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Essays on Financial Accounting and Banks

by

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1. INTRODUCTION

1.1 Introduction

The four papers in this thesis focus mainly on the impact of accounting standards on banks' investment decisions. As noted by Holthausen and Leftwich [1983], accounting standards not only reflect the results of firms' operations but also can impact these operations. The impact of accounting standards on banks' operations is especially important given banks' special role in the economy (*e.g.*, Bernanke [1983]). In addition, accounting standards play an important role in regulatory capital requirements, which are one of the primary tools regulators use to evaluate banks' financial condition. The papers in this thesis focus on accounting standards alone as well as their use in the context of regulatory capital requirements.

In "Fair-Value Accounting, Financial Crises, and Asset Sales by Banks," I focus on the effect of fair-value accounting on the types of assets banks sell during financial crises. While asset sales by banks are a hallmark of crises, the types of assets, "safe" (*e.g.*, United States Treasuries) or "toxic" (*e.g.*, sub-prime-backed mortgage-backed securities (MBS)), banks choose to sell has received little attention. Theoretically, I show that relative to historic-cost accounting, fair-value accounting can induce banks to sell more toxic assets and fewer safe assets. Empirically, I find that in the 2007–8 crisis, larger write-downs on private-label MBS are linked with more sales of these securities. Hence, fair value's use can have an important impact on which type of assets banks sell during crises.

Fair value's impact in inducing more sales of toxic assets and fewer sales of safe assets has a two-sided impact on crises. With certain exceptions (*e.g.*, Greek government debt), toxic

assets tie up substantial capital. Hence, in selling these capital-intensive, poorly performing assets, banks free up capital to put toward new, more-productive loans. Also, selling toxic assets while holding on to safe assets improves balance-sheet strength, enhancing the ability of banks to raise external capital. As a result, crises could come to a quicker close, with fewer negative spillovers to the real economy. These benefits are more likely under fair value than under historic cost. As a drawback, sales of toxic assets reduce prices. These price declines further impair banks' capital and liquidity, making crises worse by amplifying banks' distress. *A priori*, the net effect of these two conflicting effects is not clear and is an interesting area for future research.

In "DVA and Systemic Risk," I focus on how debit valuation adjustments (DVA) can increase systemic risk by inducing banks to take long positions in other banks' credit. DVA is a valuation adjustment whose earnings profile is equivalent to that of an unhedged, undiversified short position in own-credit risk. An increase in own-credit risk results in a gain; a decline, in a loss. As a result of the potential for large swings in banks' credit risk, DVA can have a large effect on earnings and in increasing volatility in earnings. This rise in volatility increases the present value of expected tax liabilities (Smith and Stulz [1985], Graham and Smith [1999]). Hence, tax concerns give banks incentives to hedge DVA so as to mitigate its impact on earnings.

DVA is relevant only for global banks. These banks are among the large, "too-big-to-fail" financial institutions at the heart of the 2007–8 financial crises. To hedge DVA, these banks take long positions in the credit of other global banks. Given that DVA is effectively a short position in own-credit risk, banks can best hedge by taking positions that are akin to a long position in own-credit risk. Common factors account for 62 percent of the changes in global banks' credit risk (Eichengreen *et al.* [2009]). Consequently, changes in these banks' credit risk have a strong positive link. In good states, credit risk falls, leading to DVA losses and gains on banks' long positions in other banks' credit. In bad states, an increase in credit risk

gives rise to DVA gains and losses on hedges.

DVA hedging thus increases systemic risk by strengthening the links between large, global banks. These banks already are hedging DVA, increasing the systemic scope of future crises. Goldman Sachs hedges DVA by selling credit protection on other financial firms (Moyer and Burne [2011]); several others use some type of DVA hedging or are thinking about doing so (Carver [2012]). In addition, in 2008, several banks hedged prospective DVA gains by selling credit protection on Lehman Brothers (Alloway [2012]). DVA hedging gives banks direct exposure to other banks' credit. Hence, in a crisis, when one bank becomes distressed, other banks book losses, reducing capital while increasing credit risk. In turn, more banks book losses, and so on. Concomitant DVA gains do nothing substantive to offset these losses. In addition, Basel III calls for DVA to be excluded from capital (BCBS [2011]). As a result, DVA gains during crises would offer no capital relief. Losses on DVA hedges thus could have an important role in amplifying the scope and magnitude of crises.

In “Balance-Sheet Management by Large Banks,” I focus on whether banks use balance-sheet management (BSM) to strengthen their reported financial ratios. During the 2007–8 financial crisis, Lehman Brothers used its “Repo 105” program to cut its reported leverage. Due to Repo 105, BSM by financial institutions has drawn regulatory attention. The Securities and Exchange Commission (SEC), for instance, sent 24 financial institutions a “Dear CFO” letter regarding their use of reverse repurchase agreements (repo). Banks can use BSM to give a temporary boost to financial ratios that are based on positions at quarter-end, *à la* Lehman and Repo 105. Banks thus can use BSM to report financial ratios that are stronger than those they maintain during the quarter, in between reporting dates. I focus separately on BSM by large banks and BSM by other banks; differences in business models give large banks stronger incentives to use BSM to improve their financial ratios.

Empirically, I find that for large banks, weaker financial ratios give rise to more BSM in assets. A fall in regulatory capital ratios and a rise in raw leverage are linked with a larger

fall in quarter-end assets relative to average assets during the quarter. Also, this link between lower capital ratios and more BSM in assets is stronger when banks have less capital and have assets whose disposal has a larger effect in increasing capital ratios. These results suggest large banks react to weaker financial ratios by using BSM in assets to improve these ratios. For other banks, capital ratios and raw leverage have no effect on BSM in assets, in line with the notion that large banks have stronger incentives to engage in financial-ratio-motivated BSM.

These results imply that large banks use BSM in assets to improve their reported financial ratios. These results do not imply that banks have used Repo 105-like programs. Lehman cut its reported (*i.e.*, end-of-quarter) leverage relative to its average leverage during the quarter by accounting for reverse repos as true sales and using the cash from these transactions to pay down debt. Banks could generate the same balance-sheet and financial-ratio effects via transaction timing or similar methods—by, for instance, selling assets right before quarter-end and buying similar assets early in the next quarter. These results, however, have similar implications: Banks with weak financial ratios can use BSM to improve the reported quarter-end value of these ratios relative to their average value during the quarter.

In “Fair-Value Accounting, Derivatives, and Hedging,” I show that derivatives can reduce fair value’s adverse effect on financial-sector stability. Theoretically, prior studies show that fair value can have adverse effects by letting asset-price changes affect earnings—by exposing banks to market risk, the risk of profit or loss due to changes in asset prices. A rise in credit spreads, for instance, decreases the prices of corporate bonds. Under fair value, banks book losses on their corporate bonds because of this fall in prices. In this respect, fair value exposes banks to market risk. These studies, however, all look at the application of fair value only to banks’ assets, but fair value is applied also to derivatives. Banks thus could use derivatives to lay off unwanted market risk—to hedge. As a result, insofar as banks use derivatives to hedge, and insofar as derivatives are effective in hedging, derivatives could play a useful role

in blunting fair value's negative effects.

Empirically, I find that banks use derivatives to hedge and that derivatives are effective in hedging. As a concrete example, suppose that a bank has a fair-valued corporate bond and thus is exposed to credit-risk-related market risk: The first result means that this bank, for instance, buys credit protection using a credit-default swap (CDS) to protect itself against the price effects of credit-spread changes. Hence, this bank hedges *ex ante*, in anticipation of possible price changes. The second result means that once credit spreads do change, the CDS reduces the bond's net impact on earnings. Should credit spreads rise, the bond's price falls, resulting in fair-value losses on this bond, but the CDS's price increases, leading to offsetting gains. Should credit spreads fall, the bond's price increases, resulting in fair-value gains, but the CDS's price falls, resulting in offsetting losses. In this respect, the CDS reduces the net effect on earnings and capital of changes in asset prices.

In sum, these results suggest that derivatives help blunt fair value's impact on earnings. These results relate to the debate about fair value's potential to have a negative effect on financial-sector stability. Fair value could do so by exposing banks to market risk, with asset-price changes thus affecting earnings and capital. My results suggest banks use derivatives to mitigate these effects. Derivatives were useful in this respect even during the 2007–8 financial crisis, when fair value's negative impact was strongest. Morgan Stanley's 2008 trading losses of \$3.1 billion, for instance, "reflected fair value losses on loans and commitments that were partly offset by gains on related hedges" (source: Morgan Stanley's 2008 10-K, p. 43). These \$3.1 billion in losses were large but would have been even larger without derivatives. Hence, while my results do not imply that fair value is incapable of having destabilizing effects, they do suggest that focusing jointly on banks' assets and derivatives is essential to evaluating its impact.

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2. FAIR-VALUE ACCOUNTING, FINANCIAL CRISES, AND ASSET
SALES BY BANKS

ABSTRACT

Asset sales by banks are a hallmark of financial crises. The types of assets, “safe” (*e.g.*, US Treasuries) or “toxic” (*e.g.*, sub-prime-backed MBS), banks choose to sell, however, has received little attention. I show that relative to historic-cost accounting, fair-value accounting can lead banks to sell more toxic assets and fewer safe assets. Empirically, I find that during the 2007–8 crisis, larger write-downs on private-label mortgage-backed securities are linked with more sales of these securities. Hence, fair value’s use can have an important impact on which type of assets banks sell during crises.

2.1 Introduction

In this study, I focus on asset sales by banks during financial crises. Crises are marked by large losses and disruptions in funding markets. Consequently, banks face strong pressure to sell assets. The ongoing European crisis, for instance, is expected to force European banks to shed as much as \$4.8 trillion in assets by the end of 2013 (IMF [2012a]). Asset sales not only are a result of but also can worsen crises by reducing prices further. Hence, banks face more capital and funding pressure, potentially resulting in more sales. This sort of self-reinforcing cycle can have a large effect in making crises worse (*e.g.*, Cifuentes, Ferrucci, and Shin [2005], Brunnermeier [2009], Brunnermeier and Pedersen [2009]).

In discussing the effects of asset sales, one common assumption is that sales reduce prices. The validity of this assumption, however, depends on which types of assets are sold. Assets differ in liquidity. In 2011, for instance, the markets for United States (US) Treasuries and for corporate bonds were similar in magnitude at \$9.9 trillion and \$7.8 trillion, but average daily turnover was \$568 billion in Treasuries, compared to \$21 billion in corporates.¹ As a result, sales of different types of assets can have different price effects, with different consequences for how crises evolve. Deep, liquid markets can absorb positive supply shocks—sales—with a minimal impact on prices; thin, illiquid markets cannot. Hence, sales of “safe,” liquid assets (*e.g.*, US Treasuries) are innocuous, whereas sales of “toxic,” illiquid assets (*e.g.*, sub-prime-backed mortgage-backed securities (MBS)) can reduce prices, making crises worse.

I show how fair-value accounting² can lead banks to sell more toxic assets and fewer safe assets than under historic-cost accounting.³ First, I build a model in which banks choose the quantities to sell of both safe and toxic assets. Banks maximize returns, driven in part by how

¹ Source: <http://www.sifma.org/research/statistics.aspx>. Last accessed on August 16, 2012.

² Fair value is a broader version of mark-to-market accounting (see Laux and Leuz [2009]). For simplicity, I generally use fair value to refer to both (see Section 4 for more).

³ I use safe assets to refer to assets with minimal default risk and whose price and fundamentals stay stable during crises (see, *e.g.*, IMF [2012b], Chapter 3). I use toxic assets to refer to assets whose price collapses and fundamentals deteriorate during crises.

asset sales affect the odds of a “wholesale run”—a sudden loss of access to wholesale funding, uninsured funding which many large banks rely heavily on. Wholesale runs can impose large costs on banks. In the 2007–8 crisis, for instance, wholesale runs were an important factor in the demise of Bear Stearns and Lehman Brothers (Acharya and Öncü [2010]). Consequently, banks have strong incentives to take steps to avoid these runs.

Denoting safe assets by F , toxic assets by X , and the probability wholesale creditors roll over funds by p , I specify p as an increasing function of capital and balance-sheet strength, or asset quality, defined as F 's share in total assets—more capital and stronger balance sheets imply less credit risk, making creditors more likely to roll over funds. Sales of F and X have an ambiguous net effect on p . With respect to F , as a plus, during crises, safe assets increase in price. As a result, banks could book gains on sales, increasing capital. As a minus, selling F reduces F 's share in total assets. With respect to X , as a plus, sales increase F 's share in total assets. As a minus, during crises, toxic assets decline in price. Banks thus could book losses on sales, depleting capital. To illustrate this trade-off, in 2008, Merrill Lynch sold \$31 billion of collateralized debt obligations (CDO) for 22 cents on the dollar, reducing its CDO exposure but booking a \$4.4 billion loss on these sales (Keoun and Harper [2008]).

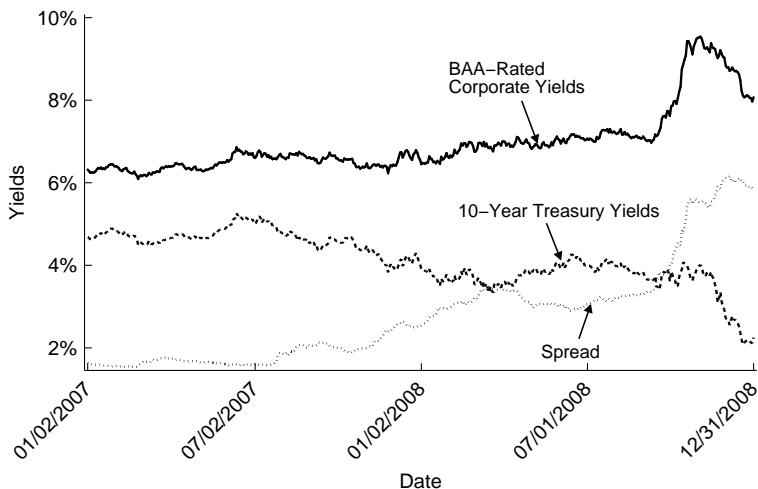
Fair value reduces gains on sales of safe assets and losses on sales of toxic assets compared to historic-cost accounting. Consequently, banks sell more toxic assets and fewer safe assets under fair value. Under fair value, banks book gains and losses on asset-price changes. Banks thus book immediate gains on the rise in the prices of safe assets and losses on the decline in the prices of toxic assets. Booking these gains and losses reduces gains and losses on sales; changes in the prices of banks' assets already are reflected in capital. Under historic cost, banks do not book gains and losses on changes in prices. As a result, sales give rise to gains and losses equal to the entire change in prices. Hence, under fair value, sales of safe assets increase capital by less, resulting in a smaller net rise or a larger net fall in p ; sales of toxic assets reduce capital by less, resulting in a larger net rise or a smaller net fall in p .

Empirically, I look at asset sales by US banks during the 2007–8 financial crisis. For toxic assets, I use private-label MBS. These MBS include the sub-prime- and Alt-A-backed MBS that were among the worst-performing assets during the crisis. I focus on how impairment write-downs on private-label MBS affect sales of these securities. My primary finding is that larger write-downs on private-label MBS are linked with more sales of these securities in the following quarter. For a given fall in prices, taking larger write-downs prior to selling reduces losses on sales. As a result, sales of private-label MBS have a less-negative effect on capital, inducing banks to sell more of these securities.

This study relates most directly to the body of literature that focuses on asset sales during financial crises (see, *e.g.*, Shleifer and Vishny [2010] for a survey). One common assumption implicit in these studies is that sales depress prices. The validity of this assumption, however, depends on which types of assets are sold. Sales of safe assets have a different effect on prices than do sales of toxic assets. Though Cifuentes *et al.* [2005] and Gauthier, Lehar, and Souissi [2010] both make this point, both assume that banks always prefer to sell either safe (liquid) assets or toxic (illiquid) assets. I relax this assumption and take as endogenous banks' asset-sale decisions. This approach helps shed light on what drives the types of assets banks choose during crises to sell.

The rest of this paper proceeds as follows: In Section 2, I describe the differences between safe and toxic assets. In Section 3, I discuss wholesale runs and the factors that affect banks' exposure to these runs. In Section 4, I go through the effect of accounting standards on the asset-sale decisions of banks; in addition, I relate this study to prior studies that look at fair value's impact on financial-sector stability. My model is in Section 5. My empirical tests are in Section 6. In Section 7, I discuss my model's main implications. Concluding remarks are in Section 8. Supplemental information about my empirical tests is in the appendix.

Fig. 2.1: Changes in Yields, US Treasuries v. BAA Corporates



Data source: Federal Reserve.

2.2 Safe Assets v. Toxic Assets

Two empirical observations motivate this study. First, during crises, different types of assets differ in performance. For safe, liquid assets, prices rise (yields fall), and fundamentals stay stable. For illiquid, relatively risky assets, prices fall (yields rise), and fundamentals worsen. At the start of 2007, for instance, the yields on 10-year Treasuries and BAA-rated corporate bonds were 468 basis points (bps) and 632 bps (Figure 1). By the end of 2008, Treasury and BAA corporate yields were 225 bps and 807 bps, a rise in spreads from 164 bps to 582 bps. For illiquid assets that become “toxic” (*e.g.*, whose fundamentals are particularly hard-hit), price declines are especially large. As an example, the ABX index is a credit derivative whose reference entity is 20 sub-prime-backed MBS. By September 2008, the ABX AAA and BBB indices were trading at 60 cents and 10 cents on the dollar (IMF [2008], p. 13).

Second, sales of different types of assets can affect prices in different ways, with different effects on how crises evolve. Sales of safe, liquid assets have few price effects, whereas sales of toxic, illiquid assets can depress prices. In perfect markets, traders stand able and willing

to pay fundamental value for an asset. For safe assets, such as US Treasuries, this perfect-markets framework is a reasonable approximation. These assets have stable fundamentals, have few information asymmetries, and are traded in deep and liquid markets with abundant capital. Hence, market frictions are of little concern. In addition, during periods of distress, flight-to-quality- and -liquidity effects strengthen demand for safe, liquid assets (*e.g.*, Beber, Brandt, and Kavajecz [2009], Noeth and Sengupta [2010]). This rise in demand reduces still further the ability of sales to depress prices.

For toxic assets, such as sub-prime-backed MBS, market frictions are pervasive. Positive supply shocks—sales—thus can reduce prices. Toxic assets have unstable fundamentals, have large information asymmetries between investors, and are traded in thin, illiquid markets by relatively few specialist traders (*e.g.*, hedge funds (Blundell-Wignall [2007])). Hence, frictions can lead to imperfect markets. Such frictions include fixed investment costs (Merton [1987]), so that investors do not invest the time and resources needed to get information on an asset class; principal-agent problems that limit the access of traders to capital (Shleifer and Vishny [1997]), so that traders cannot obtain from their financiers cash to buy assets; and increases in margin (Brunnermeier and Pedersen [2009]), so that traders can borrow less against their assets and thus have to use more of their own capital. The latter two frictions are particularly important during crises, when financial-sector-wide distress leads to a systemic shortage of capital (*e.g.*, Shleifer and Vishny [1992]).

Empirically, Coval and Stafford [2007] find that equity securities sold in distressed sales experience a rise in price of 6.1 percent in the 12 months after being sold. Mitchell, Pedersen, and Pulvino [2007] find that convertible bonds were priced by as much as four percent below fundamentals in late 1998 and early 1999 and from January 2005–September 2006, two times of widespread sales. These results show that asset sales can reduce prices. With respect to frictions, Gabaix, Krishnamurthy, and Vigernon [2007] and Griffoli and Rinaldo [2010] find evidence of limits-of-arbitrage effects in prices; Froot and O’Connell [1999] find that a decline

in the supply of capital in the reinsurance market increases the price of reinsurance. In short, frictions enable sales of assets—especially sales of illiquid assets—to depress prices, and prices can take some time to return to fundamentals.

2.3 *Financial Crises, Wholesale Runs, and Asset Sales*

2.3.1 *Financial Crises and Wholesale Runs*

During crises, banks are exposed to “wholesale runs”—a sharp and sudden loss of access to wholesale funding. Banks with liabilities sourced primarily from government-insured deposits face little threat of runs. Certain large banks, however, make heavy use of wholesale funds, such as reverse repurchase agreements (repo) (Table 1). In addition, wholesale funds often are large banks’ marginal source of funds (Carpenter and Demiralp [2010], Disyatat [2011]), amplifying their importance. Wholesale liabilities tend to have short maturities. US primary dealers, for instance, have had up to \$3 trillion in overnight repo outstanding, in the aggregate (Adrian, Burke, and McAndrews [2009]). This combination of a lack of insurance plus short maturities exposes banks, especially large banks, to wholesale runs. Duffie [2010] and Huang and Ratnovski [2011] outline how wholesale runs can arise.

In a financial crisis, large losses deplete capital (Figure 2), and asset quality deteriorates. Hence, credit risk rises, increasing the odds of a wholesale run. During the 2007–8 crisis and the ongoing European crisis, wholesale runs have imposed large costs on banks. Wholesale runs had a central role in the demise of Bear Stearns and Lehman Brothers (Acharya and Öncü [2010]). Even in less extreme cases, wholesale runs can generate costs by forcing banks to sell assets, potentially at distressed, fire-sale prices, or even to exit entire lines of business. Between end-May and end-November 2011, for instance, US money-market funds cut by 89 percent their exposure to French banks and shifted their remaining exposures into shorter maturities and secured lending (Fitch [2011a, 2011b]). Due in part to this run, French banks

Tab. 2.1: US Banks' Liability Composition, Year-End 2010 (\$ millions)

Bank	Total Liabilities	Deposits	Repo	Deposit %	Repo %
Bank of America	2,031,133	1,012,629	243,901	0.499	0.120
JP Morgan	1,940,905	930,369	273,314	0.479	0.141
Citigroup	1,748,113	844,968	189,080	0.483	0.108
Wells Fargo	1,130,239	848,328	35,007	0.751	0.031
Goldman Sachs	833,102	38,496	173,472	0.046	0.208
Morgan Stanley	742,291	63,812	176,692	0.086	0.238
Metlife	681,911	10,317	24,647	0.015	0.036
Taunus	368,305	22,471	177,497	0.061	0.482
HSBC NA	314,314	118,311	69,238	0.376	0.220
US Bancorp	277,464	204,252	9,261	0.736	0.033
PNC	231,577	183,521	4,011	0.792	0.017
BNY Mellon	214,065	145,407	5,125	0.679	0.024
Capital One	170,960	122,211	927	0.715	0.005
TD Bank US	158,334	143,926	2,047	0.909	0.013
Suntrust	149,746	123,044	2,180	0.822	0.015
Others	3,561,292	2,687,043	141,943	0.755	0.040

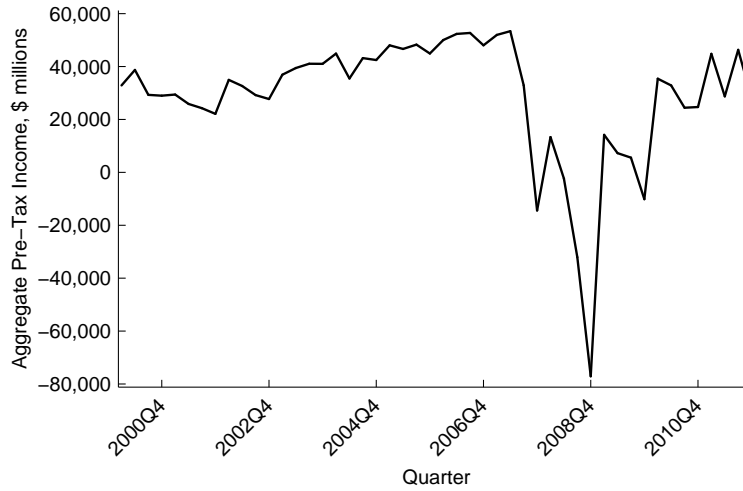
Data source: FR Y9-C. The 15 banks shown are the 15-biggest US bank holding companies as of the end of 2010, as measured by total assets. "Other banks" is aggregate data for all other US bank holding companies.

have exited or reduced scale in areas that rely on dollar funds despite previously being among the most active banks in certain of these areas, such as trade finance (HSBC [2011]).

2.3.2 Wholesale Runs, Credit Risk, and Asset Sales

Credit risk is a key factor in banks' vulnerability to a wholesale run. Two factors important to credit risk are capital and balance-sheet strength (asset quality, or asset risk). More capital and a stronger balance sheet reduce the odds that creditors will incur losses. Consequently, credit risk declines, reducing the likelihood of a wholesale run. With respect to capital, for a given base of assets (or risk-weighted assets), more capital increases banks' cushion of equity to put toward absorbing losses. With respect to balance-sheet strength, holding lower-quality assets implies lower future earnings and increases banks' exposure to adverse shocks to toxic

Fig. 2.2: US Banks' Aggregate Pre-Tax Income, 2000–2011



Period	PTI	Period	PTI	Period	PTI
2000AVG	32,470	2007Q3	32,897	2009Q4	-10,137
2001AVG	25,416	2007Q4	-14,406	2010Q1	35,415
2002AVG	31,139	2008Q1	13,329	2010Q2	32,860
2003AVG	39,613	2008Q2	-2,358	2010Q3	24,428
2004AVG	41,515	2008Q3	-32,058	2010Q4	24,700
2005AVG	46,976	2008Q4	-77,090	2011Q1	44,810
2006AVG	50,775	2009Q1	14,187	2011Q2	28,726
2007Q1	51,964	2009Q2	7,271	2011Q3	46,317
2007Q2	53,375	2009Q3	5,566	2011Q4	28,014

Data source: FR Y9-C. PTI is pre-tax income excluding extraordinary items (BHCK4300). “AVG” denotes average quarterly PTI in a given year. Data are in millions of dollars.

assets, a common feature of crises. Hence, banks are more likely to incur losses in general as well as large losses, in particular; over 2007–8, for instance, Citigroup booked \$32.6 billion in total losses on sub-prime-related exposures (source: 2008 10-K). Empirically, less capital and lower-quality (higher-risk) assets are linked with higher yields on uninsured debt (Hannan and Hanweck [1988], Goyal [2005]).

During crises, safe assets and toxic assets differ sharply in performance (Section 2, Figure 1). As a result, sales of safe and toxic assets have a different effect on credit risk and thus on

the probability of a wholesale run. With respect to safe assets, as a plus, in crises, safe assets rise in price. Hence, banks could book gains on sales, increasing capital. As a minus, sales reduce the share of safe assets in total assets, impairing balance-sheet strength. In addition, in selling safe assets, banks shed fundamentally sound interest-earning assets, impairing their ability to replenish capital via retained earnings. Selling safe assets has a positive net impact on credit risk only insofar as the first effect dominates the sum of the latter two.

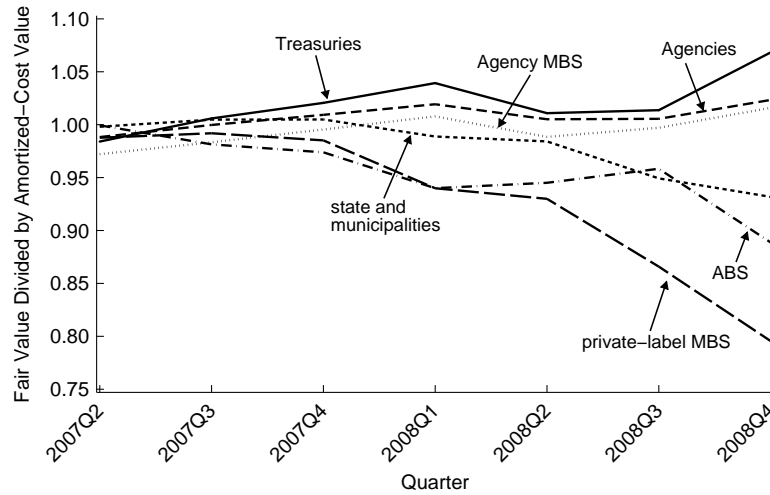
With respect to toxic assets, as a plus, sales raise the share of safe assets in total assets, improving balance-sheet strength. As a minus, sales could reduce capital, in two ways. First, because of worsening fundamentals and market “dislocations” (*e.g.*, a decline in liquidity; see also Section 3.1), banks can sell toxic assets only at a discount to par. Banks thus could book losses on sales, such as Merrill Lynch’s \$4.4 billion loss on its CDO sales in 2008 (Section 1). Second, insofar as toxic assets generate positive net interest income, sales reduce net interest income. Selling toxic assets has a positive net impact on credit risk only insofar as the first effect dominates the sum of the latter two.

2.4 *Fair-Value Accounting and Asset Sales*

2.4.1 *Fair-Value Accounting, Financial Crises, and Capital*

With respect to asset sales during crises, fair value’s use affects capital in two ways: capital in place before selling assets, and the effect of asset sales on capital. During crises, the prices of safe assets rise; the prices of toxic assets decline. Banks’ asset valuations move in the same way. From the ends of 2007Q2–2008Q4, for instance, US banks’ valuations of US Treasuries rose from par to seven percent above par; valuations for private-label MBS fell from par to 20 percent below (Figure 3). Under fair value, asset-price changes lead to recognized holding gains and losses that impact earnings and capital. Hence, under fair value, banks book gains on the rise in the prices of safe assets. These gains increase capital, but booking these gains

Fig. 2.3: US Banks' Security Valuations, 2007Q2–2008Q4 (1 = par)



Security Type	2007Q2	2007Q3	2007Q4	2008Q1	2008Q2	2008Q3	2008Q4
Treasuries	0.984	1.006	1.021	1.039	1.011	1.014	1.068
Agencies	0.988	1.000	1.009	1.019	1.005	1.006	1.023
State & Munis	0.998	1.005	1.005	0.989	0.984	0.949	0.932
Agency MBS	0.972	0.983	0.995	1.008	0.988	0.997	1.016
Private-Label MBS	0.988	0.992	0.985	0.940	0.930	0.866	0.796
Asset-Backed Securities	0.999	0.981	0.974	0.940	0.945	0.958	0.889

Data source: FR Y9-C. These ratios are for banks' aggregate banking-book securities (securities classified as available for sale or held to maturity) and are each security type's fair value divided by its amortized-cost value. Lower ratios imply lower valuations relative to par.

lowers gains on sales. Likewise, banks book losses on the decline in the prices of toxic assets, reducing capital, but booking these losses reduces losses on sales. Under historic cost, absent sales, asset-price changes impact neither earnings nor capital; sales result in gains and losses equal to the full change in prices.

Suppose, for instance, that a bank holds US Treasuries and sub-prime-backed MBS whose par value is 1 and that a crisis hits, so that its Treasuries rise in price to 1.05 and its MBS fall in price to 0.80: Under fair value, this bank recognizes a per-unit Treasury gain of 0.05 and an MBS loss of 0.20. These Treasury gains increase capital, these MBS losses reduce capital, and future Treasury and MBS sales are gain- and loss-free, respectively; the changes in these

assets' prices already are reflected in capital. Under historic cost, absent sales, capital stays the same. Treasury sales result in a per-unit gain and a rise in capital of 0.05; MBS sales, in a loss and a decline in capital of 0.20. In this respect, fair value induces more sales of MBS and fewer sales of Treasuries.

Before going on, one point: In discussing fair value, I assess its use *vis-à-vis* only earnings and regulatory capital. Fair value can be applied in different manners for different purposes. Securities classified as available for sale, for instance, are valued under fair value on banks' balance sheets but are valued under historic cost with respect to both earnings and capital, in that price changes in available-for-sale securities have no impact on earnings or capital. In addition, regulators have the option of excluding from regulatory capital fair-value-related gains and losses that impact earnings. In my model, I abstract from these issues and assume that fair value is applied in the same way with respect to both earnings and capital, where capital denotes regulatory capital, not balance-sheet equity as determined under US generally accepted accounting principles.

2.4.2 *Impairments and the SFAS No. 157 Fair-Value Hierarchy*

For simplicity, I focus primarily on “pure” forms of fair-value accounting, under which all asset-price changes flow to capital on a one-for-one basis, and historic-cost accounting, under which changes in prices and deteriorations in asset quality more generally never affect capital. For toxic assets, however, two features of accounting standards can result in deviations from these regimes. First, impairment losses: Under historic cost, banks have to take impairment losses on assets that satisfy certain criteria (*e.g.*, a decline in an asset's expected future cash flows). Notably, the Securities and Exchange Commission (SEC) requires banks to consider “the extent to which [an asset's] market value [is] . . . less than cost” when deciding whether to take an impairment (SEC [2009]). During crises, the fundamentals of toxic assets worsen, and the prices of these assets fall. Consequently, even under historic cost, banks could have

to take impairment losses on these assets.

Second, the fair-value hierarchy: When applying fair value, SFAS No. 157 stipulates that banks may use “unobservable inputs” (*e.g.*, internal models) to value “Level 3” assets—assets that have “little, if any, market activity . . . at the measurement date” (FASB [2010], ¶ 30). As a consequence, when valuing an asset whose liquidity has declined, banks can rely more on internal models and less on market-based inputs (*e.g.*, prices). During crises, the liquidity of toxic assets declines. In addition, those sales that do take place and market frictions more generally can push these assets’ prices below fundamentals (Section 2). Using fundamentals-based models helps combat these effects. Consequently, the fair-value hierarchy tends to yield higher valuations and thus smaller write-downs than does a pure mark-to-market regime (see Laux and Leuz [2010]).⁴ Hence, banks need not book on toxic assets immediate losses equal to the entire decline in the “prices” of these assets.⁵

With respect to capital, greater recognition of impairments has the same effect as moving toward fair value; greater use of internal models has the same effect as moving toward historic cost. Returning to the example in Section 4.1, suppose that the bank’s MBS decline in price from 1 to 0.80; that under fair value, the bank uses internal models to price its MBS at 0.85, not 0.80; and that under historic cost, the bank takes a per-unit impairment of 0.05, not 0: Under fair value, the per-unit write-down falls from $1.00 - 0.80 = 0.20$ to $1.00 - 0.85 = 0.15$; losses on sales increase from $0.20 - 0.20 = 0$ to $0.20 - 0.15 = 0.05$. Hence, relative to a pure fair-value regime, capital before selling assets is higher, while sales reduce capital by more.

⁴ By definition, safe assets maintain stable fundamentals and have strong liquidity, even in times of distress. Impairment losses thus are rare, and banks have an abundance of observed transaction prices to use in valuing these assets. Hence, impairments and the use of unobservable inputs (models) are of little relevance.

⁵ With respect to the fair-value hierarchy more generally, assets valued under fair value are classified as either Level 1, Level 2, or Level 3 assets. Banks value Level 1 assets using “quoted prices in active markets for identical assets,” Level 2 assets using “inputs other than quoted prices included within Level 1 that are observable . . . either directly or indirectly,” and Level 3 assets using “unobservable inputs” (FASB [2010]). For simplicity, while this hierarchy is important, I do not go into more detail regarding its application beyond the discussion in the body of the paper above. In addition, except where noted, I use fair value in a generic sense, without respect to differences in the valuation of Level 1, Level 2, and Level 3 assets.

Under historic cost, impairments lower capital by 0.05 per unit of MBS, not 0; losses on sales fall from $0.20 - 0 = 0.20$ to $0.20 - 0.05 = 0.15$. As a result, relative to a pure historic-cost regime, capital before selling assets is lower, while sales reduce capital by less.

2.4.3 Fair-Value Accounting's "Real Effects"

This study relates to three studies that focus on the "real effects" of fair value. This study is most similar to Plantin, Sapra, and Shin [2008], who likewise focus on how fair value affects asset sales by banks. This study differs in three ways from Plantin *et al.* First, Plantin *et al.* focus only on illiquid (toxic) assets, with no attention given to liquid (safe) assets. I focus on both safe and toxic assets and show fair value affects which type of asset banks sell. Second, I focus on asset sales within the context of a wholesale run, an important feature of financial crises. Third, we highlight different ways for fair value to affect banks' asset-sale decisions. In Plantin *et al.*, under fair value, banks sell illiquid assets as a result of expectations of sales by other banks. I focus on fair value's impact *vis-à-vis* the capital effects of asset sales.

In addition, Cifuentes *et al.* [2005] and Allen and Carletti [2008] both show that fair value can give rise to contagion. In these studies, when one bank sells assets, prices decline. Fair value forces other banks to take write-downs, potentially resulting in more sales and a self-reinforcing cycle of write-downs and sales. My model differs by focusing on banks' selling decisions. Cifuentes *et al.* and Allen and Carletti both take as exogenous these decisions and focus on the impact thereof. In Cifuentes *et al.*, banks strictly prefer to sell liquid assets and sell illiquid assets only after running out of liquid assets to sell. Allen and Carletti focus only on illiquid assets, with sales always reducing prices. In making endogenous banks' asset-sale decisions, I show that fair value gives banks incentives to sell more toxic (illiquid) assets and fewer safe (liquid) assets. Because sales of toxic assets depress prices but sales of safe assets do not, this investment decision makes fair-value-related contagion even worse.

2.5 *Model*

This section proceeds as follows: In Section 5.1, I sketch an overview of my model. In Section 5.2, I describe its set-up. In Section 5.3, I identify the trade-offs at play in selling safe and toxic assets. In Section 5.4, I show how accounting standards affect these trade-offs.

2.5.1 *Preliminaries*

In this model, I focus on how accounting standards affect the asset types—safe, liquid assets or toxic, illiquid assets—banks sell during financial crises. Banks maximize returns, driven in part by the probability that wholesale creditors roll over funding—by the probability of being hit by a wholesale run. I focus primarily on how asset sales affect this probability, specified as a function of capital and balance-sheet strength (asset quality). This model is most relevant for financial crises, when wholesale runs are most likely. In calmer environments, earnings and capital are strong, and asset quality is high. Hence, credit risk is low, making negligible the probability of a wholesale run. This model is most relevant for large banks due to their heavier reliance on wholesale funding (Section 3.1, Table 1).

I make five vital assumptions. First, banks’ assets are financed by wholesale liabilities, which are not government-insured. Second, banks’ liabilities mature before their assets. This combination of wholesale funding and a maturity mismatch leads to rollover risk—wholesale creditors can pull funding from banks with sufficiently high credit risk. Third, selling toxic assets reduces returns compared to holding these assets to maturity. Toxic assets have few prospective buyers even in “good states,” limiting the capital available to buy these assets. The financial-sector-wide distress that marks crises reduces still further this pool of capital (see Section 2). Banks thus can sell these assets only at a below-fundamentals price. Hence, returns on sales are lower than are returns on holding these assets to maturity.

Fourth, banks hit by a wholesale run cannot raise enough cash to meet this run by selling

only safe assets; selling at least some toxic assets is needed. Banks keep a stock of safe, liquid assets to meet short-term cash demands. When a crisis hits, however, banks face demands for cash from many parties. In June 2008, for instance, Citigroup demanded a \$2 billion comfort deposit from Lehman Brothers to continue clearing on behalf of Lehman in the Continuous Linked Settlement system (Valukas [2010]). Also, crises can give rise to tighter restrictions on selling liquid assets—these assets can become “encumbered.” Credit-rating downgrades, for instance, a common event in crises, can force banks to post to their derivative counterparties billions of dollars more in collateral—typically, cash and high-quality government debt (*e.g.*, US Treasuries). These and similar factors increase banks’ needs to raise cash while impairing their ability to sell safe, liquid assets to do so.

Fifth, creditors take at face value banks’ capital. Creditors could add to reported capital unrecognized gains on safe assets and subtract unrecognized losses on toxic assets to arrive at “true capital.” This adjustment would dampen banks’ incentives to consider the impact on capital of asset sales. With respect to banks’ asset-sale decisions, however, what matters is not whether creditors actually do make these adjustments but whether banks think creditors make these adjustments—whether banks think that they can “fool the market.” Anecdotally, capital is important, and the prospect of losses on sales can induce banks not to sell assets whose price has declined. A managing director at Deutsche Bank, for instance, states, “From a capital perspective, it is difficult to sell assets in the banking book [valued under historic cost]. Selling an asset below book value means taking a loss” (Whittaker [2012]). As long as banks think that reporting higher capital is viewed in a positive way by the markets, banks have incentives to consider how asset sales affect capital.

2.5.2 *Set-Up*

This model has five dates, $t \in \{0, 1, 2, 3, 4\}$. Banks have safe and toxic assets, F and X . F can be viewed as high-quality government securities (*e.g.*, US Treasuries, German bunds); X ,

as sub-prime-backed MBS. F and X mature at time 4 and are financed in full by wholesale debt that banks must roll over at time 3. R_F is returns on F . $R_X^H > R_X^S$ are returns on units of X that banks hold to maturity and that banks sell. R_F is the same irrespective of whether banks sell F or hold F to maturity. $0 \leq p \leq 1$ is the probability wholesale creditors roll over funds. If creditors do not roll over funds, banks must sell all of their unsold holdings of X , leading to the below-fundamentals return $R_X^S < R_X^H$. Hence, wholesale runs impose costs by forcing banks to liquidate X at a distressed, below-fundamentals price, reducing returns on X . Letting S_F and S_X denote sales of F and X , banks maximize returns, R :

$$\max_{S_F, S_X} R \equiv R_F Q_F + R_X^H [Q_X - S_X] p + R_X^S [S_X + [Q_X - S_X] [1 - p]], \quad (2.1)$$

Selling X locks in the below-fundamentals return $R_X^S < R_X^H$, a negative effect. Also, sales of both F and X affect R via their impact on p , as specified below.

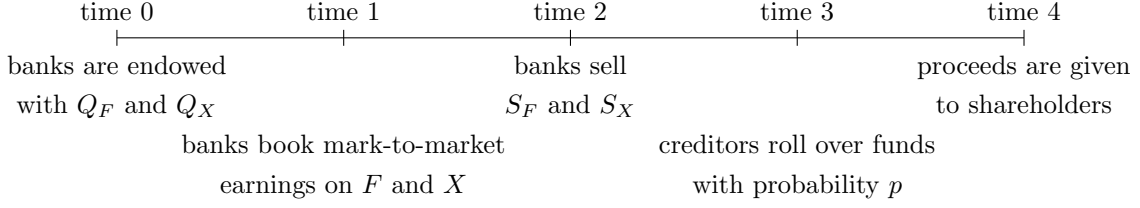
The timeline is as follows (see also Figure 4):

- At time 0, banks are exogenously endowed with K_0 in capital and Q_F and Q_X units of F and X . P_F^0 and P_X^0 are time-0 prices (and also time-0 book values).
- At time 1, a negative shock—for instance, a housing-price drop that increases mortgage default rates—hits the economy. P_F rises to $P_F^1 > P_F^0$. P_X falls to $P_X^1 < P_X^0$. P_F 's rise can be seen as the outcome of a rise in demand for safe assets; P_X 's fall, of deteriorating fundamentals and market “dislocations.”

These changes in prices result in per-unit valuation earnings, or mark-to-market earnings, of $M_F [P_F^1 - P_F^0] \geq 0$ and $M_X [P_X^1 - P_X^0] \leq 0$. Banks book these earnings on each of the Q_F and Q_X units of F and X they are endowed with at time 0.

$0 \leq M \leq 1$ is the share of the time-1 price changes banks book earnings on. $M = 1$ corresponds to a pure fair-value, or mark-to-market, regime, under which price changes

Figure 4: Model Timeline



flow fully to earnings and capital, on a one-for-one basis; $M = 0$, to a pure historic-cost regime, under which price changes never affect earnings or capital.

- At time 2, banks sell S_F units of F and S_X units of X , with per-unit gains on sales of $G_F \equiv [1 - M_F][P_F^1 - P_F^0] \geq 0$ and $G_X \equiv [1 - M_X][P_X^1 - P_X^0] \leq 0$ —banks book gains and losses equal to the entire change at time 1 in the prices of F and X less any gains and losses already booked on these changes in prices. Sales result in returns of R_F and $R_X^S < R_X^H$. Banks use the cash from sales to retire debt, not to reinvest. $Q_F \geq S_F$, and $Q_X \geq S_X$, effectively ruling out short sales. (These last two assumptions help simplify the model and exposition.)

Between time 2 and time 3, banks book net interest income of $I_F > 0$ and $I_X > 0$ on each unit of F , $Q_F - S_F$, and X , $Q_X - S_X$, not sold at time 2.

- At time 3, creditors evaluate banks' credit risk and decide whether to roll over funding. Creditors roll over funding either in full or not at all. If creditors pull funds, banks sell all of their unsold units of F and X . (Letting banks sell only some fraction of F and X complicates the model without qualitatively altering any results.) Creditors roll over funding with probability p . Sales result in returns of R_F and R_X^S .
- At time 4, F and X mature. Banks collect interest and principal and give the proceeds to shareholders. Returns on units of F and X held to time 4 are R_F and $R_X^H > R_X^S$.

$p = p(K, H)$, the probability that creditors roll over funding, is an increasing and concave

function of capital as of time 3, K , and the percentage of F in total assets as of time 3, H . H is a measure of balance-sheet strength, or asset quality. K and H are as follows:

- K , capital, consists of initial capital, K_0 , and the change in capital before time 3. This change in capital is equivalent to total earnings before time 3. K is

$$K = K_0 + \overbrace{M_F [P_F^1 - P_F^0] Q_F}^{\text{time-1 MTM gains on } F} + \overbrace{M_X [P_X^1 - P_X^0] Q_X}^{\text{time-1 MTM losses on } X} + \overbrace{[1 - M_F] [P_F^1 - P_F^0] S_F}^{\text{gains on time-2 sales of } F} \\ + \overbrace{[1 - M_X] [P_X^1 - P_X^0] S_X}^{\text{losses on time-2 sales of } X} + \overbrace{I_F [Q_F - S_F]}^{\text{net int. inc. on } F} + \overbrace{I_X [Q_X - S_X]}^{\text{net int. inc. on } X}.$$

- $H = \frac{Q_F - S_F}{A}$, where $A \equiv Q_F - S_F + Q_X - S_X$ is total assets.

Hence, more capital and a stronger balance sheet reduce credit risk, reducing the probability of a wholesale run. $p()$'s concavity reflects diminishing returns to increasing capital and to improving asset quality in increasing the probability that creditors roll over funding. Strictly speaking, p should be a function of banks' capital-to-asset ratios, not capital, but using only capital helps simplify the math without qualitatively changing any results.

Under fair value, $M_F = M_X = 1$. Under historic cost, $M_F = M_X = 0$. As a consequence, per-unit mark-to-market earnings and gains and losses on sales are as follows:

MTM earnings, fair value:	$1 [P_F^1 - P_F^0]$	$= P_F^1 - P_F^0 > 0$
	$1 [P_X^1 - P_X^0]$	$= P_X^1 - P_X^0 < 0$
gains on sales, fair value:	$[1 - 1] [P_F^1 - P_F^0]$	$= 0$
	$[1 - 1] [P_X^1 - P_X^0]$	$= 0$
MTM earnings, historic cost:	$0 [P_F^1 - P_F^0]$	$= 0$
	$0 [P_X^1 - P_X^0]$	$= 0$
gains on sales, historic cost:	$[1 - 0] [P_F^1 - P_F^0]$	$= P_F^1 - P_F^0 > 0$
	$[1 - 0] [P_X^1 - P_X^0]$	$= P_X^1 - P_X^0 < 0$.

As a result, under fair value, banks book mark-to-market gains and losses equal to the entire time-1 change in prices; sales result in no gains or losses at all and thus do not affect capital. Under historic cost, the time-1 change in prices leads to no gains or losses; sales lead to gains or losses equal to the entire time-1 change in prices. A higher M_X can be seen also as a more-aggressive impairment regime under historic cost, so that a given change in prices results in larger immediate write-downs. In this case, mark-to-market losses on X are larger; losses on sales are smaller. A lower M_X can be seen also as letting banks rely under fair value more on internal models and less on market prices, so that a given change in prices results in smaller immediate write-downs. In this case, mark-to-market losses on X are smaller; losses on sales are larger. (These examples are less relevant for F (see Section 4.2).)

2.5.3 The Trade-Offs of Asset Sales

Letting sub-scripts denote partial derivatives, differentiating equation (1) with respect to S_F and S_X yields two first-order conditions,

$$\frac{\partial R}{\partial S_F} = \alpha \left[p_K () [G_F - I_F] + p_H () \frac{S_X - Q_X}{A^2} \right] = 0 \quad (2.2)$$

$$\frac{\partial R}{\partial S_X} = [R_X^S - R_X^H] p () + \alpha \left[p_K () [G_X - I_X] + p_H () \frac{Q_F - S_F}{A^2} \right] = 0 \quad (2.3)$$

$$\alpha \equiv [R_X^H - R_X^S] [Q_X - S_X] > 0.$$

α is the per-unit increase in R_X due to holding X to maturity instead of selling X , $R_X^H - R_X^S$, multiplied by the number of units of X banks hold to maturity should creditors not withdraw funding, $Q_X - S_X$. Hence, the $\alpha []$ terms are the net impact of asset sales on the probability of avoiding a wholesale run, as captured by the $p_K () []$ and the $p_H ()$ terms, multiplied by the benefits of avoiding a wholesale run—of not having to liquidate X at a below-fundamentals price should creditors pull funding.

Re-arranging the first-order condition (2),

$$\alpha p_K () [G_F - I_F] = \alpha p_H () \frac{Q_X - S_X}{A^2}. \quad (2.4)$$

In (4), the right-hand side is always positive and captures the costs of marginal sales of F . This cost is the decline in H , F 's share in total assets, due to selling F . Selling F weakens banks' balance sheets. As a result, credit risk rises, reducing p . The left-hand side could be either positive or negative, depending on whether gains on sales, G_F , or net interest income, I_F , dominates. If $G_F > I_F$, so that gains on sales exceed the net interest income foregone by selling F , this term is positive. Sales of F increase capital compared to not selling F . Hence, credit risk falls, increasing p . If $I_F > G_F$, this term is negative. Sales reduce capital, credit risk rises, and p thus declines. In this situation, sales of F are strictly negative, in that sales both reduce balance-sheet strength and reduce capital. Consequently, banks choose $S_F = 0$. If $G_F > I_F$, banks choose S_F so as to equate the costs and benefits of marginal sales of F .

Re-arranging the first-order condition (3),

$$\alpha p_H () \frac{Q_F - S_F}{A^2} = [R_X^H - R_X^S] p () - \alpha p_K () [G_X - I_X]. \quad (2.5)$$

In (5), the left-hand side captures the benefits of marginal sales of X . This benefit is the rise in H due to selling X . This increase in H reduces credit risk, raising p . The first right-hand side term is the cost of selling X in passing up with certainty the fundamentals-based return $R_X^H > R_X^S$, multiplied by the probability banks can hold to maturity—do not have to sell at time 3—units of X not sold at time 2. The second right-hand side term is the cost of selling X in reducing K . This decline in K increases credit risk, reducing p . In equilibrium, banks choose S_X so as to equate the first effect with the sum of the latter two.

Differentiating (2) with respect to S_F and (3) with respect to S_X yields the second-order

conditions

$$\frac{\partial^2 R}{\partial S_F^2} = \alpha^* \left[p_{KK} () [G_F - I_F]^2 + p_{HH} () \left[\frac{S_X^* - Q_X}{A^{*2}} \right]^2 + p_H () \frac{2A^* [S_X^* - Q_X]}{A^{*4}} \right] < 0 \quad (2.6)$$

$$\begin{aligned} \frac{\partial^2 R}{\partial S_X^2} &= 2 [R_X^S - R_X^H] \left[p_K () [G_X - I_X] + p_H () \frac{Q_F - S_F^*}{A^{*2}} \right] \\ &+ \alpha^* \left[p_{KK} () [G_X - I_X]^2 + p_{HH} () \left[\frac{Q_F - S_F^*}{A^{*2}} \right]^2 + p_H () \frac{2A^* [Q_F - S_F^*]}{A^{*4}} \right] \leq 0, \end{aligned} \quad (2.7)$$

where an * denotes an equilibrium value. Since $\frac{\partial^2 R}{\partial S_F^2} < 0$, S_F^* is a maximum. Technically, (7)'s sign is ambiguous. This ambiguity is due to the $\alpha^* []$ term—the first two terms in brackets are negative, but the third term is positive. In the top-line term, however, the $p_H ()$ term is larger in magnitude than is the $p_K ()$ term.⁶ As a result, since the $p_H ()$ term is positive and $R_X^S - R_X^H < 0$, the top-line term is negative. Hence, assuming the three terms in brackets in $\alpha^* []$ largely cancel out, or that the $p_H ()$ term is not “too dominant” *vis-á-vis* the first two terms in brackets, $\frac{\partial^2 R}{\partial S_X^2} < 0$, so that S_X^* is a maximum. Going forward, I assume $\frac{\partial^2 R}{\partial S_X^2} < 0$, which is equivalent to assuming sales of X have diminishing returns.

2.5.4 Accounting Standards and Asset Sales

In this section, I focus on how changes in M_F and M_X impact S_F^* and S_X^* . A rise in M_F and M_X can be seen as a move toward fair value; a rise in M_X can be seen also as more-aggressive impairment recognition under historic cost, or as relying less on models under fair value. To start, in Section 5.4.1, I go over the partial effects of M_F and M_X . In Section 5.4.2, I focus on the total effects of M_F and M_X .

⁶ In equilibrium, from the first-order condition (3), $[R_X^S - R_X^H] p () + \alpha \left[p_K () [G_X - I_X] + p_H () \frac{Q_F - S_F^*}{A^2} \right] = 0$. $[R_X^S - R_X^H] p () < 0$. As a result, to satisfy (3), the $\alpha []$ term has to be positive. $\alpha > 0$. Since $G_X - I_X < 0$, the $p_K () []$ term in brackets is negative. Consequently, the $p_H ()$ term in brackets must be positive and larger in magnitude than the $p_K () []$ term for (3) to hold.

Fair Value's Impact: Partial Effects

S_F^* and S_X^* are jointly determined. Intuitively, this joint determination means that the effect of M_F and M_X on S_F^* and S_X^* rests not only on the direct effects of M_F and M_X —how M_F affects S_F^* and S_X^* , and how M_X affects S_F^* and S_X^* —but also on the indirect effects of M_F and M_X . These indirect effects are driven by the link between S_F^* and S_X^* . To illustrate, I show later in Section 5.4 that a rise in M_F reduces S_F^* and that S_F^* and S_X^* are complements, so that sales of one type of asset increase sales of the other type. As a result, the decline in S_F^* that results from a rise in M_F reduces S_X^* . This indirect effect comes on top of the direct effect of a rise in M_F on S_X^* . The total effect of M_F depends on how this direct and indirect effect interact.

In this section, I work through the partial effects of M_F and M_X , saving the total effects for Section 5.4.2. Implicitly differentiating S_F^* with respect to M_F and M_X , where $\beta \equiv \frac{\partial^2 R}{\partial S_F^2} < 0$,

$$\frac{\partial S_F^*}{\partial M_F} = - \frac{\alpha^* [p_{KK} () [G_F - I_F] [[Q_F - S_F^*] [P_F^1 - P_F^0]] - p_K () [P_F^1 - P_F^0]]}{\beta} < 0 \quad (2.8)$$

$$\frac{\partial S_F^*}{\partial M_X} = - \frac{\alpha^* [p_{KK} () [G_F - I_F] [[Q_X - S_X^*] [P_X^1 - P_X^0]]]}{\beta} \lesseqgtr 0. \quad (2.9)$$

In (9), the impact of a marginal rise in M_F on S_F^* depends on whether G_F or I_F dominates. An increase in M_X lowers capital, K , by increasing total losses on units of X not sold at time 2.⁷ Because of diminishing returns to K , a marginal increase in K is more beneficial, and a marginal fall in K , more harmful, when K is lower. If G_F dominates, sales of F increase K , on net. In this case, $\frac{\partial S_F^*}{\partial M_X} > 0$ —a marginal rise in M_X increases S_F^* . A rise in M_X reduces K . Consequently, the increase in K that results from selling F is more beneficial, increasing S_F^* . If I_F dominates, sales reduce K , on net. In this case, $\frac{\partial S_F^*}{\partial M_X} < 0$. Sales of F reduce K ,

⁷ For those units of X banks sell, a rise in M_X increases time-1 mark-to-market losses but reduces losses on time-2 sales. Hence, total losses on X are independent of M_X . In the same way, total gains on units of F banks sell are independent of M_F ; M_F affects capital only via its impact on unsold units of F .

and a decline in K is more harmful at lower levels of K . Hence, S_F^* declines.

In (8), a marginal increase in M_F reduces S_F^* . $-p_K () [P_F^1 - P_F^0]$ is negative. A rise in M_F increases mark-to-market gains on F . Hence, for any given increase in P_F , gains on sales of F and the rise in capital that results are smaller, reducing S_F^* . The $p_{KK} ()$ term could be either positive or negative, depending on whether G_F or I_F dominates. A marginal increase in M_F increases K by increasing total gains on those units of F that banks do not sell at time 2. Due to diminishing returns to K , when K is higher, a marginal rise in K is less beneficial, and a marginal fall in K , less harmful. As a result, if G_F dominates, so that the $p_{KK} ()$ term is negative, the increase in K that stems from selling F is less beneficial, reducing S_F^* . If I_F dominates, so that the $p_{KK} ()$ term is positive, the fall in K that stems from selling F is less harmful, increasing S_F^* . In signing (8), I assume G_F and I_F roughly offset, or that I_F is not dominant enough to offset the unambiguous impact of $-p_K () [P_F^1 - P_F^0]$.

Implicitly differentiating S_X^* with respect to M_F and M_X , where $\gamma \equiv \frac{\partial^2 R}{\partial S_X^2} < 0$,

$$\frac{\partial S_X^*}{\partial M_F} = - \frac{\alpha^* [p_{KK} () [G_X - I_X] [[Q_F - S_F^*] [P_F^1 - P_F^0]]]}{\gamma} > 0 \quad (2.10)$$

$$\frac{\partial S_X^*}{\partial M_X} = - \frac{\alpha^* [p_{KK} () [G_X - I_X] [[Q_X - S_X^*] [P_X^1 - P_X^0]] - p_K () [P_X^1 - P_X^0]] + \kappa}{\gamma} \leq 0 \quad (2.11)$$

$$\kappa \equiv [R_X^S - R_X^H] p_K () [[Q_X - S_X^*] [P_X^1 - P_X^0]] > 0.$$

In (10), a marginal increase in M_F increases S_X^* . Sales of X reduce capital, K , due to losses on sales and the loss of net interest income. For any given rise in the price of F , a marginal increase in M_F increases K by increasing total gains on units of F banks do not sell at time 2. As a result of diminishing returns to K , declines in K are less harmful when K is higher. Consequently, the decline in K that results from selling X is less harmful. Hence, banks sell more units of X . This rise in S_X^* contrasts with the fall in S_F^* that results from a marginal rise in M_F .

In (11), a marginal increase in M_X has an ambiguous impact on S_X^* . The $p_{KK}()$ term is negative. Sales of X reduce K . A rise in M_X reduces K by increasing total losses on unsold units of X . Due to diminishing returns to K , a marginal decline in K is more harmful when K is lower. As a result, the decline in K that stems from selling X is more harmful, reducing S_X^* . The other two terms are positive. With respect to the $p_K()$ term, an increase in M_X increases mark-to-market losses on X . As a consequence, for any given decline in P_X , banks book smaller losses on sales. Consequently, sales of X reduce K by less, increasing S_X^* . With respect to κ , a rise in M_X reduces K by increasing total losses on unsold units of X . A fall in K reduces the probability that creditors will roll over funds. Sales of X thus are less costly, increasing S_X^* —because banks are more likely to have to sell X at time 3, selling X at time 2 is less harmful. A rise in M_X reduces S_X^* , on net, only insofar as the first effect dominates the sum of the latter two. Otherwise, a rise in M_X increases S_X^* .

In sum, marginal increases in M_F and M_X have the following effects:

- (1) A marginal rise in M_F reduces S_F^* , so that banks sell fewer safe assets;
- (2) a marginal rise in M_F increases S_X^* , so that banks sell more toxic assets; and
- (3) a marginal rise in M_X has an ambiguous effect on both S_F^* and S_X^* .

Fair Value's Impact: Total Effects

In this section, I go through the total effects of M_F and M_X . The Hessian matrix of partials, E , is

$$E \equiv \begin{bmatrix} S_{F S_F}^* & S_{F S_X}^* \\ S_{X S_F}^* & S_{X S_X}^* \end{bmatrix}.$$

Differentiating S_F^* with respect to S_X^* (by Young's Theorem, $\frac{\partial S_F^*}{\partial S_X^*} = \frac{\partial S_X^*}{\partial S_F^*}$),

$$\begin{aligned} \frac{\partial S_F^*}{\partial S_X^*} = & \alpha^* [p_{KK} () [G_F - I_F] [G_X - I_X] \\ & + p_{HH} () \left[\frac{S_X^* - Q_X}{A^{*2}} \right] \left[\frac{Q_F - S_F^*}{A^{*2}} \right] + p_H () \frac{Q_F^2 + S_F^{*2} + Q_X^2 + S_X^{*2}}{A^{*4}} \right] > 0. \end{aligned} \quad (2.12)$$

Technically, (12)'s sign is indeterminate. The $p_{KK} ()$ term could be negative if $I_F > G_F$, so that selling F effectively reduces capital. In signing (12), I assume G_F and I_F roughly offset, or that I_F is not dominant enough to offset the other two terms, both of which are positive. Assuming $\frac{\partial S_F^*}{\partial S_X^*} > 0$, S_F^* and S_X^* are complements, so that selling one type of asset increases sales of the other. Since $S_{F S_X}^* = S_{X S_F}^* > 0$, $S_{F S_F}^* < 0$, and $S_{X S_X}^* < 0$, the determinant of E , $\text{Det}[E]$, is positive, so that (S_F^*, S_X^*) is a maximum.

The first-order conditions (2) and (3) can be written as the pair of implicit functions

$$\begin{aligned} S_F^* &= S_F^* (S_F^*, S_X^*; M_F, M_X) = 0 \\ S_X^* &= S_X^* (S_F^*, S_X^*; M_F, M_X) = 0. \end{aligned}$$

The resulting system of equations is

$$\begin{aligned} S_F^* () &= S_{F S_F}^* dS_F + S_{F S_X}^* dS_X + S_{F M_F}^* dM_F + S_{F M_X}^* dM_X = 0 \\ S_X^* () &= S_{X S_F}^* dS_F + S_{X S_X}^* dS_X + S_{X M_F}^* dM_F + S_{X M_X}^* dM_X = 0. \end{aligned}$$

Focusing first on M_F , converting dM_F into ∂M_F , setting $dM_X = 0$, re-arranging, and writing in matrix notation,

$$\begin{bmatrix} S_{F S_F}^* & S_{F S_X}^* \\ S_{X S_F}^* & S_{X S_X}^* \end{bmatrix} \begin{bmatrix} \frac{\partial S_F^*}{\partial M_F} \\ \frac{\partial S_X^*}{\partial M_F} \end{bmatrix} = - \begin{bmatrix} S_{F M_F}^* \\ S_{X M_F}^* \end{bmatrix}.$$

Re-arranging, where the numerators are the determinants of the relevant matrix:

$$\begin{aligned}
S_{F M_F}^* &= \begin{bmatrix} -S_{F M_F}^* & S_{F S_X}^* \\ -S_{X M_F}^* & S_{X S_X}^* \end{bmatrix} \\
&= \frac{-S_{F M_F}^* S_{X S_X}^* + S_{F S_X}^* S_{X M_F}^*}{\text{Det}[E]} \begin{matrix} \leq 0 \\ > 0 \end{matrix}
\end{aligned} \tag{2.13}$$

$$\begin{aligned}
S_{X M_F}^* &= \begin{bmatrix} S_{F S_F}^* & -S_{F M_F}^* \\ S_{X S_F}^* & -S_{X M_F}^* \end{bmatrix} \\
&= \frac{-S_{F S_F}^* S_{X M_F}^* + S_{F M_F}^* S_{X S_F}^*}{\text{Det}[E]} \begin{matrix} \leq 0 \\ > 0 \end{matrix}
\end{aligned} \tag{2.14}$$

In both (13) and (14), the indirect effects run counter to—can help offset—the direct effects of a marginal rise in M_F . Hence, theoretically, the total effect of a rise in M_F is ambiguous. In (13), on the margin, an increase in M_F lowers S_F^* , the direct effect. A rise in M_F , however, also increases S_X^* , and a rise in S_X^* increases S_F^* , the indirect effect. Likewise, in (14), the direct effect of a rise in M_F is to increase S_X^* , but a rise in M_F also reduces S_F^* , and a decline in S_F^* reduces S_X^* .

Turning to M_X , following the same steps as for M_F :

$$\begin{bmatrix} S_{F S_F}^* & S_{F S_X}^* \\ S_{X S_F}^* & S_{X S_X}^* \end{bmatrix} \begin{bmatrix} \frac{\partial S_F^*}{\partial M_X} \\ \frac{\partial S_X^*}{\partial M_X} \end{bmatrix} = - \begin{bmatrix} S_{F M_X}^* \\ S_{X M_X}^* \end{bmatrix} .$$

Re-arranging, where the numerators are the determinants of the relevant matrix:

$$\begin{aligned}
S_{F M_X}^* &= \begin{bmatrix} -S_{F M_X}^* & S_{F S_X}^* \\ -S_{X M_X}^* & S_{X S_X}^* \end{bmatrix} \\
&= \frac{-S_{F M_X}^* S_{X S_X}^* + S_{F S_X}^* S_{X M_X}^*}{\text{Det}[E]} \begin{matrix} \leq 0 \\ > 0 \end{matrix}
\end{aligned} \tag{2.15}$$

$$\begin{aligned}
S_{X M_X}^* &= \begin{bmatrix} S_{F S_F}^* & -S_{F M_X}^* \\ S_{X S_F}^* & -S_{X M_X}^* \end{bmatrix} \\
&= \frac{-S_{F S_F}^* S_{X M_X}^* + S_{F M_X}^* S_{X S_F}^*}{\text{Det}[E]} \begin{matrix} \leq 0 \\ > 0 \end{matrix}
\end{aligned} \tag{2.16}$$

Similar to M_F , the total effect of a rise in M_X is ambiguous. In (15), a marginal rise in M_X can either increase or reduce S_F^* , the direct effect. With respect to the indirect effect, a rise in M_X has an ambiguous effect on S_F^* ; if M_X increases S_X^* , this rise in S_X^* increases S_F^* , but if M_X reduces S_X^* , S_F^* falls. In (16), an increase in M_X has an ambiguous impact on S_X^* , the direct effect. With respect to the indirect effect, an increase in M_X has an ambiguous effect on S_X^* ; the indirect effect increases S_X^* if a rise in M_X increases S_F^* and reduces S_X^* if a rise in M_X reduces S_F^* .

In sum, theoretically, the indirect effects identified above can help offset the direct effects of a change in M_F and a change in M_X . Hence, these indirect effects can dampen fair value's total effects. Empirically, however, S_F and S_X are uncorrelated, while a rise in M_X increases S_X^* and reduces S_F^* , although the impact of M_X on S_F^* is not robust to how M_X is defined (Section 6.6). Consequently, the indirect effects of M_F and M_X likely have a limited impact in offsetting the direct effects thereof. As a result, focusing on the partial effects of M_F and M_X yields useful insights into fair value's impact on the asset-sale decisions of banks. In the rest of this paper, I assess empirically how M_X affects S_F^* and S_X^* .

2.6 Empirical Tests

2.6.1 The 2007–8 Financial Crisis, Safe Assets, and Toxic Assets

In the empirical tests that follow, I examine security sales by US banks from 2007Q4–2008Q4. With respect to the sample period, 2007Q4—2008Q4 covers the worst part of the crisis, when banks' distress was strongest. In 2007Q3, banks had \$33 billion in aggregate pre-tax income (Section 3.1, Figure 2). Over the next five quarters, aggregate income fell to -\$14 billion, \$13 billion, -\$2 billion, -\$32 billion, and -\$77 billion. Earnings turned positive once again in 2009, albeit smaller than before the crisis. With respect to security sales, prior studies (Bernanke and Gertler [1995], Hancock, Laing, and Wilcox [1995], Kashyap and Stein [2000]) find that

securities bear the brunt of banks' short-run asset-side adjustments to adverse shocks.

For safe assets, F , I use US Treasury securities, US Agency securities, and government-issued or -sponsored MBS (Agency MBS). These securities have either the explicit or implicit backing of the US government and were among the best-performing assets in the crisis (*e.g.*, Noeth and Sengupta [2010]). Banks' valuations were higher as of the end of 2008 than as of the end of 2007Q2 (Section 4.1, Figure 3). Liquidity stayed strong. For toxic assets, X , I use private-label MBS. Private-label MBS are MBS backed largely by low-quality sub-prime and Alt-A mortgages whose fundamentals collapsed starting in 2007. This collapse led to a sharp drop in the prices of private-label MBS and similar securities (*e.g.*, IMF [2008], p. 13). By the end of 2008, banks valued their private-label MBS at 20 percent below par (Section 4.1, Figure 3). The market for these securities evaporated (Gorton [2008]). In short, private-label MBS were among the most toxic of banks' assets during the 2007–8 crisis.

2.6.2 *Impairments and Asset Sales*

In my model, I focus on the impact of accounting standards on the quantities of safe and toxic assets banks sell. I focus primarily on how asset sales and the gains and losses thereon impact capital under fair-value accounting and historic-cost accounting. Compared to historic cost, fair value reduces gains on sales of safe assets, inducing fewer sales of these assets; fair value also decreases losses on sales of toxic assets, among other effects, potentially inducing more sales of these assets. Also, my model yields insights into the effect of impairment losses under historic cost and the fair-value hierarchy under fair value (see Section 4.2). More-aggressive impairment recognition is equivalent to a move toward fair value—to a rise in M_X . Greater use of internal models under the fair-value hierarchy is equivalent to a move toward historic cost—to a fall in M_X .

Ideally, I would take the assets of banks valued under fair value, calculate mark-to-market gains on safe assets and losses on private-label MBS compared to the change in the prices of

each type of asset, and examine how these gains and losses affect sales of both safe assets and private-label MBS. Using publicly available data, this approach is not viable. For regulatory-capital purposes, fair value is applied primarily to trading-account assets. Banks' regulatory reports and financial statements both give only a rough proxy for mark-to-market gains and losses on all trading assets, grouped together. Gains and losses by specific asset type are not given. In addition, regulatory reports and financial statements provide only the fair value of trading assets. Changes in these values are due to both price and quantity effects—to both changes in prices and asset sales. To the best of my knowledge, making a reliable adjustment that strips out price effects is not possible using available data.

As a second-best solution, I focus on impairments on private-label MBS. I examine the impact of impairments on sales of safe assets and private-label MBS. Securities are classified as trading, available for sale (AFS), or held to maturity (HTM). AFS and HTM securities are valued under historic cost in calculating earnings and regulatory capital. Banks thus do not book mark-to-market gains and losses on AFS and HTM securities. Banks, however, do have to take impairment losses on securities that satisfy certain criteria. In taking impairments, banks write down the book value of the impaired security by the amount of the impairment. I assess how more-aggressive recognition of impairments—taking larger write-downs—affects asset sales. Since impairments generally are irrelevant for safe assets, I focus on impairments only on private-label MBS.

More-aggressive recognition of impairments is akin to a rise in M_X . For a given decline in prices, an increase in impairments increases losses before selling assets and reduces losses on sales. Technically, impairments are endogenous in that banks have discretion in determining whether to take an impairment and how large an impairment to take. Banks' annual reports, however, are subject to external audits. Also, the SEC has specified criteria banks must use when determining whether an asset is impaired (SEC [2009]).⁸ In addition, taking inadequate

⁸ These criteria include how long and the extent to which the price of a security has been below cost, the

impairments exposes banks to lawsuits. Citigroup, for instance, paid \$590 million in 2012 to settle a lawsuit with plaintiffs who alleged that Citi, among other actions, took insufficiently large write-downs on certain collateralized debt obligations (Stempel [2012]). Hence, though impairments are not completely exogenous, banks do face certain constraints on their ability to avoid taking appropriate impairments.

2.6.3 Data Sources and Sample

I get all financial-statement data from the FR Y9-C. (Y9-C mnemonics are in the appendix.) I hand-collect from banks' 10-Ks and 10-Qs data on impairments and reclassifications. Banks tend to identify the specific security type impairments and reclassifications relate to, and in a way that maps into the Y9-C's security accounts. Citigroup's 2008 10-K, for instance, states that Citi took "\$1.611 billion of [impairment] losses [on Alt-A-backed MBS]." Hence, I can distinguish private-label MBS impairments from impairments on other security types, and I can map impairments on private-label MBS into the Y9-C's private-label MBS account. Two exceptions are Bank of America and Wachovia. Both banks refer to impairments mainly on "ABS CDO," or CDO backed by asset-backed securities, sometimes private-label MBS. The Y9-C security account these securities are classified in is unclear. As a result, I run my tests with and without these two banks. In both instances, my results are the same.

My sample covers each quarter t from 2007Q4–2008Q4. I impose two criteria for inclusion. First, since I get impairment and reclassification data from public financial statements, banks have to be publicly traded. Second, banks have to hold (AFS) private-label MBS at the start of t . Banks may be net buyers, net sellers, or inventory-neutral in t ; I impose no restrictions on the change in private-label MBS during t . I impose this condition so as to focus solely on relevant banks. In each quarter in my sample, roughly 35 percent of banks held private-label MBS. Banks that do not hold private-label MBS cannot sell private-label MBS. Hence, given

"financial condition and near-term prospects of the [security's] issuer," and the ability of banks to hold the security until its price recovers. Each of these factors becomes important during crises.

my focus, these banks are irrelevant. Each bank with private-label MBS at the beginning of t has safe assets, as well. My sample consists of 417 bank-quarters and 92 individual banks. In each quarter from 2007Q4–2008Q4, my sample accounts for between 68 and 73 percent of total (AFS) safe assets and 87 and 90 percent of total (AFS) private-label MBS.⁹

2.6.4 Models and Hypotheses

Models and Variables

I estimate the models below (see the appendix for more-precise variable definitions):

$$\begin{aligned} \Delta SAFE_{it} = & \beta_0 + \beta_1 \Delta MBS_{it} + \beta_2 IMP_{it-1} + \beta_3 CAP_{it-1} + \beta_4 LLP_{it} \\ & + \beta_5 DEP_{it-1} + \beta_6 SAFEEXP_{it-1} + \beta_7 MBSQUAL_{it-1} + \varepsilon_{it} \end{aligned} \quad (1)$$

$$\begin{aligned} \Delta MBS_{it} = & \gamma_0 + \gamma_1 \Delta SAFE_{it} + \gamma_2 IMP_{it-1} + \gamma_3 CAP_{it-1} + \gamma_4 LLP_{it} \\ & + \gamma_5 DEP_{it-1} + \gamma_6 MBSEXP_{it-1} + \gamma_7 MBSQUAL_{it-1} + \epsilon_{it}. \end{aligned} \quad (2)$$

The i and t sub-scripts denote banks and time, $SAFE$ and MBS are safe assets and private-label MBS, ε and ϵ are error terms, and

$$\begin{aligned} \Delta SAFE_{it} &= \ln [1 + SAFE_{it}] - \ln [1 + SAFE_{it-1}] \\ \Delta MBS_{it} &= \ln [1 + MBS_{it} + RAWIMP_{it} - RECLASS_{it}] - \ln (1 + MBS_{it-1}). \end{aligned}$$

Models (1) and (2) include also time and bank fixed effects. Using time fixed effects controls for period-specific shocks that affected all banks' asset-sale decisions. Using bank fixed effects controls for cross-sectional differences in banks' propensity to take impairments (Vyas [2011]) and other unobservable, time-invariant differences across banks. CAP , banks' Tier 1 capital

⁹ This sample consists mainly of large banks (*e.g.*, Bank of America), as these banks accounted for most of banks' private-label MBS.

ratio in excess of a six-percent baseline, and *DEP*, the fraction of deposits in total liabilities, control for the impact of capital (in levels) and funding pressure, where a higher *DEP* implies less reliance on wholesale funding. *LLP*, loan-loss provisions divided by average total assets, controls for the impact of changes in capital. *LLP* aside, I use lags so as to avoid endogeneity.

Absent suitable controls, impairments could effectively be a proxy for asset quality, with more impairments representing lower-quality private-label MBS. To control for asset quality, I use *MBSQUAL*, defined as fair value divided by the amortized-cost value of banks' private-label MBS. Fair values are banks' estimates of the value of their private-label MBS, calculated by using market prices, internal models, or some combination of the two. The fair value of an asset varies with changes in its price, or its value. Roughly stated, amortized-cost values are par values. An asset's amortized-cost value does not vary with changes in its price.¹⁰ A lower *MBSQUAL* indicates a lower fair value compared to amortized-cost value, implying lower-quality private-label MBS. Hence, *MBSQUAL* controls for changes over time in the quality of each bank's own private-label MBS. (Using bank fixed effects controls for differences across banks in the quality of banks' private-label MBS.)

With respect to *SAFE* and *MBS*, four comments: First, *SAFE* and *MBS* are based on amortized-cost values, not on fair values. As a consequence, $\Delta SAFE$ and ΔMBS are driven only by quantity effects—by sales and purchases. Second, $\Delta SAFE$ and ΔMBS include only AFS securities. (AFS securities account for over 70 percent of banks' safe assets and private-label MBS.) The Y9-C gives only the fair value of trading securities, and banks face penalties upon selling HTM securities (see FRB of Kansas City [2010], p. 76). Third, impairments in t reduce amortized-cost values at the end of t . Hence, I add to ΔMBS *RAWIMP*, total raw impairments. Fourth, banks may reclassify securities into and out of their trading, AFS, and

¹⁰ Taking an impairment reduces an asset's amortized-cost value. Hence, technically, impairments should be added back to the amortized-cost value in *MBSQUAL*. Even without this adjustment, however, impairments and *MBSQUAL* are strongly correlated, leading to multicollinearity concerns. Adjusting *MBSQUAL* for impairments exacerbates this problem. Hence, I do not adjust *MBSQUAL* for impairments.

HTM accounts. As a result, I subtract from $\Delta MBS RECLASS$, net transfers into the AFS account.¹¹ Based on financial-statement disclosures, no impairments on or reclassifications of safe assets occurred during my sample period.

I estimate models (1) and (2) with three-stage least squares (3SLS). $\Delta SAFE$ and ΔMBS are jointly determined and endogenous, with sales of one asset type affecting sales of the other (Section 5.4.2, equation (12)). 3SLS generates efficient, consistent estimates that account for this simultaneity and endogeneity (Zellner and Thiel [1962]). 3SLS requires instruments for $\Delta SAFE$ and ΔMBS . For $\Delta SAFE$, I use $SAFEEXP$, the share of AFS safe assets in total assets; for ΔMBS , I use $MBSEXP$, the share of AFS private-label MBS in total assets. On a within-bank, cross-temporal basis, a higher-than-average percentage of safe assets implies that a bank is overweight these assets, inducing more sales. Likewise, a higher-than-average percentage of private-label MBS implies that a bank is overweight these assets, inducing more sales. Due to banks' large holdings of assets other than safe assets and private-label MBS, $MBSEXP$ is uncorrelated with $\Delta SAFE$, and $SAFEEXP$ is uncorrelated with ΔMBS (Section 6.5, Table 3¹²).¹³

Impairment Definitions and Hypotheses

My empirical tests focus on IMP , defined in two ways. One is $IMPTOT$, defined as the log of $[1 + \text{total impairments}]$. $IMPTOT$ measures only the magnitude of banks' impairments, without reference to the change in the price of the private-label MBS of banks. M_X , however, is defined as mark-to-market losses as a share of the total fall in the price of X . As a result,

¹¹ More precisely, to calculate $RECLASS$, I subtract private-label MBS transferred from banks' trading to AFS accounts and add private-label MBS transferred from banks' AFS to HTM accounts. To be clear, $RECLASS$ concerns reclassifications only into and out of banks' AFS account, without respect for whether these transfers involved Level 1, Level 2, or Level 3 assets (though most of banks' private-label MBS were classified during the crisis as Level 2 or Level 3 assets).

¹² Based on supplemental estimations of models (1) and (2) (results not shown), $\Delta SAFE$ and $MBSEXP$ and ΔMBS and $SAFEEXP$ are uncorrelated on a partial-correlation basis, as well.

¹³ For my sample of banks, in the aggregate, in each quarter from 2007Q4–2008Q4, AFS safe assets equaled seven percent of total assets; AFS private-label MBS, between two and three percent of total assets.

as a more precise measure of M_X , I use *IMPPER*, defined as

$$IMPPER_{it-1} = \frac{RAWIMP_{it-1}}{[MBS_{it-1}^{ACV} + RAWIMP_{it-1} - MBS_{it-1}^{FV}] - [MBS_{it-2}^{ACV} - MBS_{it-2}^{FV}]},$$

where *ACV* and *FV* are the amortized-cost values and fair values on private-label MBS. Over my sample period, amortized-cost values generally exceeded fair values. Hence, $MBS^{ACV} - MBS^{FV}$ is the total fall in the price, or value, of banks' private-label MBS since these assets' acquisition date. A rise in $MBS^{ACV} - MBS^{FV}$ from quarter $t - 2$ to $t - 1$ implies a decline in value from $t - 2$ to $t - 1$, with a larger rise implying a larger decline in value. Impairments reduce amortized-cost values by the amount of the impairment. As a consequence, I add to the denominator $RAWIMP_{it-1}$, raw impairments taken during quarter $t - 1$.

Hence, *IMPPER* is a measure of M_X —of how much of a given fall in price, or value, banks take a write-down on. To give an example, suppose MBS_{it-2}^{ACV} and MBS_{it-2}^{FV} are 100 and 80, MBS_{it-1}^{ACV} and MBS_{it-1}^{FV} are 90 and 60, and $RAWIMP_{it-1}$ is 10: $IMPPER_{it-1} = \frac{10}{[90+10-60]-[100-80]} = \frac{10}{40-20} = 0.5$. The MBS were valued at 20 below par at the end of $t - 2$ and at 40 below par at the end of $t - 1$, after adjusting for impairments, for a fall in value of 20. This bank took impairments of 10, implying an “impairment intensity” of 0.5. Suppose that $RAWIMP_{it-1}$ is 5, not 10: $IMPPER_{it-1} = \frac{5}{[95+5-60]-[100-80]} = \frac{5}{40-20} = 0.25$. In this case, this fall in value of 20 led only to 5 in impairments, implying a lower impairment intensity, or less-aggressive recognition of impairments.

I test the two hypotheses below, both expressed in alternative form:

- (1) Larger impairments on private-label MBS are uncorrelated with $\Delta SAFE$, and
- (2) larger impairments on private-label MBS are uncorrelated with ΔMBS .

Tab. 2.2: Summary Statistics

Variable	Mean	Standard Deviation	Percentiles				
			10 th	25 th	50 th	75 th	90 th
$\Delta SAFE$	0.024	0.152	-0.096	-0.047	-0.003	0.070	0.177
ΔMBS	-0.017	0.793	-0.060	-0.040	-0.027	0.015	0.260
$IMPTOT$	0.938	3.055	0.000	0.000	0.000	0.000	0.000
$IMPPER$	0.040	0.202	0.000	0.000	0.000	0.000	0.000
CAP	0.050	0.066	0.019	0.028	0.037	0.052	0.071
LLP	0.003	0.004	0.000	0.001	0.002	0.004	0.008
DEP	0.715	0.149	0.534	0.691	0.743	0.799	0.840
$SAFEEXP$	0.113	0.066	0.034	0.076	0.104	0.138	0.192
$MBSEXP$	0.030	0.031	0.003	0.009	0.020	0.037	0.070
$MBSQUAL$	0.957	0.047	0.892	0.937	0.970	0.988	0.999

My sample consists of each bank in each quarter t from 2007Q4–2008Q4 with AFS private-label MBS at the start of t , for a total of 417 observations and 92 different banks. $\Delta SAFE$: change in log AFS Treasuries, Agencies, and Agency MBS; ΔMBS : change in log AFS private-label MBS; $IMPTOT$: log impairments on private-label MBS; $IMPPER$: impairments on private-label MBS relative to the decline in the value of these securities; CAP : Tier 1 ratio in excess of a six-percent baseline; LLP : loan-loss provisions divided by average assets; DEP : share of deposits in total liabilities; $SAFEEXP$: share of AFS Treasuries, Agencies, and Agency MBS in total assets; $MBSEXP$: share of AFS private-label MBS in total assets; $MBSQUAL$: ratio of fair-value to amortized-cost value of AFS private-label MBS.

IMP has an ambiguous effect on $\Delta SAFE$ and ΔMBS , as a result of the ambiguous signs of $\frac{\partial S_F^*}{\partial M_X}$ and $\frac{\partial S_X^*}{\partial M_X}$, equations (9) and (11) in Section 5.4.1. With respect to $\Delta SAFE$, a rise in M_X reduces capital. Because of diminishing returns to capital, this decline in capital induces more sales of safe assets if gains on sales dominate net interest income, so that sales increase capital, and induces fewer sales if net interest income dominates, so that sales reduce capital. With respect to ΔMBS , an increase in M_X reduces losses on sales and, by reducing capital, increases the probability banks have to liquidate toxic assets due to a loss of access to funding. These effects induce more sales of toxic assets. Sales of toxic assets, however, reduce capital due to losses on sales and the loss of net interest income. An increase in M_X reduces capital. Due to diminishing returns to capital, the impact of sales in reducing capital is more harmful when capital is lower. This effect induces fewer sales of toxic assets.

Tab. 2.3: Correlation Matrix

Variable	$\Delta SAFE$	ΔMBS	$IMPTOT$	$IMPPER$	CAP	LLP	DEP	$SAFEEXP$	$MBSEXP$	$MBSQUAL$
$\Delta SAFE$	1.000									
ΔMBS	0.007	1.000								
$IMPTOT$	0.225*	-0.035	1.000							
$IMPPER$	0.052	-0.027	0.580*	1.000						
CAP	-0.050	0.039	0.054	0.013	1.000					
LLP	0.252*	-0.042	0.165*	0.083	0.016	1.000				
DEP	0.065	0.040	0.021	0.102*	0.083	0.079	1.000			
$SAFEEXP$	-0.345*	-0.029	-0.023	0.026	0.017	-0.014	0.008	1.000		
$MBSEXP$	0.058	-0.156*	-0.120*	-0.044	-0.104*	0.105*	-0.004	-0.109*	1.000	
$MBSQUAL$	-0.288*	0.099*	-0.407*	-0.150*	0.014	-0.451*	0.136*	-0.031	0.043	1.000

Values are Pearson correlations, calculated on a within-bank basis. * denotes statistical significance at the five-percent level.

2.6.5 Descriptive Statistics

In Table 2 and Table 3, I show summary statistics and a correlation matrix. Four comments: First, the median of $\Delta SAFE$ is roughly zero, and its mean is positive. Banks were split 50-50 in being net buyers or net sellers of safe assets, but net purchases were greater in magnitude. Second, the mean and median of ΔMBS are negative. Most often, banks were net sellers of private-label MBS, in line with the view that banks wanted to dump these assets. Third, few banks—37 of my 417 observations, or nine percent—took impairments on private-label MBS. Even $IMPTOT$'s and $IMPPER$'s 90th-percentile values are 0. Consequently, impairments were not too common during the crisis, even among banks' worst-performing assets. Fourth, $MBSQUAL$ has a negative link with $IMPTOT$ and $IMPPER$ —lower-quality private-label MBS are linked with more impairments, capturing the intuition that impairments imply low-quality private-label MBS. Due to the collinearity between $MBSQUAL$ and IMP , I estimate models (1) and (2) with and without $MBSQUAL$.

Tab. 2.4: Regression Results

Dep. Var. Est. #	$\Delta SAFE$ (I)	ΔMBS	$\Delta SAFE$ (II)	ΔMBS	$\Delta SAFE$ (III)	ΔMBS	$\Delta SAFE$ (IV)	ΔMBS
ΔMBS	-0.044 (0.057)		-0.071 (0.050)		-0.004 (0.058)		-0.054 (0.047)	
$\Delta SAFE$		0.702 (0.547)		0.683 (0.495)		0.627 (0.504)		0.649 (0.535)
$IMPTOT$	0.010*** (0.004)	-0.026** (0.012)	0.007** (0.003)	-0.011* (0.006)				
$IMPPER$					0.021 (0.027)	-0.168** (0.080)	0.018 (0.032)	-0.187** (0.080)
CAP	-0.523 (0.596)	1.475 (1.123)	-0.458 (0.585)	1.264 (1.321)	-0.475 (0.595)	1.210 (1.027)	-0.411 (0.553)	1.132 (1.182)
LLP	8.379** (3.718)	-16.577 (12.478)	7.068** (3.029)	-10.548 (7.994)	8.963** (3.873)	-16.613 (11.333)	7.091** (3.600)	-10.549 (8.831)
DEP	0.275 (0.235)	1.078 (0.672)	0.350 (0.239)	0.846 (0.604)	0.293 (0.234)	1.075 (0.658)	0.376* (0.213)	0.970* (0.583)
$SAFEEXP$	-3.158*** (0.650)		-3.226*** (0.626)		-3.169*** (0.701)		-3.252*** (0.613)	
$MBSEXP$		-12.525*** (2.785)		-14.390*** (2.869)		-11.571*** (2.752)		-14.290*** (2.869)
$MBSQUAL$			-0.968** (0.467)	5.510* (3.142)			-1.220*** (0.412)	5.765* (3.248)
R^2 (within)	0.197	0.022	0.167	0.069	0.205	0.196	0.020	0.072
N	417	417	417	417	417	417	417	417
# groups	92	92	92	92	92	92	92	92
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

1. Bootstrapped (250 replications) standard errors are in parentheses.
2. All estimations include time and bank fixed effects.
3. *, **, and *** denote statistical significance at the 10-, five-, and one-percent level, respectively, using two-tailed tests.

2.6.6 Results

Results for models (1) and (2) are in Table 4.¹⁴ My central result is that for model (2), sales of private-label MBS, IMP is negative and significant—a marginal increase in impairments on private-label MBS induces more sales of these securities. This result holds across definitions

¹⁴ In estimations (I) and (III), I exclude $MBSQUAL$; in estimations (II) and (IV), I include $MBSQUAL$. In addition, estimations (I) and (II) use $IMPTOT$, the log of [1 + total impairments], while estimations (III) and (IV) use $IMPPER$, a measure of impairment intensity (Section 6.4.2). Finally, since the residuals are not normally distributed, I compute bootstrapped standard errors (250 replications) (Efron and Tibshirani [1982]).

of impairments and after including *MBSQUAL*, suggesting asset-quality effects do not drive this result. A rise in M_X can induce more sales of toxic assets by reducing losses on sales and raising the odds of being hit by a wholesale run—of having to sell toxic assets at a later date. The results above suggest that these effects dominate. *IMP*'s effect is economically modest—using *IMPPER*'s coefficients, a rise of 10 percentage points in impairment intensity implies an increase of 0.02 percent in sales of private-label MBS. One possible reason for this limited effect is that during the crisis, selling private-label MBS would have led to losses of as high as 20 cents on the dollar (Section 4.1, Figure 3). Still, these results suggest that on the margin, taking larger impairments on private-label MBS led to more sales of these securities.

In addition, for model (1), sales of safe assets, *IMP* and $\Delta SAFE$ have a positive link, though this result is not robust to how I define *IMP*; *IMPPER*, the more precise measure of M_X , has a positive sign but is statistically insignificant. This result provides some evidence, albeit relatively weak, that a marginal increase in impairments induces fewer net sales of safe assets. By equation (9) in Section 5.4.1, this result suggests the net interest income foregone by selling safe assets exceeds gains on sales, so that sales lower capital, in effect. An increase in M_X reduces capital. Due to diminishing returns to capital, this decline in capital makes more harmful the decline in capital on sales.

Three more results are worth noting: First, *MBSQUAL* has a positive link with ΔMBS . A marginal decline in the quality of private-label MBS induces more sales of these securities, in line with the view that banks were particularly eager to sell low-quality private-label MBS. *MBSQUAL* has a negative link with ΔMBS —a decline in the quality of private-label MBS induces fewer net sales of safe assets. Holding especially toxic private-label MBS could have led banks to load up on safe assets as a way to guard against future negative shocks. Second, *SAFEEXP* has a negative link with $\Delta SAFE$, so that a marginal rise in the portfolio weight of safe assets gives rise to more sales of these assets. *MBSEXP* likewise has a negative link with ΔMBS , with the same implications. Third, *LLP* has a positive link with $\Delta SAFE$. A

marginal rise in loan losses leads to fewer net sales of safe assets. Loan losses reduce Tier 1 capital, potentially inducing banks to invest more in capital-light safe assets.

With respect to weak instruments, the minimum eigenvalues of $\Delta SAFE$ and ΔMBS are 55.40 and 14.60 (Table 5). Hence, for $\Delta SAFE$, the nulls of a maximum endogeneity bias of at least five percent and size bias of at least 10 percent relative to OLS can be rejected at the five-percent level (see Stock and Yogo [2002]). For ΔMBS , the nulls of an endogeneity bias of at least 30 percent and a size bias of at least 15 percent can be rejected at the five-percent level. These results suggest that weak instruments are not a problem, especially for $\Delta SAFE$. With respect to instrument validity, since $\Delta SAFE$ and ΔMBS are just-identified, no tests of overidentifying restrictions are possible. When I estimate models (1) and (2) via two-stage least squares and via ordinary least squares, I get the same results (not tabulated).

2.7 Implications

The theoretical and empirical results above show how under fair value, banks have incentives to sell more toxic assets and fewer safe assets than under historic cost. In this way, fair value has a two-sided impact on crises. As a plus, with certain exceptions (*e.g.*, Greek government debt), toxic assets consume substantial capital because of their high risk-weights.¹⁵ Hence, in selling these capital-intensive, poorly performing assets, banks free up capital to put toward new, more-productive loans. Also, selling toxic assets while holding on to safe assets improves balance-sheet strength, enhancing banks' ability to raise external capital. As a result, crises could come to a quicker conclusion, with fewer negative spillover effects to the real economy. As a minus, sales of toxic asset depress prices, further impairing capital and reducing banks' access to funding. Banks thus might reduce lending, or even trigger a self-reinforcing cycle by selling more toxic assets (Cifuentes *et al.* [2005]). The net effect of these conflicting forces

¹⁵ Although most structured-finance products (*e.g.*, private-label MBS) had high credit ratings at inception and thus required little capital, large and widespread credit-rating downgrades (Moody's [2009], [2010]) made these assets capital-intensive during and after the 2007–8 crisis.

Tab. 2.5: US Banks' Asset Composition, Year-End 2010 (\$ millions)

Bank	Total Assets	Trading Assets	AFS Securities	Trading %	AFS %
Bank of America	2,268,347	265,091	360,389	0.117	0.159
JP Morgan	2,117,605	489,892	312,671	0.231	0.148
Citigroup	1,913,902	317,272	274,270	0.166	0.143
Wells Fargo	1,258,128	51,414	172,654	0.041	0.137
Goldman Sachs	911,330	345,538	3,643	0.379	0.004
Morgan Stanley	807,698	284,798	29,649	0.353	0.037
Metlife	730,906	18,590	343,036	0.025	0.469
Taunus	372,556	98,386	2,319	0.264	0.006
HSBC NA	343,700	44,729	48,859	0.130	0.142
US Bancorp	307,786	1,701	51,509	0.006	0.167
PNC	264,414	2,546	57,310	0.010	0.217
BNY Mellon	247,222	20,397	62,368	0.083	0.252
Capital One	197,503	427	41,531	0.002	0.210
TD Bank US	176,972	0	76,270	0.000	0.431
Suntrust	172,875	5,378	26,206	0.031	0.152
Others	4,008,737	44,870	731,540	0.011	0.182

Data source: FR Y9-C. The 15 banks shown are the 15-biggest US bank holding companies as of the end of 2010, as measured by total assets. “Other banks” is aggregate data for all other US bank holding companies.

is unclear *a priori* and would be an interesting area for future research.

These results are particularly important since fair value’s scope is set to increase sharply under Basel III. Under current US banking regulations, fair value is applied for regulatory-capital purposes primarily to trading assets. Very few banks—large banks, with large market-making operations—have trading assets (Table 6). Basel III, however, calls for fair value to be applied for regulatory-capital purposes to AFS securities, in addition to trading assets.¹⁶ AFS securities account for between 15 and 20 percent of the assets of all banks, large banks and smaller banks alike. Fair value thus could have a larger impact in future crises than in the 2007–8 crisis (see Laux and Leuz [2010]).

¹⁶ At present, under US accounting standards, AFS securities are valued under fair value on banks’ balance sheets. Unrealized gains and losses on most of banks’ AFS securities, however, are excluded from regulatory capital. Basel III calls for this exclusion to be eliminated (BCBS [2011], p. 13, footnote 10).

2.8 Conclusion

Asset sales by banks are one of the key features of financial crises. I show how under fair-value accounting, banks have incentives to sell more toxic assets and fewer safe assets than under historic-cost accounting. Empirically, I find that in the 2007–8 crisis, larger write-downs on private-label MBS are linked with more sales of these securities, even after controlling for the quality of these securities. These results indicate that fair value can have an important role in determining which asset types banks sell during crises. Since sales of toxic assets depress prices, whereas sales of safe assets do not, fair value’s impact in this respect can play a vital role in how crises evolve.

Appendix

The Y9-C mnemonics I use in my empirical tests are as follows:

Item	Y9-C Mnemonic(s)
Treasuries	BHCK1286
Agencies	BHCK1291 + BHCK1297
Agency MBS	BHCK1701 + BHCK1706 + BHCK1716 + BHCK1731
Private-label MBS	BHCK1711 + BHCK1735
Tier 1 capital	BHCK8274
Risk-weighted assets	BHCKA223
Deposits	BHDM6631 + BHDM6636 + BHFN6631 + BHFN6636
Total liabilities	BHCK2948
Total assets	BHCK2170
Loan-loss provisions	BHCK4230

Impairment and reclassification data come from banks’ public financial statements.

Variable definitions are as follows:

$$\begin{aligned}
\Delta SAFE_{it} &= \ln [1 + SAFE_{it}] - \ln [1 + SAFE_{it-1}] \\
\Delta MBS_{it} &= \ln [1 + MBS_{it} + RAWIMP_{it} - RECLASS_{it}] - \ln [1 + MBS_{it-1}] \\
IMPTOT_{it} &= \ln [1 + \text{total impairments on private-label MBS}_{it}] \\
IMPPE_{it} &= \frac{RAWIMP_{it}}{[MBS_{it}^{ACV} + RAWIMP_{it} - MBS_{it}^{FV}] - [MBS_{it-1}^{ACV} - MBS_{it-1}^{FV}]} \\
CAP_{it} &= \frac{\text{Tier 1 capital}_{it} - 0.06 [\text{risk-weighted assets}_{it}]}{\text{risk-weighted assets}_{it}} \\
LLP_{it} &= \frac{\text{loan-loss provisions}_{it}}{[\text{total assets}_{it} + \text{total assets}_{it-1}] / 2} \\
DEP_{it} &= \frac{\text{deposits}_{it}}{\text{total liabilities}_{it}} \\
SAFEEXP_{it} &= \frac{\text{AFS Treasuries, Agencies, and Agency MBS}_{it}}{\text{total assets}_{it}} \\
MBSEXP_{it} &= \frac{\text{AFS private-label MBS}_{it}}{\text{total assets}_{it}} \\
MBSQUAL_{it} &= \frac{\text{AFS private-label MBS, fair value}_{it}}{\text{AFS private-label MBS, amortized-cost value}_{it}}.
\end{aligned}$$

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3. DVA AND SYSTEMIC RISK

ABSTRACT

DVA is a valuation adjustment on derivative liabilities. DVA's earnings profile is akin to that of a short position in own-credit risk. A rise in own-credit risk results in a gain; a decline, in a loss. Theoretically, I show that tax effects can lead banks to hedge DVA's impact on earnings and that banks do so by taking long positions in other banks' credit. DVA is relevant mainly for large, global banks. DVA hedging thus increases systemic risk by tightening the links between global banks, the systemically important financial institutions at the center of the 2007–8 financial crisis. Global banks are hedging DVA in this way, increasing the systemic scope of future crises.

3.1 Introduction

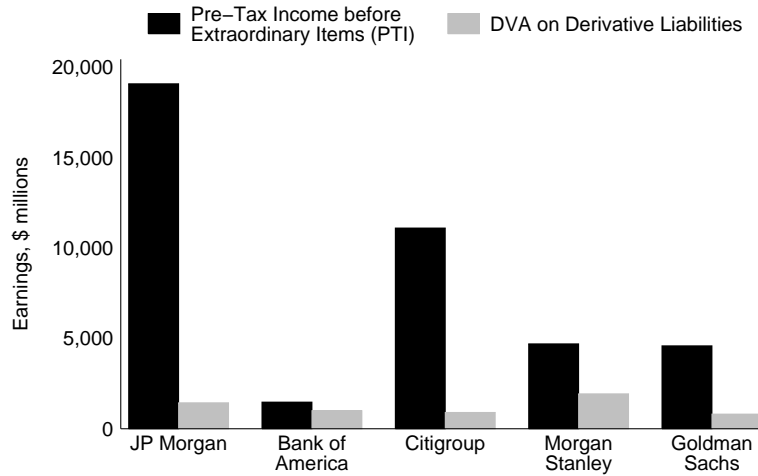
Systemic risk has become a key policy concern after the 2007–8 financial crisis. Many recent studies look at systemic risk (*e.g.*, Huang, Zhou, and Zhu [2009], [2010]; Acharya *et al.* [2010]; Adrian and Brunnermeier [2011]). Most of these studies take as exogenous the systemic risk in the financial sector and focus instead on measuring this risk or on assessing how much each individual bank contributes to this risk (see Acharya [2009] for an exception). Systemic risk, however, is an endogenous outcome of banks’ investment decisions. Hence, examining banks’ incentives to make investment decisions that increase systemic risk is useful in understanding how systemic risk can arise. In addition, this type of examination can help identify regulatory responses that limit the build-up of systemic risk.

In this study, I show that debt valuation adjustments (DVA) can increase systemic risk by inducing large, global banks to take long positions in the credit of other global banks. United States (US) and international accounting standards require DVA on derivative liabilities.¹ DVA is a valuation adjustment whose earnings profile is equivalent to that of a short position in own-credit risk. A rise in own-credit risk results in a gain; a fall, in a loss. DVA is “paper income,” a pure accounting exposure with no economic substance. DVA reflects the change in the value of derivative liabilities due to changes in own-credit risk. DVA has no impact on the obligations of banks on these liabilities. Still, DVA affects both accounting earnings and taxable income. Hence, insofar as DVA is exogenous and has negative effects (*e.g.*, increases earnings volatility), banks have incentives to mitigate its impact on earnings.

DVA is relevant only for global banks. For these banks, DVA is exogenous and can have a strong impact on earnings. With respect to US banks, DVA accounted for eight percent of 2011 pre-tax income for both JP Morgan and Citigroup and for 18 percent, 41 percent, and 68 percent of income for Goldman Sachs, Morgan Stanley, and Bank of America (Figure 1). DVA

¹ Unless otherwise noted, I use DVA to refer only to credit-risk-related DVA on derivative liabilities (see Section 2.1 for more).

Fig. 3.1: 2011 Full-Year Earnings, Large, Global US Banks (\$ millions)



2011 Quarterly and Full-Year Earnings (\$ millions)

Period	JP Morgan	Bank of America	Citigroup	Morgan Stanley	Goldman Sachs
Q1, PTI	5,558	2,279	3,031	1,128	2,821
Q1, DVA	-69	-357	-227	-193	-90
Q2, PTI	5,481	-8,810	3,332	1,402	1,103
Q2, DVA	92	121	76	204	140
Q3, PTI	4,274	5,983	3,742	2,268	-401
Q3, DVA	915	1,709	1,304	2,263	702
Q4, PTI	3,770	2,022	998	-102	1,064
Q4, DVA	499	-474	-251	-342	59
FY, PTI	19,083	1,474	11,103	4,696	4,587
FY, DVA	1,437	1,000	902	1,932	811

Data source: FR Y9-C. DVA is credit-risk-related DVA on derivative liabilities. PTI is pre-tax income before extraordinary items.

is irrelevant for other US banks (Table 1). Media anecdotes indicate that internationally, too, DVA is relevant only for global banks (*e.g.*, Barclays; Carver [2012b]). These banks have extensive market-making operations. Though banks can avoid DVA by not using derivatives, derivatives are vital to market-making. In market-making in cash instruments (*e.g.*, bonds), banks use derivatives to hedge risks that arise from holding inventory. In market-making in

derivatives, banks necessarily trade in derivatives on a large scale. Due to the importance of derivatives in market-making, global banks cannot avoid using derivatives. Hence, derivatives and the resulting DVA on derivative liabilities are substantively exogenous.

I build a model in which banks mitigate the impact of DVA on earnings by hedging DVA. In doing so, banks balance the tax benefits against the distress costs of DVA hedging. DVA's impact on earnings and on taxable income is equivalent to that of an unhedged, undiversified short position in own-credit risk. Consequently, given the potential for large swings in banks' own-credit risk, DVA can have a large impact in increasing volatility in taxable income. As a result of tax-function convexity, this rise in volatility increases the present value of expected tax liabilities (Smith and Stulz [1985], Graham and Smith [1999]). Hedging DVA reduces the net impact of DVA on taxable income. Hence, this increase in volatility is smaller, reducing the rise in the present value of expected tax liabilities.

As a cost, DVA hedging raises distress costs, modeled as the costs of having to sell assets at a below-fundamentals price after losing access to private-sector wholesale (*i.e.*, uninsured) funding. DVA is a short position in own-credit risk. Hence, banks hedge by taking positions that are akin to a long position in own-credit risk. Common (*i.e.*, systematic) factors drive most of the changes in global banks' credit risk (Eichengreen *et al.* [2009]). Global banks thus hedge by taking long positions in other global banks' credit. In good states, banks' credit risk declines, leading to gains on DVA hedges. In good states, however, banks' balance sheets are strong, and capital and liquidity are abundant. Hence, the odds of losing access to funding are negligible even without these gains. Consequently, these gains do little to reduce distress costs. In bad states (*e.g.*, financial crises), credit risk rises, leading to losses on DVA hedges. These losses amplify banks' distress, increasing the odds of losing access to funding. Because of this asymmetric impact on distress costs, DVA hedging increases these costs.

I develop a baseline model and two extensions; in each version, banks maximize post-tax returns on capital. In my baseline model, banks internalize fully the tax benefits and distress

Tab. 3.1: 2011 Derivatives and DVA, US Banks (\$ millions)

Bank Holding Company	Total Assets	Trading Derivatives	Derivative Liabilities	DVA
JP Morgan	2,265,792	64,617,524	74,477	1,437
Bank of America	2,136,578	62,285,711	55,838	1,000
Citigroup	1,873,878	47,169,692	56,273	902
Wells Fargo	1,313,867	2,653,753	12,512	40
Goldman Sachs	923,718	44,122,216	58,459	811
Metlife	799,625	0	4	0
Morgan Stanley	749,898	47,163,209	46,320	1,932
Taunus	354,737	762,140	5,909	0
US Bancorp	340,122	72,246	378	0
HSBC North America	331,403	3,578,233	5,422	0
Bank of New York	325,793	1,325,470	7,116	0
PNC	271,407	152,948	381	-4
State Street	216,436	1,385,450	6,396	0
Capital One	206,104	15,426	395	-1
TD Bank US	201,057	0	N/A	0
Other banks	4,145,066	947,135	12,500	0

Data source: FR Y9-C. N/A: not available. Trading derivatives are given in notional values and account for over 98 percent of banks' total derivatives. Derivative liabilities are the aggregate fair value of trading derivatives whose fair value is negative. DVA is credit-risk-related DVA on derivative liabilities. The banks above are the 15-largest US bank holding companies, as ranked by total assets. "Other banks" is aggregate data for all other US bank holding companies.

costs of DVA hedging. As a result, an increase in exposure to other banks never is costless. A marginal increase in exposure lowers expected tax liabilities on any given amount of pre-tax earnings by reducing the effect of DVA in increasing earnings volatility. A marginal increase in exposure, however, also increases distress costs by increasing the probability of being cut off from funding. Banks balance these two effects when deciding how much exposure to take. Hence, distress costs have a central role in limiting the extent to which banks take exposure to other banks.

Next, I alter my baseline model by stipulating that banks do not internalize fully the distress costs of DVA hedging. I allow for public-sector support should private-sector creditors pull funds. The public sector—central banks and governments—cannot commit *ex ante* not

to support banks *ex post*, once a crisis hits. The prospect of this support helps insulate banks from the adverse consequences of losing access to private-sector funding. Central banks, for instance, can respond to a systemic crisis by lending against lower-quality collateral, ensuring that banks do not have to liquidate assets at a below-fundamentals price. This commitment problem and the moral hazard that results are especially acute *vis-à-vis* large, global banks, the banks DVA is most relevant for. In addition, public-sector support is most likely in bad states, the states in which losses on DVA hedges are likely to be highest.

In this altered model, DVA hedging is more pervasive, in equilibrium, in that the prospect of public-sector support leads banks to take more exposure to other banks. In the limit, when public-sector support is certain, public-sector support eliminates distress costs by eliminating the risk of having to sell assets at a below-fundamentals price. As a result, taking exposure to other banks is strictly beneficial. In this case, banks' hedging strategy is a corner solution—banks take as much exposure to other banks as possible. More generally, as the probability of public-sector support increases, the likelihood of having to sell assets at a below-fundamentals price declines. Hence, distress costs decline, inducing more DVA hedging.

Finally, I stipulate that taking more exposure to other banks forces banks to hold more capital. In this set-up, DVA hedging is less pervasive, in equilibrium. As a result of the moral hazard arising from public-sector support, banks likely will do too much DVA hedging relative to the social optimum. As a result, regulators have an interest in curbing its practice. Capital requirements can help to do so. A marginal rise in exposure to other banks is beneficial in reducing the present value of expected tax liabilities. A rise in exposure, however, in addition to possibly raising distress costs, forces banks to hold more capital. Consequently, returns on capital for any given amount of post-tax earnings are lower. Banks balance these conflicting effects when determining how much exposure to take. Hence, an increase in exposure always is costly, even when public-sector support is certain. More generally, this additional cost of DVA hedging induces banks to take less exposure than when capital is independent of banks'

exposure to other banks.

Global banks were at the heart of the 2007–8 financial crises and likely would have a vital role in any future crisis. These banks already are hedging DVA, increasing the systemic scope of future crises. Goldman Sachs hedges DVA by selling credit protection on other financial firms (Moyer and Burne [2011]); several others use some type of DVA hedging or are thinking about doing so (Carver [2012b]). Also, in 2008, several banks hedged prospective DVA gains by selling credit protection on Lehman Brothers (Alloway [2012]). DVA hedging gives banks direct exposure to other banks' credit. Hence, in a crisis, when one bank becomes distressed, other banks book losses, reducing capital while increasing credit risk. In turn, more banks book losses, and so on. Concomitant DVA gains do nothing substantive to offset these losses. In addition, Basel III calls for DVA to be excluded from capital (BCBS [2011]). As a result, DVA gains during crises would offer no capital relief. Losses on DVA hedges thus could have an important role in amplifying the scope and magnitude of crises.

The rest of this paper is as follows: In Section 2, I discuss the accounting standards that govern DVA and banks' operations that result in DVA. In Section 3, I discuss DVA's impact on earnings *vis-à-vis* the rest of banks' portfolios. In Section 4, I lay out my model's primary features and describe the costs and benefits of DVA hedging. In Section 5, I build my model and discuss its implications. In the appendix, I show the FR Y9-C mnemonics for the data I show.

3.2 *Accounting Standards, DVA, and Global Banks*

DVA is a valuation adjustment on liabilities banks value under fair-value accounting. DVA is included in earnings and also in taxable income. With respect to how to calculate DVA and the liabilities to calculate DVA on, US and international accounting standards are essentially the same. DVA is a function of, *inter alia*, changes in own-credit risk. In the US, ASC 820-

10-35-17 states,² “The fair value of a liability [must incorporate] the effect of nonperformance risk. Nonperformance risk includes . . . a reporting entity’s own credit risk.” Internationally, International Financial Reporting Standards (IFRS) 13 makes the same requirement. Hence, as a bank’s own-credit risk declines, its probability of default falls, the value of its liabilities increases, and a loss thus results. A rise in own-credit risk works similarly to generate gains. DVA reflects the change in the value of the liabilities of a bank. DVA does not affect a bank’s obligations in connection with its liabilities. In this respect, DVA is an accounting exposure with no underlying economic substance (*i.e.*, with no cash-flow implications).

Banks calculate DVA on two types of liabilities. One is liabilities valued under the “fair-value option.” DVA on these liabilities is endogenous. Banks have total discretion in choosing whether to apply fair value to each liability, subject to certain eligibility restrictions. In the US, ASC 825-10-15 and its predecessor, SFAS No. 159, govern the fair-value option. SFAS No. 159 states (emphasis added), “This Statement permits all entities to *choose*, at specified election dates, to measure eligible items at fair value” and that “[t]he decision about whether to elect the fair value option is applied instrument by instrument” Internationally, IFRS 9 likewise gives banks discretion in applying this option. Banks do not have to use this option at all. Insofar as DVA has undesirable effects, banks may avoid these effects by not applying this option. Consistent with the notion that this option is benign, if not beneficial, Fiechter [2011] finds that banks use this option to reduce earnings volatility.³

The second is derivative liabilities (*i.e.*, derivatives that have a negative fair value). To a large extent, derivative-liability DVA is endogenous only insofar as banks have discretion in using derivatives. In general, gains and losses on derivatives affect earnings. In the US, ASC 815-10-35-2 states, “[Gains or losses on derivatives] not designated as a hedging instrument”

² US and international accounting standards can be accessed through <http://www.fasb.org> and <http://www.iasb.org>, the respective home pages of the Financial Accounting Standards Board and the International Accounting Standards Board.

³ A bank, for instance, could reduce volatility in earnings by applying the fair-value option to only those liabilities whose changes in value have a strong negative link with changes in the value of its assets.

Tab. 3.2: Accounting Treatment of Derivatives, Fiscal-Year-End 2011

Bank	Notional Values		Gross Deriv. Assets		Gross Deriv. Liabilities	
	Accounting Hedge		Accounting Hedge		Accounting Hedge	
	Yes	No	Yes	No	Yes	No
JP Morgan (\$)	N/A	N/A	16	1,869	4	1,833
Bank of America (\$)	N/A	N/A	20	1,862	15	1,847
Citigroup (\$)	294	49,522	N/A	N/A	N/A	N/A
Morgan Stanley (\$)	91	52,208	8	1,192	0	1,166
Goldman Sachs (\$)	N/A	N/A	22	964	0	875
Barclays (£)	244	43,096	4	535	3	525
Deutsche Bank (€)	N/A	N/A	4	852	3	834

Data source: 2011 annual reports. N/A: not available. Data are in billions of the denoted unit of currency. “Accounting Hedge” denotes derivatives designated as an accounting hedge. Gross derivative assets and liabilities are derivative assets and liabilities before netting and collateral adjustments.

impact earnings. Internationally, accounting for derivatives under IFRS 39 and IAS 9 is the same. Hence, DVA on derivatives designated as a hedging instrument could bypass earnings. To qualify as a hedging instrument, however, a derivative has to meet certain conditions that can be hard to satisfy (see, *e.g.*, Citigroup’s 2011 10-K, pp. 144–5). As a result, even those derivatives banks use as a hedge cannot necessarily be accounted for as such; also, banks can opt not to designate as an accounting hedge derivatives that could be accounted for as such. Essentially none of global banks’ derivatives are designated as a hedging instrument (Table 2). Gains and losses, DVA included, on the derivatives of these banks thus affect earnings.

3.2.1 Exogenous DVA, Global Banks, and Market-Making

DVA’s impact differs depending on whether DVA is endogenous or exogenous. Insofar as DVA is endogenous, banks can choose to operate so as to avoid DVA. With respect to the fair-value option, banks can elect not to apply this option. With respect to derivative liabilities, banks can elect not to use derivatives. These decisions are within banks’ control. With endogenous DVA, banks balance the costs and benefits of accounting or investment decisions that would require DVA. A bank that wishes to use derivatives to hedge, for instance, could balance the

benefits of its hedging program against the costs of booking DVA should its derivatives end up as a derivative liability (have a negative fair value). Banks would not necessarily have to mitigate DVA's impact on earnings. Insofar as DVA's adverse effects are "too costly," banks could choose to operate in a way that avoids DVA.

Exogenous DVA, by contrast, gives banks no discretion in avoiding DVA. DVA effectively is imposed on banks, regardless of its costs. Hence, banks have stronger incentives to mitigate the earnings effects of exogenous DVA due to its potentially higher costs. For global banks, DVA on derivative liabilities is exogenous. Given the difficulty in designating derivatives as a hedging instrument, banks can avoid derivative-liability DVA only by not using derivatives. For global banks, this option is not viable. These banks have large market-making operations. Derivatives are a vital part of market-making. By definition, in market-making in derivatives, banks trade in derivatives as an ordinary matter. In market-making in cash instruments (*e.g.*, bonds), derivatives are a critical risk-management tool. Goldman Sachs, for instance, "enters into derivative transactions with clients and other market participants to provide liquidity and to facilitate the transfer and hedging of risk . . . [and] to actively manage risk exposures that arise from market-making" (Goldman's 2011 10-K, p. 130).

In large part due to market-making, global banks trade in derivatives on a massive scale. Notional values overstate true exposures but do capture the extent of these banks' derivative activity: As of year-end 2011, the five global US banks in Figure 1 all had between \$44 trillion and \$65 trillion notional in derivatives outstanding (Section 1, Table 1). International banks trade on a similarly large scale. At year-end 2011, for instance, Barclays and Deutsche Bank had £43 trillion and €59 trillion notional in derivatives outstanding (source: annual reports). Global banks thus have either to tolerate passively DVA's exogenous impact on earnings or to take steps to mitigate its impact. Based on a 2010 survey, the G-14—a group of 14 global banks—account for 82 percent of over-the-counter derivatives outstanding (Mengle [2010]). Hence, DVA on derivative liabilities is relevant mainly for these banks.

Tab. 3.3: 2011 DVA, CVA, and Pre-Tax Income

Bank	Assets		Derivative	Net PTI	CVA	DVA	Returns		
	Non-Deriv.	Derivatives	Liabilities				Assets	CVA	DVA
JPM	2,176,245	89,547	74,477	20,220	-2,574	1,437	0.97 %	-2.87 %	1.93 %
BAC	2,073,288	63,290	55,838	1,080	-606	1,000	0.05 %	-0.96 %	1.79 %
C	1,811,551	62,327	56,273	12,718	-2,517	902	0.73 %	-4.04 %	1.60 %
MS	703,016	46,882	46,320	1,177	1,587	1,932	0.18 %	3.39 %	4.17 %
GS	845,558	78,160	58,459	4,014	-238	811	0.52 %	-0.30 %	1.39 %

Data source: FR Y9-C. Data are in millions of dollars. “Net PTI” is pre-tax earnings excluding extraordinary items, CVA, and DVA. Returns are earnings divided by ending book values.

3.3 DVA, CVA, and Earnings on Non-Derivative Assets

In principle, DVA could covary negatively with two other parts of earnings, reducing the need of banks to hedge. The first is credit valuation adjustments (CVA), a valuation adjustment on derivative assets. CVA is driven by changes in counterparty credit risk. A fall in counterparty credit risk increases the value of derivative assets, resulting in a gain; a rise results in a loss. Hence, insofar as a bank’s credit risk is positively correlated with that of its counterparties, CVA and DVA offset. In good states, both its own and its counterparties’ credit risk decline, giving rise to a DVA loss and a CVA gain. In bad states, a DVA gain and a CVA loss result. The second is earnings on non-derivative assets. In good states, credit risk falls, leading to a DVA loss, but high profits on non-derivative assets could help offset this loss. In bad states, losses on non-derivative assets could offset DVA gains. In these respects, CVA and earnings on non-derivative assets could act as natural hedges against DVA, reducing the need of banks to hedge DVA explicitly.

Empirically, however, DVA has had only a weak negative correlation, if any, with both CVA and earnings on non-derivative assets (Table 3). With respect to CVA, in 2011, Morgan Stanley had \$1.9 billion in DVA gains and \$1.6 billion in CVA gains. Although the other four global US banks all had DVA gains and CVA losses, these gains and losses differed sharply in magnitude, with differences from \$0.4 billion–\$1.6 billion. These outcomes likely are not one-

Tab. 3.4: Derivative-Asset Counterparty Exposure, Year-End 2011 (\$ millions)

	Banks		Monolines		Hedge Funds		Sovereigns		Corporations	
Bank	Net Exp.	Cash Collateral	Net Exp.	Cash Collateral	Net Exp.	Cash Collateral	Net Exp.	Cash Collateral	Net Exp.	Cash Collateral
JPM	95,602	81,339	380	1	2,007	9,225	7,968	3	66,755	10,440
BAC	68,505	56,949	1,652	0	3,997	4,620	2,645	85	55,953	11,055
C	55,846	39,783	10	0	2,649	4,741	14,456	2,946	38,370	13,500
MS	70,225	64,981	447	1	1,587	7,527	5,041	87	47,877	19,172
GS	143,808	114,491	0	0	2,096	7,172	3,953	529	43,381	12,515
Bank	Cash Coll. %	Total Exp. %	Cash Coll. %	Total Exp. %	Cash Coll. %	Total Exp. %	Cash Coll. %	Total Exp. %	Cash Coll. %	Total Exp. %
JPM	85.08 %	19.89 %	0.26 %	0.53 %	459.64 %	-10.07 %	0.04 %	11.11 %	15.64 %	78.54 %
BAC	83.13 %	19.25 %	0.00 %	2.75 %	115.60 %	-1.04 %	3.22 %	4.26 %	19.76 %	74.78 %
C	71.24 %	31.90 %	0.00 %	0.02 %	178.97 %	-4.15 %	20.38 %	22.85 %	35.18 %	49.38 %
MS	92.53 %	15.70 %	0.22 %	1.33 %	474.29 %	-17.78 %	1.73 %	14.83 %	40.04 %	85.92 %
GS	79.61 %	50.09 %	N/A	0.00 %	342.18 %	-8.67 %	13.38 %	5.85 %	28.85 %	52.73 %

Data source: FR Y9-C. The top row lists the five types of banks' derivative-asset counterparties the Y9-C identifies. "Net Exp." is exposure after accounting for netting agreements but before accounting for collateral posted. "Cash Collateral" is cash collateral posted by the relevant counterparty type. "Cash Coll. %" is cash collateral divided by net exposure. "Total Exp. %" is the share of total cash-collateral-adjusted exposure each counterparty type accounts for.

time flukes. CVA is driven by changes in counterparty credit risk on derivative assets, whereas DVA reflects changes in own-credit risk, which is driven by banks' entire balance sheet.⁴ Also, the heavy use of cash collateral limits banks' derivative-asset counterparty exposure to other banks (Table 4). Banks' counterparty exposure thus is mainly to corporates. Consequently, changes in corporate credit risk, not in bank credit risk, drive CVA. Different factors drive changes in corporate credit risk and in bank credit risk (Amato [2005], Raunig and Scheicher [2009]), limiting the positive correlation between changes in the two.

Similarly, the limited data that are available imply a weak link between DVA and earnings on assets. JP Morgan and Bank of America, for instance, had the highest and lowest returns on assets (0.97% and 0.05%) but the second- and third-highest DVA as a fraction of derivative liabilities, with similar returns of 1.93% and 1.79%. As with DVA and CVA, this weak link likely is not a one-time fluke. Most credit-risk measures (*e.g.*, spreads on credit-default swaps

⁴ Most banks, for instance, have large mortgage books, the credit quality of which need not be correlated with that of their derivative-asset counterparties.

(CDS)) are forward-looking measures that reflect all available information, but banks' assets are valued primarily under historic-cost accounting, so that changes in asset values typically do not affect earnings. Over 2007Q3–2008Q4, for instance, US banks took only \$11.7 billion in impairment losses on the \$67.7 billion decline in value of their banking-book private-label mortgage-backed securities (sources: FR Y9-C, financial statements, author's calculations). CDS spreads likely reflected the fall in asset quality and the resulting increase in credit risk this decline in value implied; for the most part, accounting earnings did not.

3.4 DVA, DVA Hedging, and Moral Hazard

In this section, I detail the intuition behind my model. In Section 4.1, I discuss DVA and its impact on earnings volatility. In Sections 4.2 and 4.3, I go over the tax benefits and distress costs of DVA hedging. In Section 4.4, I discuss why regulators have incentives to discourage DVA hedging.

3.4.1 DVA, Earnings Volatility, and DVA Hedging

My starting point is that banks can best mitigate the impact of DVA on earnings by hedging DVA. DVA is akin to an unhedged, undiversified short position in own-credit risk. In addition, based on the limited data that are available, DVA has a weak negative link, if any, with the rest of banks' earnings (Section 3, Table 3). As a result, DVA can have a strong effect in increasing volatility in earnings and in taxable income. Consistent with this notion, a recent survey finds that DVA is one of “the larger drivers of volatility in the quarterly results of large financial institutions” (Ernst & Young [2012]). Banks can mitigate this rise in volatility by taking positions whose earnings profile is opposite to that of DVA—by hedging.

To hedge DVA, global banks take long positions in the credit of other global banks. Since DVA is in effect a short position in own-credit risk, banks can hedge by taking positions that

are akin to a long position in own-credit risk. Common factors account for 62 percent of the changes in global banks' credit risk (Eichengreen *et al.* [2009]). Hence, changes in these banks' credit risk have a strong positive link. In good states, credit risk falls, leading to DVA losses and gains on banks' long positions in other banks' credit. In bad states, an increase in credit risk gives rise to DVA gains and losses on hedges. Banks can take exposure to other banks via simple means, such as selling credit protection via CDS or buying bonds.

DVA hedging can play a useful role in reducing DVA's net impact on earnings. In 2011Q3, for instance, banks' credit spreads increased. As a consequence of this rise in own-credit risk, JP Morgan, Citigroup, and Bank of America booked \$1.9 billion, \$1.9 billion, and \$1.7 billion, respectively, in DVA gains (Moyer and Burne [2011]).⁵ Goldman Sachs, by contrast, booked only a \$450 million net DVA gain. This relatively small gain was due to Goldman's decision to hedge DVA by "selling credit default swaps on a range of financial firms." The increase in banks' credit spreads resulted in losses on these CDS. These losses helped negate Goldman's DVA gains due to the increase in its own-credit risk.

3.4.2 DVA Hedging: Tax Benefits

Banks have incentives to hedge DVA only insofar as the impact of DVA in increasing volatility in earnings and in taxable income is costly. This rise in volatility could generate costs in two ways. First, higher volatility in earnings implies higher credit risk (*e.g.*, Trueman and Titman [1988]), potentially increasing banks' cost of (wholesale) funding. In line with this concern, the Ernst & Young survey cited in Section 4.1 reports, "[Banks are] thinking actively about stakeholder communication around measurement, management and reporting [of DVA . . . and] are focused on hedging strategies to manage . . . [the] income statement volatility" that arises from DVA. Anecdotally, however, investors ignore DVA when evaluating the earnings of banks (*e.g.*, Burne [2011]) because of its lack of economic substance. As a result, although

⁵ These figures are for total DVA rather than for credit-risk-related DVA on derivative liabilities and thus differ from the figures in Section 1, Table 1.

DVA increases volatility in earnings, this increase in volatility likely has a limited impact in increasing banks' credit risk, as perceived by markets participants.

Second, DVA is included in taxable income. Hence, due to tax-function convexity, DVA's impact in increasing volatility in taxable income increases the present value of expected tax liabilities (Smith and Stulz [1985], Graham and Smith [1999]). Consequently, given DVA's strong impact on earnings (Section 1, Figure 1), tax concerns give banks incentives to hedge DVA. As stated by the risk manager of a US bank, "I don't care about truth in accounting rules. I have to use it [DVA], it goes into my reports, I'm charged tax on it—and that makes it real" (Carver [2012a]). Due to its inclusion in taxable income, DVA is relevant for banks despite its lack of economic substance.

Absent tax-function convexity, DVA would have no effect on the present value of expected tax liabilities. DVA gains would increase tax liabilities by the amount of the gain multiplied by the marginal tax rate, while DVA losses would reduce tax liabilities by the amount of the loss multiplied by the marginal tax rate. Hence, DVA would be tax-neutral, in expectation. When taxable income is beneath zero before DVA losses, however, or when DVA losses drive taxable income beneath zero, DVA losses do not reduce taxable income by the amount of the losses multiplied by the marginal tax rate. While these outcomes would result in tax benefits (net-operating-loss carryforwards) that could offset future tax liabilities, banks could not use these benefits until future periods. Consequently, on a per-dollar basis, the present value of these benefits is less than the present value of the taxes banks always pay on DVA gains. In this respect, DVA increases the present value of expected tax liabilities.

3.4.3 *DVA Hedging: Distress Costs*

Banks hedge DVA by going long other banks' credit (Section 4.1). This approach to hedging raises distress costs. In good states, banks' credit risk falls, leading to gains on DVA hedges. In good states, however, capital and liquidity are abundant, and banks' earnings and balance

sheets are strong. Distress costs thus are low even apart from these gains. Hence, these gains have minimal scope to reduce distress costs. In bad states, banks' credit risk rises, leading to losses on DVA hedges. In bad states, even apart from these losses, losses reduce capital, and asset quality declines. Exposure to other banks leads to even larger losses and a larger decline in asset quality, amplifying banks' distress. Due to this asymmetric impact on distress costs, DVA hedging increases these costs, in expectation.

Distressed banks are subject to a “wholesale run”—a loss of access to wholesale funding, uninsured funding most global banks rely heavily on, particularly on the margin (Carpenter and Demiralp [2010], Disyatat [2011]). Wholesale runs can force banks to liquidate assets at a distressed, fire-sale price. In a perfect-market setting, without frictions, a bank can always sell assets at their fundamentals-based price. In this setting, forced liquidations are costless. Most of banks' assets, however, are illiquid and are traded in markets that have only a small number of traders, such as hedge funds (*e.g.*, Blundell-Wignall [2007]). Consequently, banks have a small pool of buyers even in normal times. Also, during periods of systemic distress, aggregate capital is low (Shleifer and Vishny [1992]). Hence, prospective buyers can pay only a low, below-fundamentals price. Selling at these low prices imposes costs on banks. Duffie [2010] and Huang and Ratnovski [2011] illustrate how wholesale runs can arise.

Wholesale runs have imposed large costs on banks in the 2007–8 crisis and in the ongoing European crisis. Wholesale runs were vital to the demise of Bear Stearns and Lehman Brothers (Acharya and Öncü [2010]). Even in less extreme settings, wholesale runs have generated costs by forcing banks to sell assets or even to exit entire lines of business. Between end-May and end-November 2011, for instance, US money-market funds cut by 89 percent their exposure to French banks and shifted their remaining exposures toward shorter maturities and secured lending (Fitch [2011a, 2011b]). Due in part to this run, French banks have exited or reduced scale in areas that rely on dollar funding despite previously being among the most active banks in certain of these areas, such as trade finance (see, *e.g.*, HSBC [2011]).

3.4.4 DVA Hedging, Moral Hazard, and Systemic Risk

In a world with no frictions, banks would internalize in full the distress costs of DVA hedging. Moral hazard, however, prevents banks from doing so. The public sector—central banks and governments—cannot commit *ex ante* not to support banks *ex post*, once a crisis hits, leading to moral hazard. As a result, banks assume more risk *ex ante* (e.g., Bhattacharya, Boot, and Thakor [1998]). At a minimum, banks can borrow from their central bank’s discount window. Throughout the 2007–8 crisis and the ongoing European crisis, public-sector support has far exceeded this minimum. Consequently, the prospect of public-sector support during a crisis reduces distress costs in general. With respect to wholesale runs in particular, central-bank liquidity gives banks access to an alternative funding source. Hence, banks hit by a wholesale run do not necessarily have to sell assets at a below-fundamentals, fire-sale price.

Regulators have an interest in curbing DVA hedging. Given that banks do not internalize in full the distress costs of DVA hedging, banks likely will do too much DVA hedging—take too much exposure to other banks—compared to the social optimum. Furthermore, public-sector support and the moral hazard that results are particularly acute *vis-à-vis* systemically important, “too big to fail” banks. These banks are the class of banks DVA and DVA hedging are most relevant for. In hedging DVA, these banks take more exposure to other global banks, tightening the links between these banks. In this respect, DVA increases systemic risk, giving regulators an especially strong reason to limit its practice.

3.5 Model

3.5.1 Preliminaries

I have two goals in this model: to show that DVA can induce banks to take long positions in other banks’ credit and to show that regulators can discourage DVA hedging by imposing a higher capital charge on positions that increase banks’ exposure to other banks. Banks max-

imize returns on capital (equity), driven in part by the probability that wholesale creditors roll over funding. I make four essential assumptions.

- (1) Banks' assets are financed by uninsured wholesale debt that matures before their assets;
- (2) DVA increases volatility in earnings, increasing expected tax liabilities;
- (3) to blunt DVA's impact in increasing earnings volatility, banks hedge DVA; and
- (4) liquidating assets due to a loss of access to funding results in distress costs—for instance, the cost of selling assets at a below-fundamentals price.

To simplify the exposition, I assume earnings are equivalent to taxable income. Also, I take as exogenous banks' derivatives and the resulting DVA on derivative liabilities, consistent with the substantively exogenous nature of the derivatives global banks use in market-making.

I specify the model so that DVA's only role is to raise earnings volatility. More specifically, I assume that DVA is excluded from post-tax earnings available to shareholders and also that creditors ignore DVA when deciding whether to roll over funds (when assessing banks' credit risk). DVA is a pure accounting exposure that lacks economic substance, in that DVA has no cash-flow implications. A DVA gain does not mean that banks can pay less on their derivative liabilities⁶; a DVA loss does not mean that banks must pay more. Banks' obligations on these liabilities are independent of—are not affected by—DVA. Hence, tax effects aside, DVA gains and losses have no direct impact on the cash available to give to shareholders or to pay back creditors. I thus specify the model so that DVA's only impact relates to its tax effects.

Banks balance the tax benefits against the distress costs of DVA hedging, where distress costs are modeled as having to liquidate assets at a below-fundamentals price should creditors pull funding. I build a baseline model and two extensions, as outlined below:

⁶ Technically, a DVA gain implies that banks are less likely to pay out on their derivative liabilities, but banks realize this benefit only upon defaulting. In this model, I exclude this possible outcome.

- (1) In my baseline model, banks internalize in full the distress costs of DVA hedging, public-sector support is ruled out, and capital is taken as a constant.
- (2) In my first extension, banks have some probability of getting public-sector support should private-sector creditors pull funding. The prospect of this support reduces distress costs. Capital is taken as a constant.
- (3) In my second extension, banks have some probability of public-sector support, if required. Capital is an endogenous function of how much exposure banks take to other banks, with positions that increase banks' exposure requiring more capital.

In (3), the punitive capital charge reduces DVA hedging. This effect rests on the assumption that banks maximize returns on capital, not returns, in violation of Modigliani-Miller (MM). MM's relevance for banks is a controversial subject. Bolton and Freixas [2006], for instance, argue that information asymmetries that increase the cost of equity could lead to a violation of MM, while Admati *et al.* [2011] argue that MM largely applies. Regardless, banks operate as if holding more equity capital is costly. In light of Basel III's tougher capital requirements, for instance, the capital charge of a position has a large effect on banks' investment decisions (see, *e.g.*, Wood [2012]).⁷ Hence, requiring more capital against positions that result in more exposure to other banks likely would discourage banks from taking such positions.

3.5.2 Set-Up

This model consists of five dates, $t \in \{0, 1, 2, 3, 4\}$, and banks that maximize post-tax returns on capital. The timeline is as follows (see Figure 2):

⁷ Along similar lines, banks almost invariably target returns on equity. Credit Suisse CEO Brady Dougan, for instance, highlighted Credit Suisse's return on equity of 15 percent when going through the bank's 2012Q3 earnings (Schäfer and Shotter [2012]). As a result, assuming that banks maximize returns on equity is useful in focusing on a performance metric most banks place heavy weight on.

- At time 0, banks are endowed with A in assets (*e.g.*, loans, securities), D in derivatives, and H in a hedging security used to blunt D 's impact on earnings.

A matures at time 4 and is financed fully by wholesale liabilities that mature at time 3. Holding A to maturity yields earnings of π . Having to sell A at time 3 yields earnings of $\phi < \pi$.

For simplicity, all of D are derivative liabilities, and earnings on D are a result only of changes in own-credit risk. D thus represents DVA. A rise in own-credit risk results in a gain on D ; a decline, in a loss.

H can be seen as a CDS on which the bank is the protection seller and another bank (or group of banks) is the reference entity; H can be seen also as another bank's bond. To simplify, I suppress the impact of H on earnings and focus solely on its role in hedging. Assuming credit-risk measures (*e.g.*, CDS spreads) follow a martingale process, so that the expected value tomorrow is same as the actual value today, H 's expected earnings are zero. Hence, suppressing earnings on H does not omit anything of substance.

Banks have K in capital. At first, K is fixed and exogenous, but in my second extension, I make K an endogenous function of σ_{DH} , the covariance between earnings on D and H . To simplify the exposition, I stipulate that $\sigma_{DH} < 0$.

- At time 1, banks select σ_{DH} . D is akin to a short position in own-credit risk. Hence, as σ_{DH} becomes lower (more negative), H becomes closer to a long position in own-credit risk. Earnings on H thus have a stronger positive link with changes in other banks' credit—a given decline in other banks' credit risk results in a larger gain, while a given rise leads to a larger loss. Consequently, as σ_{DH} becomes lower, banks effectively have more exposure to other banks.
- At time 2, a shock hits the economy—for instance, a housing-price decline, or a change in corporate credit risk. This shock impacts every bank in the same way (qualitatively).

Negative shocks result in a gain on D and a loss on H ; positive shocks, in a loss on D and a gain on H .

- At time 3, banks refinance A . Private-sector creditors roll over funding with probability $0 \leq p \leq 1$. Conditional on the private sector withdrawing funds, public-sector entities provide support with probability $0 \leq q \leq 1$. As a consequence, the probability of being cut off from private- and public-sector funding is $[1 - p][1 - q]$.

Public-sector support can be viewed as, for instance, expanded central-bank liquidity facilities.

Losing access to both private- and public-sector funding forces banks to liquidate A at a fire-sale price, yielding earnings of $\phi < \pi$. $\pi - \phi$ is the distress costs of having to sell assets at a below-fundamentals price.

In deciding whether to refinance, private-sector creditors focus on A and H . If the time-2 shock is positive, A is seen as “high-quality.” As a result, creditors have no reason to pull funds. Hence, gains on H are redundant in inducing creditors to refinance. If the time-2 shock is negative, A is viewed as “low-quality.” Creditors thus have incentives to pull funds. Losses on H amplify these incentives. Due to these asymmetric outcomes, a decline in σ_{DH} effectively increases p . As discussed above, creditors ignore D (DVA) when deciding whether to roll over funding.

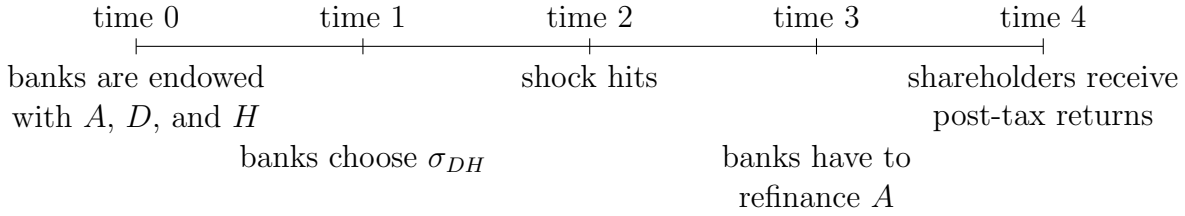
- At time 4, banks that maintain access to funding collect π in earnings on A . Thereafter, banks pay taxes on either π or ϕ and distribute to shareholders post-tax earnings.

Letting T and V denote the effective tax rate and returns on capital, banks’ problem is

$$\max_{\sigma_{DH}} V \equiv \frac{[\pi [p + q - pq] + \phi [1 - p] [1 - q]] [1 - T]}{K}. \quad (3.1)$$

Breaking down (1),

Figure 2: Model Timeline



- $p = p(\sigma_{DH})$, where $p()$ is increasing and concave in σ_{DH} . A decline in σ_{DH} increases exposure to other banks, reducing the probability that creditors roll over funding. $p()$'s concavity reflects diminishing returns to increasing σ_{DH} in increasing p .
- $T = T(\sigma_{DH})$, where $T()$ is increasing and convex in σ_{DH} . A decline in σ_{DH} reduces D 's net effect on earnings, reducing volatility in earnings and thus in taxable income. Hence, banks' effective tax rates fall, increasing post-tax earnings for any given amount of pre-tax earnings. The convexity of $T()$ reflects diminishing returns to reducing σ_{DH} in reducing T .⁸
- $K = K(\sigma_{DH})$, where $K()$ is decreasing in σ_{DH} .⁹ When σ_{DH} is lower, banks have more exposure to other banks. As a consequence, a decline in σ_{DH} forces banks to hold more capital against H in the models in which K is endogenous.¹⁰

As a consequence, hedging DVA—choosing a lower σ_{DH} —is beneficial in reducing banks' tax liabilities but is costly in increasing the odds that private-sector creditors withdraw funds. In

⁸ $T()$'s convexity means that when σ_{DH} is "high," a marginal change in σ_{DH} has a stronger impact on T than when σ_{DH} is "low." As a result, when σ_{DH} is high, a marginal decline in σ_{DH} has a stronger impact in reducing T . As banks reduce σ_{DH} , the marginal impact of a decline in σ_{DH} in reducing T becomes smaller. Hence, marginal declines in σ_{DH} have diminishing returns in reducing T .

⁹ I assume that $K()$ is linear in σ_{DH} , so that a marginal change in σ_{DH} has the same effect on K regardless of σ_{DH} 's value prior to this change.

¹⁰ For simplicity, I suppress banks' cost of funding. In my second extension, an increase in K is harmful in reducing post-tax returns on capital for any given amount of post-tax earnings. An increase in K , however, reduces leverage, implying less credit risk. Hence, banks' cost of funding likely would fall, increasing post-tax earnings. I suppress this effect, with the implicit assumption that this effect is not large enough to offset the adverse effect of lower post-tax returns on capital for any given amount of post-tax returns.

addition, when K is endogenous, a decline in σ_{DH} increases K , reducing returns on capital for any given amount of post-tax returns.

3.5.3 Results

Baseline Model: No Public-Sector Support, Constant Capital

In this section, I solve for banks' equilibrium hedging choice in my baseline model, in which K is constant and $q = 0$, so that public-sector support is ruled out. Differentiating (1) with respect to σ_{DH} yields the first-order necessary and second-order sufficient conditions below, where the σ sub-script denotes a partial derivative with respect to σ_{DH} :

$$\frac{\partial V}{\partial \sigma_{DH}} = \frac{p_{\sigma}() [\pi - \phi] [1 - T()] - T_{\sigma}() [\pi p() + \phi [1 - p()]]}{K} = 0 \quad (3.2)$$

$$\frac{\partial^2 V}{\partial \sigma_{DH}^2} = \frac{p_{\sigma\sigma}() [[\pi - \phi] [1 - T()]^2 - 2p_{\sigma}() [\pi - \phi] T_{\sigma}() - T_{\sigma\sigma}() [[\pi p() + \phi [1 - p()]]^2]}{K} < 0. \quad (3.3)$$

Re-arranging (2),

$$\frac{p_{\sigma}() [\pi - \phi] [1 - T()]}{K} = \frac{T_{\sigma}() [\pi p() + \phi [1 - p()]]}{K}. \quad (3.4)$$

In (4), the left-hand side is the impact of a marginal fall in σ_{DH} in reducing p , the probability creditors roll over funds, multiplied by the fall in post-tax earnings due to having to liquidate A should creditors pull funds. The right-hand side is the effect of a marginal decline in σ_{DH} in reducing the effective tax rate, T , multiplied by pre-tax earnings. In this situation, taking more exposure never is strictly costless, in that a rise in exposure always lowers the likelihood that creditors roll over funding. Banks choose σ_{DH} so as to equate the distress costs and tax benefits of a marginal fall in σ_{DH} . Since $\frac{\partial^2 V}{\partial \sigma_{DH}^2} < 0$, this choice is a maximum.

Extended Model: Public-Sector Support, Constant Capital

In this section, K is again held constant, but $q > 0$, so that public-sector support is possible.

Differentiating (1) with respect to σ_{DH} yields the first- and second-order conditions

$$\frac{\partial V}{\partial \sigma_{DH}} = \frac{p_{\sigma}() [1 - q] [\pi - \phi] [1 - T()] - T_{\sigma}() [\pi [p() + q - p() q] + \phi [1 - p()] [1 - q]]}{K} = 0 \quad (3.5)$$

$$\frac{\partial^2 V}{\partial \sigma_{DH}^2} = \frac{\alpha}{K} < 0 \quad (3.6)$$

$$\begin{aligned} \alpha &= p_{\sigma\sigma}() [[1 - q] [\pi - \phi] [1 - T()]]^2 - 2p_{\sigma}() [1 - q] [\pi - \phi] T_{\sigma}() \\ &\quad - T_{\sigma\sigma}() [\pi [p() + q - p() q] + \phi [1 - p()] [1 - q]]^2 < 0. \end{aligned}$$

Re-arranging (5),

$$\frac{p_{\sigma}() [1 - q] [\pi - \phi] [1 - T()] }{K} = \frac{T_{\sigma}() [\pi [p() + q - p() q] + \phi [1 - p()] [1 - q]]}{K} \quad (3.7)$$

(7) differs from (4) only through its inclusion of q . Hence, (7) has the same interpretation as (4)—(7)'s left- and right-hand sides capture the distress costs and tax benefits of a marginal fall in σ_{DH} . In equilibrium, banks choose σ_{DH} so as to equate these costs and benefits. The second-order condition (6) is negative. Consequently, banks' equilibrium choice of σ_{DH} is a maximum.

Allowing for public-sector support, so that $q > 0$, has a large effect on the trade-offs DVA hedging involves. In the extreme, with $q = 1$, so that public-sector support is certain should private-sector creditors pull funding, the left-hand side of (7) becomes

$$\frac{p_{\sigma}() [1 - 1] [\pi - \phi] [1 - T()] }{K} = \frac{0}{K} = 0.$$

Hence, in equilibrium, choosing a lower σ_{DH} is costless. A fall in σ_{DH} reduces the probability that private-sector creditors roll over funds, but the guarantee of public-sector support makes banks indifferent to this effect; banks can always replace private-sector funding with public-

sector funding. Hence, banks' equilibrium choice of σ_{DH} is a corner solution, in that banks set σ_{DH} as low as possible—maximize their exposure to other banks—so as to minimize T .

More generally, the prospect of public-sector support leads banks to choose a lower σ_{DH} —to take more exposure to other banks. Comparing the right-hand sides of (7) and (4),

$$\frac{\overbrace{T_{\sigma}(\cdot) [\pi [p(\cdot) + q - p(\cdot)q] + \phi [1 - p(\cdot)] [1 - q]]}^{\text{public-sector support}}}{K} > \frac{\overbrace{T_{\sigma}(\cdot) [\pi p(\cdot) + \phi [1 - p(\cdot)]]}^{\text{no public-sector support}}}{K}.$$

In equilibrium, the rise in tax benefits due to a marginal decline in σ_{DH} is higher with public-sector support than without. Public-sector support reduces the odds banks have to sell A at time 3. Hence, pre-tax earnings rise, increasing the tax savings due to a marginal fall in T . As a result, to satisfy the first-order conditions (5) and (2), the rise in distress costs due to a marginal decline in σ_{DH} must be higher with public-sector support than without. Because $p(\cdot)$ is concave, a marginal change in σ_{DH} has a larger effect on p when σ_{DH} is lower. A fall in σ_{DH} thus has a larger effect in reducing p when σ_{DH} is lower. Consequently, in equilibrium, banks choose a lower σ_{DH} with public-sector support.

Extended Model: Public-Sector Support, Endogenous Capital

In this section, $q > 0$, so that public-sector support is allowed, and K is a decreasing function of σ_{DH} , so that a lower σ_{DH} increases K . Endogenous K can be regarded as a punitive capital charge regulators impose against positions that increase banks' exposure to other banks.¹¹

¹¹ One alternative set-up would be to make K an increasing function of risk-weighted assets and to stipulate that a lower σ_{DH} increases the risk-weighting factor of H . Consequently, a lower σ_{DH} would increase the risk-weighted assets on a given quantity of H ; this rise in risk-weighted assets, in turn, would require more capital. This approach yields identical results but makes the notation more burdensome.

Differentiating (1) with respect to σ_{DH} yields the first- and second-order conditions¹²

$$\frac{\partial V}{\partial \sigma_{DH}} = \frac{\beta}{K(\cdot)^2} = 0 \quad (3.8)$$

$$\begin{aligned} \beta \equiv & K(\cdot) [p_\sigma(\cdot) [1 - q] [\pi - \phi] [1 - T(\cdot)] \\ & - T_\sigma(\cdot) [\pi [p(\cdot) + q - p(\cdot)q] + \phi [1 - p(\cdot)] [1 - q]] \\ & - K_\sigma(\cdot) [\pi [p(\cdot) + q - p(\cdot)q] + \phi [1 - p(\cdot)] [1 - q]] [1 - T(\cdot)] \end{aligned}$$

$$\frac{\partial^2 V}{\partial \sigma_{DH}^2} = \frac{\alpha}{K(\cdot)} < 0, \quad (3.9)$$

where $\alpha < 0$ is the same as in Section 5.3.2. Re-arranging,

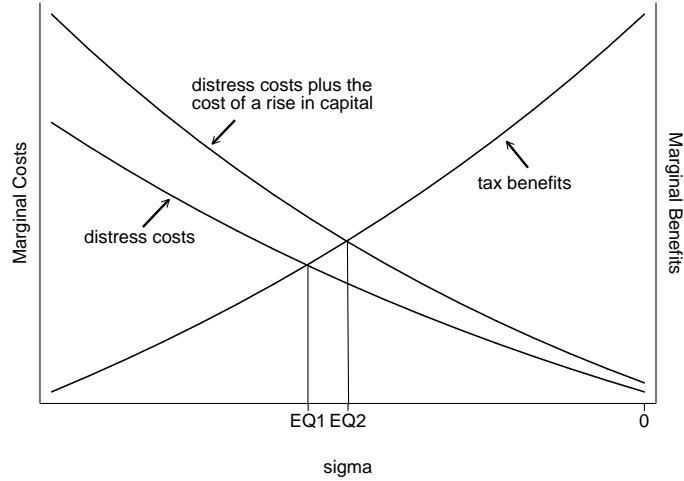
$$\begin{aligned} \frac{p_\sigma(\cdot) [1 - q] [\pi - \phi] [1 - T(\cdot)]}{K(\cdot)} - \gamma &= \frac{T_\sigma(\cdot) [\pi [p(\cdot) + q - p(\cdot)q] + \phi [1 - p(\cdot)] [1 - q]]}{K(\cdot)} \quad (3.10) \\ \gamma \equiv & \frac{K_\sigma(\cdot) [\pi [p(\cdot) + q - p(\cdot)q] + \phi [1 - p(\cdot)] [1 - q]] [1 - T(\cdot)]}{K(\cdot)^2} < 0. \end{aligned}$$

In (10), the first left-hand-side term and the right-hand side capture the impact of a marginal fall in σ_{DH} in increasing, respectively, distress costs and tax benefits. These costs and benefits are the same as those in Section 5.3.2, where public-sector support is possible but capital is taken as a constant.

(10) differs from (7) via the inclusion of γ . γ captures the impact of a marginal decline in σ_{DH} in forcing banks to hold more capital. This rise in capital reduces post-tax returns on capital for any given amount of post-tax earnings. In sum, a marginal fall in σ_{DH} increases tax benefits, forces banks to hold more capital, and possibly increases distress costs, with the magnitude of this effect depending on q . In equilibrium, banks choose σ_{DH} so as to equate the first effect with the sum of the second and third. Even when distress costs are zero (*i.e.*, $q = 1$), a marginal decline in σ_{DH} forces banks to hold more capital. As a result, as opposed

¹² The second-order condition (9) should include in the denominator also a second term, $-2K(\cdot)K_\sigma(\cdot)\beta$. The first-order condition (8), however, implies $\beta = 0$, in equilibrium. Hence, I drop this term from (9).

Fig. 3.2: Equilibrium Choices of σ_{DH} —Constant v. Endogenous Capital



“EQ1” is σ_{DH} ’s equilibrium value when capital is constant. “EQ2” is σ_{DH} ’s equilibrium value when capital is a decreasing function of σ_{DH} .

to the set-up with constant K , a marginal decline in σ_{DH} never is costless.

The impact of γ —of forcing banks to hold more capital when σ_{DH} is lower—leads banks to choose a higher σ_{DH} relative to a setting with constant K . Hence, banks take less exposure to other banks, in equilibrium. In Figure 2, “EQ1” and “EQ2” denote the equilibrium value of σ_{DH} when capital is, respectively, a constant and a decreasing function of σ_{DH} . Requiring banks to hold more capital when σ_{DH} is more negative pushes to the right the marginal-cost curve. This rightward shift makes less negative the value of σ_{DH} at which the marginal-cost and marginal-benefit curves intersect. Consequently, in equilibrium, σ_{DH} is less negative, so that banks are less exposed to other banks.

Implications

My model’s results have two main implications. First, due to moral hazard, banks likely will do too much DVA hedging relative to the social optimum—global banks will take too much exposure to other global banks, increasing systemic risk. The primary cost of DVA hedging

is distress costs. In bad states, losses on hedges would amplify banks' distress. Hence, banks would face higher odds of a wholesale run, among other undesirable outcomes. Expectations of public-sector support mitigate this concern. A bank, for instance, might expect its central bank to establish special liquidity facilities should a crisis occur, reducing funding pressure. In addition, expectations of public-sector support are strongest for the global, systemically important banks most relevant to DVA. These banks are especially unlikely to internalize in full the distress costs of DVA hedging.

Second, regulators can limit DVA hedging by imposing a punitive capital charge on positions that expose banks to other banks' credit. Due to the excessive DVA hedging that results from moral hazard and the rise in systemic risk that results, regulators have incentives to reduce its practice. A punitive capital charge would impose non-trivial costs on banks. To keep the same capital ratio, banks would have to increase capital, putting downward pressure on returns on capital, or reduce risk-weighted assets—by, for instance, selling assets, which likely would harm banks' earning power. Alternatively, banks could maintain a lower capital ratio, which would risk inducing a negative reaction from regulators and market participants. None of these options are attractive. Either way, banks' equilibrium choice of σ_{DH} is higher than when K is constant. As a result, banks are less exposed to other banks.

3.6 Conclusion

For large, global banks, DVA is akin to an exogenously imposed short position in own-credit risk that can have a strong impact in increasing earnings volatility. Tax concerns give banks incentives to hedge DVA so as to mitigate this rise in volatility. Global banks do so by going long other global banks' credit. Hence, DVA hedging tightens the link between global banks, increasing systemic risk. I show that moral hazard likely will induce global banks to do too much DVA hedging—to take too much exposure to other global banks—relative to the social

optimum. Regulators thus have incentives to reduce DVA hedging. In this vein, I show that regulators can reduce DVA hedging by imposing a punitive capital charge on positions that expose banks to other banks.

Appendix

The FR Y9-C mnemonics corresponding to the data I show are as follows:

Item	Mnemonic	Table
Total Assets	BHCK2170	Tables 1, 3
Trading Derivatives	BHCKA126–A127, BHCK8723–8724	Table 1
Derivative Assets	BHCM3543	Table 3
Derivative Liabilities	BHCK3547	Tables 1, 3
DVA	BHCKK094	Tables 1, 3
CVA	BHCKK090	Table 3
Pre-Tax Income	BHCK4300	Table 3
Net Exposure	BHCKG418–G422	Table 4
Cash Collateral	BHCKG423–G432	Table 4

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4. BALANCE-SHEET MANAGEMENT BY LARGE BANKS

ABSTRACT

I examine whether banks engage in balance-sheet management (BSM) to improve their reported financial ratios (*e.g.*, capital ratios). I argue that large banks' business models give these banks stronger incentives to do so and that BSM in assets has a larger effect in improving banks' financial ratios than does BSM in liabilities. Consistent with these arguments, for large banks, weaker financial ratios lead to more BSM in assets but not in liabilities; for other banks, weaker financial ratios do not lead to more BSM in either assets or liabilities. These results suggest that large banks use BSM in assets to improve their reported financial ratios.

4.1 Introduction

During the 2007–8 financial crisis, Lehman Brothers used its “Repo 105” program to cut its reported leverage (Valukas [2010], Vol. 4).¹ In light of Repo 105, balance-sheet management (BSM) by financial institutions has drawn regulatory attention. The Securities and Exchange Commission (SEC), for instance, sent 24 financial institutions a “Dear CFO” letter regarding their use of reverse repurchase agreements (repo). Banks can use BSM to give a temporary boost to financial ratios that are based on positions at quarter-end, *à la* Lehman and Repo 105. Consequently, banks can use BSM to report financial ratios that are stronger than those maintained during the quarter, in between reporting dates.

I focus on whether banks use BSM to strengthen their reported financial ratios. By BSM, I mean reducing assets and liabilities at quarter-end relative to average assets and liabilities during the quarter. I focus separately on BSM by large banks and on BSM by small and mid-size banks (“other banks”). Due to differences in business models, large banks have stronger incentives to use BSM to strengthen their reported financial ratios. Large banks have weaker financial ratios, rely more on wholesale (*i.e.*, uninsured) debt, and have stronger incentives to maintain a high credit rating. These differences strengthen large banks’ incentives to engage in financial-ratio-driven BSM (see Sections 3.3 and 3.4 for more).

My two main findings are as follows: First, for large banks, weaker financial ratios induce more BSM in assets. A fall in regulatory capital ratios and a rise in raw leverage (in contrast with regulatory leverage; see below) are linked with a larger fall in quarter-end assets relative to average assets during the quarter. Furthermore, this link between lower capital ratios and more BSM in assets is larger when banks have less capital and have assets whose disposal has a stronger effect in increasing capital ratios. These results suggest that large banks respond

¹ In Repo 105, right before quarter-end, Lehman entered into reverse repurchase agreements, moved off-balance-sheet the assets used as collateral, and used the cash obtained to retire debt. Lehman reversed this sequence of transactions at the start of the next quarter. Hence, Lehman effectively used Repo 105 to reduce its reported size and leverage relative to its size and leverage during the quarter.

to weaker financial ratios by using BSM in assets to strengthen these ratios. For other banks, capital ratios and raw leverage have no effect on BSM in assets.

Second, for large banks, weaker financial ratios do not consistently give rise to more BSM in liabilities. Higher raw leverage is linked with more BSM in short-term liabilities (fed funds purchased plus reverse repo) but with less BSM in “other borrowings” (see Section 4.1 for a definition). Also, higher raw leverage has no effect on BSM in short-term liabilities and other borrowings, taken together. Short-term liabilities have short durations, often overnight, and are seen as a relatively risky type of debt. Consequently, a rise in raw leverage and the rise in credit risk that results could lead banks to report less of this relatively high-risk type of debt and more relatively low-risk debt, such as other borrowings, with no effect on end-of-quarter total liabilities. Consistent with this notion, BSM in short-term liabilities and BSM in other borrowings have a negative link—a larger drop in end-of-quarter short-term liabilities implies a larger increase in end-of-quarter other borrowings. For other banks, weaker financial ratios do not induce more BSM in either short-term liabilities or other borrowings.

In addition, I examine the effect of regulatory leverage on BSM. Regulatory capital ratios and raw leverage are based on end-of-quarter assets, whereas regulatory leverage is based on average assets during the quarter. As a result, BSM in assets has a larger effect in improving capital ratios and raw leverage than in improving regulatory leverage. Consequently, banks have stronger incentives to use BSM to improve their capital ratios and raw leverage. In line with this argument, for large banks, regulatory leverage does not affect BSM in assets. This result differs from the findings that lower capital ratios and higher raw leverage induce more BSM in assets.

These results have two main implications. First, large banks use BSM in assets to improve their reported financial ratios. These results do not indicate banks have used Repo 105-like programs. Lehman cut its reported (*i.e.*, quarter-end) leverage relative to its average leverage during the quarter by accounting for reverse repos as true sales and using the cash from these

transactions to retire debt. Banks could generate the same balance-sheet and financial-ratio effects via transaction timing or similar methods—by, for instance, selling assets right before quarter-end and buying similar assets early in the next quarter. These results, however, have similar implications: Banks with weak financial ratios can use BSM to improve the reported quarter-end value of these ratios relative to their average value during the quarter.

Second, focusing on regulatory ratios and financial ratios more generally that use average assets, not end-of-quarter assets, could reduce BSM in assets. Banks are opaque institutions (Morgan [2002]) with much flexibility in carrying out transactions. Regulatory capital ratios use assets at the end of the quarter. As a result, disposing of assets at quarter-end is an easy way for banks to improve these ratios. Regulatory leverage, by contrast, uses average assets during the quarter. Hence, disposing of assets at quarter-end has little effect on regulatory leverage. My results suggest that for large banks, capital ratios have a large effect in inducing BSM in assets, whereas regulatory leverage has little effect in doing so. Consequently, more regulatory emphasis on regulatory leverage, or on any ratio that uses average positions during the quarter, could discourage BSM by large banks.

The rest of this paper is as follows: Related literature is in Section 2. In Section 3, I go over banks' main financial ratios, how BSM affects these ratios, and banks' incentives to use BSM to improve these ratios; I also discuss why large banks have more incentives to use BSM to improve these ratios. My empirical tests' set-up is in Section 4. Results are in Section 5. Concluding remarks are in Section 6. Supplemental information is in the appendix.

4.2 *Related Literature*

The notion that banks use BSM to improve their financial ratios rests on two premises. First, reporting strong financial ratios is important enough for banks to take steps to improve these ratios. Many studies find that banks do so, especially with respect to their regulatory capital

ratios. Lower capital ratios are linked with fewer charge-offs on loans (Beatty, Chamberlain, and Magliolo [1995], Collins, Shackelford, and Wahlen [1995]) and with more “gains trading,” where banks boost capital by selling at a gain assets whose price has increased (Moyer [1990], Scholes, Wilson, and Wolfson [1990]). Furthermore, Ahmed, Takeda, and Thomas [1999] find that banks use loan-loss provisions to manage their capital ratios.

Second, BSM is useful in strengthening banks’ reported financial ratios and balance sheets more generally. BSM has a long history. In the late 19th century, British banks used BSM to report in their financial statements high cash balances relative to their average cash balances during the quarter (Capie and Webber [1985], p. 266]). Empirically, previous studies find that financial institutions use BSM, or window-dressing, to disclose higher-quality assets. Pension funds, for instance, sell poorly performing stocks prior to their year-end sponsor evaluations (Lakonishok *et al.* [1991]); institutional investors do the same before their required year-end portfolio disclosures (He, Ng, and Wang [2004]). Also, Musto [1999] finds that money-market mutual funds that invest in both government and private paper hold more of the former and less of the latter around disclosure dates than at other times during the year.

For banks in particular, Allen and Saunders [1992] find that end-of-quarter assets exceed average assets, suggesting that banks report higher-than-normal assets at quarter-end. Allen and Saunders, however, look mainly at whether banks do engage in BSM, without examining what drives banks (*e.g.*, financial-ratio concerns) to do so. In addition, Kotomin and Winters [2006] argue that these results are due to customer-driven behavior and thus do not capture explicit BSM by banks. Most closely connected to this study, Yang and Shafer [2010] focus on BSM in assets, while Owens and Wu [2011] focus on BSM in liabilities. Yang and Shafer find mixed evidence of a link between capital ratios and BSM in assets; Owens and Wu find a link between higher leverage and more BSM in short-term liabilities.

Most fundamentally, this study differs from Yang and Shafer [2010] and Owens and Wu [2011] in examining separately BSM by large banks and BSM by other banks. Large banks’

business models increase these banks’ incentives to use BSM to improve their financial ratios. Consequently, focusing on BSM among all banks, taken together, risks overlooking differences among types of banks in financial-ratio-driven BSM. Also, with respect to liability-side BSM, I examine BSM in both short-term liabilities and other borrowings, whereas Owens and Wu focus on BSM solely in short-term liabilities. Examining BSM in both short-term liabilities and other borrowings allows for a closer look at liability-side BSM—at whether, for instance, weaker financial ratios lead banks to report at quarter-end fewer liabilities in general or more of one type of liability and less of another.

4.3 Institutional Details

4.3.1 Banks, Regulatory Ratios, and Raw Leverage

In this section, I go through the details of banks’ financial ratios. Three of the main ratios of United States (US) banks are regulatory capital ratios, regulatory leverage, and raw leverage. These ratios are calculated as follows²:

$$\begin{aligned}
 \text{Tier 1 capital ratio (total capital ratio)} &= \frac{\text{Tier 1 capital (total capital)}}{\text{risk-weighted assets}} \\
 \text{regulatory leverage} &= \frac{\text{Tier 1 capital}}{\text{regulatory average assets}} \\
 \text{raw leverage} &= \frac{\text{raw total assets}}{\text{balance-sheet equity}}.
 \end{aligned}$$

In evaluating banks, regulators focus on capital ratios and regulatory leverage, classifying as “well-capitalized” banks that have a Tier 1 capital ratio, a total capital ratio, and regulatory leverage of at least six percent, 10 percent, and five percent, respectively. Regulators give no formal attention to raw leverage. Anecdotally, market participants (*e.g.*, wholesale creditors,

² Regulatory average assets excludes certain intangible assets (*e.g.*, goodwill). Also, Tier 1 capital includes only core capital (*e.g.*, retained earnings); total capital includes a wider range of capital (*e.g.*, subordinated debt). FDIC [1992] has more information on the use of these ratios in regulating banks.

credit-rating agencies) tend to focus on capital ratios and raw leverage.

With respect to BSM, these ratios have two key features. First, regulatory capital ratios and raw leverage are based on assets at quarter-end, whereas regulatory leverage uses average assets during the quarter. Ignoring differences across ratios in how assets are defined, suppose a bank has on days 1, 2, and 3 assets of 120, 110, and 70: For capital ratios and raw leverage, its assets are 70, its day-3 assets, while for regulatory leverage, its assets are 100, its average assets over these three days. Hence, BSM—reducing assets at quarter-end relative to average assets during the quarter—has a smaller impact on regulatory leverage than on capital ratios and raw leverage.

Second, regulatory capital ratios are based on risk-weighted assets, not on total raw assets. Each asset has a risk-weighting factor that depends on its risk; riskier assets have higher risk-weights and thus count more toward risk-weighted assets. The risk-weighted equivalent of an asset is its book value multiplied by its risk-weight. US Treasuries, US Agency securities, and corporate bonds, for instance, have risk-weights of zero percent, 20 percent, and 100 percent.³ Hence, risk-weighted assets for 100 notional of Treasuries, Agencies, and corporates are zero, 20, and 100. Consequently, disposing of assets with a higher risk-weight has a larger effect in reducing risk-weighted assets, putting more upward pressure on banks' capital ratios. Sales of Treasuries, for instance, do not affect risk-weighted assets at all, whereas selling corporate bonds lowers risk-weighted assets on a dollar-for-dollar basis (*i.e.*, by \$1 for each dollar sold). When I examine BSM in assets, I exploit variation in risk-weights.

4.3.2 *The Financial-Ratio Effects of BSM*

In this section, building on the discussion above, I go over how shedding assets and liabilities at quarter-end affects banks' regulatory ratios and raw leverage.

Capital Ratios

³ See http://www.ots.treas.gov/_files/422020.pdf, Section 120B.7.

- With respect to assets, capital ratios are based on end-of-quarter risk-weighted assets. Most of banks' assets have a non-zero risk-weight. Hence, disposing of assets at quarter-end generally reduces risk-weighted assets, increasing capital ratios.
- With respect to liabilities, in retiring debt, cash is the only asset removed from banks' balance sheets.⁴ Cash has a zero-percent risk-weight. Consequently, reducing liabilities at quarter-end has no effect on capital ratios.

Regulatory Leverage

- With respect to assets, regulatory leverage is based on average regulatory assets during the quarter, not on end-of-quarter assets. Consequently, reducing assets at quarter-end has little effect on regulatory leverage.
- With respect to liabilities, retiring debt reduces cash. Cash is part of the asset base of regulatory leverage, but regulatory leverage is based on average assets. Hence, reducing liabilities at quarter-end has a limited impact on regulatory leverage.

Raw Leverage

- With respect to assets, raw leverage is based on total raw assets at quarter-end. Hence, in general, reducing assets at quarter-end reduces raw leverage.
- With respect to liabilities, using cash to retire debt reduces total raw assets, reducing raw leverage.

In sum, BSM in assets can have a strong impact in improving capital ratios and raw leverage but not regulatory leverage. Liability-side BSM can have a strong impact in improving raw leverage but not capital ratios or regulatory leverage.

⁴ Notably, reducing even reverse repos has no effect on capital ratios. To a first approximation, the proper accounting for a reverse repo is to debit cash and to credit short-term liabilities; upon terminating a reverse repo, the reverse entry is made. The assets used as collateral stay on banks' balance sheets. Hence, changes in reverse repos have no impact on any asset-side accounts except cash. Cash has a zero-percent risk-weight. As a result, changes in reverse repos do not affect capital ratios.

4.3.3 Incentives to Use BSM

In this section, I detail banks' incentives to improve their financial ratios via BSM. Banks face discipline from two sources: regulators and market participants. With respect to regulators, government support (*e.g.*, deposit insurance) can give rise to moral hazard, inducing banks to assume more risk (Bhattacharya, Boot, and Thakor [1998]). Banking regulators can mitigate this problem by, among other tactics, imposing capital and leverage requirements on banks and imposing sanctions on banks that fail to satisfy these requirements. In 2011, for instance, the Federal Reserve deemed First Chicago Bank & Trust "significantly undercapitalized" and forced First Chicago either to raise equity or to sell itself.⁵ Reporting weak regulatory ratios increases the odds of these and other regulatory sanctions.

With respect to market participants, two dynamics give banks incentives to report strong financial ratios. First, the wholesale and interbank markets are important sources of funding for (large) banks, especially on the margin (Carpenter and Demiralp [2010], Disyatat [2011]). Wholesale and interbank debt is not government-insured. As a result, in these markets, credit risk matters, even in secured-lending markets (*e.g.*, the repo market), wherein borrowers must post collateral (Copeland, Martin, and Walker [2010], Fitch [2012]). Weaker financial ratios imply higher credit risk, increasing the cost of or reducing access to wholesale and interbank financing. Empirically, lower capital ratios are linked with higher bond yields (Hannan and Hanweck [1988], Goyal [2005]).

In addition, financial ratios are important inputs in banks' credit ratings.⁶ Credit ratings matter, for two reasons. First, (large) banks make extensive use of derivatives. Credit-rating downgrades can force banks to put up additional collateral to their derivative counterparties. As of November 2011, for instance, a one-notch credit-rating downgrade would have required Morgan Stanley to post another \$1.29 billion in collateral (Campbell [2011]). Second, certain

⁵ See <http://www.federalreserve.gov/newsevents/press/enforcement/enf20110412a1.pdf>.

⁶ See, for instance, http://www.fitchratings.com.cn/en/method_3_3.php.

investors in the wholesale markets are prohibited from investing in firms whose credit rating is below some threshold (*e.g.*, investment grade). Weaker financial ratios imply higher credit risk, increasing the odds of a credit-rating downgrade.

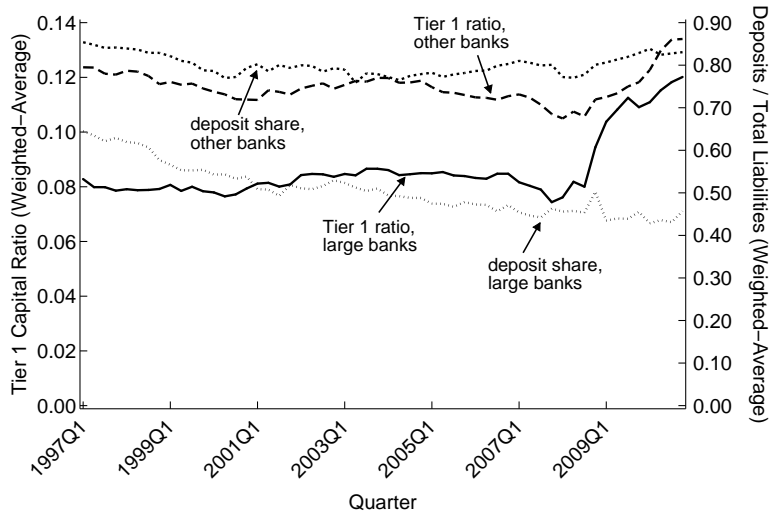
With respect to market participants, the notion that banks use BSM to strengthen their financial ratios implies banks can “fool the market”—that reporting better quarter-end ratios is seen in a positive way by, for instance, wholesale creditors, even if these ratios are stronger than banks’ intra-quarter ratios and if creditors can infer this difference (using, for instance, financial-statement information). What matters, however, is not whether banks can fool the market but whether banks think they can do so. In Repo 105, for instance, one of Lehman’s main aims was to avoid a credit-rating downgrade by reducing its reported leverage (Valukas [2010]). As a result, as long as banks think that reporting stronger quarter-end ratios reduces perceived credit risk, banks have incentives to use BSM to improve these ratios.⁷

4.3.4 *Large Banks v. Other Banks*

Three factors strengthen large banks’ incentives to use BSM to improve their financial ratios compared to other banks. First, large banks have weaker financial ratios, particularly capital ratios. During the 56 quarters from 1997Q1–2010Q4, the median quarterly weighted-average Tier 1 ratio of the 30-largest banks was 8.3 percent, compared to 11.6 percent for other banks (Figure 1, left y-axis). Second, large banks rely less on deposits and more on wholesale and interbank funding, which is not government-insured. During 1997–2010, large banks’ median quarterly weighted-average fraction of deposits in total liabilities was 50 percent, compared to other banks’ deposit share of 80 percent (Figure 1, right y-axis). Hence, credit-risk concerns are stronger for large banks. Third, large banks dominate derivative activity. In each quarter during 1997–2010, large banks accounted for over 99 percent of the total derivatives of banks. Consequently, the collateral calls that can result from a credit-rating downgrade are a bigger

⁷ In addition, market participants might regard quarter-end positions as more relevant going forward than average positions during the quarter and thus give more weight to these positions.

Fig. 4.1: Tier 1 Ratio and Deposit Share, Large Banks v. Other Banks



“Large banks” are the 30-biggest banks in each different quarter, as measured by total assets. “Other banks” are all other banks. Figures are on a weighted-average basis.

concern for large banks.

To be clear, these differences between large banks and other banks are driven primarily by differences in operations and in business models, not by size *per se*. Most large banks, for instance, have large market-making arms in addition to their lending arms, whereas smaller banks focus primarily on lending. Hence, small banks whose operations are similar to those of large banks would have stronger incentives to engage in financial-ratio-motivated BSM; likewise, large banks whose operations are similar to those of small banks would have weaker incentives to engage in financial-ratio-motivated BSM. In general, however, few small banks operate in the same way as large banks, while most large banks operate in a similar way. As a result, I divide my sample by size (see Section 4.2).

4.4 Empirical Tests: Set-Up

4.4.1 Definition of BSM

I define BSM as reducing positions as of quarter-end relative to average positions during the quarter. Using this definition, one important factor to consider is secular trends in positions. Banks with weak capital ratios, for instance, could report low end-of-quarter assets in quarter t relative to average assets in t due to a permanent reduction in assets, not to BSM. Hence, I define BSM in assets as follows, where $EOQASS$ is end-of-quarter total assets and $AVGASS$ is average total assets during the quarter:

$$BSMASS_{it} = \frac{EOQASS_{it} - [AVGASS_{it+1} + AVGASS_{it}] / 2}{[AVGASS_{it+1} + AVGASS_{it}] / 2}.$$

This definition is consistent with previous studies (*e.g.*, Owens and Wu [2011]). I use the same definition of BSM for two liability-side accounts. One is short-term liabilities, $BSMSTL$, the sum of fed funds sold and reverse repos. The second is “other borrowings,” $BSMOTH$, the sum of commercial paper and “other borrowed money”; other borrowed money includes, *inter alia*, re-discounted notes and bills and borrowings on promissory notes.⁸ Also, I examine BSM in short-term liabilities and other borrowings taken jointly, denoted by $BSMLIAB$.

A lower (more negative) value of $BSMASS$ implies more BSM in assets, in that end-of-quarter assets in quarter t are lower relative to the average of average assets in quarters t and $t+1$. Defining $BSMASS$ in this way is useful in capturing as BSM declines in end-of-quarter assets that do not translate into lower average assets in the next quarter. Insofar as a bank permanently reduces assets, $BSMASS$ would imply little, if any, BSM. Suppose that a bank has 100 in assets at the start of quarter t and subsequently shrinks, leading to average assets in t and $t + 1$ of 90 and 70 and end-of-quarter assets in t of 80: The numerator of $BSMASS$

⁸ These two specific accounts are taken directly from the FR Y9-C. The Federal Reserve Bank of Chicago’s “Data Dictionary,” found at http://www.chicagofed.org/webpages/banking/financial_institution_reports/bhc_data.cfm, has further details on the liabilities included in other borrowings.

would be $80 - \frac{70+90}{2} = 80 - 80 = 0$, reflecting this bank's permanent contraction. *BSMASS* thus implies more BSM only insofar as quarter-end assets are low relative to average assets over the prior and subsequent quarters.

4.4.2 Data, Sample Selection, and Sample Partition

All data are from the FR Y9-C.⁹ My sample is a quarterly panel, unbalanced, that consists of each bank in each quarter t from 1997Q2–2010Q3 that has data in t and $t + 1$ for average positions during the quarter in total assets, short-term liabilities, and other borrowings; data in t for end-of-quarter positions in these three accounts; and data in $t - 1$ for the non-BSM-related variables I use (Section 4.3). This initial sample consists of 59,167 bank-quarters and 2,680 different banks. Because of large banks' stronger incentives to engage in BSM (Section 3.4), I divide this sample into large banks and other banks. I do so as follows:

- (1) For each quarter in my sample, I rank banks by total assets at the start of the quarter;
- (2) I compute each bank's average size, so that a bank, for instance, ranking 25th in size in one quarter, 30th in the next, and 20th in the third has an average size of 25th; and
- (3) I classify as "large banks" those banks with an average size of 30th or lower, and I classify as "other banks" all the rest.

I follow this approach so that banks do not change between groups over time. When I define as large banks the 35- or 40-largest banks, I get largely the same results (not tabulated).

⁹ The FR Y9-C is a regulatory report that all banks, large banks and small banks alike, file in each quarter. Hence, my initial sample includes banks of all types.

4.4.3 Models

I estimate the models below (more-precise variable definitions are in the appendix):

$$\begin{aligned}
 BSMASS_{it} &= \beta_0 + \beta_1 CAP_{it-1} + \beta_2 SIZE_{it-1} + \beta_3 STLIAB_{it-1} + \beta_4 OTHBORR_{it-1} \\
 &\quad + \beta_5 NPA_{it-1} + \beta_6 BSMSTL_{it} + \beta_7 BSMOTH_{it} \\
 &\quad + \beta_8 RISK_{it-1} + \beta_9 CAP^2 + \beta_{10} CAPRISK + \epsilon_{it}
 \end{aligned} \tag{1}$$

$$\begin{aligned}
 BSMSTL_{it} &= \gamma_0 + \gamma_1 CAP_{it-1} + \gamma_2 SIZE_{it-1} + \gamma_3 STLIAB_{it-1} + \gamma_4 OTHBORR_{it-1} \\
 &\quad + \gamma_5 NPA_{it-1} + \gamma_6 BSMASS_{it} + \gamma_7 BSMOTH_{it} + \epsilon_{it}
 \end{aligned} \tag{2}$$

$$\begin{aligned}
 BSMOTH_{it} &= \delta_0 + \delta_1 CAP_{it-1} + \delta_2 SIZE_{it-1} + \delta_3 STLIAB_{it-1} + \delta_4 OTHBORR_{it-1} \\
 &\quad + \delta_5 NPA_{it-1} + \delta_6 BSMASS_{it} + \delta_7 BSMSTL_{it} + \nu_{it}.
 \end{aligned} \tag{3}$$

$$\begin{aligned}
 BSMLIAB_{it} &= \omega_0 + \omega_1 CAP_{it-1} + \omega_2 SIZE_{it-1} + \omega_3 STLIAB_{it-1} + \omega_4 OTHBORR_{it-1} \\
 &\quad + \omega_5 NPA_{it-1} + \omega_6 BSMASS_{it} + \nu_{it}
 \end{aligned} \tag{4}$$

ϵ , ε , and ν are error terms. In line with prior studies (*e.g.*, Gambacorta [2004]), I define *CAP* as banks' Tier 1 capital ratio above a six-percent baseline, the level below which regulators no longer classify banks as well-capitalized. Also, I estimate each model using *RAWLEV* and, separately, *REGLEV* rather than *CAP*. *RAWLEV* is raw leverage (*i.e.*, total assets divided by balance-sheet equity). *REGLEV* is regulatory leverage above a five-percent baseline, the level beneath which regulators no longer classify banks as well-capitalized. Finally, I include in each model also time and bank fixed effects. The other variables are controls of no inherent interest given my focus. *SIZE* is the log of total assets. *STLIAB* and *OTHBORR* are the share of short-term liabilities and other borrowings in total liabilities; these variables control for debt-composition effects (Allen and Saunders [1992]). *NPA* is non-performing assets as a share of total assets and controls for asset-quality effects.

Two aspects of these models warrant comments. First, in each model, I include as controls BSM in the other balance-sheet accounts. In model (1), for instance, BSM in assets, I include as controls *BSMSTL* and *BSMOTH*. BSM in assets likely has liability-side effects, while

BSM in liabilities likewise has asset-side effects.¹⁰ Suppose, for instance, that banks engage in BSM in short-term liabilities: Retiring debt at the end of the quarter necessarily involves a decline in cash (in assets). Hence, focusing on BSM in assets without controlling for BSM in liabilities runs the risk of identifying BSM in assets that actually is BSM in liabilities that has asset-side effects. Including as controls BSM in banks' other accounts helps alleviate this concern and ensures that each model focuses in BSM in the relevant balance-sheet account. More formally, this approach helps guard against omitted-variable bias.¹¹

Second, to avoid endogeneity, I use lags for the non-BSM-related independent variables. Consequently, I examine the effect of these variables as measured at the start of the period on BSM during the upcoming quarter. This decision is especially important with respect to the financial-ratio variables. Expected end-of-quarter financial ratios should drive BSM, not financial ratios at the start of the quarter, but end-of-quarter financial ratios are endogenous with respect to BSM, in that BSM affects these ratios. With respect to CAP , for instance, expectations of a lower CAP_{it} should induce more BSM during quarter t . Quarter- t BSM, however, raises CAP_{it} , weakening the link between a lower observed CAP_{it} and more quarter- t BSM. To avoid this problem, I use lags for the financial-ratio variables. This decision likely weakens my ability to detect a link between financial ratios and BSM.

Also, two more notes: First, customer- and creditor-driven changes in assets and liabilities can occur just before quarter-end. Hence, gaps between end-of-quarter and average positions are not fully endogenous (*i.e.*, are not fully within banks' control). These exogenous forces, however, would affect my results only insofar as they are systematically linked with the financial ratios of banks. To the best of my knowledge, no empirical evidence or theoretical arguments identify this type of relationship. Second, though a bank with weak financial ratios could lose access to funding, its creditors could just as easily pull funding early in the quarter

¹⁰ Insofar as banks engage in BSM by selling non-cash financial assets for cash, BSM in assets has no effect on liabilities, but using this cash to pay down debt, *à la* Lehman in Repo 105, does.

¹¹ When I estimate these models without these controls, my results are essentially the same.

as just before quarter-end. Consequently, this sort of behavior would not systematically bias my measures of BSM in liabilities.

4.4.4 Hypotheses

Banks have incentives to use BSM to improve their financial ratios (Section 3.3). As a result, I focus on the following hypotheses, stated in alternative form:

- (1) Weaker financial ratios—lower *CAP*, higher *RAWLEV*, and lower *REGLEV*—induce more BSM in assets, short-term liabilities, other borrowings, and the sum of short-term liabilities and other borrowings.

BSM in assets and liabilities, however, impact *CAP*, *RAWLEV*, and *REGLEV* in different ways (Section 3.2). BSM in assets can have a large impact in improving banks' capital ratios and raw leverage but has little effect in improving regulatory leverage. BSM in liabilities can have a strong impact in improving raw leverage but has little impact in improving regulatory leverage and no impact in improving banks' capital ratios. As a result, *a priori*, *CAP* should have a strong effect only on BSM in assets, *RAWLEV* should have a strong effect on BSM in each account, and *REGLEV* should have a small impact on BSM in each account. Insofar as weaker financial ratios induce more BSM, *CAP* and *REGLEV* should have a positive sign, and *RAWLEV*, a negative sign—weaker financial ratios result in a larger fall in quarter-end positions relative to average positions during the quarter.

With respect to BSM in assets, I examine two hypotheses that allow for non-linearity in *CAP*. First, a marginal capital-ratio rise likely has a stronger effect in preventing regulatory sanctions or in boosting market confidence when this rise is from a lower capital ratio—going, for instance, from a six- to a seven-percent Tier 1 ratio is more helpful along these lines than is moving from a 14- to a 15-percent Tier 1 ratio. More formally, the benefits of using BSM to improve capital ratios have diminishing marginal returns. I thus examine the hypothesis

below:

- (2) The negative link between capital ratios and BSM in assets is stronger when the capital ratios of banks are lower.

Since BSM in assets affects the capital ratios of banks but BSM in liabilities does not, I test this hypothesis only for model (1), BSM in assets, where $CAP^2 = CAP \times CAP$. Hypothesis (2) implies that the sign of CAP^2 is negative—the positive link between CAP and $BSMASS$ (the link between lower capital ratios and more BSM in assets) is greater when CAP is lower.

Second, shedding assets with a higher risk-weight leads to a larger decline in risk-weighted assets, increasing capital ratios by more (Section 3.1). I thus examine the hypothesis below:

- (3) The negative link between capital ratios and BSM in assets is larger when banks' assets have higher risk-weights.

This hypothesis states that capital-ratio-motivated BSM is more prevalent when banks have assets whose disposal has a larger impact in improving their capital ratios. To test hypothesis (3), I include in model (1) $RISK$, risk-weighted assets divided by total raw assets, and the interaction term $CAPRISK = CAP \times RISK$.¹² A higher value for $RISK$ means that banks' assets have higher risk-weights. Hence, shedding assets at quarter-end reduces risk-weighted assets by more, putting more upward pressure on capital ratios. As a result, banks can better use BSM to improve their capital ratios when $RISK$ is high, strengthening the link between lower capital ratios and more BSM in assets. Hypothesis (3) implies that $CAPRISK$'s sign is positive—the positive link between CAP and $BSMASS$ (the link between lower capital ratios and more BSM in assets) is larger when banks have more high-risk-weight assets.¹³

¹² In the appendix, I examine $CAPRISK$ in more detail.

¹³ I focus only on the interaction effect of $RISK$, not on its main effect. *A priori*, $RISK$'s sign is unclear. In shedding high-risk-weight assets, BSM has a stronger impact in increasing banks' capital ratios, so that higher $RISK$ implies more BSM. High-risk-weight assets, however, tend to be illiquid assets that are relatively hard to dispose of, while low-risk-weight assets tend to be liquid assets that are relatively easy to sell (*e.g.*, US Treasuries). In its Repo 105 program, for instance, Lehman used mainly US Treasuries and other government-related securities (Valukas [2010], Vol. 4, pp. 795–6). In this way, higher $RISK$ implies less BSM.

Tab. 4.1: Summary Statistics

Bank Type	Large Banks ($N = 1,571$; # groups = 60)							P-Value, Wilcoxon Test
Variable	Mean	Standard Deviation	Percentiles					
			10 th	25 th	50 th	75 th	90 th	
<i>BSMASS</i>	-0.004	0.053	-0.047	-0.015	0.002	0.017	0.034	0.618
<i>BSMSTL</i>	-0.110	0.364	-0.445	-0.242	-0.091	0.018	0.141	0.000
<i>BSMOTH</i>	0.017	0.210	-0.146	-0.056	0.002	0.059	0.167	0.581
<i>BSMLIAB</i>	-0.034	0.139	-0.172	-0.094	-0.029	0.023	0.088	0.000
<i>CAP</i>	0.030	0.035	0.010	0.017	0.026	0.042	0.066	0.000
<i>RAWLEV</i>	15.417	17.989	9.001	10.426	12.093	14.036	17.157	0.000
<i>REGLEV</i>	0.022	0.037	0.003	0.012	0.020	0.031	0.044	0.000
<i>SIZE</i>	18.630	1.088	17.399	17.785	18.405	19.345	20.246	0.000
<i>STLIAB</i>	0.105	0.120	0.015	0.036	0.066	0.132	0.239	0.000
<i>OTHBORR</i>	0.145	0.094	0.041	0.077	0.131	0.194	0.258	0.000
<i>NPA</i>	0.007	0.008	0.001	0.003	0.005	0.009	0.015	0.000
<i>RISK</i>	0.755	0.196	0.511	0.656	0.770	0.881	0.980	0.000
Bank Type	Other Banks ($N = 57,596$; # groups = 2,620)							P-Value, Wilcoxon Test
Variable	Mean	Standard Deviation	Percentiles					
			10 th	25 th	50 th	75 th	90 th	
<i>BSMASS</i>	0.001	0.032	-0.021	-0.007	0.002	0.012	0.025	
<i>BSMSTL</i>	0.472	42.038	-1.000	-0.326	-0.045	0.089	0.451	
<i>BSMOTH</i>	0.652	51.542	-0.251	-0.066	0.000	0.077	0.295	
<i>BSMLIAB</i>	0.034	0.983	-0.197	-0.074	-0.002	0.075	0.222	
<i>CAP</i>	0.066	0.057	0.026	0.039	0.056	0.081	0.116	
<i>RAWLEV</i>	531.575	41,551.460	8.404	9.933	11.761	14.109	16.925	
<i>REGLEV</i>	0.039	0.030	0.014	0.024	0.036	0.049	0.066	
<i>SIZE</i>	13.376	1.137	12.163	12.493	13.172	13.897	14.940	
<i>STLIAB</i>	0.037	0.057	0.000	0.004	0.021	0.049	0.089	
<i>OTHBORR</i>	0.074	0.070	0.005	0.022	0.057	0.105	0.162	
<i>NPA</i>	0.007	0.011	0.001	0.002	0.004	0.008	0.016	
<i>RISK</i>	0.714	0.112	0.573	0.645	0.719	0.790	0.850	

My sample runs from 1997Q2–2010Q3. Large banks are those banks that have an average size of 30th or lower; other banks are all other banks. *BSMASS*: end-of-quarter assets in quarter t minus the average of average assets in quarters t and $t + 1$, divided by the average of average assets in t and $t + 1$; *BSMSTL*, *BSMOTH*, and *BSMLIAB* are defined in the same way for short-term liabilities, other borrowings, and short-term liabilities plus other borrowings. *CAP*: Tier 1 capital ratio in excess of a six-percent baseline; *RAWLEV*: total raw assets divided by balance-sheet equity; *REGLEV*: regulatory leverage in excess of a five-percent baseline; *SIZE*: log of total assets; *STLIAB*: short-term liabilities as a share of total liabilities; *OTHBORR*: other borrowings as a share of total liabilities; *NPA*: non-performing assets as a share of total assets; *RISK*: risk-weighted assets divided by total raw assets. In the far-right column, I show the p-values for a Wilcoxon rank-sum test that assesses whether differences across bank types in a given variable are statistically significant.

With respect to BSM in liabilities, financial-ratio concerns likely have a stronger impact in inducing BSM in short-term liabilities than in other borrowings. Short-term liabilities are a relatively high-risk form of funding. These liabilities have short maturities, often overnight. Creditors thus can pull these liabilities on short notice, exposing banks to rollover risk (*e.g.*, Acharya, Gale, and Yorulmazer [2011]). This exposure to rollover risk increases banks' credit

Tab. 4.2: Correlation Matrices

Variable	<i>BSMASS</i>	<i>BSMSTL</i>	<i>BSMOTH</i>	<i>BSMLIAB</i>	<i>CAP</i>	<i>RAWLEV</i>	<i>REGLEV</i>	<i>SIZE</i>	<i>STLIAB</i>	<i>OTHLIAB</i>	<i>NPA</i>	<i>RISK</i>
<i>BSMASS</i>	1.000	0.001	-0.004	0.065*	-0.011*	0.004	0.015*	0.048*	-0.005	0.021*	-0.010*	0.029*
<i>BSMSTL</i>	0.155*	1.000	0.000	0.047*	0.002	0.000	0.007	0.000	-0.006	0.002	0.008	-0.003
<i>BSMOTH</i>	0.285*	-0.046	1.000	0.147*	0.003	0.000	0.005	0.011*	-0.009*	-0.008*	0.008*	0.003
<i>BSMLIAB</i>	0.459*	0.307*	0.674*	1.000	-0.003	0.000	-0.008*	-0.009*	-0.011*	-0.008	0.015*	-0.005
<i>CAP</i>	0.027	0.088*	0.006	0.037	1.000	-0.013*	0.711*	-0.171*	-0.015*	-0.086*	-0.082*	-0.309*
<i>RAWLEV</i>	-0.141*	-0.039	0.051*	-0.077*	-0.263*	1.000	-0.014*	0.001	0.006	0.004	0.011*	-0.003
<i>REGLEV</i>	0.031	0.049	-0.002	0.032	0.266*	-0.058*	1.000	-0.026*	-0.033*	-0.059*	-0.085*	0.105*
<i>SIZE</i>	0.074*	-0.003	0.031	0.085*	0.060*	0.067*	0.040	1.000	0.083*	0.237*	0.278*	0.379*
<i>STLIAB</i>	-0.111*	-0.001	-0.037	-0.104*	-0.095*	0.300*	-0.081*	-0.232*	1.000	-0.079*	-0.061*	-0.053*
<i>OTHLIAB</i>	0.016	-0.001	0.085*	0.138*	-0.062*	-0.039	-0.016	0.292*	-0.390*	1.000	0.011*	0.073*
<i>NPA</i>	0.016	0.002	-0.008	0.011	0.302*	-0.069*	0.113*	0.316*	-0.272*	0.070*	1.000	0.080*
<i>RISK</i>	0.026	-0.048	0.009	0.011	-0.295*	-0.182*	0.024	-0.093*	-0.305*	0.073*	-0.048	1.000

Large banks and other banks are on the lower and the upper diagonal, respectively. Values are Pearson correlations, computed on a within-bank basis. * denotes statistical significance at the five-percent level. Variable definitions are the same as in Table 1.

risk. In 2011, for instance, Moody’s downgraded two large French banks, Cr dit Agricole and Soci t  G n rale, in part due to their extensive use of short-term wholesale funding (Moody’s [2011a], [2011b]). Weaker financial ratios imply higher credit risk. Consequently, the rise in credit risk that results from reporting more short-term liabilities could be especially harmful when banks’ financial ratios are weaker. Hence, weaker financial ratios could have a stronger impact in inducing more BSM in short-term liabilities than in other borrowings.

4.4.5 Descriptive Statistics

Summary statistics and a correlation matrix are in Tables 1 and 2.¹⁴ I show separate data for large banks and other banks. The data in Table 1 stress further the differences between these groups of banks. Large banks have a median *CAP* of 0.026 (*i.e.*, a median Tier 1 ratio of 8.6 percent), compared to 0.056 (Tier 1 ratio of 11.6 percent) for other banks. In addition, large banks have a median *STLIAB* and *OTHBORR* of 6.6 percent and 13 percent, compared to 2.1 percent and 5.7 percent for other banks. Large banks thus have weaker capital ratios and rely more on wholesale and interbank funding. Both factors increase these banks’ incentives

¹⁴ For other banks, the mean of *RAWLEV* is driven by a small number of outliers whose values are driven by a minuscule equity base. When I estimate my models without these banks, I get the same results.

to use BSM to improve their financial ratios.

4.5 Results

4.5.1 BSM in Assets

Results for model (1), BSM in assets, are in Table 3.¹⁵ My main findings are that for large banks, *CAP* is positive and significant, while *RAWLEV* is negative and significant. Also, *CAP*² is negative and significant, so that the impact of a marginal decline in *CAP* in inducing more BSM is larger when the capital ratio of a bank is lower, and *CAPRISK* is positive and significant, so that a marginal rise in *RISK*—in having high-risk-weight assets—strengthens the impact of a marginal fall in *CAP* in inducing more BSM. Economically, financial ratios have a modest effect: a fall of 100 basis points (bps) in a bank’s Tier 1 capital ratio—from, for instance, 11 to 10 percent—implies a rise of 0.20 percentage points in BSM—end-of-quarter assets are 0.20 percentage points lower than the average of average assets. This modest effect could be driven by the use of lagged *CAP* and *RAWLEV* instead of contemporaneous *CAP* and *RAWLEV*, as the latter likely have a stronger impact in inducing BSM.

Two more results are worth noting: First, for large banks, *REGLEV* does not affect BSM in assets, in contrast with the findings for *CAP* and *RAWLEV*; one possible reason for this difference is that regulatory leverage is based on average assets, limiting the ability of banks to use BSM to strengthen this ratio. Second, for other banks, *CAP*, *CAP*², *CAPRISK*, and *RAWLEV* have no effect on BSM in assets, consistent with the argument that other banks have weaker incentives to use BSM to improve their financial ratios. Although *REGLEV*’s coefficient is positive, so that a marginal decline (deterioration) in regulatory leverage induces more BSM, its impact is an order of magnitude smaller than is the impact of *CAP* for large banks, implying less economic importance.

¹⁵ Since the residuals of each model are not normally distributed, I compute bootstrapped standard errors, with 250 replications (Efron and Tibshirani [1982]).

Tab. 4.3: BSM in Assets

Bank Type Dep. Var.	Large Banks <i>BSMASS</i>			Other Banks <i>BSMASS</i>		
<i>CAP</i>	0.199* (0.116)			0.015 (0.017)		
<i>RAWLEV</i>		-6.2E-4*** (2.0E-4)			9.5E-9 (5.3E-8)	
<i>REGLEV</i>			0.035 (0.118)			0.048*** (0.015)
<i>SIZE</i>	0.018*** (0.007)	0.017*** (0.006)	0.017** (0.007)	0.009*** (0.001)	0.009*** (0.001)	0.009*** (0.001)
<i>STLIAB</i>	-0.167*** (0.044)	-0.108** (0.049)	-0.165*** (0.045)	-0.011 (0.008)	-0.011 (0.008)	-0.010 (0.008)
<i>OTHBORR</i>	-0.060** (0.030)	-0.068** (0.032)	-0.071** (0.030)	0.004 (0.004)	0.004 (0.004)	0.005 (0.004)
<i>NPA</i>	-0.566* (0.306)	-0.485 (0.353)	-0.359 (0.303)	-0.015 (0.022)	-0.018 (0.022)	-0.009 (0.022)
<i>BSMSTL</i>	0.023** (0.011)	0.022** (0.010)	0.023** (0.011)	8.4E-7 (1.9E-5)	8.2E-7 (1.9E-5)	6.8E-7 (1.9E-5)
<i>BSMOTH</i>	0.068*** (0.022)	0.069*** (0.024)	0.067*** (0.025)	-1.7E-6 (2.2E-6)	-1.7E-6 (2.2E-6)	-1.7E-6 (2.2E-6)
<i>RISK</i>	0.020 (0.025)	0.004 (0.024)	0.012 (0.026)	0.012*** (0.004)	0.010*** (0.003)	0.010*** (0.003)
<i>CAP²</i>	-1.697** (0.687)			0.004 (0.071)		
<i>CAPRISK</i>	0.667** (0.270)			0.054 (0.048)		
R ² (within)	0.136	0.147	0.130	0.004	0.004	0.004
<i>N</i>	1,571	1,571	1,571	57,596	57,596	57,596
# groups	60	60	60	2,620	2,620	2,620
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors	bootstrapped (250 replications), clustered by bank and quarter					

Notes:

- (1) Large banks are those with an average size of 30th or lower. Other banks are all the rest.
- (2) All estimations include time and bank fixed effects.
- (3) $CAP^2 = CAP \times CAP$. $CAPRISK = CAP \times RISK$. In the estimations with CAP , to reduce multicollinearity, CAP and $RISK$ are centered (Aiken and West [1991]).
- (4) Bootstrapped (250 replications) standard errors, clustered by both bank and quarter, are in parentheses.
- (5) *, **, and *** denote significance at the 10-, five-, and one-percent level, respectively, using two-tailed tests.

4.5.2 BSM in Liabilities

Results for models (2), (3), and (4)—BSM in short-term liabilities, other borrowings, and the sum of the two, respectively—are in Tables 4, 5, and 6. My primary finding is that for large banks, weaker financial ratios are not consistently linked with more BSM. *RAWLEV*, for instance, has a negative sign with respect to *BSMSTL* but a positive sign with respect to *BSMOTH*. A marginal increase in raw leverage induces more BSM in short-term liabilities but less BSM in other borrowings. If leverage concerns drove liability-side BSM, an increase in raw leverage would be linked with more BSM in both types of liabilities. For other banks, I find no link between financial ratios and BSM in short-term liabilities, other borrowings, or the sum of the two.

These large-bank results suggest a rise in raw leverage induces a shift away from reported short-term liabilities and toward reported other borrowings—an increase in raw leverage leads banks to alter the composition of their end-of-quarter liabilities, without necessarily affecting total reported liabilities. Short-term liabilities are a relatively risky source of funding (Section 4.4). Banks thus could respond to the rise in credit risk that results from a rise in raw leverage by reporting fewer of these high-risk liabilities. In a similar vein, *CAP* and *BSMSTL* have a positive link (Table 4), so that a marginal decline in *CAP* results in more BSM in short-term liabilities. A capital-ratio decline likewise implies higher credit risk, possibly inducing banks to report fewer short-term liabilities even though BSM in liabilities does not improve capital ratios (Section 3.1).

This argument—that financial-ratio concerns induce large banks to alter the mix of their reported liabilities, without necessarily affecting total liabilities—has two implications. First, banks borrow to fund assets. Consequently, in reducing short-term liabilities at quarter-end, banks have to turn to other funding sources (*e.g.*, other borrowings) to avoid having to dump assets. As a result, a larger decline in quarter-end short-term liabilities should be linked with a larger rise in quarter-end other borrowings. Consistent with this argument, *BSMSTL* and

Tab. 4.4: BSM in Short-Term Liabilities

Bank Type Dep. Var.	Large Banks <i>BSMSTL</i>			Other Banks <i>BSMSTL</i>		
<i>CAP</i>	1.715*			3.260		
	(0.889)			(12.282)		
<i>RAWLEV</i>		-8.8E-4*			-9.6E-7	
		(4.9E-4)			(2.2E-5)	
<i>REGLEV</i>			0.474			22.574
			(1.295)			(14.473)
<i>SIZE</i>	-0.082***	-0.096***	-0.094***	0.046	-0.010	0.274
	(0.031)	(0.033)	(0.033)	(0.478)	(0.346)	(0.460)
<i>STLIAB</i>	0.458**	0.549***	0.480**	-8.293	-8.289*	-7.767
	(0.178)	(0.192)	(0.192)	(5.361)	(4.869)	(5.729)
<i>OTHBORR</i>	0.231	0.209	0.219	2.000	1.912	2.503
	(0.187)	(0.197)	(0.191)	(1.807)	(1.637)	(1.642)
<i>NPA</i>	-4.430***	-3.891**	-3.862***	33.118	32.468	36.647
	(1.516)	(1.527)	(1.438)	(52.534)	(48.443)	(48.957)
<i>BSMASS</i>	1.459***	1.445***	1.465***	1.538	1.547	1.264
	(0.166)	(0.157)	(0.161)	(9.972)	(9.292)	(10.424)
<i>BSMOTH</i>	-0.181***	-0.176***	-0.180***	-2.4E-5	-2.0E-5	-4.0E-5
	(0.064)	(0.064)	(0.063)	(3.2E-4)	(4.8E-5)	(3.2E-4)
R ² (within)	0.045	0.041	0.042	0.000	0.000	0.000
<i>N</i>	1,571	1,571	1,571	57,596	57,596	57,596
# groups	60	60	60	2,620	2,620	2,620
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors	bootstrapped (250 replications), clustered by bank and quarter					

Notes:

- (1) Large banks are those with an average size of 30th or lower. Other banks are all the rest.
- (2) All estimations include time and bank fixed effects.
- (3) Bootstrapped (250 replications) standard errors, clustered by both bank and quarter, are in parentheses.
- (4) *, **, and *** denote significance at the 10-, five-, and one-percent level, respectively, using two-tailed tests.

BSMOTH have a negative link (Table 4). On the margin, a fall in quarter-end short-term liabilities results in a rise in quarter-end other borrowings, consistent with the notion that cutting back on short-term liabilities forces banks to turn to other funding sources. Second, weaker financial ratios have a limited effect, if any, on BSM in liabilities overall. In line with this argument, financial ratios do not impact *BSMLIAB*, BSM in short-term liabilities plus other borrowings, taken together (Table 6).

Tab. 4.5: BSM in Other Borrowings

Bank Type Dep. Var.	Large Banks <i>BSMOTH</i>			Other Banks <i>BSMOTH</i>		
<i>CAP</i>	0.112 (0.374)			3.935 (5.942)		
<i>RAWLEV</i>		0.002** (0.001)			5.7E-8 (2.1E-5)	
<i>REGLEV</i>			-0.036 (0.373)			10.556 (11.868)
<i>SIZE</i>	-0.032* (0.020)	-0.034* (0.020)	-0.034* (0.019)	0.507 (0.448)	0.439 (0.435)	0.572 (0.476)
<i>STLIAB</i>	0.196 (0.149)	4.2E-4 (0.174)	0.195 (0.140)	-17.957 (13.433)	-17.957 (13.664)	-17.711 (14.406)
<i>OTHBORR</i>	0.401*** (0.123)	0.384*** (0.123)	0.399*** (0.117)	-12.456* (6.785)	-12.565* (6.988)	-12.288* (7.221)
<i>NPA</i>	1.406 (1.168)	1.940* (1.164)	1.471 (1.081)	-65.176 (43.439)	-65.978 (44.542)	-64.015 (45.233)
<i>BSMASS</i>	1.324*** (0.249)	1.377*** (0.284)	1.325*** (0.258)	-5.155 (5.509)	-5.146 (5.123)	-5.277 (5.662)
<i>BSMSTL</i>	-0.055** (0.026)	-0.053** (0.024)	-0.055** (0.025)	-3.7E-5 (0.001)	-3.1E-5 (0.001)	-6.2E-5 (0.001)
R ² (within)	0.097	0.107	0.097	0.000	0.000	0.000
<i>N</i>	1,571	1,571	1,571	57,596	57,596	57,596
# groups	60	60	60	2,620	2,620	2,620
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors	bootstrapped (250 replications), clustered by bank and quarter					

Notes:

- (1) Large banks are those with an average size of 30th or lower. Other banks are all the rest.
- (2) All estimations include time and bank fixed effects.
- (3) Bootstrapped (250 replications) standard errors, clustered by both bank and quarter, are in parentheses.
- (4) *, **, and *** denote significance at the 10-, five-, and one-percent level, respectively, using two-tailed tests.

4.5.3 Synopsis and Implications

In sum, the results in Sections 5.1 and 5.2 suggest large banks use BSM in assets to improve their financial ratios, especially their capital ratios and raw leverage. Also, capital ratios have an especially large effect when banks have low capital ratios and have assets whose disposal has a larger effect in increasing their capital ratios. For large banks, BSM in liabilities seems

Tab. 4.6: BSM in Short-Term Liabilities plus Other Borrowings

Bank Type Dep. Var.	Large Banks <i>BSMLIAB</i>			Other Banks <i>BSMLIAB</i>		
<i>CAP</i>	0.150 (0.176)			-0.157 (0.132)		
<i>RAWLEV</i>	-2.8E-4 (2.2E-4)			5.6E-9 (3.4E-7)		
<i>REGLEV</i>	0.065 (0.197)			-0.499 (0.307)		
<i>SIZE</i>	-0.033*** (0.012)	-0.034** (0.013)	-0.034*** (0.013)	-0.005 (0.013)	-0.002 (0.013)	-0.009 (0.013)
<i>STLIAB</i>	0.102 (0.095)	0.129 (0.100)	0.105 (0.090)	-0.295*** (0.092)	-0.295*** (0.099)	-0.306*** (0.090)
<i>OTHLIAB</i>	0.377*** (0.085)	0.377*** (0.082)	0.377*** (0.082)	-0.162*** (0.052)	-0.157*** (0.056)	-0.171*** (0.054)
<i>NPA</i>	-0.911 (0.619)	-0.910 (0.647)	-0.870 (0.621)	1.542* (0.873)	1.574* (0.872)	1.481* (0.842)
<i>BSMASS</i>	1.317*** (0.128)	1.311*** (0.147)	1.317*** (0.132)	2.007*** (0.150)	2.007*** (0.155)	2.013*** (0.151)
R ² (within)	0.231	0.231	0.231	0.005	0.005	0.005
<i>N</i>	1,571	1,571	1,571	57,596	57,596	57,596
# groups	60	60	60	2,620	2,620	2,620
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Std. Errors	bootstrapped (250 replications), clustered by bank and quarter					

Notes:

- (1) Large banks are those with an average size of 30th or lower.
- (2) All estimations include time and bank fixed effects.
- (3) Bootstrapped (250 replications) standard errors, clustered by both bank and quarter, are in parentheses.
- (4) *, **, and *** denote significance at the 10-, five-, and one-percent level, respectively, using two-tailed tests.

geared toward affecting the composition of banks' reported liabilities, not toward improving their financial ratios. Finally, for other banks, financial ratios have little impact in inducing BSM, consistent with the idea that other banks have relatively weak incentives to use BSM to improve their financial ratios.

These results imply large banks react to weak financial ratios by using BSM—by reducing assets at quarter-end—so as to improve these ratios. These results do not suggest banks use Repo 105-like programs. Banks can shed assets and improve their financial ratios in a variety

of ways (see, *e.g.*, Jones [2000]). The British banks cited in Section 2, for instance, increased their reported cash balances by holding assets that matured right before the banks' reporting dates. Still, disposing of assets at quarter-end can have a strong impact in improving banks' reported financial ratios. Lehman, for instance, used Repo 105 to cut its reported net leverage in 2007Q4, 2008Q1, and 2008Q2 from 17.8 to 16.1, from 17.3 to 15.4, and from 13.9 to 12.1, an average reduction of 180 bps (Valukas [2010], Vol. 4, p. 748). BSM need not involve Repo 105-like tactics but can have the same balance-sheet and financial-ratio effects.

Newly proposed banking regulations give large banks still further incentives to use BSM to improve their capital ratios. Most importantly, Basel III requires banks to hold more and higher-quality capital than before. Anecdotally, banks are using numerous tactics to do so. JP Morgan CEO Jamie Dimon, for instance, has expressed his intent to “manage the hell out of [risk-weighted assets]” so as to comply with Basel III (Braithwaite [2011]). Capital ratios use end-of-quarter assets. Together with banks' opacity (Morgan [2002]) and their flexibility in carrying out transactions, basing capital ratios on assets as of quarter-end makes BSM an easy way for banks to strengthen these ratios. Going forward, large banks will have greater incentives to do so. Focusing more on regulatory ratios that are based on average positions during the quarter rather than positions at quarter-end could help combat this behavior.

4.6 Conclusion

BSM in assets is an important tool large banks use to improve their financial ratios. Capital ratios, in particular, have a statistically significant and economically large impact in inducing BSM in assets. BSM in liabilities, by contrast, seems aimed toward altering the composition of large banks' liabilities, not toward improving their financial ratios. Large banks' business models, however, differ from those of other banks in ways that increase large banks' incentives to improve their financial ratios via BSM. For other banks, weak financial ratios have little

effect in inducing BSM in either assets or liabilities, highlighting the importance of focusing separately on BSM by large banks and by other banks.

Appendix

Variable definitions are as follows:

$$\begin{aligned}
BSMASS_{it} &= \frac{EOQASS_{it} - [AVGASS_{it+1} + AVGASS_{it}]/2}{[AVGASS_{it+1} + AVGASS_{it}]/2} \\
BSMSTL_{it} &= \frac{EOQSTL_{it} - [AVGSTL_{it+1} + AVGSTL_{it}]/2}{[AVGSTL_{it+1} + AVGSTL_{it}]/2} \\
BSMOTH_{it} &= \frac{EOQOTH_{it} - [AVGOTH_{it+1} + AVGOTH_{it}]/2}{[AVGOTH_{it+1} + AVGOTH_{it}]/2} \\
BSMLIAB_{it} &= \frac{[EOQSTL_{it} + EOQOTH_{it}] - [AVGSTL_{it+1} + AVGSTL_{it} + AVGOTH_{it+1} + AVGOTH_{it}]/2}{[AVGSTL_{it+1} + AVGSTL_{it} + AVGOTH_{it+1} + AVGOTH_{it}]/2} \\
CAP_{it} &= \frac{\text{Tier 1 capital}_{it} - 0.06 [\text{risk-weighted assets}_{it}]}{\text{risk-weighted assets}_{it}} \\
RAWLEV_{it} &= \frac{\text{total raw assets}_{it}}{\text{balance-sheet equity}_{it}} \\
REGLEV_{it} &= \frac{\text{Tier 1 capital}_{it} - 0.05 [\text{average regulatory assets}_{it}]}{\text{average regulatory assets}_{it}} \\
SIZE_{it} &= \log \text{total assets}_{it} \\
STLIAB_{it} &= \frac{\text{short-term liabilities}_{it}}{\text{total liabilities}_{it}} \\
OTHBORR_{it} &= \frac{\text{other borrowings}_{it}}{\text{total liabilities}_{it}} \\
NPA_{it} &= \frac{\text{non-performing assets}_{it}}{\text{total assets}_{it}}
\end{aligned}$$

With respect to *CAPRISK*, writing out this variable in terms of its components,

$$\begin{aligned}
CAP \times RISK &= \left[\frac{\text{Tier 1 capital}}{\text{risk-weighted assets}} - 0.06 \right] \times \frac{\text{risk-weighted assets}}{\text{total raw assets}} \\
&= \frac{\text{Tier 1 capital}}{\text{risk-weighted assets}} \times \frac{\text{risk-weighted assets}}{\text{total raw assets}} - 0.06 \times \frac{\text{risk-weighted assets}}{\text{total raw assets}} \\
&= \frac{\text{Tier 1 capital}}{\text{total raw assets}} - 0.06 \times \frac{\text{risk-weighted assets}}{\text{total raw assets}}.
\end{aligned}$$

A marginal increase in risk-weighted assets, by raising the second term in the bottom-most line, decreases *CAPRISK*. Hence, *CAPRISK*'s positive coefficient (Section 5.1, Table 3) means that a rise in risk-weighted assets relative to total raw assets and the fall in *CAPRISK*

that results amplifies the effect of a fall in *CAP* in inducing more BSM in assets—when banks hold more high-risk-weight assets, a decline in a bank’s capital ratio has a larger impact in inducing more BSM in assets.

The Y9-C line-items I use are as follows:

Balance-Sheet Item	Y9-C Mnemonic
total assets, raw	end-of-quarter: BHCK2170 average: BHCK3368
short-term liabilities	end-of-quarter: BHCK2800 (1997Q1–2001Q4) end-of-quarter: BHDMB993 + BHCKB995 (2002Q1–2010Q4) average: BHCK3365
other borrowings	end-of-quarter: BHCK2309 + BHCK2332 + BHCK2333 average: BHCK2635
total liabilities	BHCK2948
balance-sheet equity	BHCK3210
Tier 1 capital	BHCK8274
total risk-weighted assets	BHCKA223
regulatory average assets	BHCKA224
non-performing assets	BHCK5525 + BHCK5526

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5. FAIR-VALUE ACCOUNTING, DERIVATIVES, AND HEDGING

ABSTRACT

Prior studies show that fair-value accounting can negatively affect financial-sector stability. Fair value can do so by allowing changes in asset prices to impact banks' earnings and capital. Empirically, I find that banks' use of derivatives helps shield their earnings and capital from asset-price changes; for any given change in prices, derivatives reduce the net effect on earnings of banks' assets that are valued under fair value. Derivatives thus dampen fair value's negative effects. These findings suggest that in assessing fair value's impact, focusing jointly on banks' assets and derivatives is necessary.

5.1 Introduction

Fair-value accounting¹ often is criticized for adversely affecting financial-sector stability. Fair value can amplify the pro-cyclical nature of banks' lending (ECB [2004], Novoa, Scarlata, and Solé [2008], Bernanke [2009]). Also, fair value can result in contagion, with price-depressing asset sales by one bank requiring others to take write-downs. The impact of fair value in this respect can lead to asset-price downward spirals (Cifuentes, Ferrucci, and Shin [2005]), to the liquidation of fundamentally solvent banks (Allen and Carletti [2008]), and to an increase in asset-price volatility that is driven by the impact of fair value on banks' investment decisions, not by fundamentals (Plantin, Sapra, and Shin [2008]).

In this study, I show that derivatives can reduce fair value's negative impact by insulating banks' earnings (and capital) from changes in asset prices. In the studies above, fair value has negative effects by letting asset-price changes impact earnings—by exposing banks to market risk, the risk of profit or loss due to changes in asset prices. An increase in credit spreads, for instance, reduces the prices of corporate bonds. Under fair value, banks book losses on their corporate bonds because of this decline in price. In this respect, fair value exposes banks to market risk. The studies above, however, all focus on fair value's application only to banks' assets, but fair value is applied also to derivatives. Banks thus could use derivatives to lay off unwanted market risk—to hedge. As a result, insofar as banks use derivatives to hedge, and insofar as derivatives are effective in hedging, derivatives could play a useful role in blunting fair value's negative effects.

My two main results are as follows: First, I find a positive link between banks' quantity of assets that are valued under fair value (“fair-valued assets”) and banks' derivative use. On the margin, a rise in fair-valued assets and the market risk thereon induces more hedging via derivatives. To translate this result into a concrete example, suppose that a bank acquires a

¹ Fair value is a broader version of mark-to-market accounting (see Laux and Leuz [2009]). For simplicity, I use fair value to refer to both.

fair-valued corporate bond: Rather than staying exposed to the interest-rate-related market risk on this bond, this bank uses interest-rate derivatives to lay off this risk. As a result, this bank hedges *ex ante*, in anticipation of possible changes in prices due to changes in interest rates. I obtain this result using fixed effects. In the cross-section, large dealer banks (*e.g.*, JP Morgan) have the largest holdings of fair-valued assets and dominate trading in derivatives. Hence, cross-sectionally, fair-valued assets and derivative use have a positive link for reasons possibly unrelated to hedging. Using fixed effects helps ensure that this result is driven solely by cross-temporal, within-bank variation, mitigating this concern.

Second, derivatives blunt fair-valued assets' net effect on earnings. I regress (the absolute value of) total fair-value income on assets and derivatives on fair-valued assets, derivatives, and the interaction between the two. I find a positive link between fair-value income and fair-valued assets. A marginal rise in fair-valued assets increases fair-value income, in magnitude (see Section 4.1). This result is not my main finding. My main finding is that the interaction term is negative. On the margin, an increase in derivatives reduces the impact of a rise in fair-valued assets in increasing the magnitude of fair-value income. In this respect, derivatives are effective in hedging. Returning to the corporate-bond example, for any given change in interest rates, the bank's interest-rate derivatives reduce its net profit or loss on its corporate bonds. As a consequence, *ex post*, once prices change, derivatives are effective in hedging—in reducing the net effect on earnings of any given change in prices.

In sum, these results suggest that derivatives help blunt fair value's impact on earnings. These results relate to the debate about fair value's potential to have a negative effect on financial-sector stability. Fair value could do so by exposing banks to market risk, with asset-price changes thus affecting earnings and capital. My results suggest banks use derivatives to mitigate these effects. Derivatives were useful in this respect even during the 2007–8 financial crisis, when fair value's negative impact was strongest. Morgan Stanley's 2008 trading losses of \$3.1 billion, for instance, “reflected fair value losses on loans and commitments that were

partly offset by gains on related hedges” (source: Morgan Stanley’s 2008 10-K, p. 43). These \$3.1 billion in losses were large but would have been even larger without derivatives. Hence, while my results do not imply that fair value is incapable of having destabilizing effects, they do suggest that focusing jointly on banks’ assets and derivatives is essential to evaluating its impact.

The rest of this paper is as follows: In Section 2, I discuss fair-value-related literature. In Section 3, I discuss fair value, market risk, and how banks deal with this risk. My empirical tests’ set-up and results are in Sections 4 and 5. In Section 6, I use two examples to show how derivatives could blunt the adverse effects of fair value. Concluding remarks are in Section 7. Supplemental information on my empirical tests is in the appendix.

5.2 *Related Literature: Fair-Value Accounting*

In surveys of the trade-offs involved between fair-value accounting and historic-cost accounting, Landsman [2006] and Laux and Leuz [2009] argue that asset and liability values under fair value are more relevant but could have less reliability. Early studies that focus on fair value examine empirically whether the fair values of banks’ assets and liabilities are reflected in stock prices; most conclude that they are. Barth [1994], Eccher, Ramesh, and Thiagarajan [1996], and Nelson [1996] find that the fair values of securities are impounded in banks’ stock prices. Barth, Beaver, and Landsman [1996] obtain the same result for securities, loans, and long-term debt. Furthermore, Barth, Landsman, and Wahlen [1995] find that fair values help predict future violations of prudential capital requirements, even though these requirements are based largely on historic-cost values.

Recent studies, however, focus theoretically on how fair value could have a negative effect on financial-sector stability. ECB [2004] and Novoa *et al.* [2008] highlight how fair value can amplify the through-the-cycle volatility in banks’ capital and lending. Other studies focus on

how fair value can result in contagion—because asset sales (in illiquid markets) reduce prices, fair value’s use can force banks to take write-downs, even if fundamentals remain unchanged. Cifuentes *et al.* [2005] show how fair value’s impact in this respect can help cause asset-price downward spirals; Allen and Carletti [2008] and Plantin *et al.* [2008] identify other ways for this sort of contagion to have destabilizing effects.

5.3 Fair Value, Market Risk, and Hedging

Fair value and historic cost expose banks to different types of risks. Under historic cost, banks are exposed primarily to interest-rate risk and credit risk. Banks fund long-term assets with short-term liabilities. Hence, in general, a rise in interest rates lowers net interest income; a decline increases net interest income. Also, a rise in the credit risk of entities on which banks have claims results in higher loan-loss provisions, with outright defaults reducing net interest income. Interest-rate risk and credit risk thus have a central effect on earnings. Price changes *per se*, by contrast, do not affect earnings. Roughly put, an asset valued under historic cost is carried at its acquisition-date value, irrespective of how its price has changed since being acquired. As result, when prices change, banks do not book gains and losses.

Fair value differs from historic cost by exposing banks to market risk, the risk of profit or loss due to asset-price changes. Under fair value, when prices change, banks book immediate gains and losses. Under historic cost, banks do not. Suppose, for instance, that a bank buys corporate bonds and credit spreads later rise, reducing the price of these bonds: Under fair value, this bank books a loss on the decline in the price of these bonds. Under historic cost, this decline in price does not result in losses. Hence, under fair value and historic cost, banks are exposed to and insulated from, respectively, asset-price changes. Fair value’s impact in exposing banks to market risk can have a strong impact on earnings. Moreover, in the second set of studies in Section 2.1, fair value has negative effects by exposing banks to market risk,

so that changes in prices affect earnings and capital.

One question these studies do not ask is why banks would stay exposed to the market risk that arises under fair value. These studies focus on fair value's application to banks' assets, but fair value is applied also to derivatives. Prior studies (Gorton and Rosen [1995], Carter and Sinkey [1995], Purnanandam [2007]) find that derivatives are a useful risk-management device for banks. As a result, banks could use derivatives to hedge their market risk on fair-valued assets. Insofar as banks do use derivatives to hedge this risk, and insofar as derivatives are effective in hedging this risk, derivatives insulate banks' earnings and capital from changes in asset prices. In doing so, derivatives blunt the negative effects of fair value. Anecdotally, derivatives are a critical tool banks use to lay off unwanted market risk. Goldman Sachs, for instance, states in its 2012 10-K, "We manage our market risk by . . . establishing economic hedges in related securities or derivatives," among other tactics.

5.4 Empirical Tests: Preliminaries

5.4.1 Fair-Valued Assets, Fair-Value Income, and Market-Making

My three main variables are banks' assets and derivatives valued under fair value and income on these assets and derivatives, or total fair-value income.² While none of these variables are explicitly provided in the financial statements or regulatory reports of banks, useful proxies are available. I define these variables as follows:

- Fair-valued assets: I use trading assets. Since 1996, fair value has been applied to all of the trading assets and to virtually none of the other assets of banks. As a result, trading assets and fair-valued assets have close to a one-to-one correspondence. Trading assets consist mainly of debt securities.

² Fair value's negative effects arise via its impact on earnings and regulatory capital. Hence, I always refer to fair value's use *vis-à-vis* only earnings and capital, not *vis-à-vis* banks' balance sheets. Securities classified as available for sale are valued under fair value with respect to banks' balance sheets but under historic cost with respect to earnings and capital. As a result, I ignore this class of securities in my empirical tests.

Banks face market risk on all of their trading assets, even default-risk-free government securities (*e.g.*, United States (US) Treasuries). Changes in interest rates, for instance, affect Treasury prices; under fair value, banks book gains and losses on these changes in prices. The FR Y9-C trading-assets line-item includes trading assets and the aggregate fair value of trading derivatives with a positive fair value. In calculating trading assets, I exclude the latter.

- Derivatives: I use the notional value of trading derivatives. Trading derivatives account for over 98 percent of banks' total derivatives, and fair value is applied to almost all of banks' derivatives.³

Notional values are not a perfect measure of banks' true exposures on derivatives. A bank, for instance, could enter into a derivative as part of its market-making operations (*e.g.*, with a corporate customer) and use the inter-dealer market to take an offsetting position in another derivative. While these transactions would increase notional values, net exposure would stay the same. A more useful measure of derivative use, however, is not available, and using notional values is in line with prior studies (*e.g.*, Demsetz and Strahan [1997]). The substantial noise that results from using notional values weakens the power of my tests. As a result, any results I find are in spite of using, not because of using, notional values.

- Fair-value income: I use trading income, which includes all earnings on changes in the prices of trading assets and trading derivatives. Trading income includes also earnings from other sources (*e.g.*, incidental income and expenses on trading-book transactions). The inclusion of these sources makes trading income an imperfect measure of fair-value income, but a more useful measure is not available.

³ Technically, banks do not apply fair value *vis-à-vis* earnings and capital to derivatives that are designated as a "hedging instrument." Only a trivial share of banks' derivatives, however, are designated as a hedging instrument. As of fiscal-year-end 2011, for instance, only \$294 billion of Citigroup's \$49,816 billion in total derivatives (notional values) were designated as a hedging instrument.

I use trading income's absolute value. A bank with more exposure to market risk could end up booking either larger gains or larger losses, depending on which way prices move. Holding more Treasuries, for instance, would result in larger losses on a given increase in interest rates and in larger gains on a given decline, but these outcomes have identical implications—holding more fair-valued assets increases exposure to market risk, so that any given price change has a larger impact on earnings (before accounting for any of the offsetting effects of derivatives). Using trading income's absolute value helps mitigate this problem.

In focusing on trading assets, I focus on assets whose risks banks are especially likely to hedge. In large part, banks' trading accounts are linked to their market-making operations. In market-making, banks profit from bid-ask spreads, not from price changes *per se*. Banks thus aim for as little exposure to price changes—to market risk—as possible. In an overview of market-making, Stigum and Crescenzi [2007] (p. 885), for instance, state that “[d]ealers who run swap books . . . are of the opinion that they are neither paid to nor supposed to incur a lot of market risk. Dealers *hedge* their swaps books.” This aversion to market risk implies risk-aversion. Also, the possibility of regulatory sanctions should banks violate prudential capital requirements likewise could encourage risk-aversion in market-making (and less-risky behavior more generally (Milne [2002])). Empirically, Lyons [1995], Reiss and Werner [1998], and Gârleanu, Pedersen, and Poteshman [2009] all find that market-makers trade in a risk-averse way.

5.4.2 *Set-Up and Hypotheses*

Empirically, I take a two-step approach to examining the derivative use of banks with respect to their fair-valued assets. First, I focus on whether banks use derivatives to hedge *ex ante*, in anticipation of changes in prices—do banks with fair-valued assets remain exposed to the market risk on these assets, or do banks use derivatives to lay off this risk? Second, I examine

whether derivatives are effective in hedging *ex post*—once prices change, so that banks book gains or losses on their fair-valued assets, do derivatives decrease the net impact on earnings of these changes in prices? The first question concerns banks’ hedging strategies; the second, the efficacy of these strategies.

In line with previous studies, I take as exogenous banks’ fair-valued assets (*i.e.*, trading assets) and the market risk thereon. I focus instead on banks’ derivative use in mitigating this risk. In taking as exogenous banks’ fair-valued assets, I abstract from banks’ decisions to hold assets in their trading account, as opposed to, for instance, in their held-to-maturity account. In addition, I abstract from banks’ decisions in choosing the size and the composition of their trading books (*e.g.*, whether banks hold mainly high- or low-risk trading assets). These issues are important but have been ignored by prior studies. To ensure my results relate as closely as possible to those of prior studies, I abstract from these issues.

In my first set of tests, I examine whether banks use derivatives to hedge *ex ante*, after their fair-valued assets are in place but before prices change. When banks hold more fair-valued assets, a given price change results in more fair-value income, in magnitude. Banks thus have more upside and downside, with larger gains should prices rise but larger losses should prices fall. In this respect, banks have more exposure to market risk, in expectation. *A priori*, banks’ response to this rise in exposure is unclear. Moral hazard can lead banks to take more risk (*e.g.*, Bhattacharya, Boot, and Thakor [1998]), making attractive this rise in exposure. This effect discourages hedging. Risk-aversion, however (Section 4.1), encourages hedging. Insofar as banks use derivatives to hedge, a rise in fair-valued assets should increase derivative use. Hence, my first hypothesis, stated in null form, is as follows:

- (1) Banks’ quantity of fair-valued assets and banks’ derivative use are uncorrelated.

Also, I examine how the relationship between fair-valued assets and derivatives changes with the capital ratios of banks. Shrieves and Dahl [1992] and Haubrich and Wachtel [1993]

find that banks with less capital bear less risk. These findings suggest that insofar as fair-valued assets and derivatives have a positive link, so that a rise in fair-valued assets induces more derivative use, this positive link is stronger when banks' capital ratios are lower. One key reason why low-capital banks might tolerate less risk is that banks that violate prudential capital requirements are subject to regulatory sanctions; for low-capital banks, a given decline in capital has a stronger impact in increasing the odds of regulatory sanctions. Consequently, the rise in exposure to market risk that results from a rise in fair-valued assets is potentially more damaging when capital is lower. As a consequence, a rise in fair-valued assets could have a stronger effect in increasing banks' use of derivatives. I thus test the following hypothesis, stated in alternative form:

- (2) Any positive link between fair-valued assets and derivatives is stronger when the capital ratios of banks are lower.

In my second set of tests, I examine whether derivatives are effective in hedging *ex post*, after prices change. Hedging exposes banks to basis risk. In general, changes in the prices of a derivative and of the hedged asset do not have a perfect negative correlation; the derivative's price might move less sharply, more sharply, or even in the same way as that of the hedged asset. Hence, even if banks use derivatives to hedge *ex ante*, in anticipation of price changes, basis risk could reduce derivatives' hedging efficacy *ex post*—in general, when prices change, the change in the price of the derivative does not offset fully, or even at all, the change in the price of the hedged asset. Insofar as basis risk does limit derivatives' hedging efficacy, banks still face market risk on their fair-valued assets. Consequently, asset-price changes still affect earnings and capital, allowing fair value to have negative effects.

As a preliminary issue, I look at the link between fair-valued assets and fair-value income. This link should be positive. For a given change in prices, an increase in fair-valued assets should increase fair-value income (in absolute values); a rise in Treasuries, for instance, leads

to larger gains on a given decline in interest rates. I assess how this positive link varies with the derivative use of banks. Insofar as derivatives are effective in hedging, a rise in derivatives lowers this positive link between fair-valued assets and fair-value income; an increase in fair-valued assets might still increase fair-value income, in magnitude, but derivatives reduce this rise, on net. While a rise in Treasuries results in larger gains on a given fall in interest rates, a rise in derivatives reduces the extent of these gains, on net—the net increase in gains due to an increase in Treasuries is lower with derivatives than without. I thus examine the two hypotheses below, both stated in alternative form:

- (3) Banks' quantity of fair-valued assets and banks' fair-value income have a positive link, and
- (4) a rise in derivatives weakens this positive link.

5.4.3 Data & Sample Selection

My data are from the FR Y9-C, a regulatory report US bank holding companies file in each quarter. My sample runs from 1996Q1–2010Q4 and includes each bank over this period that meets two criteria. First, banks must complete the “Trading Assets and Liabilities” schedule in the Y9-C. I use the data in this schedule to adjust trading assets and trading liabilities for derivatives (Sections 4.1, 4.4). From 1996–2000, banks with at least \$1 billion in total assets or \$2 billion in derivatives (notional values) had to complete this schedule (Schedule HC-B, part II); since 2001, banks that have at least \$2 million in average trading assets have had to complete this schedule (Schedule HC-D). The only banks that do not complete this schedule are those with minimal trading books (*i.e.*, fair-valued assets). Imposing this criterion thus has the effect of getting rid of banks that are of no interest in the first place.

Second, banks must have held fair-valued assets in at least half of the quarters they filed the Y9-C. My interest is in banks' use of derivatives in hedging their fair-valued assets, not in

their use of derivatives more generally. Few banks hold trading assets. Over 1996Q1–2010Q4, the median share of banks in each quarter with trading assets was 6.8 percent. Consequently, a broader sample would include many irrelevant banks. To avoid double-counting, I exclude subsidiary bank holding companies whose parent files the Y9-C (*i.e.*, holding companies with BHCK9802 = 2). My sample consists of 4,891 bank-quarters and 196 different banks. Since a 50-percent cut-off point is arbitrary, I show in Section 5.3 results using cut-off points of 40 percent, 60 percent, and 75 percent; nothing of substance changes.

5.4.4 Model: Banks, Market Risk, and Hedging

In my first set of regressions, I estimate the model

$$\begin{aligned}
 DERIV_{it} = & \beta_0 + \beta_1 DERIV_{it-1} + \beta_2 TRAD_{it-1} + \beta_3 CAP_{it-1} \\
 & + \beta_4 LIAB_{it-1} + \beta_5 SIZE_{it-1} + \beta_6 TRADCAP + \epsilon_{it}.
 \end{aligned} \tag{1}$$

$DERIV$, $TRAD$, and $LIAB$ are $\log[1 + \text{derivatives}]$, trading assets,⁴ and trading liabilities⁵; CAP is banks' Tier 1 capital ratio less a six-percent baseline; $SIZE$ is \log total assets less trading assets; $TRADCAP = TRAD \times CAP$; and ϵ is an error term. To avoid endogeneity, I use lags for all of the regressors.⁶ Model (1) includes also time and bank fixed effects. Large dealer banks (*e.g.*, JP Morgan) have the largest trading books and also dominate trading in

⁴ I elect not to use trading assets as a share of total assets because banks face risks on all of their assets, not only on their fair-valued assets. Examining the link between derivative use and the share of fair-valued assets in total assets would test whether a rise in fair-valued assets relative to other types of assets increases derivative use. This test effectively would assess whether banks are more or less inclined to use derivatives to hedge their risks on fair-valued assets than on other types of assets. I want to focus on whether banks hedge their market risk on fair-valued assets, without concern for whether this risk induces more or less derivative use than risks on other types of assets. Using raw fair-valued assets is necessary to do so.

⁵ I calculate $TRAD$ and $LIAB$ as trading assets and trading liabilities less the total fair value of trading derivatives with, respectively, a positive and a negative fair value. In addition, to clarify, $TRAD$ and $LIAB$ are $\log[1 + \text{trading assets}]$ and $\log[1 + \text{trading liabilities}]$, respectively.

⁶ With respect to $TRAD$, banks' trading assets and derivatives are jointly determined. Hence, $TRAD_{it}$ is endogenous with respect to $DERIV_{it}$. To be consistent with previous fair-value-focused studies, I want to take as exogenous banks' fair-valued assets and examine banks' derivative use in hedging their market risk on these assets. To do so, using $TRAD_{it-1}$ is necessary.

derivatives. Hence, in the cross-section, *DERIV* and *TRAD* have a natural positive link. In using fixed effects, model (1) captures only cross-temporal, within-bank variation, mitigating this concern. Using time fixed effects controls for period-specific shocks that affect *DERIV* and *TRAD* across all banks—during periods of heavy financial-market activity (*e.g.*, market-making), for instance, all banks could have large holdings of derivatives and trading assets. Using time fixed effects strips out the impact of this type of banking-sector-wide shock.

In model (1), I examine whether banks use derivatives to hedge *ex ante*, in anticipation of asset-price changes. I focus on *TRAD*. The fair-valued assets and trading assets of banks essentially have a one-to-one correspondence (Section 4.1). Hence, I focus on whether a rise in fair-valued assets and the rise in market-risk exposure that results induces more derivative use (hypothesis (1), Section 4.2). Insofar as banks do use derivatives to hedge, *TRAD*'s sign should be positive. In addition, the increase in market-risk exposure that results from a rise in fair-valued assets is potentially more damaging when a bank's capital is lower (hypothesis (2), Section 4.2). As a result, a capital-ratio decline should strengthen the rise in derivatives that results from a rise in fair-valued assets, implying a negative sign for *TRADCAP*.

Banks face risks on all of their positions, not only on their fair-valued assets. *SIZE* and *LIAB* control for derivatives used to hedge risks on banking-book assets (*i.e.*, assets valued under historic cost) and trading liabilities (*e.g.*, short positions); both variables should have a positive sign. *TRAD* thus captures whether a marginal rise in fair-valued assets increases derivative use after controlling for banks' use of derivatives in mitigating other risks. With respect to *CAP*, *a priori*, its main effect is ambiguous. Holding fair-valued assets constant, a marginal decline in capital might make banks want to hedge more, implying an increase in derivative use. Derivatives themselves, however, expose banks to market risk. This exposure could lead banks to react to a decline in capital by hedging less, all else equal.

I include lagged *DERIV* since *DERIV* has strong positive serial correlation and lagged *DERIV* and lagged *TRAD* have a strong positive correlation ($\rho = 0.646$). Excluding lagged

DERIV thus would bias upward *TRAD*'s coefficient. While including both lagged *DERIV* and fixed effects results in inconsistent estimates (Nickell [1981]), with $T = 59$, this inconsistency is small.⁷ Generalized-method-of-moment (GMM) estimators (*e.g.*, Blundell and Bond [1998]) can handle dynamic panel data, but these estimators are designed mainly for small- T panels. When T is large, GMM tends to encounter serious problems (Roodman [2009]), and tests of instrument validity have little power (Bowsher [2002]).⁸ With $T = 59$, these issues seem more severe than those due to using fixed effects with lags. Hence, I use the latter.

5.4.5 Model: The Hedging Efficacy of Derivatives

In my second set of regressions, I estimate the model

$$\begin{aligned} TRADINC_{it} = & \gamma_0 + \gamma_1 TRADINC_{it-1} + \gamma_2 DERIV_{it-1} + \gamma_3 TRAD_{it-1} + \gamma_4 CAP_{it-1} \\ & + \gamma_5 LIAB_{it-1} + \gamma_6 SIZE_{it-1} + \gamma_7 DERIVTRAD + \epsilon_{it}. \end{aligned} \quad (2)$$

TRADINC is the absolute value of trading income,⁹ $DERIVTRAD = DERIV \times TRAD$ and ϵ is an error term. I include also time and bank fixed effects. I include lagged *TRADINC* since $\rho = 0.926$ between contemporaneous and lagged *TRADINC*, and lagged *TRADINC* has a strong positive correlation with lagged *DERIV* and lagged *TRAD*. Similar to model (1), including both lagged *TRADINC* and fixed effects gives rise to inconsistent estimates, but this inconsistency is minimal, with a bias of only -0.033 (based on Nickell [1981], p. 1422, eq. [19]). In addition, with $T = 59$, using GMM would lead to the same problems discussed in Section 4.4 in the context of model (1).

In model (2), I examine whether derivatives are effective in hedging *ex post*, once prices

⁷ Inserting into equation (19) from Nickell [1981; p. 1422] $\rho = 0.975$ for $DERIV_{it}$ and $DERIV_{it-1}$ and $T = 59$ yields a bias of only -0.034.

⁸ Consistent with this concern, when I estimate model (1) with GMM, the Sargan test's p-value is 1.000.

⁹ I define *TRADINC* also by taking trading income, subtracting different minimum required returns on trading assets (*e.g.*, 15 percent), and using the absolute value of the resulting figure. Using this definition of *TRADINC*, I get essentially the same results (not reported).

change. As a result, I focus on *DERIVTRAD*, not on *DERIV* and *TRAD*. *TRADINC* is a proxy for the absolute value of fair-value income (Section 4.1)—for net profits due to price changes on fair-valued assets and on derivatives. *DERIV*'s and *TRAD*'s coefficients capture the impact on fair-value income of an increase in derivatives and in fair-valued assets. Banks face market risk on both derivatives and fair-valued assets. As a consequence, both *DERIV* and *TRAD* should have a positive sign. With respect to *DERIV*, holding fixed fair-valued assets and changes in prices, a marginal rise in derivatives should increase fair-value income, in magnitude. Similar reasoning applies with respect to *TRAD*. (I use the time fixed effects to control for differences over time in price changes.)

I focus on *DERIVTRAD*. *DERIVTRAD* concerns how the link between *TRAD* and *TRADINC* varies with *DERIV*. A positive sign for *TRAD* would mean that on the margin, a rise in fair-valued assets increases the absolute value of fair-value income, so that a given change in prices has a stronger impact on earnings and capital (hypothesis (3), Section 4.2). I focus on how this increase in fair-value income varies with banks' derivative use. A negative sign for *DERIVTRAD* would mean that on the margin, a rise in derivatives dampens this rise in fair-value income that results from a rise in fair-valued assets (hypothesis (4), Section 4.2). Hence, a given change in prices has a smaller net effect on earnings and capital. In this respect, derivatives would be effective in hedging.

5.4.6 Descriptive Statistics

Summary statistics and a correlation matrix are in Tables 1 and 2. Two points on these data: First, 1,937 of my 4,891 observations (40 percent) have no derivatives, so that $DERIV = 0$. In my second set of tests, I take steps to remedy this zero-value problem. Second, in the final two rows of Table 1, I show raw (non-logged) data for derivatives and trading assets. These data show that banks' derivative portfolios often are several orders of magnitude larger than are their portfolios of fair-valued assets. Hence, given the relative enormity in raw terms of

Tab. 5.1: Summary Statistics

Variable	Mean	Standard Deviation	Percentiles				
			10th	25th	50th	75th	90th
<i>DERIV</i>	9.605	8.157	0.000	0.000	12.005	16.307	19.420
<i>TRAD</i>	10.159	4.510	3.638	8.186	10.528	12.936	15.462
<i>TRADINC</i>	7.073	3.702	0.000	5.147	7.662	9.587	11.397
<i>CAP</i>	0.056	0.083	0.015	0.025	0.041	0.064	0.097
<i>LIAB</i>	4.761	6.181	0.000	0.000	0.000	10.629	13.991
<i>SIZE</i>	16.612	1.841	14.128	15.328	16.551	17.903	18.970
<i>DERIV</i> , raw	1,136,620	6,758,124	0	0	164	12,084	271,529
<i>TRAD</i> , raw	8,634	40,430	0	4	37	415	5,189

I use unbalanced quarterly panel data from 1996Q1–2010Q4. My sample includes each bank with trading assets at least 50 percent of the time, for a sample of 4,891 observations and 196 different banks. Variable definitions: *DERIV*: log trading derivatives, notional value; *TRAD*: log trading assets less derivatives that have a positive fair value; *TRADINC*: absolute value of log trading income; *CAP*: Tier 1 ratio less a six-percent baseline; *LIAB*: log trading liabilities less derivatives that have a negative fair value; *SIZE*: log total assets less total trading assets. *DERIV*, raw and *TRAD*, raw are non-logged derivatives and trading assets, respectively, in millions of dollars. In my regressions, I always use logged *DERIV* and *TRAD*.

Tab. 5.2: Correlation Matrix

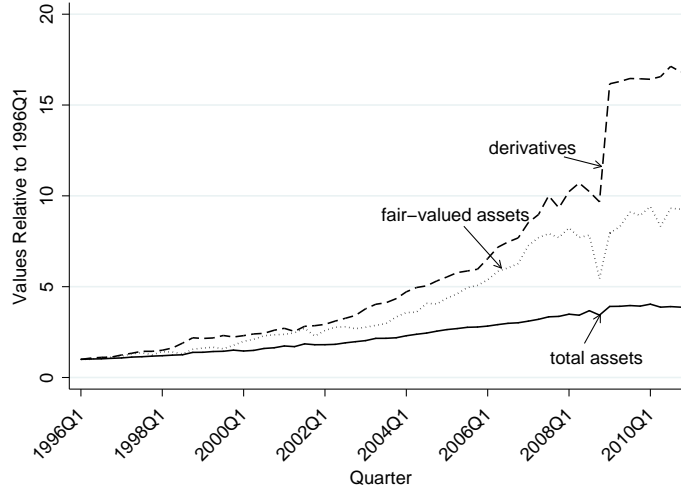
Variable	<i>DERIV</i>	<i>TRAD</i>	<i>TRADINC</i>	<i>CAP</i>	<i>LIAB</i>	<i>SIZE</i>
<i>DERIV</i>	1.0000					
<i>TRAD</i>	0.2980*	1.0000				
<i>TRADINC</i>	0.3766*	0.4659*	1.0000			
<i>CAP</i>	-0.0215	0.0257	-0.0032	1.0000		
<i>LIAB</i>	0.1621*	0.2893*	0.1919*	-0.0150	1.0000	
<i>SIZE</i>	0.4628*	0.3066*	0.3998*	-0.0749*	0.1589*	1.0000

Values are Pearson correlations, calculated on a within-bank basis. * denotes statistical significance at the five-percent level.

banks' derivatives, even a small percentage change in derivatives could suffice to hedge much of the rise in market risk that comes from a given percentage rise in fair-valued assets.

Four more bits of data: First, fair-valued assets account for a small share of banks' assets. Of the 60 quarters from 1996–2010, the aggregate median share of fair-valued assets in total assets was 8.9 percent, with a high of 13.3 percent (2008Q1). Second, fair-valued assets and derivatives have been increasing over time, in raw terms and relative to total assets (Figure

Fig. 5.1: Time Trends in Total Assets, Fair-Valued Assets, and Derivatives

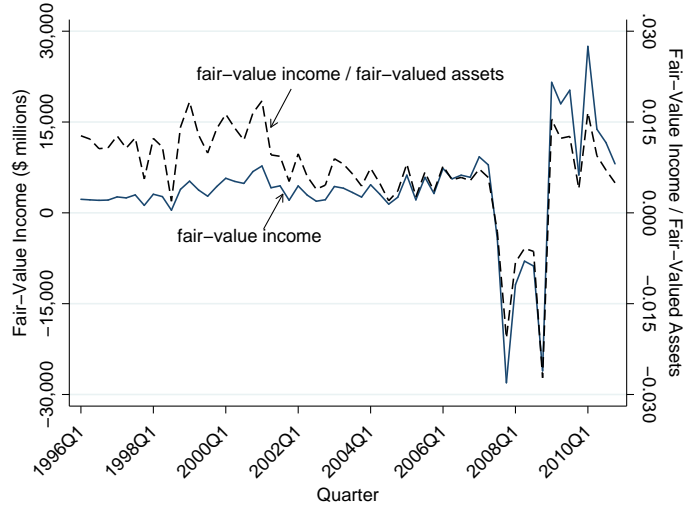


Tab. 5.3: Banks' Aggregate Derivative Composition

Quarter	Interest Rate	Foreign Exchange	Equity	Commodity & Other
1998Q1	71.90 %	26.47 %	1.38 %	0.67 %
2002Q1	83.18 %	14.52 %	1.84 %	0.48 %
2006Q1	87.80 %	9.63 %	1.91 %	0.66 %
2010Q1	88.10 %	8.35 %	2.29 %	1.25 %

1). In model (1), I use time fixed effects and, alternatively, a time trend to control for these trends as a way to avoid a spurious correlation between *DERIV* and *TRAD* (Granger and Newbold [1974]). Third, banks use mainly interest-rate derivatives (Table 3). Fourth, in the aggregate and on a bank-level basis, fair-value income generally has been positive except for 2007Q3–2008Q4, the worst of the financial crisis (Figure 2).

Fig. 5.2: Aggregate Fair-Value Income



Fair-Value Income Relative to Fair-Valued Assets, Bank-Level Data

Quarter	Mean	Standard Deviation	Percentiles				
			10 th	25 th	50 th	75 th	90 th
1996Q1	0.172	1.813	-0.021	0.005	0.025	0.082	0.227
2000Q1	0.313	0.828	-0.001	0.011	0.046	0.212	0.735
2004Q1	0.313	1.350	0.000	0.009	0.036	0.126	0.395
2008Q1	0.261	1.266	-0.071	-0.019	0.004	0.110	0.452
2010Q1	0.235	1.093	0.000	0.007	0.028	0.111	0.254

Values are trading income divided by trading assets. In 2008Q1, a small number of large banks booked large fair-value losses. Consequently, while most banks had positive fair-value income, fair-value income in the aggregate was negative.

5.5 Results

5.5.1 Banks, Market Risk, and Hedging

Model (1)'s results are in Table 4.¹⁰ My main finding is that $TRAD$ is positive and significant. On the margin, a rise in fair-valued assets induces more derivative use. A rise in fair-valued assets increases banks' exposure to market risk. To mitigate this increase in exposure, banks

¹⁰ Since models (1) and (2) both have non-normal residuals, I compute bootstrapped standard errors (250 replications) for both (Efron and Tibshirani [1982]).

use more derivatives. This finding holds using both time fixed effects (estimation [1]) and a time trend, *TIME* (estimation [2]). Again, I estimate model (1) using fixed effects. Hence, this positive link between *DERIV* and *TRAD* is not due to large dealer banks' both having more trading assets and using more derivatives. In estimation [3], I include the interaction $TRADCAP = TRAD \times CAP$. *TRADCAP* is not significant, but its sign is negative, with a p-value (0.131) just outside standard significance levels. A marginal fall in a bank's capital ratio amplifies the positive link between *DERIV* and *TRAD*—a decline in capital amplifies the effect of a rise in fair-valued assets in inducing more hedging. This finding provides some more support, albeit relatively weak, for the notion that banks use derivatives to hedge.

One limitation of model (1) is that *DERIV* includes derivatives used to hedge and also those used to “speculate.” Hence, the positive link between *DERIV* and *TRAD* could be due to cross-temporal variation in banks' propensity to take risks. A bank, for instance, expecting interest rates to fall could buy US Treasuries and enter at the same time into interest-rate derivatives whose value rises when interest rates fall (*e.g.*, receive-fixed, pay-floating swaps). Banks thus could use derivatives and trading assets to take the same economic exposure. Based on publicly available data, distinguishing between hedging and speculative derivatives is not possible, and the extant derivatives literature does not identify a good way of doing so. As a result, I let model (2)'s results speak to this story's validity. Insofar as banks use cash instruments (*e.g.*, bonds) and derivatives to assume the same economic exposure, derivatives would have no hedging efficacy. Finding that derivatives have a strong effect in hedging, by contrast, would suggest that hedging motives drive model (1)'s results.

5.5.2 Results: The Hedging Efficacy of Derivatives

The results of model (2) are in Table 5. My main finding is that *DERIVTRAD* is negative and significant. *TRAD* is positive and significant. On the margin, a rise in fair-valued assets increases fair-value income, or realized market risk, in magnitude. *DERIVTRAD*'s negative

Tab. 5.4: Baseline Results—Banks, Market Risk, and Hedging

Dep. Var. Est. #	<i>DERIV</i>		
	[1]	[2]	[3]
<i>DERIV</i> , lag	0.8028*** (0.0202)	0.8041*** (0.0175)	0.8030*** (0.0171)
<i>TRAD</i>	0.0248** (0.0125)	0.0235* (0.0125)	0.0303** (0.0118)
<i>CAP</i>	0.5898 (1.5705)	0.5884 (1.6923)	1.1206 (1.6094)
<i>LIAB</i>	-0.0009 (0.0114)	-0.0025 (0.0122)	-0.0035 (0.0117)
<i>SIZE</i>	0.2969** (0.1324)	0.3216** (0.1298)	0.2905** (0.1321)
<i>TIME</i>		0.0107*** (0.0034)	
<i>TRADCAP</i>			-0.2661 (0.1762)
R ² (within)	0.6766	0.7422	0.6773
<i>N</i>	4,891	4,891	4,891
# groups	196	196	196
Time FEs	Yes	No	Yes
Bank FEs	Yes	Yes	Yes
Std. Errors	bootstrapped (250 reps.), clustered by bank and quarter		

Notes:

- (1) All estimations include bank fixed effects, all estimations aside from estimation [2] include time fixed effects, and all regressors are lagged. *TIME* is a time trend.
- (2) In estimation (3), I center *TRAD* and *CAP* so as to reduce multicollinearity (Aiken and West [1991]).
- (3) Bootstrapped standard errors (250 replications), clustered at the bank- and quarter-level, are in parentheses.
- (4) *, **, and *** denote statistical significance at the 10-, five-, and one-percent level (two-tailed tests).

sign means that on the margin, a rise in derivatives reduces this increase in fair-value income caused by a rise in fair-valued assets. In this respect, derivatives are effective in hedging. In addition, this result suggests hedging motives drive the results of model (1). In estimations [1] and [2], 40 percent of my observations have $DERIV = 0$. Hence, in estimations [3]–[8], I show model (2)’s results after imposing minimum cut-off points for *DERIV*. As with my baseline results, *DERIVTRAD* always is negative and significant. *TRAD*, although always

Tab. 5.5: Baseline Results—The Hedging Efficacy of Derivatives

Dep. Var.	<i>TRADINC</i>							
Est. #	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
<i>TRADINC</i> , lag	0.5837*** (0.0232)	0.5674*** (0.0234)	0.5436*** (0.0324)	0.5167*** (0.0327)	0.4773*** (0.0383)	0.4525*** (0.0363)	0.4589*** (0.0392)	0.4509*** (0.0389)
<i>DERIV</i>	0.0303*** (0.0086)	0.0281*** (0.0088)	0.0510*** (0.0104)	0.0353*** (0.0115)	0.0518*** (0.0132)	0.0351** (0.0139)	0.0390*** (0.0106)	0.0272** (0.0107)
<i>TRAD</i>	0.0915*** (0.0123)	0.0573*** (0.0116)	0.0546*** (0.0162)	0.0181 (0.0127)	0.0445*** (0.0168)	0.0168 (0.0146)	0.0648*** (0.0160)	0.0439*** (0.0162)
<i>CAP</i>	1.1334 (1.1121)	1.2659 (1.1209)	0.9162 (1.4028)	1.6079 (1.5334)	-1.3524 (1.5430)	-0.2522 (1.5431)	-1.1164 (1.3213)	-0.6466 (1.3251)
<i>LIAB</i>	0.0067 (0.0090)	0.0157* (0.0087)	0.0182** (0.0086)	0.0254*** (0.0071)	0.0099 (0.0073)	0.0145** (0.0071)	0.0086 (0.0067)	0.0103 (0.0065)
<i>SIZE</i>	0.1708** (0.0850)	0.2106** (0.0955)	0.1908** (0.0873)	0.2551*** (0.0963)	0.3020*** (0.0926)	0.3373*** (0.0896)	0.2411*** (0.0804)	0.2910*** (0.0779)
<i>DERIVTRAD</i>		-0.0061*** (0.0013)		-0.0066*** (0.0016)		-0.0076*** (0.0022)		-0.0063*** (0.0020)
R ² (within)	0.4566	0.4604	0.4263	0.4327	0.3274	0.3351	0.2810	0.2851
<i>N</i>	4,891	4,891	3,094	3,094	2,718	2,718	2,626	2,626
# groups	196	196	102	102	90	90	87	87
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Min. <i>TRAD</i> %	50.0 %	50.0 %	50.0 %	50.0 %	50.0 %	50.0 %	75.0 %	75.0 %
Min. <i>DERIV</i> %	0.0 %	0.0 %	50.0 %	50.0 %	75.0 %	75.0 %	75.0 %	75.0 %
Std. Errors	bootstrapped (250 reps.), clustered by bank and quarter							

Notes:

- (1) All estimations include time and bank fixed effects, and all regressors are lagged.
- (2) $DERIV = DERIV \times TRAD$. In estimations that include *DERIVTRAD*, I center both *DERIV* and *TRAD* (Aiken and West [1991]).
- (3) Min. *TRAD* %: minimum share of quarters in which a bank had to hold trading assets (*i.e.*, to have $TRAD > 0$) to be in the sample.
- (4) Min. *DERIV* %: minimum share of quarters wherein a bank had to use derivatives (*i.e.*, to have $DERIV > 0$) to be in the sample.
- (5) Bootstrapped standard errors (250 replications), clustered at the bank- and quarter-level, are in parentheses.
- (6) *, **, and *** denote significance at the 10-, five-, and one-percent level, respectively.

positive, loses its significance in estimations [4] and [6] but regains significance in estimation [8], which uses a higher cut-off for fair-valued assets.¹¹

Derivatives have an economically large effect in mitigating the impact on fair-value income

¹¹ One potentially surprising finding is that based on estimation [2]’s results, a one-percent rise in trading assets increases the absolute value of trading income by only 0.06 percent. This result could be due to the strong positive correlation between lagged *TRADINC* and *TRAD* ($\rho = 0.752$) and the multicollinearity that results. My focus, however, is on the hedging efficacy of derivatives, not on *TRAD*’s impact on *TRADINC*. Hence, I do not explore further this result.

of a rise in fair-valued assets. Based on estimation [2]’s coefficients, a one-standard-deviation rise in fair-valued assets works via *TRAD* to increase *TRADINC* by 0.258; a one-standard-deviation rise in derivatives works through *DERIVTRAD* to reduce *TRADINC* by -0.504. Hence, derivatives more than cancel out the effect on fair-value income of a rise in fair-valued assets. While *DERIV* is positive and significant, so that a marginal increase in derivatives increases fair-value income, in magnitude, a one-standard-deviation rise in *DERIV* works via *DERIV* to increase *TRADINC* by 0.229, with $0.258 + 0.229 = 0.487$ being smaller in magnitude than -0.504. Doing this exercise using estimation [4]’s, [6]’s, and [8]’s coefficients, the same story results: Derivatives go a long way toward reducing fair-value income, in magnitude, even after accounting for their own impact on fair-value income. Hence, derivatives mitigate the impact on earnings and capital of fair-valued assets.¹²

Going over an example can make more concrete the results above. Suppose, for instance, a bank acquires a corporate bond as part of its market-making operations and thus is exposed to credit-risk-related market risk: Model (1)’s results mean that this bank, for instance, buys credit protection using a credit-default swap (CDS) to protect itself against the price effects of credit-spread changes. Consequently, this bank hedges *ex ante*, in anticipation of possible price changes. Model (2)’s results mean that once credit spreads do change, the CDS reduces the bond’s net effect on earnings. Should credit spreads rise, the bond’s price falls, resulting in fair-value losses on this bond, but the CDS’s price rises, leading to offsetting gains. Should credit spreads fall, the bond’s price increases, leading to fair-value gains, but the CDS’s price falls, resulting in offsetting losses. In this respect, the CDS reduces the net effect on earnings and capital of changes in asset prices.

¹² Another way to view the link between fair-valued assets and derivatives is within a risk-return framework. In general, apart from the 2007–8 crisis, banks have had positive fair-value income (Section 4.6, Figure 2), implying earnings on fair-valued assets are positive. In using derivatives to hedge, banks reduce earnings, in expectation, but also are exposed to less risk. Consequently, in deciding how much to hedge, banks balance the decline in expected earnings versus the decline in risk that results from hedging.

5.5.3 Supplemental Results: Alternative Cut-Off Points

Initially, I use a plausible but arbitrary 50-percent cut-off point for trading assets. In Table 6, I present the results of models (1) and (2) with trading-asset cut-off points of 40 percent, 60 percent, and 75 percent. Nothing changes. With respect to model (1), *TRAD* is positive and significant, with point estimates of 0.030, 0.028, and 0.032 using cut-off points of 50, 60, and 75 percent. With respect to model (2), *TRAD* is positive and significant, and *DERIVTRAD* is negative and significant, with point estimates of -0.0061, -0.0057, and -0.0059 using cut-off points of 50, 60, and 75 percent. Also, the coefficients in Table 6 for *DERIV*, *TRAD*, and *DERIVTRAD* imply similar economic importance for derivatives as those in Table 5. Based on estimation [5]’s results, for instance, a one-standard-deviation increase in *TRAD* works via *TRAD* to increase *TRADINC* by 0.225; a one-standard deviation rise in *DERIV* works via *DERIVTRAD* to reduce *TRADINC* by -0.491 and via *DERIV* to increase *TRADINC* by 0.201, with $0.225 + 0.201 = 0.426$ being smaller in magnitude than -0.491.

5.6 Derivatives and Fair Value’s Negative Effects

Before concluding, I use two examples to show more explicitly how derivatives could mitigate fair-value accounting’s negative effects. First, fair value has been criticized for exacerbating banks’ (naturally occurring) pro-cyclical lending. For now, suppose that banks do not hedge: During upturns, asset prices rise, banks can write up the value of their assets, these write-ups increase capital, and so banks lend more. During downturns, the opposite dynamics operate: Prices decline, and so banks take write-downs and thus issue less credit. As a consequence, banks’ through-the-cycle volatility in capital and in lending is greater under fair value than under historic cost, under which asset-price changes do not affect capital.

ECB [2004] and Novoa *et al.* [2008] run simulations that show these boom-bust dynamics. Both, however, focus on the application of fair value only to banks’ assets, effectively ruling

Tab. 5.6: Supplemental Results, Alternative Cut-Off Points

Dep. Var. Est. #	<i>DERIV</i>			<i>TRADINC</i>		
	[1]	[2]	[3]	[4]	[5]	[6]
<i>DERIV</i> , lag	0.8095*** (0.0181)	0.7981*** (0.0207)	0.8039*** (0.0233)	0.0329*** (0.0075)	0.0248*** (0.0082)	0.0345*** (0.0084)
<i>TRAD</i>	0.0188* (0.0107)	0.0284** (0.0143)	0.0319* (0.0192)	0.0494*** (0.0112)	0.0539*** (0.0143)	0.0640*** (0.0150)
<i>CAP</i>	0.8490 (1.4750)	1.2308 (1.5853)	0.7134 (1.7648)	0.8816 (1.0503)	1.3767 (1.1825)	1.2241 (1.1089)
<i>LIAB</i>	-0.0073 (0.0109)	0.0044 (0.0121)	0.0017 (0.0120)	0.0137 (0.0090)	0.0214** (0.0101)	0.0121 (0.0085)
<i>SIZE</i>	0.2530* (0.1345)	0.3335** (0.1395)	0.4694*** (0.1379)	0.1364 (0.0867)	0.2684*** (0.0818)	0.2145** (0.0845)
<i>TRADCAP</i>	-0.2495 (0.1843)	-0.2706 (0.2038)	-0.2674 (0.2204)			
<i>TRADINC</i> , lag				0.5740*** (0.0215)	0.5653*** (0.0242)	0.5388*** (0.0290)
<i>DERIVTRAD</i>				-0.0066*** (0.0012)	-0.0057*** (0.0014)	-0.0059*** (0.0015)
R ² (within)	0.6825	0.6687	0.6747	0.4647	0.4426	0.4004
<i>N</i>	5,280	4,494	3,996	5,280	4,494	3,996
# groups	211	174	154	211	174	154
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes
Min. <i>TRAD</i> %	40.0 %	60.0 %	75.0 %	40.0 %	60.0 %	75.0 %
Std. Errors	bootstrapped (250 reps.), clustered by bank and quarter					

Notes:

- (1) All estimations include time and bank fixed effects, and all regressors are lagged.
- (2) $TRADCAP = TRAD \times CAP$; $DERIV = DERIV \times TRAD$. In estimations that have interactions, I center the components of the interaction terms (Aiken and West [1991]).
- (3) Min. *TRAD* %: minimum share of quarters in which a bank had to hold trading assets (*i.e.*, to have $TRAD > 0$) to be in the sample.
- (4) Bootstrapped standard errors (250 replications), clustered at the bank- and quarter-level, are in parentheses.
- (5) *, **, and *** denote significance at the 10-, five-, and one-percent level, respectively.

out the possibility that banks use derivatives to hedge. Suppose that banks do use derivatives to hedge: During upturns, when asset prices increase, the value of banks' derivatives declines. These declines in value offset the impact on capital of the rise in asset prices. Consequently, banks cannot expand. Similarly, during downturns, when prices fall, banks still have to take write-downs, but the value of banks' derivatives increases. Hence, banks do not have to cut

back on lending. In both instances, derivatives mitigate realized market risk and thus help head off fair value's pro-cyclical effects.

Second, fair value has come under attack for contributing to asset-price downward spirals (see, *e.g.*, Cifuentes *et al.* [2005]). Fair value has a role in downward spirals by giving rise to contagion—when one bank sells assets (in an illiquid market), prices decline, and the use of fair value forces others to take write-downs. These write-downs deplete the capital of these other banks. Consequently, assuming no hedging, these banks sell assets, prices decline once more, and the cycle continues. Under historic cost, by contrast, sales still reduce prices, but banks do not have to take write-downs due to these declines in prices. As a result, fair value, by allowing asset-price declines to reduce banks' capital, has a central role in these sort of downward spirals.

As in the example above, however, derivatives could stop these dynamics from arising. When banks hedge, the initial asset sales still force banks to take write-downs. These write-downs deplete capital, but the value of banks' derivatives rises. Hence, on net, capital stays at its pre-write-down level. Consequently, banks are not forced to sell assets; the downward spiral thus does not arise. In the examples above, I assume perfect hedging, which overstates the offsetting effects of derivatives. Nonetheless, these two examples highlight how derivatives can dampen fair value's negative effects—in reducing realized market risk, on net, derivatives help insulate banks' capital from the effects of changes in asset prices.

5.7 Conclusion

My two main findings are that banks use derivatives to hedge their market risk on fair-valued assets and that derivatives are effective in hedging this risk. Derivatives thus are an important risk-management tool banks use to guard against market risk. In using derivatives in this way, banks reduce the net effect of asset-price changes on earnings and capital, blunting fair

value's capacity to have negative effects. These results suggest that focusing jointly on banks' assets and derivatives is essential to assessing the effects of fair value. These results, however, have at least one limitation. I focus only on banks' portfolio-level derivatives and fair-valued assets. I thus do not examine variation across types of assets or types of derivatives in either banks' decision to hedge or derivatives' hedging efficacy. Addressing these issues would yield additional insights into the interplay between fair-valued assets and derivatives.

Appendix

The Y9-C line-items I use are as follows:

Balance-Sheet Item	Y9-C Mnemonic
trading derivatives, notional values	BHCKA126 + BHCKA127 + BHCK8723 + BHCK8724
trading assets, total	BHCK3545
trading derivatives with a positive fair value	BHCK3543 + BHFN3543 (1996Q1–2007Q4) BHCM3543 (2008Q1–2010Q4)
trading income	BHCKA220
Tier 1 capital	BHCK8274
risk-weighted assets	BHCKA223
trading liabilities, total	BHCK3548
trading derivatives with a negative fair value	BHCK3547
total assets	BHCK2170

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