	128.168
		(1.44)		(0.33)	(1.28)
*X*Post*		0.198		0.01	0.276
		(1.45)		(0.31)	(1.28)
Trade Count	-0.061***	0.028	-0.036	-0.072***	0.062
	(-5.24)	(0.85)	(-1.18)	(-5.53)	(0.16)
Gap btw [T0, T(n+1)]	-0.001***	-0.000	-0.002***	-0.001***	0.001
	(-9.51)	(-0.34)	(-5.65)	(-9.00)	(0.51)
Gap btw [Vn, T(n+1)]	0.001	0.020	-0.014	0.002	0.001
	(0.07)	(0.67)	(-0.29)	(0.17)	(0.00)
Observations	48,053	18,653	12,436	14,854	16,964
Adj R-squared	0.09055	0.07726	0.01489	0.12847	0.25761
Controls	Yes	Yes	Yes	Yes	Yes
CUSIP Cluster	Yes	Yes	Yes	Yes	Yes
Date Cluster	Yes	Yes	Yes	Yes	Yes

Clustered t-statistics by both date and CUSIP in parentheses *(continued)*

*** p<0.01, ** p<0.05, * p<0.1

$$Y = \alpha_0 + \alpha_1 \cdot X + \alpha_2 \cdot Post_{i,t} + \alpha_3 \cdot X \times Post_{i,t} + Controls + \epsilon_{i,t}$$

$$Model1: \begin{cases} Y_1 = TRACE_{i,(n+1)} \\ X_1 = Vendor_{i,n} \end{cases} \quad and \quad Model2: \begin{cases} Y_2 = \Delta TRACE = TRACE_{i,(n+1)} - TRACE_{i,0} \\ X_2 = \Delta Vendor = Vendor_{i,n} - Vendor_{i,0} \end{cases}$$

Model 1 and Model 2 have yielded identical regression coefficients and standard errors, except for the estimates for the constant α_0. Only Model 2 results are shown here. Model 2 are fundamentally connected to equation $(*)$ in Table 3

$$y = \kappa \cdot x + \epsilon \quad (*)$$

$$\begin{cases} Y_2 = \Delta TRACE = y \cdot TRACE_0 \\ X_2 = \Delta Vendor = x \cdot Vendor_0 \end{cases}.$$

Model 2 differs from equation $(*)$ is that Model 2 has extra terms of $Post_{i,t}$ and $Controls$.

Panel B: Summary Statistics for Regression Control Variables

	Mean	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl	Std Dev
1. Gap of days between two adjacent trading days: [TRACE_0, TRACE_(n+1)]							
ABS	26.2	2	6	12	28	312	41.1
CMO	46.2	2	6	16	45	1,136	92.9
MBS	72.6	2	9	27	76	1,668	127.9
TBA	193.4	2	6.5	16.5	218.5	1,064	338.1
Entire Sample	67.4	2	8	25	70	1,668	122.5
2. Gap of days between : [Vendor_n, TRACE(n+1)]							
ABS	1.4	1	1	1	1	3	0.8
CMO	1.4	1	1	1	1	3	0.8
MBS	1.4	1	1	1	1	3	0.8
TBA	1.5	1	1	1	2	3	0.9
Entire Sample	1.4	1	1	1	1	3	0.8
3. Number of Trades by the same CUSIP on day TRACE_(n+1)							
ABS	1.3	1	1	1	1	6	0.7
CMO	1.6	1	1	1	2	20	1.2
MBS	1.3	1	1	1	2	25	0.8
TBA	1.4	1	1	1	2	3	0.7
Entire Sample	1.4	1	1	1	2	25	0.8

(continued)

Definitions for $TRACE_{i,n}$ and $\Delta TRACE$ can be found in Table 3. And $Post$ is an indicator variable specifying the post TRACE dissemination (reported in Table 3). Independent variable $Gap\ btw\ [T_0, T_{n+1}]$ denotes the timespan between two adjacent trades; and $Gap\ btw\ [V_n, T_{n+1}]$ represents gaps between $Vendor_n$ and $TRACE_{n+1}$, including possible holiday and weekend.

Panel A shows that significant and positive coefficients for $X = \Delta Vendor$, indicating a significant improvement of vendor performance over the historical cost $TRACE_0$. Also, there are no significant performance improvements after TRACE dissemination (the interaction terms are not significant), suggesting that vendors had other timelier channels to acquire information before TRACE started to disseminate trade information.

For the entire sample, CMO, and MBS, coefficients for $Gap\ btw\ [T_0, T_{n+1}]$ are both negative and significant. Negative and significant coefficients suggest that vendors' accuracy forecasting the next trade price $TRACE_{n+1}$ decreases with the timespan between $TRACE_0$ and $TRACE_{n+1}$. Because TRACE only started to report CMO transaction data on March 20, 2017, no post data are available for CMO.

Panel C: Estimation of Managerial Discretion Reduction from Regression Results (Model 2)

	Model 2 Coefficients	Means for Entire Sample
Model 2 Independent Variables		
$x = \Delta Vendor$	0.721	0.3077
Trade Count	-0.061	1
Gap btw [T0, T(n+1)]	-0.001	25
Gap btw [Vn, T(n+1)]	0.001	1
Constant	0.224	

Define managerial discretion as:

$$Discretion \equiv Managers' Reported\,Value - Reference\,Value$$

Accordingly, managerial discretion in the pre- and post- vendor periods can be defined as:

$$E\left[Discretion_{pre}\right] = TRACE_{n+1} - TRACE_0 = \Delta T;\; E\left[Discretion_{post}\right] = TRACE_{n+1} - Vendor_n$$

where $Reference\,Value = \begin{cases} TRACE_0 & for\ pre \\ Vendor_n & for\ post \end{cases}$. Then the decrease in managerial discretion is:

$$\Delta D = Discretion_{pre} - Discretion_{post} = Vendor_n - TRACE_0 = Vendor_n - Vendor_0 \equiv \Delta V$$

$\Delta D = Discretion_{pre} - Discretion_{post} \equiv \Delta V$ can be precisely estimated from Model 2[54]:

$$\Delta TRACE = \alpha_0 + \alpha_1 \cdot \Delta Vendor + \alpha_2 \cdot TradeCount + \alpha_3 \cdot Gap1 + \alpha_4 \cdot Gap2 + \epsilon \Rightarrow$$

$$\Delta T \approx 0.224 + 0.721 \times \Delta V - 0.061 \times TradeCount - 0.001 \times Gap1 + 0.001 \times Gap2 \Rightarrow$$

$$\frac{\Delta T}{\Delta V} \approx 0.721 + \frac{0.224 - 0.061 \times TradeCount - 0.001 \times Gap1 + 0.001 \times Gap2}{\Delta V}$$

For convenience and simplicity, I evaluate the right-hand side using the sample means for each variable, we have:

$$\frac{\Delta T}{\Delta V} \approx 0.721 + \frac{0.224 - 0.061 \times 1 - 0.001 \times 25 + 0.001 \times 1}{0.3077} = 1.173$$

Then, managerial discretion has decreased by:

$$\frac{\Delta D}{Discretion_{pre}} \approx \frac{\Delta V}{\Delta T} = \frac{1}{1.173} = 85.27\%$$

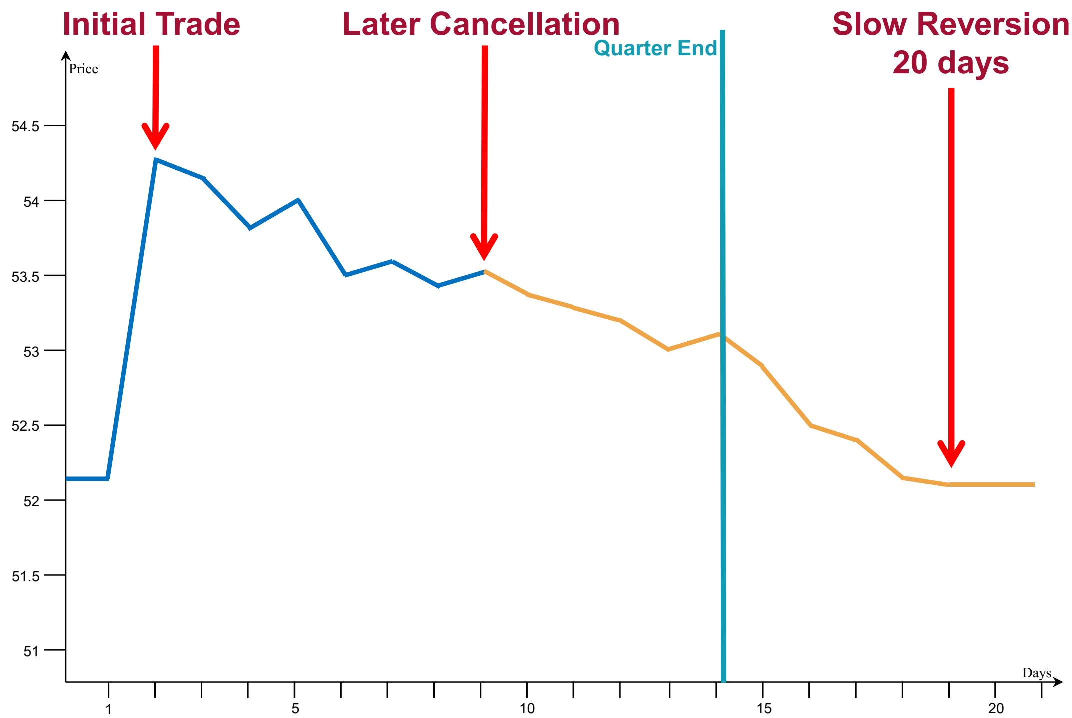
[54] It is obvious that $TRACE_0 = Vendor_0$

T A B L E 5

Channel Three - Spoofing the Vendors

(Cancelled-Single Trades)

Panel A1: Schematic Illustration of "Canceled-Single" Trades



Panel A2: Selection Procedure of "Canceled-Single" Trades

"Cancelled-Single" Trades Selection Procedure	No. of Transactions	% of Dataset1 # Transactions	% of Dataset1 Total Volume	% of Dataset1 Day Volume
Original TRACE (Dataset0)	25,185,925			
After Initial Cleaning (Dataset1)	16,020,744	100%		
Total Cancelled Tranactions	379,321	2.37%		
ABS	6,688	0.04%		
CMO	84,279	0.53%		
MBS	151,519	0.95%		
TBA	136,835	0.85%		
Total "Cancelled-Single" Trades	4,144	0.03%	0.02%	0.28%
Total # of Unique CUSIPs for "Cancelled-Single" Trades	4,144	0.03%	0.02%	0.28%
ABS	50	0.00%	0.04%	1.29%
CMO	535	0.00%	0.13%	0.50%
MBS	3,399	0.02%	0.09%	0.20%
TBA	160	0.00%	0.00%	0.01%

(continued)

Panel A3: Descriptive Statistics of “Canceled-Single” Trades

	No. of Security	"Canceled-Single Trades" Days between Initial Report and Later Cancellation					Entire Sample Days between Report and Cancellation			
		Mean	STD	Max	75% Q3	Median	Mean	STD	75% Q3	Median
Security Type										
ABS	50	4.58	4.37	20	6	3	2.94	2.91	2	4
CMO	535	3.62	3.79	27	5	2	3.85	3.90	3	5
MBS	3,399	4.48	6.33	27	4	2	3.44	3.69	2	4
TBA	160	7.54	8.14	28	10	4	4.56	4.95	3	6
Entire Sample	4,144	4.49	6.16	28	5	2	3.90	4.18	5	2

(continued)

Panel A1 illustrates Cancelled-Single trades.

- “Cancelled” means that on Day_0 a trade is posted on TRACE; on Day_{Cancel}, this exact trade is cancelled. The average timespan between $[Day_0, Day_{Cancel}]$ is 4.49 days (Panel A3);
- The initial legal *agreement* of the trade itself is cancelled. The ownership of the security has not changed hands. No real transaction has ever happened;
- “Single” means the cancelled transaction is the *only* trade for the particular CUSIP on Day_0, that is, there are no parallel, concurrent, or side trades for the same CUSIP on Day_0;
- There are no other trades between $[Day_0, Day_{Cancel}]$ for this particular security, there are no contamination nor interference from the inter $[Day_0, Day_{Cancel}]$ trades;
- Cancelled-Single trades provide a very clear setting to test vendors’ asymmetric response to the advent and disappearance of the same economic information.

Panel A2 indicates that the scope of the Cancelled-Single trades is very limited. Out of the 16,020,744 total transactions, there are only 4,144 Cancelled-Single trades, with 50 from ABS, 535 from CMO, 3,399 from MBS, and 160 from TBA. These Cancelled-Single trades are quite rare, and account for only 0.02% of the total trading volume of the entire sample and 0.28% of the daily trading volume.

Panel A3 shows that on average, cancellations occur 4.49 days after the initial posted transactions, slightly longer than those from the entire sample (3.90).

Panel B1: Effects of Initial Report and Later Cancellation for Positive "Jumps"

VARIABLES	(1) PositiveEntire	(2) PositiveABS	(3) PositiveCMO	(4) PositiveMBS	(5) PositiveTBA
Initial Report (Day0)	0.385***	0.381***	0.300***	0.165***	0.384***
	(11.67)	(11.58)	(7.88)	(3.97)	(11.63)
Later Cancellation	-0.042*	-0.042*	-0.038	-0.019	-0.043*
	(-1.89)	(-1.87)	(-1.58)	(-0.97)	(-1.91)
Observations	26,850	455	3,301	22,936	158
Adj R-squared	0.479	0.64565	0.43788	0.29468	0.581
CUSIP Fixed	Yes	Yes	Yes	Yes	Yes
Date Fixed	Yes	Yes	Yes	Yes	Yes

Clustered t-statistics by both date and CUSIP in parentheses *(continued)*
*** p<0.01, ** p<0.05, * p<0.1

Panel B2: Effects of Initial Report and Later Cancellation for Negative "Jumps"

VARIABLES	(1) NegativeEntire	(2) NegativeABS	(3) NegativeCMO	(4) NegativeMBS	(5) NegativeTBA
Initial Report (Day0)	-0.405***	-0.200**	-0.894***	-0.330***	-0.419*
	(-6.94)	(-2.47)	(-3.59)	(-6.28)	(-2.63)
Later Cancellation	0.052	-0.021	0.069	0.051	-0.058
	-1.37	(-0.31)	-0.46	-1.42	(-0.26)
Observations	14,801	151	2,021	12,583	46
R-squared	0.457	0.540	0.595	0.324	0.422
CUSIP Cluster	Yes	Yes	Yes	Yes	Yes
Date Cluster	Yes	Yes	Yes	Yes	Yes
CUSIP Fixed	Yes	Yes	Yes	Yes	Yes
Date Fixed	Yes	Yes	Yes	Yes	Yes

Clustered t-statistics by both date and CUSIP in parentheses *(continued)*
*** p<0.01, ** p<0.05, * p<0.1

Panels B1-2 present regression results for positive and negative jumps. $Initial\ Report$, $Later\ Cancellation$ are both dummy variables specifying the two events. Positive (negative) and significant coefficients of $Initial\ Report$ suggest that vendor prices reacts *significantly and promptly* to the initial posted trades for positive (negative) jumps. Negative (positive) and less-significant coefficients of $Later\ Cancellation$ suggest that vendor prices reacts *only gradually and less markedly* to the later cancelled trades for positive (negative) jumps.

Panel B3: Regression Results for Reversion back to Original Price Levels (Positive "Jumps")

VARIABLES	(1) PositiveEntire	(2) PositiveABS	(3) PositiveCMO	(4) PositiveMBS	(5) PositiveTBA
Day5	0.032*	0.041*	0.031*	0.027	0.036*
	(1.72)	(1.85)	(1.70)	(1.01)	(1.73)
Day10	0.023	0.014	0.020	0.023	0.025
	(0.92)	(0.78)	(0.93)	(0.99)	(0.99)
Day15	0.011	0.015	0.020	0.018	0.015
	(0.70)	(0.78)	(0.90)	(0.85)	(0.80)
Day20	-0.008	-0.004	-0.001	0.004	0.004
	(-0.53)	(-0.29)	(-0.05)	(0.31)	(0.32)
Observations	26,850	455	3,301	22,936	158
Adj R-squared	0.599	0.382	0.804	0.367	0.489
CUSIP Fixed	Yes	Yes	Yes	Yes	Yes
Date Fixed	Yes	Yes	Yes	Yes	Yes

Clustered t-statistics by both date and CUSIP in parentheses *(continued)*
*** p<0.01, ** p<0.05, * p<0.1

Panel B4: Regression Results for Reversion back to Original Price Levels (Negative "Jumps")

VARIABLES	(1) NegativeEntire	(2) NegativeABS	(3) NegativeCMO	(4) NegativeMBS	(5) NegativeTBA
Day5	-0.035*	-0.049*	-0.032*	-0.031*	-0.040*
	(-1.74)	(-1.90)	(-1.70)	(-1.69)	(-1.84)
Day10	-0.019	-0.012	-0.023	-0.012	-0.019
	(-0.83)	(-0.73)	(-0.94)	(-0.68)	(-0.81)
Day15	-0.011	-0.016	-0.020	-0.014	-0.013
	(-0.70)	(-0.77)	(-0.82)	(-0.71)	(-0.68)
Day20	0.009	0.000	0.001	-0.003	-0.004
	(0.51)	(0.00)	(0.04)	(-0.15)	(-0.20)
Observations	14,801	151	2,021	12,583	46
Adj R-squared	0.513	0.579	0.672	0.338	0.460
CUSIP Fixed	Yes	Yes	Yes	Yes	Yes
Date Fixed	Yes	Yes	Yes	Yes	Yes

Clustered t-statistics by both date and CUSIP in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panels B3-4 presents regression results for the reversion after the initial positive or negative jumps. $Day5$, $Day10$, $Day15$, $Day20$ are all dummy variables specifying event dates. For example, $Day5$ is dummy variable for day 5 after cancellation. Panel B3-4 results show that vendor prices revert back to the original pre-trade levels quickly, on average within 10-15 days.

T A B L E 6

Channel Three - Spoofing the Vendors

(Comparison of “Canceled-Single” Trades to Normal Trades)

Panel A: % of Dealer-Customer Trade (Cancelled-Single Trades vs. Entire Sample)

	% of Dealer_Customer Trade		Percentage Difference Significance
	Cancelled Single Trade	Entire Sample	
Security Type			
ABS	90.70%	75.16%	***
CMO	80.84%	60.13%	***
MBS	92.15%	52.03%	***
TBA	88.78%	23.49%	***
Total	89.00%	36.68%	***

*** p<0.01, ** p<0.05, * p<0.1

Panel B: Descriptive Statistics for Trading Volume of Cancelled-Single Trades vs. Non-cancelled Normal Trades (Controls)

Security Type	Order Status	No. of Trades	Mean Volume ($10,000)	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl	Std Dev
ABS	Cancelled-Single	43	1,685	0.4	65	178	953	3,141	5,813
	Normal Control	1,500	611	3.25	35	131	500	2,627	1,491
CMO	Cancelled-Single	426	4,891	0.3	10	256	1,520	10,000	57,438
	Normal Control	8,626	517	0.5	3	13	200	2,728	2,379
MBS	Cancelled-Single	2,902	716	2.996	48	145	444	2,914	2,474
	Normal Control	30,389	638	1	9	82	272	2,299	11,569
TBA	Cancelled-Single	122	1,501	38.27	207	860	1,908	5,000	1,838
	Normal Control	1,519	1,104	47.2986	191	500	1,130	4,520	1,905
Entire Sample	Cancelled-Single	3,493	1,264	2.5	47	156	536	4,006	20,224
	Normal Control	42,034	629	0.8	7	75	300	2,500	9,907

Panel C: Cancelled-Single Trades vs. Normal Trades for the Same CUSIP at Different Times

VARIABLES	(1) Entire	(2) ABS	(3) CMO	(4) MBS	(5) TBA
Canceled vs. Normal	122.643***	69.227***	198.061***	113.253***	46.578***
	(9.80)	(3.55)	(4.80)	(8.43)	(3.38)
Observations	37,208	1,049	5,767	28,570	1,125
Adj R-squared	0.06778	0.51651	0.31619	0.08679	0.51632
CUSIP Fixed	Yes	Yes	Yes	Yes	Yes
Date Fixed	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes

Clustered t-statistics by both date and CUSIP in parentheses
*** p<0.01, ** p<0.05, * p<0.1

$$TradingVolume_{it} = \alpha_0 + \alpha_1 \cdot CanceledSingleIndicator_{it} + Controls + \epsilon_{it}$$

This table presents comparison of "Canceled-Single" trades to normal non-cancelled trades (controls). Panel A shows that the percentage of dealer-customer trades are significantly higher in Cancelled-Single trades than the entire sample. According to FINRA rules, in trades between a dealer and a customer, only the dealer need to report to TRACE, while in an inter-dealer trade, both dealers need to report to TRACE. Therefore, price manipulation in inter-dealer trades requires a higher level of collusion than the dealer-customer trades.

Panel B shows the comparison of trading volumes of "Canceled-Single" trades vs. normal non-cancelled trades (controls) for the same security. The trading volumes for "Canceled-Single" trades are generally (significantly) larger than those of the controls.

Panel C shows the regression results. $TradingVolume$ is the dollar value of a trade in (\$10,000), $CanceledSingleIndicator$ is an indicator variable where $CanceledSingleIndicator = 1$ for Canceled-Single trades and 0 for normal non-cancelled trades. Control variables include liquidity score, Weighted Average Life (WAL), trade counts, and gap between trades. Data is winsorized at 5% and 95%. For the same security, trading volumes for Canceled-Single trades are significantly higher than those for normal non-cancelled trades.

Results from Panels B and C suggest that in order to augment the spoofing effects, bank managers have to post an artificially and significantly higher volume to make the spoofing trades more "sensational".

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