Risk Management in Financial Institutions*

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Abstract

We study risk management in financial institutions using data on hedging of interest rate risk by U.S. banks and bank holding companies. Theory predicts that more financially constrained institutions hedge less and that institutions whose net worth declines due to adverse shocks reduce hedging. We find strong evidence consistent with the theory in both the cross-section of institutions and within institutions over time. We use shocks to institutions' net worth resulting from loan losses due to drops in house prices for identification. Institutions which sustain such losses reduce hedging substantially relative to otherwise similar institutions. We find no evidence that risk shifting, changes in interest rate risk exposures, or regulatory capital explain hedging behavior.

Keywords: Risk management; Financial institutions; Interest rate risk; Financial constraints; Derivatives

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1 Introduction

The potential of the market for financial derivatives for use in risk management remains unrealized. Limited risk management leaves firms and households more exposed to shocks than they could be and is arguably a key factor in financial crises. Why the gains from using traded securities for risk management are exploited to such a limited extent remains a central question in financial economics. To address this question, we study the determinants of risk management in the quantitatively largest market for such financial instruments – the interest rate derivatives market – in which the main participants are financial institutions.

We show that the net worth of financial institutions is a principal determinant of their risk management: better capitalized institutions hedge more and institutions whose net worth declines reduce hedging. We find a statistically and economically significant positive relation between interest rate risk management and financial institutions' net worth both in the cross section and within-institution over time. Moreover, we propose a novel identification strategy. We instrument variation in financial institutions' net worth using losses on real estate loans attributable to local house price shocks, and use this shock to estimate difference-in-differences models. We find that financial institutions which suffer such shocks substantially reduce interest rate risk management. We also show that institutions reduce hedging significantly several quarters before failing or entering financial distress. We conclude that the financing needs associated with hedging are a key barrier to risk management.

We focus on the financial intermediary sector for several reasons. First, despite much debate about bank risk management and its failure during the financial crisis, even the basic patterns of risk management in financial institutions are not known and its key determinants are not well understood. Second, financial intermediaries are the largest users of derivatives and comprise more than 97% of all gross derivatives exposures globally according to the BIS' *Derivatives Statistics* (December 2014). Third, interest rate derivatives comprise 80% of the notional value of all derivatives globally according to the BIS and hence are the bulk of such exposures. The management of interest rate risk is a primary concern of financial institutions; indeed, in our data on U.S. financial institutions, interest rate derivatives represent on average 94% of the notional value of all derivatives used for hedging, far exceeding other derivatives positions.[1]

We use risk management theory to inform our measurement. A key theory of corporate

[1]Other derivatives positions include foreign exchange derivatives (5.4% of notional value), equity derivatives (0.7%) and commodity derivatives (0.1%). Not included in these calculations are credit derivatives, as no breakdown between uses for hedging and trading is available.

risk management argues that firms subject to financial constraints are effectively risk averse, giving them an incentive to hedge (see Froot, Scharfstein, and Stein, 1993). Given this rationale for risk management, Rampini and Viswanathan (2010, 2013) show that when financing and risk management are subject to the same financial constraints, both hedging and financing investment and current operations require net worth. Therefore, an important trade-off between financing and risk management arises: financially constrained firms must allocate their limited net worth between both. Since hedging requires net worth, it has an opportunity cost in terms of foregone investment. The basic prediction of this theory is that more financially constrained firms, that is, firms with lower net worth, hedge less. This is because the cost of foregoing additional investment or downsizing operations more is higher at the margin for such firms.

We test this prediction in panel data on U.S. financial institutions. We show that the theory is consistent with the main empirical patterns in the data, which had not been documented previously for financial institutions. In the cross section, better capitalized financial intermediaries hedge interest rate risk to a greater extent. Over time, financial institutions whose net worth falls reduce their hedging and institutions that approach financial distress drastically cut back on risk management. We propose a novel identification strategy by focusing on drops in financial institutions' net worth due to loan losses attributable to falls in house prices. Instrumenting financial institutions' net income with the deposit-weighted average of changes in local house prices, we find a significant positive relation between hedging and net worth. Using a difference-in-differences estimation approach and 2009 as the treatment year, we find that financial institutions *(i)* with the lower net income, *(ii)* the largeer decrease in local house prices, and *(iii)* the lower local housing supply elasticity, cut hedging substantially relative to institutions in the relevant control groups.[2]

Importantly, we are able to rule out alternative explanations consistent with a positive relation between net worth and hedging. First, we find that the trading activities of financial institutions are also positively related to net worth, both between and within institutions. This evidence is inconsistent with the idea that financially constrained institutions cut hedging because they engage in risk shifting. Second, we show that more constrained financial institutions do not substitute financial hedging with operational risk

[2] A growing literature uses house prices to instrument for the collateral value of firms (see, for example, Chaney, Sraer, and Thesmar, 2012) and entrepreneurs (see, for example, Adelino, Schoar, and Severino, 2015). For financial institutions, a measure of local house prices in a similar spirit to ours, albeit at a higher level of aggregation, is used in several recent studies of the determinants of the supply of bank loans, for example, by Bord, Ivashina, and Taliaferro (2014), Cuñat, Cvijanović, and Yuan (2014), and Kleiner (2015).

management by holding more net floating-rate assets; instead, we find that net floating-rate assets are strongly positively related to net worth and that institutions which approach distress dramatically cut their net floating-rate assets. If anything, institutions that do more financial hedging also do more operational hedging. Finally, we find that it is the net worth of financial institutions, that is, their market value, which determines their hedging policy rather than their regulatory capital; in fact, regulatory capital is not a significant determinant of bank risk management, suggesting that the emphasis on regulatory capital in much of the literature may be misplaced.

Data availability presents a major challenge for inference regarding the determinants of risk management. Much of the literature is forced to rely on data that includes only dummy variables on whether firms use any derivatives or not.[3] In contrast, our data provides measures of the intensive margin of hedging, not just of the extensive margin. Further, much of the literature has access to only cross-sectional data or data with at best a limited time dimension.[4] In contrast, we have panel data for U.S. financial institutions, both bank holding companies and banks, at the quarterly frequency for up to 19 years, that is, up to 76 quarters. This enables us to exploit the within-variation separately from the between-variation.

The closest paper to ours in terms of the empirical approach is Rampini, Sufi, and Viswanathan (2014) who study fuel price risk management by U.S. airlines. Like us, they have panel data on the intensive margin, albeit for a more limited sample; they have data at the annual frequency for up to 15 years and up to 23 airlines, 270 airline-year observations in all, whereas we use a much larger data set. One advantage of their data is that hedging is arguably measured more precisely, as airlines report the fraction of next year's expected fuel expenses that they hedge. We discuss our hedging measures in greater detail in Section 3. Another major difference is the identification strategy, as we are able to exploit exogenous variation in net worth due to house price changes. Moreover, we focus on risk management in the financial intermediary sector, which is of quantitative importance from a macroeconomic perspective and has received widespread attention both among researchers and policy makers. Nevertheless, our basic findings are consistent with theirs as they find similar patterns in airline fuel price risk management. Together, these findings suggest that the specifics of the industry are not driving the results.

[3] Guay and Kothari (2003) emphasize that such data may be misleading when interpreting the economic magnitude of risk management. Their hand-collected data on the size of derivatives hedging positions suggests that these are quantitatively small for most non-financial firms.

[4] For example, Tufano (1996)'s noted study of risk management by gold mining firms uses only three years of data, albeit the data is on the intensive margin of hedging.

When describing the basic patterns of risk management, the existing literature has mostly emphasized a strong positive relation between firm size and hedging (see Nance, Smith Jr, and Smithson (1993) and Géczy, Minton, and Schrand (1997) for large U.S. corporations). For financial institutions, the fact that users of derivatives are larger than non-users is shown by Purnanandam (2007).[5] From the vantage point of previous theories, the positive relation between firm size and hedging has long been considered a puzzle (see, for example, Stulz, 1996), because larger firms are considered less constrained. Based on a large sample of 3,022 firms, Mian (1996) reaches the stark conclusion that "evidence is inconsistent with financial distress cost models; evidence is mixed with respect to contracting cost, capital market imperfections and tax-based models; and evidence uniformly supports the hypothesis that hedging activities exhibit economies of scale."[6] The hypothesis which we test, in contrast, is consistent with the idea that large financial institutions hedge more. Guided by the new dynamic theory of risk management, we are also able to provide a much more detailed description of both cross-sectional and time-series patterns in hedging by financial institutions. We show that the key determinant of these patterns is not size as such, but net worth, as measured by several variables.

Finally, related to this paper is also the literature on interest rate risk in banking. Purnanandam (2007) shows that the lending policy of financial institutions which engage in derivatives hedging is less sensitive to interest rate spikes than that of non-user institutions. More recently, Landier, Sraer, and Thesmar (2013) find that the exposure of financial institutions to interest rate risk predicts the sensitivity of their lending policy to interest rates. Theoretically, the optimal management of interest rate risk by financial institutions, as well as its impact on lending, is modelled by Vuillemey (2015). In a recent study, Begenau, Piazzesi, and Schneider (2015) quantify the exposure of financial institutions to interest rate risk. The overall literature on risk management using interest rate derivatives, however, is surprisingly small, given the enormous size of this market and the central role of financial institutions in the macro finance nexus. Our paper contributes to a better understanding of this market, by documenting new empirical regularities in the cross-section and time-dimension, consistent with dynamic risk management theory.

The paper proceeds as follows. Section 2 discusses the theory of risk management

[5] Ellul and Yerramilli (2013) construct a risk management index to measure the strength and independence of the risk management function at bank holding companies and find that larger bank holding companies have a higher risk management index, that is, stronger and more independent risk management.

[6] Other theories of risk management include managerial risk aversion (see Stulz, 1984) and information asymmetries between managers and shareholders as in DeMarzo and Duffie (1995) and Breeden and Viswanathan (1998).

subject to financial constraints, and formulates our main hypothesis. Section 3 describes the data and the measurement of interest rate hedging by financial institutions. Section 4 provides between-institution and within-institution evidence on the relation between net worth and hedging, and studies hedging before distress. Section 5 provides our identification strategy, using changes in house prices to assess the effect of changes in net worth on hedging, both in instrumental variables and difference-in-differences estimations. Section 6 considers alternative hypotheses. Section 7 concludes.

2 Risk management subject to financial constraints

Why do firms, and financial institutions in particular, hedge? Arguably, the leading rationale for risk management is that firms subject to financial constraints are effectively risk averse. This rationale is formalized in an influential paper by Froot, Scharfstein, and Stein (1993), who show that financially constrained firms are as if risk averse in the amount of internal funds they have, that is, in their *net worth*, giving them an incentive to hedge. They conclude that such firms should completely hedge the tradable risks they face.[7] Moreover, since risk management should not be a concern for unconstrained firms, they conclude that more financially constrained firms should hedge more. This prediction, however, is at odds with some of the basic empirical patterns in the data on corporate risk management, especially the strong positive relation between firms' derivatives use and size.

Building on the insight that financial constraints provide a raison d'être for risk management, Rampini and Viswanathan (2010, 2013) show in a dynamic model that when risk management and financing are subject to the same financial constraints, an important trade-off between financing and risk management arises. While the key state variable remains net worth, the conclusion on the relation between financial constraints and net worth is reversed: more financially constrained firms hedge less, not more, as the financing needs for ongoing operations dominate hedging concerns. Essentially, financially constrained firms choose to use their limited net worth to retain more capital instead of committing part of their limited internal funds to risk management. The key difference is that Froot, Scharfstein, and Stein (1993) consider hedging in frictionless financial markets and no concurrent investment, whereas Rampini and Viswanathan (2010, 2013) impose

[7] Froot and Stein (1998) reach the same conclusion in a model of risk management for financial institutions. Holmström and Tirole (2000), in contrast, argue that credit-constrained entrepreneurs may choose not to buy full insurance against liquidity shocks, that is, that incomplete risk management may be optimal. Mello and Parsons (2000) also argue that financial constraints could constrain hedging.

the same financial constraints on both hedging and financing, thus linking financing and risk management, and consider concurrent investment, implying a choice between committing internal funds to finance operations or risk management. The basic prediction of this dynamic theory is that there should be a positive relation between measures of the net worth of firms, including financial institutions, and the extent of their risk management. This is the main hypothesis that we test in this paper. The theory predicts such a positive relation between hedging and net worth both across institutions, that is, for the between-variation, as well as within institutions over time, that is, for the within-variation; a drop in a financial institution's net worth should lead to a cut in its risk management.

We stress that the theory implies that the appropriate state variable is net worth, that is, total assets, including the current cash flow, net of liabilities. Thus, net worth includes unused debt capacity, such as unused credit lines and unencumbered assets. Importantly, the key explanatory variable according to the theory is our measure of net worth and not cash or collateral per se.

Vuillemey (2015) explicitly considers interest rate risk management in a dynamic quantitative model of financial institutions subject to financial constraints. Consistent with the previous results, he finds that optimal interest rate risk management is limited. Moreover, he shows that the sign of the hedging demand for interest rate risk can vary across institutions, which is important in interpreting our data below.

3 Data and measurement

This section describes the data and the measurement of hedging and trading of interest rate derivatives by financial institutions. We describe the data sources, the units of observation, as well as our two main measures of risk management, gross and net hedging. We also discuss how to measure balance sheet interest rate exposure and relate hedging patterns to financial institutions' underlying exposure to interest rate risk. Finally, we provide our measures of net worth, the state variable in the theory, including a net worth index that we construct.

3.1 Data sources

Our main dataset comprises data on two types of financial institutions, bank holding companies (BHCs) and individual banks. We discuss the distinction between these two types of institutions in more detail in the next subsection. All balance sheet data is from the call reports, obtained from the Federal Reserve Bank of Chicago (reporting forms FR

Y-9C for BHCs and FFIEC 031 and FFIEC 041 for banks). These forms are completed at a quarterly frequency by banks and, on a consolidated basis, by all domestic holding companies with total assets of USD 500 million or more.[8] BHC-level data is available from 1986Q3 on and bank-level data from 1976Q1 on. The derivatives data required for the analysis, however, is available from 1995Q1 on. Observations before this date are dropped.

We perform a number of data quality checks. We drop the main dealers, whose primary activity on derivatives markets is market making.[9] We drop U.S. branches of foreign banks, because a large part of hedging activities for these entities is likely unobserved. We drop lower-tier BHCs, that is, BHCs which are subsidiaries of other BHCs that are also in the sample. Finally, we drop a small number of observations corresponding to financial institutions with very limited banking activity, defined by a ratio of total loans to total assets below 20%.

To obtain several measures of net worth, the BHC-level balance sheet data is matched with market data from CRSP and Capital IQ. In contrast, bank-level data is not matched with market data, as market data is available for very few individual banks. From CRSP, we retrieve the market value of equity for BHCs. From Capital IQ, we retrieve credit ratings from Standard & Poors. The BHC sample size is reduced by matching the call reports data with market data; out of 2,102 unique BHCs in the sample, 753 can be matched to CRSP data. The resulting sample contains 22,723 BHC-quarter observations from 1995Q1 to 2013Q4, that is, 76 quarters with 301 observations per quarter on average. Un-matched data primarily includes non-listed BHCs, for which net worth is more difficult to measure. The total assets of the BHCs being matched to market data represent, on average per quarter, 69.7% of all assets in the banking sector. The number of BHCs that can be matched to credit ratings data is smaller. Credit ratings data are available for 3,579 out of 22,723 BHC-quarter observations. The bank-level dataset, which is not matched with market data, contains 627,219 bank-quarter observations (8,252 observations per quarter on average).

[8] BHCs with total assets below USD 500 million complete reports at a semiannual frequency. Before 2006Q1, the regulatory threshold for filling FR Y-9C forms was USD 150 million. To keep the sample consistent, we drop BHCs with total assets between USD 150 million and USD 500 million during this period. Very few of these institutions are active users of derivatives, so that the information loss is minor.

[9] These banks are: Bank of America, Citigroup, Goldman Sachs, J. P. Morgan Chase, Morgan Stanley and Wells Fargo.

3.2 Unit of observation: BHCs versus banks

We conduct our empirical work both at the BHC and at the bank level. In the United States, most banking firms are part of a larger BHC structure. A BHC controls one or several banks, but can also engage in other activities such as asset management or securities dealing. Thus, a BHC is not simply the consolidated version of one or several individual banks. The BHC-level data consolidates balance sheets of all entities within a BHC. Details on the institutional background can be found in Avraham, Selvaggi, and Vickery (2012). For clarity of exposition, we use the term financial institutions whenever we mean both BHCs and banks and use the term banks only when we refer to individual banks.

The use of both BHC-level and bank-level data is motivated by theoretical and practical considerations. From a theoretical perspective, risk management can be conducted both at the BHC level and at the bank level. In the context of liquidity management, Campello (2002) provides evidence on internal capital markets within BHCs, which provide partial insurance to individual banks within a BHC against liquidity shortfalls. Risk management, however, does not occur at the BHC level. Each individual bank within a BHC has its own managerial structure and may have its own derivatives trading desk. There can also be limits to intra-group transfers, which motivate risk management at the bank level.[10]

From a practical perspective, the BHC-level and bank-level datasets do not include an identical set of variables. Both have their advantages and disadvantages. On the one hand, balance sheet data at the BHC level can be matched with market-based data on net worth (especially data on the market capitalization and credit rating), which is not available at the bank level for most banks. Thus, net worth is more precisely measured at the BHC level. On the other hand, bank-level data has the advantage that hedging can be more precisely measured, as a measure of net derivatives hedging can be computed for a subset of banks (see Section 3.4 below). In light of these trade-offs, we report results at both the BHC and bank level wherever possible and focus on either the BHC or bank level, as appropriate, whenever data availability forces us to.

[10]Data shows that a large part of hedging activities is taking place at the bank level. Aggregating derivative exposures of individual banks within each top-tier BHC (i.e., BHCs that are not owned by other sample BHCs), we find that it represents 88.5% of the exposure reported by the BHC on average. For a subset of BHCs, however, hedging is small or inexistant at the bank level and larger at the BHC level.

3.3 Measurement: gross hedging

Our main measure of hedging is gross hedging. Gross hedging is defined as

$$\text{Gross hedging}_{it} = \frac{\begin{array}{c}\text{Gross notional amount of interest rate}\\ \text{derivatives for hedging of } i \text{ at } t\end{array}}{\text{Total assets}_{it}}. \tag{1}$$

This variable is thus the sum of the notional value of all interest rate derivatives, primarily swaps, but also options, futures and forwards, scaled by total assets. Swaps are the most commonly traded interest rate derivative, representing on average 71.7% of all outstanding notional amounts. The ratio is winsorized at the 99th percentile, to ensure that the results are not driven by extreme values. Detailed variable definitions for this and all other variables we use are provided in Table 1.

To identify derivatives used for risk management, as opposed to trading, we exploit a unique feature of BHC and bank reporting in the United States. Reported derivative exposures are broken down by contracts "held for trading" and "held for purposes other than trading." Derivatives held for trading are defined as including *(i)* dealer and market making activities, *(ii)* positions taken with the intention to resell in the short-term or to benefit from short-term price changes *(iii)* positions taken as an accomodation for customers and *(iv)* positions taken to hedge other trading activities. In our analysis, we exclude all derivative exposures held for trading when measuring risk management and focus only on exposures held for purposes other than trading, that is, primarily hedging. In other industries, researchers are typically forced to rely on indirect evidence to distinguish between hedging and trading or speculation (see, for example, Chernenko and Faulkender, 2011). In contrast, this breakdown is readily available in our data. The same variable is also used in earlier empirical studies on the use of derivatives by U.S. commercial banks (see, for example, Purnanandam, 2007; Bonaime, Hankins, and Harford, 2014). While the distinction between derivatives used for trading and for hedging is a unique feature of our data, the use of this variable also raises a number of potential measurement concerns, which we address below.

Descriptive statistics for gross hedging and gross trading are provided in Table 2 for both BHCs and banks. Panel A contains various statistics of the distribution of hedging and trading. The distribution is quite skewed with a large number of zeros, that is, of banks with no activity at all in the interest rate derivatives market. The median bank does not hedge while the median BHC hedges to a very limited extent. Moreover, even for BHCs and banks that hedge, the magnitude of hedging to total assets is fairly small, except in the highest percentiles of the distribution. Thus, risk management in derivatives markets is limited. Furthermore, Panel B shows that derivatives hedging displays a strong size pattern, both at the extensive margin (number of derivatives users) and at the intensive margin (magnitude of the use of derivatives). Larger financial institutions are more likely to use derivatives and, conditional on hedging, use derivatives to a larger extent than smaller institutions.

A potential concern about our data is whether derivative exposures for hedging purposes are economically relevant when compared to exposures for trading purposes. At an aggregate level in the U.S. banking sector, derivatives used for trading represent between 88.8% and 98.9% (depending on the quarter) of all derivatives in notional terms. Begenau, Piazzesi, and Schneider (2015) argue that these exposures are most relevant to assess banks' risk exposures. These large exposures for trading purposes, however, arise to an almost exclusive extent from the market-making activities of a small number of broker-dealers. In 2013Q4, the top-5 banks account for 96.0% of all exposures for trading, and the top-10 banks for more than 99.7% of such exposures. If market making leaves residual exposures on the balance sheet of dealers, these exposures are difficult to assess quantitatively, because they result from a very large number of offsetting long and short positions at various maturities. Residual exposures arising from market making are also likely to be kept on the balance sheet for very short periods of time only.

For the average sample bank, in contrast, the use of derivatives for trading is nonexistent, or close to nonexistent. The number of institutions engaging in hedging is much larger than that of institutions using derivatives for trading. In our sample of BHCs, 84.6% of all BHC-quarter observations for trading are zeros and 98.5% in the bank-level dataset. The fact that derivative exposures for hedging purposes are the most relevant exposure for most financial institutions can also be seen in Table 2. Panel B shows that the use of derivatives for trading is concentrated among institutions in the highest size quintile. For smaller institutions, trading is rare while hedging using derivatives remains fairly common. For banks, trading is almost equal to zero even at the 98th percentile, while hedging at that percentile is important. At the BHC level, more than half of the BHCs hedge, while less than a quarter engage in trading. Panel B further shows that sorting of derivatives use based on size is much stronger for trading than for hedging. Taken together, these observations suggest that the relevant exposures to be looked at for institutions other than the main broker-dealers are those associated with derivatives used for hedging purposes. In notional terms, after excluding the main dealers, interest rate derivatives held for hedging represent between 10% and 26% of the total assets of all BHCs, depending on the quarter.

3.4 Measurement: net hedging

Gross notional exposures may aggregate long and short derivative positions (for example, pay-fixed and pay-float interest rate swap positions). A potential and indeed rather plausible concern is that gross hedging is a poor measure of net hedging (that is, long minus short positions), which is economically more relevant. The data does not provide information on net hedging directly. However, to address this concern, we proceed as follows. First, we are able to construct a measure of net hedging for a subset of banks. Second, we show that gross and net hedging are highly correlated for banks in this subset.

A measure of net hedging cannot be constructed for BHCs. In contrast to BHCs, a measure of net hedging can be constructed at the bank level for banks which report that they use only swaps and no other types of interest rate derivatives. Banks report the notional amount of interest rate *derivatives* held for hedging. In addition, banks report the notional amount of *swaps* held for hedging on which they pay a fixed rate. The notional amount of swaps held for hedging on which they pay a floating rate, however, is not reported, but can be inferred from the previous two numbers for the subset of banks that only use swaps. In contrast, this number cannot be inferred for banks that use other types of interest rate derivatives as well, because the total notional amount of all derivatives held for hedging includes contracts which are not swaps (such as futures, forwards and options).

Thus, for an institution i at date t which reports using only swaps and no other interest rate derivatives, we can construct a measure of net hedging as follows:

$$\text{Net hedging}_{it} = \frac{\text{Pay-fixed swaps}_{it} - \text{Pay-float swaps}_{it}}{\text{Total assets}_{it}}. \tag{2}$$

A positive value of this ratio means that an institution is taking a net pay-fixed position, that is, that it hedges against increases in the referenced interest rate. A negative value of the ratio means that the bank is hedging decreases in interest rates. Bank-quarter observations for which this ratio can be computed represent 28.7% of all bank-quarter observations for banks that use derivatives. Descriptive statistics on net hedging are in Table 3. To our knowledge, this variable has not been constructed previously and has not been used in previous research.

What is the relation between net hedging and gross hedging? While net hedging can be both positive and negative, gross hedging is bounded below by zero. To document the relation between gross and net hedging, we use the absolute value of net hedging from Equation 2. Thus, we recognize the fact that both net pay-fixed and pay-float swap positions can be used by banks to hedge. Vuillemey (2015) shows that both types of positions can be optimal for banks depending on their maturity mismatch.

In Panel B of Table 3, we report the estimates from a regression of gross hedging on net hedging. Both a pooled OLS and a specification with bank fixed effects are estimated. Gross and net hedging are positively correlated, with coefficients being statistically significant at the 1% level and an adjusted R^2 of 57% in the pooled sample (implying a correlation of 0.75). Within banks, it is also the case that gross hedging is high at times when net hedging is high. The fact that a positive and significant relation between gross and net hedging exists both between banks and within banks is reassuring and suggests that our main hedging variable, expressed in gross terms, is a good proxy for the underlying net hedging. This is the case because a large number of small and medium-sized institutions enter into derivatives transactions infrequently and do not take many offsetting long and short positions. A similar pattern has been documented in the CDS market, in which end-users typically have a high ratio of net exposure to gross exposure (see Peltonen, Scheicher, and Vuillemey, 2014).

A final and related concern is whether net exposures are appropriately measured, given our reliance on notional amounts. Panel C of Table 3 provides suggestive evidence that this is indeed the case. The change in the market value of a bank's interest rate derivatives portfolio is regressed on the change in the Libor over the past quarter. The regression coefficients are estimated on subsamples of banks for which measured net hedging is positive and negative. For banks with a positive (resp. negative) net hedging ratio, that is, a net pay-fixed position (resp. a net pay-float position), an increase in the Libor results in an increase (resp. a decrease) in the market value of the bank's derivatives portfolio. The estimated coefficients are statistically significant at the 1% level, and suggest that our variable capturing net hedging in notional terms appropriately measures the underlying net exposure.

3.5 Measurement: balance sheet interest rate exposure

We now consider the measurement of financial institutions' balance sheet interest rate exposure and the relation between financial institutions' derivatives hedging and their underlying exposure to interest rate risk. First, measuring on-balance sheet exposure to interest rate risk enables us to measure the extent of operational risk management, that is, the idea that financial institutions may change the composition of their balance sheet to hedge, possibly substituting operational risk management for financial hedging with derivatives. Second, it makes it possible to assess the accuracy of our measurement of net hedging, by showing that the joint pattern of net hedging and on-balance sheet exposures is consistent with risk management.

To measure the exposure of an institution to interest rate risk, we use the one-year *maturity gap* defined as

$$\text{Maturity gap}_{it} = \frac{A_{it}^{IR} - L_{it}^{IR}}{\text{Total assets}_{it}}, \tag{3}$$

where A_{it}^{IR} and L_{it}^{IR} are respectively assets and liabilities that mature or reprice within one year for institution i at date t. The maturity gap is essentially a measure of an institution's net floating-rate assets. A positive value of the maturity gap implies that increases in the short rate increase the institution's interest income at the one-year horizon, because it holds more interest rate-sensitive assets than liabilities at this maturity. In contrast, a negative value of the maturity gap leaves institutions vulnerable to increases in the short-term interest rate, as they have net floating-rate liabilities.

The maturity gap (also called "income gap") has been used in a number of earlier academic studies (for example, Flannery and James, 1984; Purnanandam, 2007; Landier, Sraer, and Thesmar, 2013). It has been popularized in practitioners' textbooks (for example, Saunders and Cornett, 2008; Mishkin and Eakins, 2009), suggesting that it is also directly relevant to risk managers in practice. As a measure of interest rate risk, the maturity gap has the appealing property that changes in net interest income at a 1-year horizon are proportional to it, that is,

$$\Delta NII_{it} = \text{Maturity gap}_{it} * \Delta r, \tag{4}$$

where ΔNII is the change in net interest income on assets and liabilities in the 1-year maturity bucket and Δr the change in the level of the interest rate at this maturity (see Saunders and Cornett, 2008).

Computing the maturity gap makes it possible to directly relate on-balance sheet exposures to interest rate risk to derivatives hedging. In particular, it allows us to better assess the quality of the data on derivatives hedging. A potential concern is whether derivatives reported as held for hedging purposes are truly used for risk management, or for trading or speculative purposes. The existing literature has simply argued that reporting is likely truthful because all sampled institutions are monitored on a regular basis by the FDIC, the OCC, or the Federal Reserve (see, for example, Purnanandam, 2007).

In contrast, we are able to directly address this measurement concern, because we observe both net exposures on-balance sheet (that is, the maturity gap) and net hedging off-balance sheet. We show that the joint pattern of both variables is consistent with genuine risk management. First, Panel A of Table 3 shows the distribution of net hedging both for banks that have a maturity gap above and below zero as well as for banks with a maturity gap in the first and fourth quartiles. Net hedging is much more negative for banks with a positive maturity gap, and vice-versa. This pattern is consistent with hedging. Indeed, banks with negative net hedging have a pay-float swap exposure, that is, gain when the short rate goes down. On-balance sheet, in contrast, a positive maturity gap implies that they gain when the short rate goes up. The combination of a positive maturity gap with negative net hedging is thus consistent with genuine risk management. The fact that the distribution of net hedging is consistent with risk management is also illustrated in Figure 3 which shows the distribution conditional on the maturity gap being above the 75th percentile vs. being below the 25% percentile. The shift in the distributions is evident.

Panel D of Table 3 uses a regression approach to further illustrate this result. In the cross-section, a high maturity gap is associated with a more negative net hedging ratio. Across specifications, this regression coefficient is statistically significant at the 1% level. The same is also true within banks, that is, individual banks have a more negative net hedging ratio at times when their maturity gap is high.

3.6 Measurement: net worth

In both Froot, Scharfstein, and Stein (1993) and Rampini and Viswanathan (2010, 2013), the key state variable driving hedging patterns is *net worth*, and our main hypothesis pertains to the relation between hedging and net worth. Net worth, however, is not directly observable in the data. To measure it, we rely on the idea that net worth determines the tightness of financial constraints, and can thus be proxied by standard measures of financial constraints.

We use several measures of net worth. The first five are relatively standard and have been used by Rampini, Sufi, and Viswanathan (2014), for example; these are book value of assets ("size"), market value of equity ("market capitalization"), market value of equity to assets, net income to assets, and the credit rating. The sixth, a measure of cash dividends, has been used to measure financial constraints at least since Fazzari, Hubbard, and Petersen (1988). The last one is an index of net worth which we introduce. All variables are defined in more detail in Table 1.

Given the central role of net worth in our analysis, we construct a net worth index as follows. We extract the first principal component of size, market value of equity to assets, net income to assets, and cash dividends to assets. The loadings on each of these variables are in Table 1. We exclude the rating variable in the construction of the index to avoid being forced to restrict the sample for which we can construct this index to institutions for which the rating information is available. We think that this net worth index may be of independent interest.

The cross-sectional distribution of each measure of net worth is plotted at the quarterly frequency in Figure 1. Notice the substantial drop in the market value to assets, net income to assets, and dividends to assets during the financial crisis, and the corresponding drop in the net worth index we construct. Descriptive statistics for these variables are in Panel A of Table 5. Panel B of Table 5 shows the correlation between all measures of net worth. Interestingly, the net worth index is relatively less correlated with size than with the other variables such as the market value of equity to assets, net income, or cash dividends.

4 Hedging and net worth in cross section and time series

To study the determinants of risk management in financial institutions, we investigate the relation between derivatives hedging and our measures of net worth in this section, both in the cross-section and in the time series. We also examine the dynamics of hedging for financial institutions that approach distress.

4.1 Hedging and net worth across financial institutions

We provide evidence of a positive cross-sectional relation between interest rate hedging and net worth at the BHC level. To focus on the cross-sectional dimension only, we estimate a BHC-mean specification, where both the dependent and independent variables are averaged for each BHC over the sample period; this specification isolates the variation between BHCs. We also estimate a pooled OLS specification with time fixed effects, to control for time trends in hedging. The results are reported in Panel A of Table 6. In both these specifications, the estimated coefficients are positive and significant at the 1% level (and in one case at the 5% level) for six out of seven measures of net worth. The magnitude of the effect is economically relevant. Focusing on BHC-mean estimates, one standard deviation increase in size is associated with an increase in hedging equal to 53% of a standard deviation. For other measures, a one-standard deviation increase in the credit rating (resp. the net worth index) is associated with an increase in hedging by 25% (resp 23%) of a standard deviation.

One concern with the above specifications is that there are a large number of zeros in the dependent variable. In the BHC sample, 49% of observations for gross hedging are zeros. This can result in a downward bias in our estimates, because for BHCs that do not hedge the cross-sectional and time-series variation in net worth does not translate to any variation in hedging. To address this issue, we turn to several alternative estimation methods which explicitly account for the fact that hedging has a mass point at zero. We estimate *(i)* a BHC-mean Tobit, where both the dependent and independent variables are averaged for each BHC over all periods, before a Tobit specification is estimated, *(ii)* a Tobit specification in the pooled sample, with time fixed effects, and *(iii)* quantile regressions in the upper percentiles (75th, 85th and 95th) of the distribution of gross hedging.

Estimates for these specifications are in Panel B of Table 6. With two exceptions, estimated coefficients are all positive and significant at the 1% levels. The fact that hedging drops as net worth declines is also seen from regressions of hedging on credit rating dummies reported in Panel C of Table 6. Estimates are given as differences with respect to the hedging level by institutions in a bucket from A- to AAA. Institutions with low credit ratings hedge significantly less than institutions with high credit ratings in the cross-section. Overall, these results suggest that, in the cross-section, financial institutions with high net worth hedge more than institutions with low net worth. In contrast with previous work, we highlight that cross-sectional patterns in hedging are not mainly driven by size, but by net worth, proxied by several measures.

4.2 Hedging and net worth within financial institutions

We turn to the panel dimension next. We use institution fixed effects to isolate within-institution variation in hedging. The inclusion of fixed effects serves two purposes. First, it is meant to provide more stringent evidence of the positive relation between net worth and hedging. Our hypothesis is that, over time, financial institutions hedge more when they are better capitalized and cut hedging when they become more constrained. Second, the inclusion of institution fixed effects makes it possible to difference out any time-invariant unobserved heterogeneity, such as permanent differences in business models, which may affect estimates in pooled regressions.

Results for all fixed effect regressions are in Table 7. Panel A provides estimates at the BHC level. Panels B and C provide estimates at the bank level, focusing on gross and net hedging, respectively. In all cases, the fixed effect estimates in the whole sample are either positive and significant or insignificant. The economic magnitude of the effect is attenuated with respect to the cross-sectional and pooled regressions, but is still appreciable. We provide a number of additional specifications. Theory predicts that the trade-off between hedging and financing is more acute for banks with low net worth. To take this into consideration, we exclude the 10% of institutions with the highest net worth in the second specification of Panel A. When these institutions are excluded, all coefficients are positive and significant at the 1% level.

Further, we estimate two additional specifications to account for the large number of zeros in the data. We estimate a regression with BHC fixed effects excluding all institutions which never use derivatives. We also use the trimmed least absolute deviations estimator proposed by Honoré (1992), which makes it possible to estimate a model with fixed effects in the presence of censored or truncated data. In both cases, all significant coefficients are positive, although in the latter specification, only two of seven coefficients are significant. Finally, at the bank level, we find positive and significant effects for all three measures of net worth available for gross hedging, and for two of the three variables available for the absolute value of net hedging. That said, the magnitude of the effects at the bank level are somewhat smaller in size.

To sum up, we find a statistically significant and economically appreciable positive relation between hedging and net worth within financial institutions, corroborating our cross-sectional results.

4.3 Hedging before distress

This section provides additional evidence of the relation between net worth and hedging within institutions over time by focusing on hedging by institutions that enter financial distress and thus become severely constrained. Results are obtained for both BHCs and banks, as well as for gross and net hedging.

We define a distress event for a BHC (resp. a bank) as any exit from the sample with a ratio of market capitalization (resp. common equity) to total assets below 4% in the last quarter in which the institution is in the sample. There are several reasons why financial institutions exit the sample, including mergers and acquisitions or failures. The reason for exiting the sample is obtained from the National Information Center (NIC) transformation data. Distinguishing between actual failures and distress episodes leading to acquisitions is, however, of limited interest for our purposes. Mergers and acquisitions are indeed often arranged before FDIC assistance is provided and the bank actually fails (see, for example, Granja, Matvos, and Seru, 2014). Restricting attention to institutions which exit the sample with a market capitalization or common equity below 4% of total assets ensures that these institutions are distressed.

We identify all such distress events over the sample period, 1995Q1 to 2013Q4. We restrict the sample to BHCs and banks which hedge in at least one quarter. There are 49 distress events for BHCs and 636 distress events for banks. Most of these events (95.9%) involve mergers or purchases before the entity actually fails. Other distress events are failures in which FDIC assistance is provided.

We use a regression approach to investigate the extent of hedging in the eight quarters before distress. We estimate

$$\text{hedging}_{it} = FE_i + FE_t + \sum_{j=0}^{8} \gamma_j \cdot D_{\tau-j} + \varepsilon_{it}, \tag{5}$$

where τ is the quarter in which institution i exits the sample in distress and $D_{\tau-j}$ a dummy variable that equals 1 for distressed institutions at each date $\tau - j \in \{\tau - 8, ..., \tau\}$ before distress and 0 otherwise. The specification includes institution fixed effects (FE_i) and time fixed effects (FE_t), to focus exclusively on within-institution variation before distress.

The specification in Equation (5) is estimated both at the BHC and at the bank level. At the bank level, we estimate it for both gross and net hedging. These regressions are estimated on the whole sample of distressed and non-distressed banks. The regression coefficients are collected in Table 8. Hedging, both gross and net, is found to decrease by a statistically significant amount several quarters before distress. Since these specifications include time fixed effects, the results are not driven by the potential clustering of defaults in a few quarters. Interestingly, both gross and net hedging, at the bank level, are reduced by comparable amounts, again suggesting that both are relatively similar for most banks.

The economic magnitude of pre-distress reduction in hedging is large. Financial institutions cut hedging by a factor close to two. A graphical exposition of this result is in Figure 4, which plots mean and median hedging before distress. In this figure, attention is restricted to financial institutions which enter distress and for which all 8 observations before exit are available. In all cases, approaching distress is associated with a reduction of both mean and median hedging. For banks, median hedging falls to zero at the time of exit. Both the regression results and the figures are strongly suggestive of the fact that, as institutions become more constrained, the opportunity cost of hedging becomes too large. Cutting hedging for such institutions is the optimal response in the face of more severe financing constraints. Since institutions cut hedging so dramatically before distress, one might be tempted to conclude that an alternative hypothesis that could explain this particular pattern is risk shifting by distressed institutions. We discuss this alternative hypothesis, as well as several others, in Section 6 below. To anticipate our conclusion, we provide evidence on the trading behavior of financial institutions that suggests that risk shifting is not a plausible interpretation of these findings in our view.

5 Evidence using house prices

In this section we turn to our identification strategy. We use changes in house prices to assess the effect of changes in net worth on hedging. First, we use an instrumental variable approach, instrumenting net income with changes in local house prices. Second, we estimate the effect of a drop in net worth on hedging using difference-in-difference estimation.

5.1 Instrumenting net income with changes in house prices

Our instrumental variable approach uses local house prices to instrument for net income, a key component of the change in net worth. We exploit the fact that over the period from 2005 to 2013 changes in financial institutions' net income are driven to an important extent by losses on loans secured by real estate, which are in turn driven by variation in local house prices. We instrument net income by lagged changes in house prices at the local level. Because the instrument is likely stronger for financial institutions with a high exposure to real estate, we restrict attention to institutions with a ratio of loans secured by real estate to assets above the sample median.

Our identifying assumption is that house prices affect hedging only through their impact on financial institutions' net worth, as proxied by net income. We start by providing supporting evidence in favor of this instrument. First, we show that changes in net income over the 2005-2013 period arise to a large extent from provisions for loan losses caused by drops in house prices. Second, we address a potential endogeneity concern by showing that changes in net income over the sample period are not also arising to a significant extent – directly or indirectly through defaults on mortgages – from changes in interest rates.

We first conduct a variance decomposition of changes in net income over the 2005-2013 period. Net income can be written as

$$\text{Net income}_{it} = \text{Net interest income}_{it} + \text{Net noninterest income}_{it} - \text{Provisions}_{it} + \varepsilon_{it}, \quad (6)$$

where ε_{it} contains extraordinary items, income taxes, and income attributable to non-controlling (minority) interests. We use a regression approach to decompose *changes* in net income into changes in its three main components. The results of this decomposition are provided in Table 9, in which t-statistics are reported together with the regression coefficients. Two features of this decomposition are worth noting. First, as can be seen in columns (1) and (4), changes in net income arise to a large extent from provisions for loan losses. Second, as seen in column (2), variation in net interest income is not a significant driver of changes in net income over the sample period. Thus we can rule out the concern that changes in net worth, as measured by net income, may be driven to a significant extent by interest rates, as the decomposition shows that this concern is not warranted.[11] Figure 5 provides a graphical illustration of the decomposition; notice that while the variation of net interest income over time is limited, provisions increase massively exactly at the time when net income drops dramatically.

Turning to provisions for loan losses, the fourth panel in Figure 5 shows that provisions increase primarily to face losses on loans secured by real estate. Over the sample period, nonaccrual real estate loans represent the vast majority of total nonaccrual loans. For our instrument to be valid, however, two additional steps are needed. First, it has to be the case that changes in house prices drive defaults on loans secured by real estate, primarily mortgages, to a significant extent. Second, an additional endogeneity concern must be addressed. If defaults on loans secured by real estate are importantly related to changes in the interest rate environment, then such changes may also affect the incentive to engage in interest rate hedging, for reasons unrelated to net worth. To address these two concerns, we turn to the sizeable literature which studies mortgage defaults over our sample period. This literature largely concludes that house prices were the main driver of mortgage defaults from 2007 onwards (see, for example, Bajari, Sean Chu, and Park, 2008; Mayer, Pence, and Sherlund, 2009; Demyanyk and Van Hemert, 2011; Palmer, 2014). Second, a number of these papers also stress that the interest rate environment played a minor role in explaining mortgage defaults. Importantly, the interest rate environment was the same across the U.S., while there was a lot of local heterogeneity in mortgage defaults, driven by local heterogeneity in house prices drops. These findings suggest that our instrument is valid and satisfies exogeneity conditions.

To construct our instrument, we retrieve additional data from two sources. For each financial institution, we obtain data on deposits at the ZIP-code level from the FDIC's Summary of Deposits, at a yearly frequency, as of June 30 of each year. We obtain data on house prices at the ZIP-code level from Zillow. For each institution, we construct a deposit-weighted measure of house price changes, based on the structure of deposits as of the end of previous reporting year. The weighted average house price change for institution i between dates $t-1$ and t, denoted p_{it}^{avg}, is computed as

$$\Delta p_{it}^{\text{avg}} = \frac{\sum_j d_{ij,t-1} \cdot \Delta p_{jt}}{\sum_j d_{ij,t-1}}, \tag{7}$$

where $d_{ij,t-1}$ is the dollar amount of deposits of institution i in ZIP code j at date $t-1$ (or the most recent date available) and Δp_{jt} is the change in house prices in ZIP code j

[11] The other important component of changes in net income is changes in non-interest income. Unreported results show that these changes are almost exclusively attributable to goodwill impairments concentrated on a small subset of banks. For other banks, changes in provisions explain the bulk of changes in net income.

between dates $t-1$ and t. An implicit assumption when constructing this variable is that institutions make loans in ZIP codes where they collect deposits. We use data on deposits as weights as data on loans at the ZIP-code level are not publicly available and hence data on deposits are the best available proxy. The basic idea of the instrument is that institutions are likely to face loan losses in ZIP codes where house prices drop as financial institutions' loans are collateralized by real estate (see Rampini and Viswanathan, 2015). We use the change in weighted-average house prices over the past 8 quarters as our instrument.

Estimates for the uninstrumented and instrumented regressions are in Table 10. The uninstrumented estimate is statistically significant at the 10% level, both for BHCs and banks. In the IV estimation, the magnitude of the estimated effect of net income on hedging is larger, and more significant. The economic magnitude, estimated within institutions, is however relatively small. A one standard deviation increase in net income is associated with a 3.6% increase in gross hedging. Nevertheless, this instrumental variable approach suggests a causal relation between net worth and hedging, as predicted by the theory.

5.2 Difference-in-differences estimates of effect of net worth drop

To build a compelling case that a drop in net worth leads to a reduction in hedging, we provide additional evidence using difference-in-differences estimation. To construct a pseudo-natural experiment, we exploit the fact that the large drops in financial institutions' net income are largely concentrated in 2009 and that losses faced by financial institutions over the period are rather heterogenous in the cross-section. We exploit this large shock and the cross-sectional heterogeneity to construct treatment and control groups. Both the concentration of losses and the cross-sectional heterogeneity are apparent in the top left panel of Figure 5, where the year 2009, which we use to define our treatment, is shaded.

As before, we restrict attention to financial institutions with a high exposure to real estate, defined by a ratio of loans secured by real estate to total assets above the sample median in 2008Q4. Among these institutions with a high exposure to real estate, we define a *treatment group* as institutions in the bottom 30% of the net income distribution in 2009. These institutions have negative net income, that is, face losses which decrease their net worth. We define the *control group* as institutions in the top 30% of the net income distribution in that year. These institutions have positive net income on average. The event date is defined as of 2009, and we focus on a 4-year window before and after the event, that is, 2005 to 2013. We drop institutions which exit the sample over this period. We further restrict the sample to institutions which have strictly positive hedging in at least one quarter before the event. The fact that we restrict attention to institutions with a high exposure to real estate ensures that both treatment and control groups have a similar potential to face losses on real estate loans ex ante. Theory predicts that institutions in the treatment group cut hedging more than institutions in the control group.

We estimate three main specifications. In the first, we include a dummy variable that takes value one for treated banks after the treatment. In the other two specifications, we include treatment-year dummies for each year after the treatment, without and with institution fixed effects. Estimates are reported in Columns (1) to (3) in Table 11, in Panel A for BHCs and in Panel B for banks. There is a statistically significant drop in hedging by institutions in the treatment group relative to the control institutions. This is true for both BHCs and banks. Furthermore, the magnitude is economically large. Both treated BHCs and banks cut hedging by about one half in the post-2009 period, relative to the control group. Furthermore, the drop in net worth has persistent effects, as hedging by treated institutions does not recover to its pre-2009 level relative to control institutions. These effects are illustrated at the BHC level in Figure 6.

Changes in net income in 2009 are arguably exogenous to the interest rate environment, implying that financial institutions which cut hedging after the event do so because their net worth is lower, not because the incentive to engage in interest rate risk management has changed due to the change in interest rates. To nevertheless address any further endogeneity concerns, we consider two alternative treatments that are further removed from financial institutions' decisions. We continue to restrict attention to financial institutions with a ratio of loans secured by real estate over total assets above the sample median.

First, for each institution, we compute a deposit-weighted measure of the change in house prices over the period from 2007Q1 to 2008Q4, as described earlier. This measure uses data on deposits and house prices at the ZIP-code level. We define the treatment group as institutions in the bottom 30% of weighted-average house price changes. These institutions face large drops in local house prices in the two years leading up to 2009. In contrast, we define the control group as institutions in the top 30% of house price changes. Among institutions with ex ante similar exposure to real estate, treated institutions are those which face relatively large drops in local house prices. The interpretation of this pseudo-natural experiment is that such drops affect financial institutions' net worth for reasons unrelated to interest rates, as the interest rate environment is the same for the treatment and control group.

Second, we also compute, for each institution, a measure of the housing supply elasticity at a local level, namely the deposit-weighted average housing supply elasticity. To do so, we obtain data on the housing supply elasticity at the Metropolitan Statistical Area (MSA) level from Saiz (2010). This measure, available for 269 MSAs, is constructed using satellite-generated data on terrain elevation and on the presence of water bodies. It is matched with deposit data at the MSA level and used to construct an institution-specific deposit-weighted measure of housing supply elasticity, ϵ_i^{avg}, as

$$\epsilon_i^{\text{avg}} = \frac{\sum_j d_{ij} \cdot \epsilon_j}{\sum_j d_{ij}}, \tag{8}$$

where ϵ_j is the housing supply elasticity in MSA j. d_{ij} is the stock of deposits of institution i in MSA j, measured in 2008.[12] We define the treatment group as institutions in the bottom 30% of deposit-weighted average housing supply elasticity. These institutions are more likely to face large house prices drops. We define the control group as institutions in the top 30% of housing supply elasticity. The interpretation of this pseudo-natural experiment is that areas in which the housing supply is inelastic are more subject to large house price fluctuations, which may in turn affect the net worth of institutions that are highly exposed to the housing sector. Moreover, housing supply elasticity is unrelated to the interest rate environment.

We estimate the same three specifications as we did with net income before for each of these two alternative definitions of the treatment and control group. Estimates are reported in Columns (4) to (9) in Table 11. The results are consistent with those of the baseline specification and statistically significant, except at the bank-level when treatment is based on local housing supply elasticity. Institutions which face a larger decline in local house prices or a lower local housing supply elasticity cut hedging significantly more than institutions in the relevant control groups. The magnitude of the estimated effect is large and economically substantial, as with the baseline specification. When the treatment is based on house price changes, treated institutions, both BHCs and banks, cut hedging by more than one half. When the treatment is based on the local housing supply elasticity, the estimated coefficient and hence economic magnitude of the effect is even larger. In part, this is due to the fact that not all institutions can be matched with the data by Saiz (2010), as this data is available for 269 MSAs only. The sample size is lower, and hedging before treatment is higher for both the treatment and the control groups in this case. Relative to the pre-treatment level, the estimated magnitude of the effect is comparable to that estimated with other definitions of the treatment.

[12]The housing supply elasticity measure provided by Saiz (2010) is purely cross-sectional, that is, there is no within-MSA time variation that can be exploited.

To sum up, our difference-in-difference estimates imply that financial institutions whose net worth drops in 2009 relative to an otherwise similar control group cut hedging substantially. The effect of the drop in net worth on hedging is not just statistically significant but also economically sizeable; indeed, the drop in net worth leads financial institutions to cut their hedging by about half. We obtain similar estimates whether we define the treatment directly in terms of the drop in net income or in terms of the drop in local weighted-average house prices or weighted-average housing supply elasticity. We think that our approach to identifying shocks to financial intermediaries' net worth may prove useful in addressing other questions related to the corporate finance of financial institutions and is hence of independent interest.

5.3 Robustness – pre-trends and maturity gap

We now discuss the robustness of our difference-in-differences estimation. First, we provide evidence supporting the parallel trends assumption. Second, we show that financial institutions' on-balance sheet exposure to interest rate risk behaves similarly in the treatment and in the control groups over the sample period.

The parallel trends assumption is the key identifying assumption in difference-in-differences estimation. Trends in the outcome variable must be the same in the treatment and in the control group before the treatment. This assumption cannot be formally tested. Instead, we provide supporting evidence by including treatment-year dummies during the pre-treatment period in our benchmark specification. Such estimates, along with post-treatment dummies, are reported in Panel A of Table 12. These estimates, both without and with institution fixed effects, show that there are no significant differences in trends between treatment and control groups during the pre-treatment years, and that hedging in the treatment and control group diverge significantly only from 2009 onwards. The fact that trends in hedging are parallel in the treatment and the control group before 2009 in our benchmark specification can also be seen graphically in Figure 6. Thus, the key identifying assumption seems valid.

Another potential concern is that financial institutions' on-balance sheet exposure to interest rate risk in the treatment and the control group changes differentially after the treatment. If treated and control institutions are left with different hedgeable exposures, they may be induced to adjust derivatives hedging differentially not because their net worth changes differentially, but because the exposures changed. This concern is not warranted. To show this, we rerun our main difference-in-differences specification, replacing hedging by the maturity gap as the dependent variable. Estimates are in Panel B of Table 12. With the exception of the year 2009, the differences in the maturity gap between the treatment and control groups are never statistically different after the treatment. The fact that the maturity gap in both groups evolves very similarly around the treatment can also be seen visually in Figure 7. The only statistically significant difference that appears, in 2009 (that is, in the treatment year), contradicts the idea that BHCs which reduce derivatives hedging have also reduced their operational exposure. These institutions instead choose a more negative maturity gap, that is, if anything, increase their exposure to interest rate risk by taking on more pay-floating liabilities. We discuss the dynamics of the maturity gap in more detail in Section 6.2.

We conclude that there are no differential trends between the treatment and control group before the treatment and that the balance sheet interest rate risk exposures do not evolve differentially in the two groups either before or after the treatment.

6 Alternative hypotheses

So far, we have emphasized financial constraints as the main determinant of the positive relation between net worth and hedging. We now consider alternative explanations that might be consistent with this positive relation. Specifically, we consider whether the reduction in risk management by financially constrained institutions is evidence of risk shifting, by studying the extent of trading by such institutions. Next we consider whether institutions that reduce financial hedging increase operational hedging instead by adjusting the maturity structure of their balance sheet. Finally, we consider whether the determinant of hedging is financial institutions' regulatory capital instead of their market net worth. None of these three alternative hypotheses are supported by the data.

6.1 Risk shifting? Evidence from trading

An alternative explanation for the positive relation between net worth and hedging is risk shifting resulting from an agency conflict between bondholders and shareholders. Due to limited liability, the payoffs of equity holders around distress are convex, so that they may benefit from an increase in the volatility of the net income of the firm (see Jensen and Meckling, 1976), which may in turn induce them to reduce hedging (see, for example, Leland, 1998). Is the reduced hedging by financially constrained financial institutions evidence of risk shifting?

We provide evidence inconsistent with risk shifting. We rely on the idea that, if financial institutions engage in risk shifting in derivatives markets, they should reduce hedging, but they should also increase trading. In contrast, if financial constraints are the main reason why institutions reduce hedging, as the theory we test in this paper suggests, then no such increase is predicted and in fact institutions might reduce trading as well, if trading also requires net worth. Both theories provide similar predictions with respect to hedging, but make differing predictions about trading. We test these predictions in the data by focusing on financial institutions' portfolio of derivatives for *trading* purposes.

In Panel A of Table 13, we study the relation between trading and net worth. The first two specifications, a BHC-mean Tobit and a pooled Tobit, exploit cross-sectional variation in trading. For all measures of net worth, BHCs with higher net worth trade more, not less, and the relation is statistically significant in most cases. The third specification isolates within-BHC variation in net worth, and speaks thus more directly to the risk-shifting hypothesis. Again, there is a positive and significant relation between trading and net worth. Financial institutions trade more not when their net worth is low, but when it is high. This evidence is at odds with risk shifting and consistent with the existence of financial constraints.

Furthermore, because risk shifting is more of a concern for institutions in distress, we study the trading behavior of financial institutions entering distress, defined as in Section 4.3. Panel B of Table 13 analyzes gross trading before distress for institutions that exit the sample using dummies for up to eight quarters before distress. BHCs cut trading by a statistically significant amount before distress. At the bank level, coefficients are not statistically significant. Trading by banks before distress is plotted in Panel A of Figure 8. Mean trading drops before distress. Again, this is the opposite of what risk shifting would predict.

It is moreover worth noting that we find a positive relation between hedging and net worth not just for institutions in distress but in our data overall. And we do not find discontinuous hedging behavior as net worth drops. This smooth behavior of hedging is in marked contrast to the discontinuous behavior predicted by models of risk shifting. Together, these results suggest that financial constraints, not risk shifting, explain the positive relation between risk management and net worth. The results are also consistent with empirical evidence in other sectors (see Andrade and Kaplan (1998) for highly leveraged transactions and Rauh (2009) for corporate pension plans), according to which risk management concerns dominate risk shifting incentives even in the vicinity of bankruptcy. All told, evidence of risk shifting remains elusive.

6.2 Operational risk management

Another concern might be that financial institutions substitute operational risk management for financial hedging. Financial institutions which have lower net worth cut derivatives hedging, but may substitute off-balance sheet with on-balance sheet risk management, that is, reduce their on-balance sheet exposure to interest rate risk, in an attempt to engage in operational risk management as Petersen and Thiagarajan (2000) and Purnanandam (2007) suggest. We investigate this alternative hypothesis by studying the relation between financial institutions' maturity gap and their net worth. The evidence is not consistent with this alternative hypothesis.

First, Panel A of Table 14 provides evidence of a positive and significant relation between the maturity gap and net worth. Financial institutions with higher net worth have more net floating-rate assets than institutions with low net worth. If anything, they do more operational risk management, while at the same time hedging more using derivatives. This evidence suggests that financial institutions with low net worth engage less in *any type* of risk management, either on-balance sheet or off-balance sheet. The fact that any type of risk management is more costly for such institutions is consistent with the theoretical predictions by Rampini and Viswanathan (2010, 2013) and broadly inconsistent with the idea that operational risk management is used as a substitute for derivatives hedging.

Additional evidence against operational risk management is obtained by focusing on financial institutions that approach distress. Operational risk management would imply that these institutions hold more net-floating rate assets, that is, that their maturity gap increases as they approach distress. Panel B of Table 14 reports the results of regressions of the maturity gap on a set of dummies that take value one up to eight quarters before distress for both BHCs and banks that exit the sample. The maturity gap of such institutions gets more negative as they approach distress, and the drop is statistically significant several quarters before distress. These institutions thus do less operational risk management as they become more constrained, as also illustrated in Panel B of Figure 8. Quantitatively, the drop is remarkably large, exceeding 10% of assets for both banks and BHCs.

Overall, these results suggest that operational risk management cannot provide a satisfactory explanation for the positive relation between net worth and hedging. In fact, we find a remarkably strong pattern going the opposite way, as more financially constrained financial institutions have much more net floating-rate liabilities, not less. Indeed this pattern, which to the best of our knowledge has not been documented before, is of independent interest. In contrast, the existence of financial constraints is consistent with the fact that operational risk management is reduced, not increased, as financial institutions become more constrained.

6.3 Regulatory capital versus net worth

Another alternative explanation is that the positive relation between net worth and hedging is driven not by market measures of net worth, which we use, but by regulatory capital. If so, the relation which we document between net worth and hedging would spuriously arise from the positive correlation between market measures of net worth and regulatory capital. This could be the case, for example, if counterparties in the swap market pay attention not to market net worth but to regulatory capital. At the same time, if regulators monitor the hedging policies of financial institutions, they might in fact require more hedging when regulatory capital is lower, not higher. If this were the dominant force, then one would expect a negative relation between hedging and regulatory capital. To investigate the role of regulatory capital, we consider the relation between hedging and regulatory capital and provide model specification tests.

We estimate the relation between hedging and regulatory capital, using two measures of regulatory capital for BHCs. We use both total regulatory capital and Tier 1 capital, normalized by risk-weighted assets. Panel A of Table 15, provides the estimates of four regression specifications, which exploit both the cross-sectional and the within-institution variation in regulatory capital. None of the estimated coefficients, except one, are statistically significant. Neither between institutions nor within institutions is there a significant and stable relation between hedging and regulatory capital.

We further conduct the J-test proposed by Davidson and MacKinnon (1981) to test the specification with our (market-based) measures of net worth – that is, size, market capitalization, etc. – against the alternative specification with regulatory capital. The basic idea is that the residuals of the regression of hedging on regulatory capital are regressed on our market-based measures of net worth. Because tests of model specification have no natural null hypothesis (see, for example, Greene, 2012), we also regress the residuals of the models with our market-based measures of net worth on regulatory capital. Panel B in Table 15 reports t-statistics for the second stage regression of the test. The hypothesis that the model with regulatory capital is true is always rejected in favor of our specification with market-based net worth. When we reverse the order of the hypotheses, we find that our model with market-based net worth is typically not rejected in favor of the alternative hypothesis with regulatory capital.

Together with the above regression results, this test provides strong suggestive evidence against regulatory capital being a major determinant of hedging. The primary determinant of the hedging behavior of financial institutions seems to be their net worth, not their regulatory capital. The emphasis often place on regulatory capital may hence not be warranted.

7 Conclusion

The evidence on risk management in financial institutions that we present strongly suggest that the financing needs associated with hedging are a substantial barrier to risk management. Consistent with the theoretical predictions of Rampini and Viswanathan (2010, 2013), we find a strong positive relation between interest rate hedging and net worth across financial institutions and within financial institutions over time; better capitalized financial institutions hedge more. We use a novel identification strategy based on shocks to the net worth of financial institutions due to drops in house prices. This allows us to conclude that drops in financial institutions' net worth lead to a reduction in hedging.

We provide auxiliary evidence that is inconsistent with alternative hypotheses. There is a strong positive relation between trading and net worth which goes against the idea that more constrained financial institutions engage in risk shifting by trading more. Moreover, there is a strong positive relation between the maturity gap and net worth which goes against the idea that more constrained financial institutions substitute financial hedging with operational risk management; more constrained financial institutions have more net floating-rate liabilities, not less. We do not observe a strong relation between hedging and regulatory capital and model comparison tests suggest that it is market measures of net worth rather than regulatory capital that explain the hedging behavior of financial institutions. The emphasis on regulatory capital as a determinant of financial institutions' risk exposures in much of the literature and policy debate may hence be misplaced.

Overall, we conclude that the financing needs associated with risk management for financial institutions and firms are a major determinant of the extent of risk management. Similarly, in our view, the financing needs associated with insurance for households are an important determinant of the extent of insurance. We contend that financial constraints are a key impediment to risk management and insurance and result in financial institutions, firms, and households being more exposed to tradeable or insurable risks than they otherwise would be. The implications of our findings for the dynamics of financing and investment by institutions and households and the consequences for macroeconomic dynamics may be significant.

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Table 1: Variable definitions

This table provides the definitions of the variables used in the empirical analysis. In the call reports, variables for bank holding companies (BHCs) and banks are reported with different prefixes, *bhck* for BHCs and *rcon* or *rcfd* for banks. When a variable is similar for BHCs and banks, its suffix is the same. For example, total assets are denoted *bhck2170* for BHCs and *rcon2170* for banks. When the same variable exists for BHCs and banks, only the BHC-level variable is reported in our definition.

Variable	Definition	Data source
	Derivatives data	
Gross hedging	Total gross notional amount of interest rate derivative contracts held for purposes other than trading (*bhck8725*) over total assets; for the period 1995-2000, contracts not marked to market (*bhck8729*) are added; winsorized at the 99th percentile	Call reports
Net hedging	Interest rate swaps where the bank has agreed to pay a fixed rate (*rcona589*) minus pay-float swaps (computed as total swaps minus pay-fixed swaps), normalized by total assets; can be computed only for banks that report only swaps	Call reports
Gross trading	Total gross notional amount of interest rate derivative contracts held for trading (*bhcka126*)	Call reports
	Net worth and regulatory capital	
Size	Log of total assets (*bhck2170*)	Call reports
Market capitalization	Log of share mid-price at the end of each quarter, multiplied by the number of shares outstanding	CRSP
Market capitalization / Assets	Market capitalization normalized by total assets (at book value) minus book equity plus market capitalization; winsorized at the 1st and 99th percentiles	CRSP
Net income / Assets	Net income (*bhck4340*) normalized by total assets; winsorized at the 1st and 99th percentiles	Call reports
Dividends / Assets	Cash dividends on common stock (*bhck4460*); winsorized at the 1st and 99th percentiles	Call reports
Credit rating	Credit rating from Standard & Poors coded linearly from 1 (D) to 22 (AAA)	Capital IQ
Net worth index	First principal component of Size, Market capitalization / Assets, Dividends / Assets and Net income / Assets with loadings of 0.149, 0.307, 0.272 and 0.272, respectively	Call reports and CRSP
Regulatory capital / Assets	Total qualifying capital allowable under the risk-based capital guidelines (*bhck3792*) normalized by risk-weighted assets (*bhcka223*); winsorized at the 1st and 99th percentiles	Call reports
Tier 1 capital / Assets	Tier 1 capital allowable under the risk-based capital guidelines (*bhck8274*) normalized by risk-weighted assets (*bhcka223*); winsorized at the 1st and 99th percentiles	Call reports

Table 1 (continued): Variable definitions

Variable	Definition	Data source
	Decomposition of net income	
Net interest income	Net interest income (*bhck4074*); annualized	Call reports
Noninterest income	Total noninterest income (*bhck4079*); annualized	Call reports
Noninterest expense	Total noninterest expense (*bhck4093*); annualized	Call reports
Net noninterest income	Total noninterest income (*bhck4079*) minus Total noninterest expense (*bhck4093*); annualized	Call reports
Provisions	Provision for loan and lease losses (*bhck4230*); annualized	Call reports
	Other balance sheet variables	
Total assets	Total assets (*bhck2170*)	Call reports
Maturity gap	Earning assets that are repriceable or mature within one year (*bhck3197*) minus interest-bearing deposits that mature or reprice within one year (*bhck3296*) minus long-term debt that reprices or matures within one year (*bhck3298* + *bhck3409*) minus variable rate preferred stock (*bhck3408*) minus other borrowed money with a maturity of one year or less (*bhck2332*) minus commercial paper (*bhck2309*) minus Federal funds and repo liabilities (*bhdmb993* + *bhckb995*), normalized by total assets	Call reports
Noninterest bearing deposits	Noninterest-bearing depopsits (*bhdm6631* + *bhfn6631*)	Call reports
Noninterest bearing assets	Noninterest-bearing balances and currency and coin (*bhck0081*)	Call reports
Total loans	Total loans and leases, net of unearned income (*bhck2122*)	Call reports
Total for real estate	Loans secured by real estate (*bhck1410*)	Call reports
	House price and related data	
House prices	House prices by zip code	Zillow
Housing supply elasticity	Housing supply elasticity by MSA	Saiz (2010)
Deposits by zip code	Total amount of deposits by ZIP code	FDIC Summary of deposits

Table 2: Descriptive statistics on gross interest rate derivatives positions

This table provides descriptive statistics on gross hedging and trading at the BHC and bank level. Gross hedging (resp. trading) is defined as the gross notional amount of interest rate derivatives used for hedging (resp. trading), normalized by total assets. Panel A provides the basic descriptive statistics on derivatives reported for hedging and trading purposes. Panel B provides the number of hedging and trading institutions and the extent of hedging and trading across size quintiles. Both Panels A and B are institution-mean statistics. Hedging (trading) amount (cond.) is the value of the variable conditional on being non-zero. Variables are defined in Table 1. Time frame: 1995Q1-2013Q4.

Panel A: Descriptive statistics on hedging and trading

	Mean	Med.	75th	90th	95th	98th	Max.	S.D.	Obs
Gross hedging – BHC level	0.038	0.006	0.036	0.103	0.194	0.354	0.571	0.083	22,723
Gross trading – BHC level	0.071	0	0	0.017	0.075	0.589	8.801	0.532	22,699
Gross hedging – bank level	0.006	0	0	0.009	0.040	0.109	0.181	0.008	627,219
Gross trading – bank level	0.008	0	0	0	0.000	0.008	16.11	0.215	627,219

Panel B: Size patterns in hedging and trading

	Size quintiles					Total
	1st	2nd	3rd	4th	5th	
	BHC level					
Number of BHCs	61	61	61	61	60	304
Any use	17.0	20.7	28.4	40.3	56.0	162.5
Fraction any use	0.279	0.341	0.467	0.665	0.928	0.535
Use for hedging	15.9	20.0	27.5	37.5	53.4	154.4
Fraction hedging	0.260	0.330	0.452	0.619	0.885	0.508
Hedging amount (cond.)	0.048	0.048	0.052	0.064	0.119	0.077
Use for trading	1.6	1.0	2.5	8.6	31.3	45.0
Fraction trading	0.026	0.017	0.041	0.142	0.518	0.148
Trading amount (cond.)	0.017	0.018	0.023	0.091	0.475	0.351
	Bank level					
Number of banks	1,711	1,711	1,711	1,711	1,711	8,555
Any use	5.5	25.5	45.4	111.3	488.8	676.4
Fraction any use	0.003	0.015	0.027	0.065	0.286	0.079
Use for hedging	4.5	23.5	40.8	104.8	458.7	632.4
Fraction hedging	0.003	0.014	0.024	0.061	0.268	0.074
Hedging amount (cond.)	0.046	0.037	0.044	0.045	0.064	0.058
Use for trading	1.0	2.1	5.0	7.4	98.0	113.5
Fraction trading	0.001	0.001	0.003	0.004	0.057	0.013
Trading amount (cond.)	0.905	0.053	0.184	0.064	0.443	0.401

Table 3: Descriptive statistics on net interest rate hedging – Bank level

This table provides descriptive statistics on net hedging and its relation to the maturity gap, gross hedging, and changes in interest rates at the bank level. Panel A provides descriptive statistics on the distribution of the net swap position unconditionally as well as conditional on the maturity gap of a bank being either positive or negative or in the first or fourth quartile. Panel B provides estimates from regressions of gross on net hedging (in absolute value). Panel C provides estimates from regressions of the market value of banks' derivatives portfolios for hedging on interest rate changes conditional on a positive or negative net swap position. Panel D provides estimates from regressions of net hedging on the maturity gap. Variables are defined in Table 1. Standard errors are clustered at the bank level; standard errors for bank-mean regressions are robust. *p*-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 1995Q1-2013Q4.

Panel A: Net hedging position unconditional and conditional on maturity gap

	Min	10th	25th	Mean	Median	75th	90th	Max	S.D.	Obs.
Net hedging	-2.191	-0.108	-0.046	-0.016	-0.005	0.013	0.053	2.020	0.120	9,504
Conditional on maturity gap										
Negative	-0.681	-0.068	-0.026	0.000	0.001	0.019	0.060	1.320	0.084	3,717
Positive	-2.191	-0.123	-0.060	-0.027	-0.013	0.008	0.047	2.020	0.137	5,787
Below 25th pc.	-0.491	-0.070	-0.027	0.002	0.001	0.020	0.065	1.320	0.095	2,356
Above 75th pc.	-2.191	-0.156	-0.090	-0.041	-0.023	0.007	0.059	2.020	0.187	2,362

Panel B: Regression of gross hedging on net hedging

	OLS	Bank FE
Net hedging	1.05***	0.78***
(abs. value)	(0.000)	(0.000)
Obs.	10,870	10,870
R^2	0.57	0.21

Panel C: Regression of derivatives market value on interest rate changes

	Net notional exposure	
	Positive	Negative
Δ Libor	0.034***	-0.010***
	(0.000)	(0.004)
Obs.	4,155	4,852
R^2	0.010	0.002

Panel D: Regressions of net swap exposure on maturity gap

	Bank-mean OLS	Pooled OLS	Bank FE
Maturity gap	-0.103***	-0.084***	-0.090**
	(0.000)	(0.001)	(0.039)
R^2	0.051	0.024	0.010
Obs.	774	8,806	8,806

Table 4: Descriptive statistics on maturity gap and loans

This table provides descriptive statistics on the maturity gap and the composition of loans. Panel A provides descriptive statistics on the maturity gap and its components, that is, the assets and liabilities that mature or reprice within one year, at the BHC level (and for the maturity gap also at the bank level). Two additional items not included in the maturity gap, non-interest bearing balances (that is, short-term assets) and deposits, are included for reference. Panel B provides the descriptive statistics on total loans and loans secured by real estate (both for the entire sample and for 2008Q4) at the BHC and bank level. Variables are defined in Table 1. Time frame: 1995Q1-2013Q4.

	Min.	10th	25th	Mean	Med.	75th	90th	Max.	S.D.
Panel A: Maturity gap, its components, and related variables									
BHC level									
Maturity gap	-0.603	-0.150	-0.052	0.043	0.037	0.135	0.250	0.738	0.162
Earning assets < 1 yr.	0.093	0.229	0.299	0.391	0.386	0.473	0.534	0.924	0.128
Minus: interest-bearing liabilities < 1 yr.									
Interest-bearing deposits	0.002	0.153	0.198	0.286	0.264	0.353	0.466	0.699	0.124
Repricing long-term debt	0	0	0	0.011	0.002	0.013	0.031	0.192	0.021
Maturing long-term debt	0	0	0	0.000	0	0.000	0.001	0.067	0.003
Variable-rate pref. stock	0	0	0	0.000	0	0	0	0.275	0.010
Commercial paper	0	0	0	0.001	0	0	0.001	0.092	0.006
Fed funds and repo	0	0	0	0.018	0.007	0.027	0.051	0.308	0.030
Other borrowed money	0	0.002	0.009	0.029	0.021	0.038	0.067	0.189	0.029
For reference (not incl. in maturity gap):									
Non int.-bearing assets	0.003	0.012	0.018	0.028	0.026	0.035	0.047	0.215	0.016
Non int.-bearing deposits	0.000	0.048	0.077	0.116	0.110	0.143	0.195	0.679	0.063
Bank level									
Maturity gap	-0.627	-0.194	-0.119	-0.023	-0.033	0.058	0.155	0.975	0.149
Panel B: Loans and real estate loans (as fraction of total assets)									
BHC level									
Total loans	0.228	0.535	0.611	0.667	0.674	0.732	0.788	0.923	0.101
Real estate loans	0	0.302	0.378	0.478	0.489	0.580	0.670	0.871	0.152
Real estate loans 2008Q4	0.079	0.372	0.452	0.539	0.546	0.631	0.695	0.862	0.134
Bank level									
Total loans	0.200	0.443	0.551	0.626	0.643	0.717	0.777	0.972	0.132
Real estate loans	0	0.232	0.356	0.473	0.489	0.602	0.686	0.970	0.173
Real estate loans 2008Q4	0	0.341	0.434	0.531	0.539	0.635	0.716	0.984	0.148

Table 5: Descriptive statistics on net worth variables

This table provides descriptive statistics for the variables measuring net worth and for regulatory capital. Panel A provides the descriptive statistics for the net worth measures at the BHC and bank level, to the extent available; credit rating statistics are rounded to the closest notch. Panel B provides the correlations between these variables. Panel C provides descriptive statistics on the two measures of regulatory capital at the BHC level. Variables are defined in Table 1. Time frame: 1995Q1-2013Q4.

Panel A: Descriptive statistics on net worth

	Min.	10th	25th	Mean	Med.	75th	90th	Max.	S.D.	Obs.
					BHC level					
Size	13.12	13.35	13.70	14.75	14.38	15.48	16.70	20.48	1.36	22,723
Market cap.	7.63	10.91	11.55	12.67	12.39	13.60	14.86	18.56	1.62	22,723
Mkt. cap./Assets	0.00	0.06	0.10	0.14	0.14	0.17	0.20	0.33	0.06	22,723
Net inc./Assets	-0.194	0.001	0.006	0.008	0.010	0.012	0.015	0.103	0.012	20,704
Div./Assets	-0.001	0	0.000	0.001	0.001	0.001	0.002	0.040	0.001	22,426
Credit rating	CCC-	BBB-	BBB	BBB+	BBB+	A	A+	AA	2.06	3,579
Net worth ind.	-9.869	-1.677	-0.835	-0.000	0.029	0.876	1.678	12.091	1.429	20,568
					Bank level					
Size	6.87	10.16	10.78	11.68	11.53	12.38	13.31	20.05	1.34	627,219
Net inc./Assets	-0.088	0.001	0.006	0.009	0.010	0.013	0.017	0.033	0.010	581,207
Div./Assets	0	0	0	0.001	0	0.002	0.004	0.026	0.002	418,225

Panel B: Correlation between measures of net worth – BHC level

	Size	Mkt. cap.	Mkt. cap. / Assets	Net income / Assets	Cash div. / Assets	Credit rating	Net worth index
Market cap.	0.917	1					
Mkt. cap. / Assets	0.201	0.544	1				
Net inc. / Assets	0.107	0.362	0.561	1			
Div. / Assets	0.188	0.323	0.426	0.316	1		
Credit rating	0.449	0.591	0.344	0.342	0.274	1	
Net worth index	0.418	0.697	0.853	0.755	0.639	0.526	1
Reg. cap. / Assets	0.122	0.170	0.239	0.151	0.236	0.052	0.279

Panel C: Descriptive statistics on regulatory capital – BHC level

	Min.	10th	25th	Mean	Med.	75th	90th	Max.	S.D.	Obs.
Reg. cap./Assets	-0.13	0.11	0.12	0.15	0.13	0.16	0.19	0.30	0.05	21,776
Tier 1 cap./Assets	-0.13	0.09	0.10	0.13	0.12	0.14	0.18	0.28	0.04	21,776

Table 6: Cross-sectional evidence on hedging and net worth – BHC level

This table provides evidence on the relation between gross hedging and our measures of net worth at the BHC level. Panel A provides estimates from BHC-mean OLS and pooled OLS (with time fixed effects) specifications, including observations for which hedging equals zero. Panel B provides estimates from the following specifications: BHC-mean Tobit, pooled Tobit (with time fixed effects), and quantile regressions at the 75th, 85th, and 95th percentile. Panel C provides estimates from specifications with credit rating dummies; credit ratings of A- and above are excluded. Variables are defined in Table 1. Standard errors are clustered at the BHC level; standard errors for BHC-mean regressions are robust. *p*-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 1995Q1-2013Q4.

Model	Size	Mkt. cap.	Mkt. cap./ Assets	Net income	Div.	Rating	Net worth index
Panel A: OLS regressions							
BHC-mean OLS	0.034***	0.025***	0.060	0.962***	15.884***	0.014**	0.014***
	(0.000)	(0.000)	(0.313)	(0.000)	(0.004)	(0.033)	(0.000)
Pooled OLS with time FE	0.031***	0.023***	0.017	0.344***	3.304***	0.013***	0.010***
	(0.000)	(0.000)	(0.143)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Tobit and quantile regressions							
BHC-mean Tobit	0.052***	0.040***	-0.059	0.681*	17.631***	0.013**	0.018***
	(0.000)	(0.000)	(0.426)	(0.098)	(0.005)	(0.010)	(0.000)
Tobit with time FE	0.055***	0.043***	0.130***	0.695***	11.958***	0.014***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quantile regression 75th pctile	0.031***	0.019***	0.112***	0.338***	16.142***	0.016***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quantile regression 85th pctile	0.049***	0.029***	0.131***	0.599***	22.791***	0.021***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quantile regression 95th pctile	0.086***	0.053***	0.096	1.208***	29.678***	0.050***	0.026***
	(0.000)	(0.000)	(0.146)	(0.000)	(0.000)	(0.000)	(0.000)

Panel C: With rating dummies

	Pooled OLS	BHC FE
BBB- to BBB+	-0.078***	0.009***
BB- to BB+	-0.053***	0.024***
B- to B+	-0.124***	-0.043***
CCC+ and below	-0.153***	-0.132***

Table 7: Within-institution evidence on hedging and net worth

This table provides evidence on the relation between gross hedging and our measures of net worth based on within-institution variation at the BHC level (Panel A) and the bank level (Panel B). Panel A provides estimates from regressions with BHC fixed effects for the full sample, a sample that excludes BHCs in the top decile of the net worth distribution, a sample that excludes BHCs that never use interest rate derivatives, and a Tobit specification with fixed effect based on Honoré (1992). Panels B and C provide estimates based on fixed effect specifications and the full sample at the bank level for gross hedging (Panel B) and net hedging (Panel C). Variables are defined in Table 1. Standard errors are clustered at the institution level. *p*-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 1995Q1-2013Q4.

Model	Size	Mkt. cap.	Mkt. cap./ Assets	Net income	Div.	Rating	Net worth index
			Panel A: Gross hedging – BHC level				
BHC FE	0.034***	0.006***	-0.009	0.182***	0.661***	-0.001	0.002***
Full sample	(0.000)	(0.000)	(0.358)	(0.000)	(0.003)	(0.642)	(0.000)
Obs.	22,723	22,723	22,723	20,839	20,568	3,657	20,568
BHC FE	0.033***	0.008***	0.048***	0.181***	1.123***	0.015***	0.003***
Up to 90th pctile.	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Obs.	20,451	20,451	20,451	18,579	18,459	2,978	18,459
BHC FE	0.021***	0.005***	-0.010	0.185***	0.358	0.017***	0.002***
Users only	(0.000)	(0.000)	(0.319)	(0.000)	(0.182)	(0.000)	(0.000)
Obs.	16,056	16,056	16,056	15,042	14,939	3,507	14.939
Tobit - BHC FE	0.039**	0.009*	-0.014	0.292	0.714	0.019	0.003
(Honoré)	(0.011)	(0.097)	(0.779)	(0.260)	(0.723)	(0.446)	(0.364)
Obs.	22,723	22,723	22,723	20,704	20,568	3,579	20,568
			Panel B: Gross hedging – bank level				
Bank FE	0.003***			0.052***	0.032***		
Full sample	(0.000)			(0.000)	(0.003)		
Obs.	627,219			581,207	418,225		
			Panel C: Net hedging (absolute value) – bank level				
Bank FE	0.008***			0.006	0.105*		
Full sample	(0.000)			(0.773)	(0.080)		
Obs.	95,650			94,118	78,091		

Table 8: Hedging before distress

This table provides evidence on hedging before distress. The table provides estimates from regressions of hedging on dummies for up to 8 quarters before distress at the BHC and bank level. Distress events are defined as exits from the sample with a ratio of market capitalization (for BHCs) or equity (for banks) to total assets below 4%. The table provides estimates for gross hedging at the BHC level and gross and net hedging at the bank level. Variables are defined in Table 1. Standard errors are clustered at the institution level. p-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 1995Q1-2013Q4.

	BHC level		Bank level			
Event time	Gross hedging	p-value	Gross hedging	p-value	Net hedging	p-value
$\tau - 8$	-0.007	(0.439)	-0.002	(0.766)	-0.003	(0.646)
$\tau - 7$	-0.011	(0.216)	-0.000	(0.909)	-0.002	(0.714)
$\tau - 6$	-0.013	(0.136)	-0.006	(0.380)	-0.007	(0.310)
$\tau - 5$	-0.020**	(0.023)	-0.013**	(0.065)	-0.006	(0.346)
$\tau - 4$	-0.020**	(0.023)	-0.014**	(0.049)	-0.007	(0.246)
$\tau - 3$	-0.021**	(0.012)	-0.013*	(0.067)	-0.011*	(0.081)
$\tau - 2$	-0.020**	(0.022)	-0.012*	(0.083)	-0.010	(0.123)
$\tau - 1$	-0.026***	(0.002)	-0.018**	(0.011)	-0.019***	(0.004)
τ	-0.026***	(0.002)	-0.023***	(0.001)	-0.019***	(0.003)
Institution FE	Yes		Yes		Yes	
Time FE	Yes		Yes		Yes	
Obs.	16,056		51,520		8,489	
No. distressed	49		636		358	
R^2	0.013		0.036		0.011	

Table 9: Variance decomposition of net income – BHC level

This table provides a variance decomposition of net income at the BHC level. The table provides estimates from regressions of changes in net income on changes in various components of net income. Each column provides results from a separate regression. By definition, net income is the sum of three main elements: Net interest income + Net noninterest income − Provisions, plus exceptional items which are being neglected. Variables are defined in Table 1. Standard errors are clustered at the BHC level. t-statistics are in parentheses. Time frame: 2005Q1-2013Q4.

	(1)	(2)	(3)	(4)	(5)
Δ Net interest income	0.736	0.091			0.760
	(19.05)	(0.89)			(18.57)
Δ Net noninterest income	0.904		0.967		
	(34.94)		(36.39)		
Δ Noninterest income					0.807
					(22.31)
Δ Noninterest expense					0.918
					(34.45)
Δ Provisions	-0.793			-1.045	-0.790
	(-34.34)			(-21.63)	(-33.42)
R^2	0.803	0.000	0.605	0.307	0.804
Obs	9,856	9,856	9,856	9,856	9,856

Table 10: Instrumenting net income with changes in house prices

This table provides evidence on instrumental variable regressions of gross hedging on net income at the BHC and bank level. The sample is restricted to institutions with above-median loans secured by real estate. The table provides both the OLS estimates and the estimates from the first and second stage of instrumental variables regressions. Net income is instrumented by changes in weighted-average house prices over the past 8 quarters. The instrumental variable regressions include institution fixed effects. Variables are defined in Table 1. Standard errors are clustered at the institution level. *p*-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 2005Q1-2013Q4.

	BHC level		Bank level	
	OLS	IV	OLS	IV
First stage		0.251**		0.113**
		(0.037)		(0.033)
R^2		0.096		0.053
Net income	0.185*	0.254**	0.049*	0.086**
	(0.062)	(0.049)	(0.075)	(0.044)
R^2	0.008	0.003	0.003	0.001

Table 11: Effect of net worth on hedging – Difference-in-differences estimates

This table provides the difference-in-differences estimates at the BHC level (Panel A) and the bank level (Panel B) for three specifications of the treatment. The dependent variable is gross hedging. The treatment group is defined as the bottom 30% and the control group at the top 30% of institutions in 2009 in terms of net income (Columns (1) to (3)), deposit weighted-average ZIP code level house price changes in 2007Q1 through 2008Q4 (Columns (4) to (6)), and deposit weighted-average MSA level Saiz (2010) housing supply elasticity in 2008Q4 (Columns (7) to (9)). We restrict the sample to institutions with above-median loans secured by real estate to total assets in 2008Q4. In both panels, the sample is restricted to institutions that hedge at least once before the treatment. Variables are defined in Table 1. Standard errors are clustered at the institution level. p-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 2005Q1-2013Q4.

Treatment	Net income			House price change			Housing supply elasticity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Post-event dummy	Year dummies	Year dummies	Post-event dummy	Year dummies	Year dummies	Post-event dummy	Year dummies	Year dummies
Panel A: BHC level									
2009 and after	-0.029**			-0.040*			-0.042*		
	(0.042)			(0.056)			(0.051)		
2009		-0.020	-0.022**		-0.022	-0.026*		-0.027**	-0.096**
		(0.259)	(0.025)		(0.246)	(0.098)		(0.026)	(0.037)
2010		-0.039**	-0.042***		-0.022	-0.026		-0.027**	-0.092**
		(0.026)	(0.009)		(0.154)	(0.111)		(0.035)	(0.043)
2011		-0.038**	-0.035**		-0.044*	-0.051**		-0.026**	-0.059*
		(0.037)	(0.046)		(0.055)	(0.049)		(0.041)	(0.056)
2012		-0.019	-0.020*		-0.042*	-0.039*		-0.021*	-0.055*
		(0.263)	(0.089)		(0.065)	(0.085)		(0.054)	(0.062)
2013		-0.031*	-0.033*		-0.025	-0.016		-0.019*	-0.047
		(0.099)	(0.053)		(0.147)	(0.326)		(0.096)	(0.112)
BHC FE	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Bank level									
2009 and after	-0.015***			-0.018*			-0.005		
	(0.009)			(0.068)			(0.345)		
2009		-0.019**	-0.017**		-0.014*	-0.018*		-0.002	-0.003
		(0.042)	(0.031)		(0.094)	(0.087)		(0.756)	(0.621)
2010		-0.010	-0.017**		-0.014*	-0.018*		-0.002	-0.003
		(0.181)	(0.019)		(0.094)	(0.087)		(0.756)	(0.621)
2011		0.001	0.006		-0.022*	-0.025*		-0.004	-0.003
		(0.910)	(0.390)		(0.056)	(0.064)		(0.458)	(0.352)
2012		-0.021***	-0.027***		-0.019	-0.021		-0.010	-0.006
		(0.008)	(0.000)		(0.125)	(0.100)		(0.555)	(0.489)
2013		−0.028***	-0.018**		-0.008	-0.010		0.002	0.014
		(0.000)	(0.017)		(0.341)	(0.239)		(0.672)	(0.534)
Bank FE	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Robustness – Pre-treatment differences and effect on maturity gap

This table provides two sets of robustness estimates comparing the treatment and control groups using net income to define the treatment variable as in columns (1) to (3) in Table 11. Panel A provides estimates from a difference-in-differences specification at the BHC level as in columns (1) to (3) in Panel A of Table 11 but includes treatment-dummies for the pre-treatment period as well. Panel B provides estimates from a difference-in-differences specification using the maturity gap as the dependent variable using data at both the BHC and bank level. In both panels, the sample is restricted to institutions that hedge at least once before the treatment. Variables are defined in Table 1. Standard errors are clustered at the institution level. p-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 2005Q1-2013Q4.

Panel A: Difference-in-difference estimates with pre-treatment dummies

	Year dummies		Year dummies	
2005	-0.014	(0.331)	-0.003	(0.784)
2006	-0.010	(0.499)	0.008	(0.444)
2007	-0.007	(0.626)	-0.000	(0.989)
2008	–		–	
2009	-0.028*	(0.085)	-0.017	(0.134)
2010	-0.047***	(0.004)	-0.029**	(0.010)
2011	-0.046***	(0.005)	-0.028**	(0.015)
2012	-0.027*	(0.095)	-0.030***	(0.009)
2013	-0.039**	(0.019)	-0.036***	(0.002)
BHC FE	No		Yes	
Time FE	Yes		Yes	

Panel B: Effect of treatment on maturity gap

	BHC level				Bank level			
	Post-event dummy	p-value	Year dummies	p-value	Post-event dummy	p-value	Year dummies	p-value
2009 and after	-0.025	(0.352)			-0.038	(0.232)		
2009			-0.087**	(0.021)			-0.094***	(0.012)
2010			-0.019	(0.609)			-0.036	(0.303)
2011			-0.021	(0.569)			-0.041	(0.204)
2012			0.008	(0.817)			-0.006	(0.862)
2013			-0.008	(0.815)			-0.014	(0.663)

Table 13: Derivatives trading and net worth

This table provides evidence on the relation between trading and net worth. Trading is measured as gross derivatives positions held for trading normalized by total assets. Panel A provides estimates from regressions of trading on our measures of net worth at the BHC level from three specifications: a BHC-mean Tobit, a Tobit with time fixed effects, and a regression with BHC fixed effects. Panel B provides estimates from regressions of trading on dummies for up to 8 quarters before distress at the BHC and bank level. Variables are defined in Table 1. Standard errors are clustered at the institution level; standard errors for BHC-mean regressions are robust. p-values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 1995Q1-2013Q4.

Panel A: OLS and fixed effect regressions

Model	Size	Mkt. cap.	Mkt. cap./ Assets	Net income	Div.	Rating	Net worth index
BHC-mean	0.579***	0.484***	0.600	9.361*	374.661***	0.872***	0.303***
Tobit	(0.000)	(0.000)	(0.509)	(0.089)	(0.000)	(0.000)	(0.000)
R^2	0.267	0.215	0.000	0.001	0.011	0.036	0.036
Tobit	0.590***	0.511***	3.300***	11.459***	164.830***	0.809***	0.358***
with time FE	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.318	0.279	0.014	0.009	0.012	0.045	0.063
BHC FE	0.082***	0.020***	0.692***	1.172***	5.965	0.040	0.096**
	(0.000)	(0.010)	(0.000)	(0.001)	(0.471)	(0.127)	(0.024)
R^2	0.009	0.042	0.049	0.044	0.042	0.096	0.134

Panel B: Derivatives trading before distress

	BHC level		Bank level	
Event time	Gross trading	p-value	Gross trading	p-value
$\tau - 8$	-0.020	(0.458)	0.009	(0.417)
$\tau - 7$	-0.045***	(0.002)	0.011	(0.396)
$\tau - 6$	-0.038***	(0.009)	0.012	(0.357)
$\tau - 5$	-0.042***	(0.009)	0.020	(0.491)
$\tau - 4$	-0.041**	(0.014)	0.014	(0.457)
$\tau - 3$	-0.053***	(0.006)	0.009	(0.544)
$\tau - 2$	-0.052***	(0.005)	0.012	(0.250)
$\tau - 1$	-0.053**	(0.010)	0.013	(0.241)
τ	-0.059***	(0.003)	0.006	(0.599)
Institution FE	Yes		Yes	
Time FE	Yes		Yes	
Obs.	5,955		18,540	
No. distressed	10		224	
R^2	0.042		0.005	

Table 14: Maturity gap and net worth

This table provides evidence on the relation between the maturity gap and net worth. Panel A provides estimates from pooled time series-cross section OLS regressions of the maturity gap on our measures of net worth at the BHC level. Panel B provides estimates from regressions of the maturity gap on dummies for up to 8 quarters before distress at the BHC and bank level. Distress events are defined as in Table 8. Variables are defined in Table 1. Standard errors are clustered at the institution level. p-value are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 1995Q1-2013Q4.

Panel A: Maturity gap and net worth

	Size	Mkt. cap.	Mkt. cap. / Assets	Net income	Div.	Rating	Net worth index
Pooled OLS	0.030***	0.029***	0.681***	1.211***	-1.215	0.090***	0.022***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.794)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.093	0.104	0.077	0.043	0.049	0.187	0.058

Panel B: Maturity gap before distress

	BHC level		Bank level	
Event time	Maturity gap	p-value	Maturity gap	p-value
$\tau - 8$	0.001	(0.909)	0.012	(0.714)
$\tau - 7$	-0.023	(0.241)	0.005	(0.887)
$\tau - 6$	-0.019	(0.363)	-0.028	(0.428)
$\tau - 5$	-0.024	(0.227)	-0.043	(0.231)
$\tau - 4$	-0.036*	(0.090)	-0.046	(0.216)
$\tau - 3$	-0.048**	(0.040)	-0.056	(0.140)
$\tau - 2$	-0.051**	(0.030)	-0.071*	(0.060)
$\tau - 1$	-0.073***	(0.003)	-0.087**	(0.029)
τ	-0.111***	(0.000)	-0.120***	(0.004)
Institution FE	Yes		Yes	
Time FE	Yes		Yes	
Obs.	22,699		48,453	
No. distressed	49		636	
R^2	0.052		0.132	

Table 15: Hedging and regulatory capital – BHC level

This table provides evidence on the relation between hedging and the regulatory capital of BHCs using the two measures of regulatory capital. Panel A reports estimates from BHC-mean OLS, pooled OLS, pooled Tobit, and BHC fixed effect regressions of gross hedging on our measures of regulatory capital. Standard errors are clustered at the BHC level; standard errors for BHC-mean regressions are robust. p-values are in parentheses. Panel B provides the results for the Davidson-Mackinnon J-tests of whether the models with our measures of regulatory capital and marked-based net worth are nested. The t-statistics are reported and p-values are in parentheses. Variables are defined in Table 1. *, ** and *** denote statistical significance at the 10%, 5% and 1% level. Time frame: 1996Q1-2013Q4.

Panel A: Regression of hedging on regulatory capital

	BHC-mean OLS	Pooled OLS	Pooled Tobit	BHC FE
Regulatory cap. / Assets	-0.224	0.260	0.192	0.113
	(0.280)	(0.114)	(0.619)	(0.318)
R^2	0.000	0.008	0.036	0.009
Tier 1 cap. / Assets	0.193	0.086	-0.337	0.247*
	(0.529)	(0.472)	(0.259)	(0.060)
R^2	-0.000	0.008	0.036	0.009

Panel B: Davidson-Mackinnon (1981)'s J-test

	Size	Mkt. cap.	Mkt. cap. / Assets	Net income	Div.	Rating	Net worth index
Regulatory capital							
H0: Reg. cap. /Assets	10.71***	9.93***	4.41***	3.59***	4.77***	3.85***	5.35***
H1: Mkt. net worth explains residuals	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
H0: Mkt. net worth	-0.70	-5.25***	1.48	-0.71	-0.33	5.62***	-1.70*
H1: Reg. cap./Assets explains residuals	(0.486)	(0.000)	(0.139)	(0.479)	(0.741)	(0.000)	(0.090)
Tier 1 capital							
H0: Tier 1 cap. /Assets	10.71***	9.93***	4.41***	3.58***	4.76***	3.86***	5.60***
H1: Mkt. net worth explains residuals	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
H0: Mkt. net worth	-1.59	-3.53***	0.47	0.92	-1.67*	-1.44	4.53***
H1: Tier 1 cap./Assets explains residuals	(0.112)	(0.000)	(0.636)	(0.360)	(0.096)	(0.151)	(0.000)

Figure 1: Distribution of measures of BHC net worth

This figure plots the distribution of our measures of net worth. There is one cross-sectional box plot for each quarter from 1995Q1 to 2013Q4. In each of them, the horizontal dash is the median and the diamond is the mean. The whiskers represent the 5th and 95th percentiles. The grey rectangle represents the 25th and 75th percentiles. Variables are defined in Table 1.

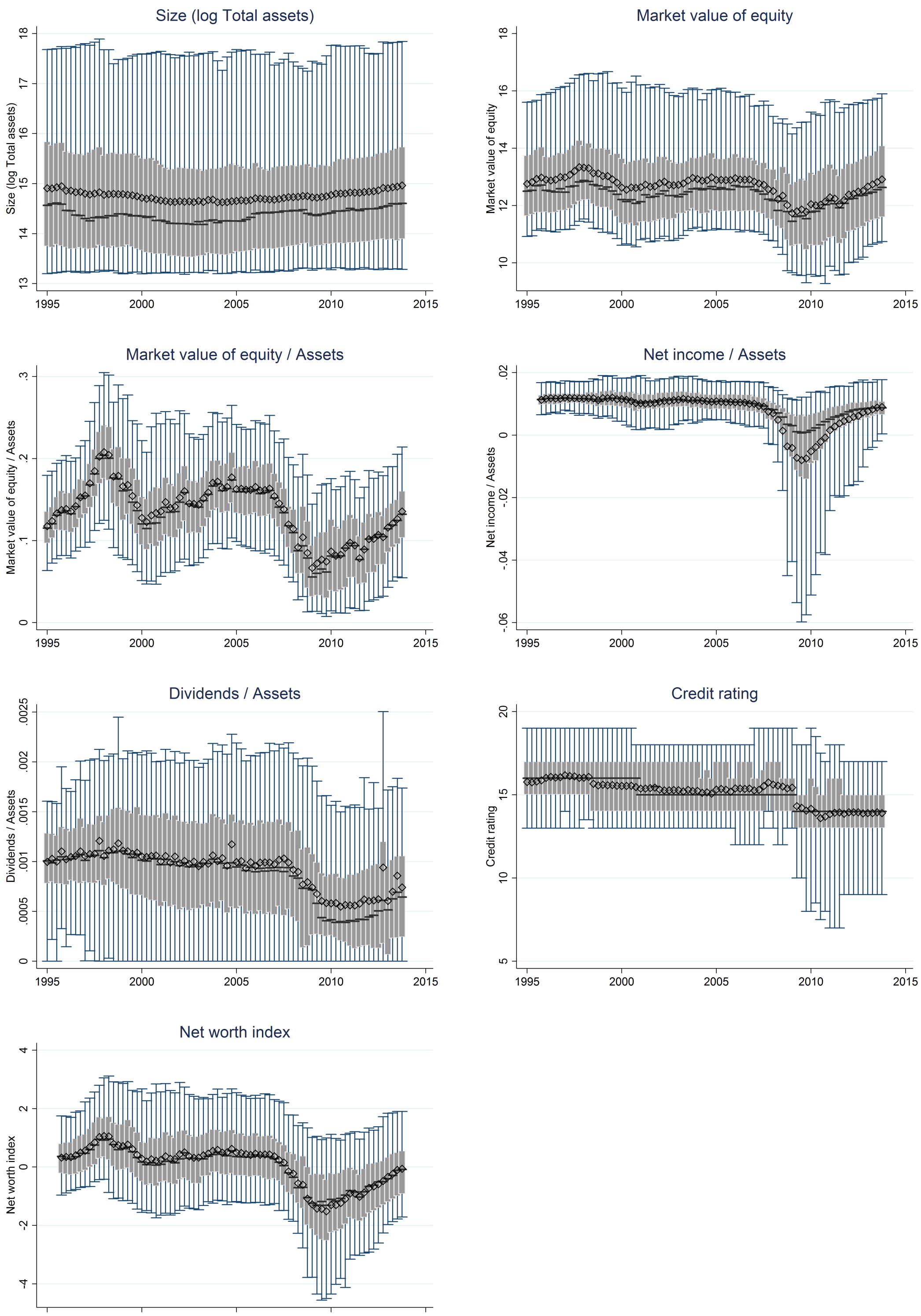


Figure 2: Distribution of measures of BHC regulatory capital

This figure shows the distribution of two measures of regulatory capital, Total regulatory capital and Tier 1 capital (normalized by risk-weighted assets) at the BHC level. There is one cross-sectional box plot for each quarter from 1996Q1 to 2013Q4. In each of them, the horizontal dash is the median and the diamond is the mean. The whiskers represent the 5th and 95th percentiles. The grey rectangle represents the 25th and 75th percentiles. Variables are defined in Table 1.

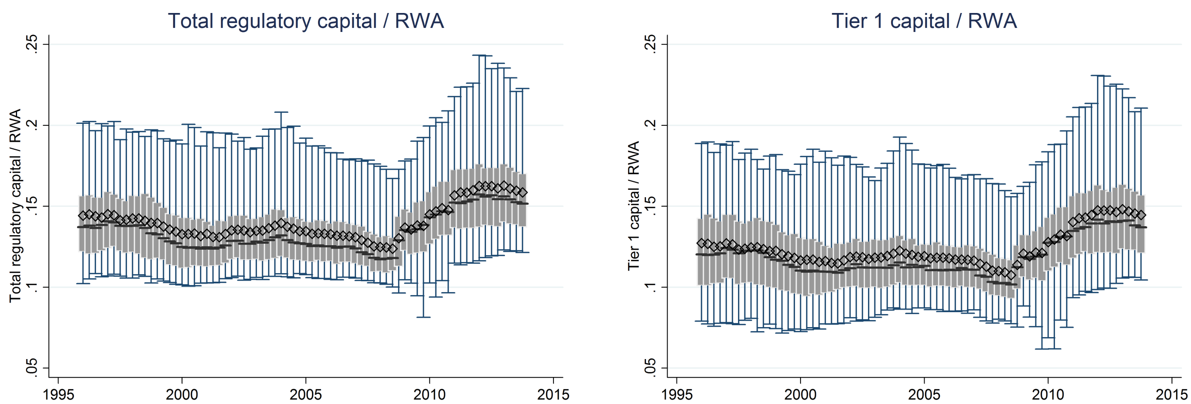


Figure 3: Net hedging conditional on maturity gap – Bank level

This figure shows the distribution of the net hedging position of banks in the first and fourth quartiles of the maturity gap distribution. Variables are defined in Table 1.

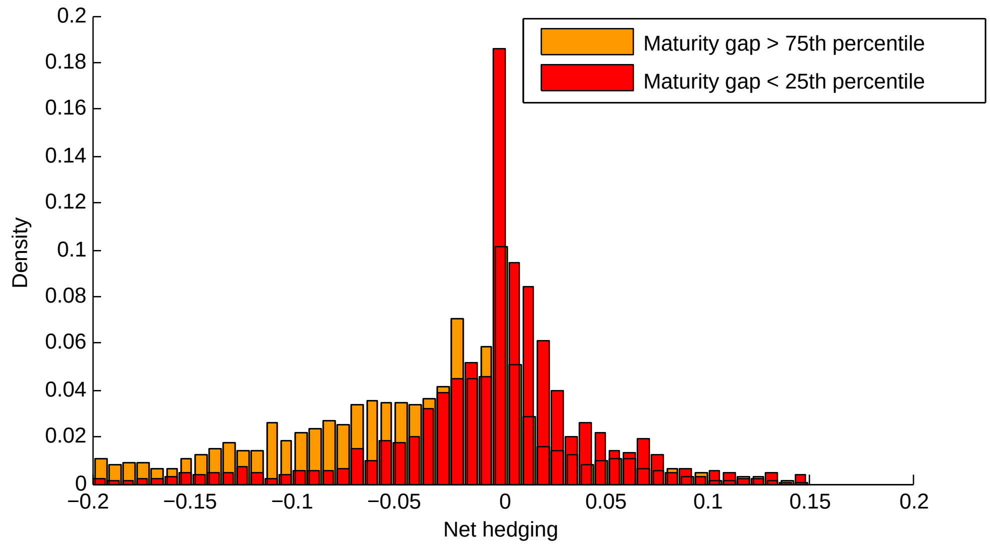
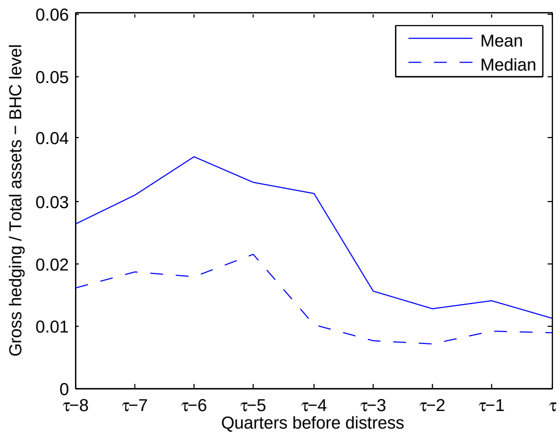


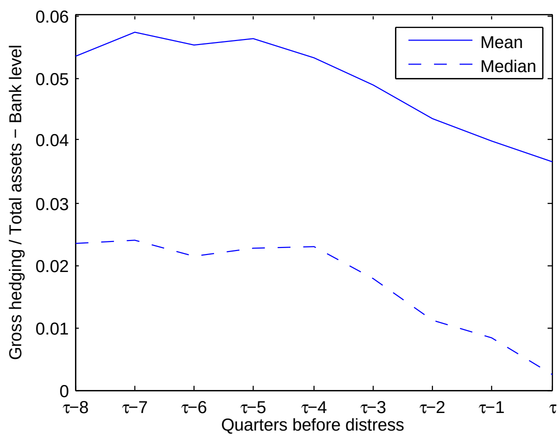
Figure 4: Hedging before distress events

This figure shows the extent of interest rate hedging in the eight quarters preceding distress. Panel A shows the mean and median gross hedging at the BHC level. Panel B shows gross hedging (left panel) and net hedging (right panel), respectively, at the bank level. Hedging measures are normalized by total assets. The sample is restricted to institutions that hedge at least once between $\tau - 8$ and τ. In both panels, the sample is restricted to institutions that are present in all quarters between $\tau - 8$ and τ. Distress events are defined as in Table 8. Variables are defined in Table 1.

Panel A: Gross hedging before distress – BHC level



Panel B: Gross hedging and net hedging before distress – bank level



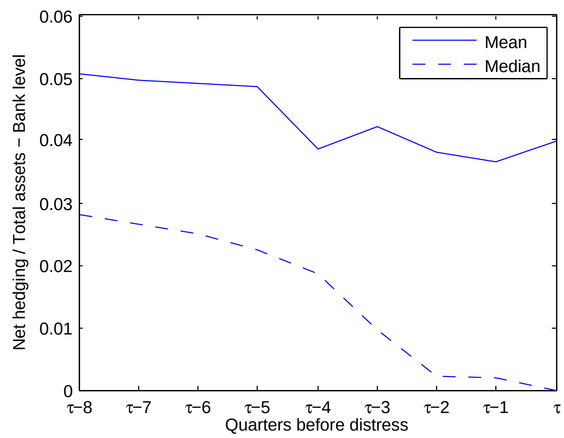


Figure 5: Decomposition of net income – BHC level

This figure shows the distribution of BHCs' net income and two key components of net income over the period from 1995Q1 to 2013Q4 in the top two panels and the bottom left panel. The top left panel shows the distribution of net income (normalized by total assets); this panel also shows the year 2009 in dark red, which is the treatment year in our difference-in-differences estimation. The top right panel shows the distribution of net interest income (normalized by total assets); the bottom left panel shows the distribution of provisions for loan losses (normalized by total assets). The bottom right panel shows the ratio of non-accrual loans to total assets, broken down by loan type. In the top two panels and bottom left panel, there is one cross-sectional box plot for each quarter. In each of them, the horizontal dash is the median and the diamond is the mean. The whiskers represent the 5th and 95th percentiles. The grey rectangle represents the 25th and 75th percentiles. Variables are defined in Table 1.

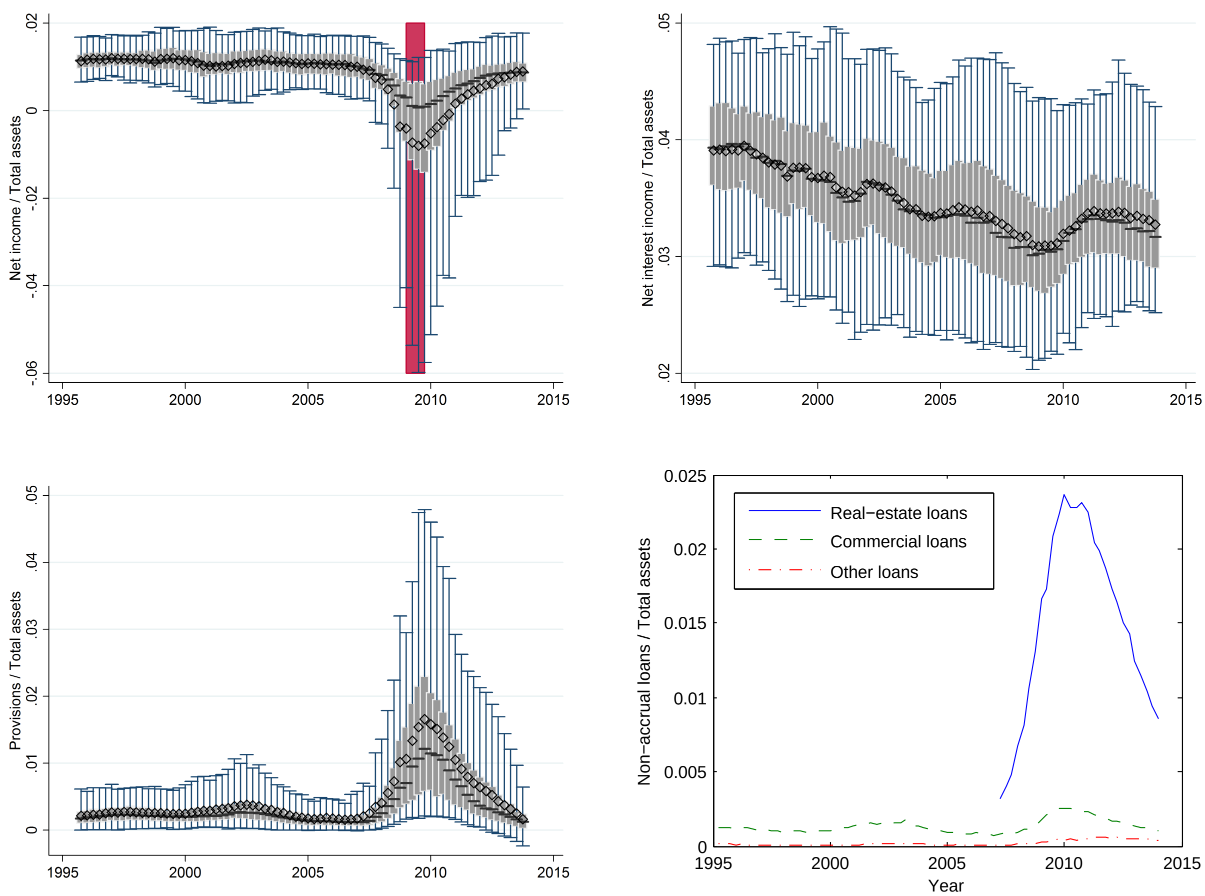


Figure 6: Effect of drop in net worth – Difference-in-differences – BHC level

This figure shows (gross) derivatives hedging (net of BHC fixed effects), normalized by total assets, for BHCs in the treatment and control group from 2005Q1 to 2013Q4. The sample is restricted to institutions that hedge at least once before the treatment year. Variables are defined in Table 1.

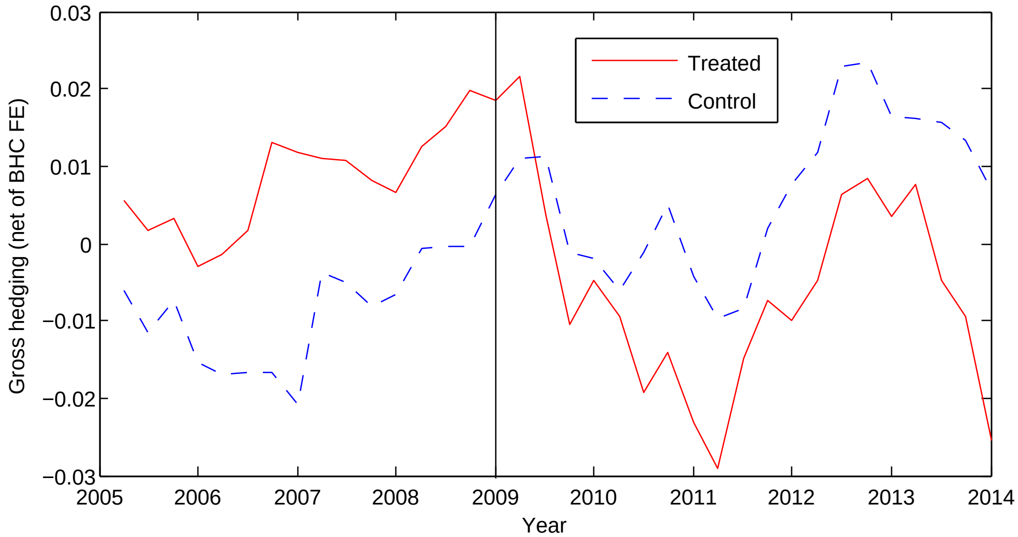


Figure 7: Maturity gap in treatment and control group – BHC level

This figure shows the maturity gap (net of BHC fixed effects) for BHCs in the treatment and control group from 2005Q1 to 2013Q4. The sample is restricted to institutions that hedge at least once before the treatment year. Variables are defined in Table 1.

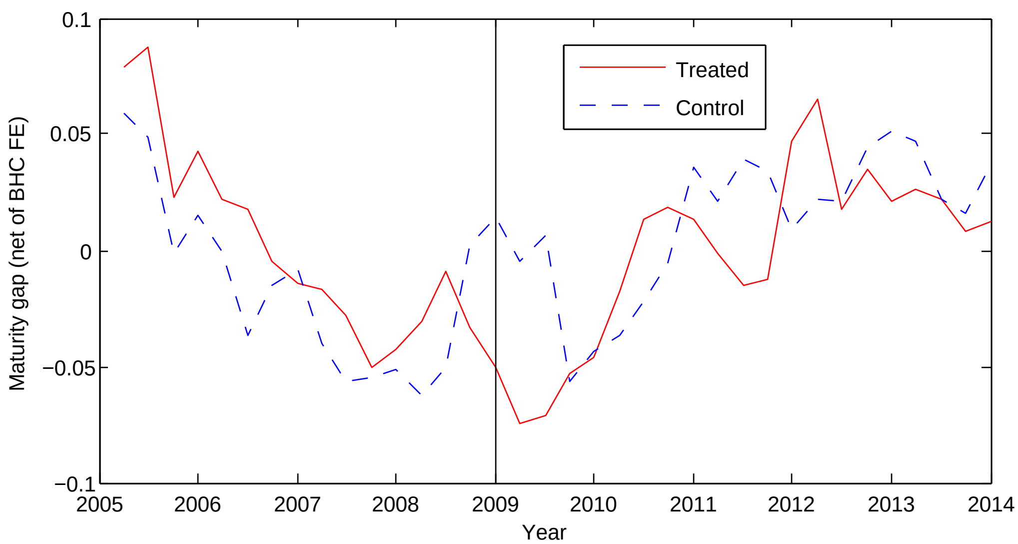
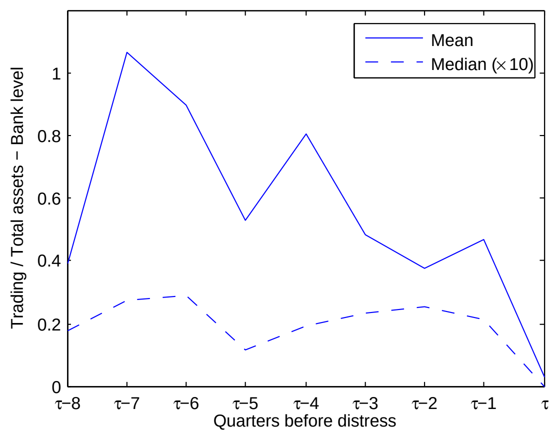


Figure 8: Trading and maturity gap before distress events

This figure shows trading by banks and the maturity gap of BHCs and banks in the eight quarters preceding distress. Panel A shows gross interest rate derivatives trading (normalized by total assets) at the bank level. The sample is restricted to banks that trade at least once between $\tau - 8$ and τ. Panel B shows the maturity gap at the BHC and bank level. In both panels, the sample is restricted to institutions that are present in all quarters between $\tau - 8$ and τ. Distress events are defined as in Table 8. Variables are defined in Table 1.

Panel A: Trading before distress – bank level



Panel B: Maturity gap before distress – BHC and bank level