

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 both in the cross-section and within institutions over time. For identification, we exploit net worth shocks resulting from loan losses due to drops in house prices. 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 financial institutions, 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 open question. To address this question, we study the determinants of risk management in the quantitatively largest market for such 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 net worth both across institutions 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 these shocks to estimate difference-in-differences models. We find that 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 major 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 main determinants are not well understood. Second, financial institutions play a key role in the macroeconomy and for the transmission of monetary policy. Understanding their exposure to interest rate shocks and the extent to which they do or do not hedge these exposures is thus essential for monetary and macro-prudential policy.¹ Third, financial intermediaries are the largest users of derivatives, measured in terms of gross notional exposures, and

¹Following [Bernanke and Gertler \(1989\)](#), the effects of the net worth of financial institutions on the availability of intermediated finance and real activity are analyzed by [Holmström and Tirole \(1997\)](#), [Gertler and Kiyotaki \(2010\)](#), [Brunnermeier and Sannikov \(2014\)](#), and [Rampini and Viswanathan \(2015\)](#), among others. Empirically, the effects of bank net worth on lending and real activity are documented by [Peek and Rosengren \(1997, 2000\)](#), and its effects on employment are studied by [Chodorow-Reich \(2014\)](#). Financial institutions’ central role in the transmission of monetary policy is examined by [Gertler and Gilchrist \(1994\)](#), [Bernanke and Gertler \(1995\)](#), [Kashyap and Stein \(2000\)](#), and [Jiménez, Ongena, Peydró, and Saurina \(2012\)](#).

interest rate derivatives comprise the bulk of such exposures.² The management of interest rate risk is a primary concern of financial intermediaries; 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.³

We use risk management theory to inform our measurement. A leading theory of corporate 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, [Rampini and Viswanathan \(2010, 2013\)](#) show that in a dynamic model where financing and risk management are subject to the same financial constraints, that is, promises to both financiers and hedging counterparties need to be collateralized, both require net worth. Therefore, a dynamic trade-off between financing investment or current operations and risk management arises: financially constrained firms must allocate their limited net worth between the two. Hedging has an opportunity cost in terms of foregone investment. The basic prediction of the dynamic theory is that more financially constrained firms, that is, firms with lower net worth, hedge less. The cost of foregoing investment or down-sizing operations is higher at the margin for such firms.

We test this prediction in panel data on U.S. banks and bank holding companies. We show that the theory is consistent with the main empirical patterns, which have not been documented previously. In the cross section, better capitalized financial intermediaries hedge interest rate risk to a greater extent. Over time, 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 and 2009 as the treatment year, we find that institutions *(i)* with a lower net income, *(ii)* a larger decrease in local house prices, and *(iii)* a lower local housing supply elasticity, cut hedging substantially relative to institutions in the relevant control groups.⁴

²According to the BIS' *Derivative Statistics* (December 2014), financial institutions account for more than 97% of all gross derivatives exposures and interest rate derivatives comprise 80% of the notional value of all derivatives globally.

³Other 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.

⁴A 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

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

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.⁵ 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.⁶ Instead, we have panel data for U.S. 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](#). One major difference is the identification strategy, as we are able to exploit exogenous variation in net worth due to house price changes.

higher level of aggregation, is used in several recent studies of the determinants of the supply of bank lending (see [Bord, Ivashina, and Taliaferro \(2014\)](#), [Cuñat, Cvijanović, and Yuan \(2014\)](#), and [Kleiner \(2015\)](#)).

⁵[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.

⁶For 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.

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, suggesting that the specifics of the industry are not driving the results.

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, 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 \(2007\)](#).⁷ 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.”⁸ The hypothesis which we test, in contrast, is consistent with the observation 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 [Vuillemeys \(2015\)](#). In a recent study, [Begenau, Piazzesi, and Schneider \(2015\)](#) quantify the exposure of financial institutions to interest rate risk. They find economically large interest rate exposures both in terms of balance sheet exposures and exposures due to the overall derivatives

⁷[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 institutions have a higher risk management index, that is, stronger and more independent risk management.

⁸Other theories of risk management include managerial risk aversion (see [Stulz, 1984](#)) and information asymmetries between managers and shareholders (see [DeMarzo and Duffie \(1995\)](#) and [Breen and Viswanathan \(1998\)](#)).

portfolios, which include trading and market making positions. In contrast, our focus is on the dynamic determinants of hedging by financial institutions based on risk management theory. 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 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 and 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.⁹ 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 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 constraints, a trade-off arises

⁹[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.

between the two, as both promises to hedging counterparties and financiers need to be collateralized. While the key state variable remains net worth, the conclusion is reversed: more 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 scarce internal funds to risk management. Two key differences are that [Froot, Scharfstein, and Stein \(1993\)](#) consider hedging in frictionless financial markets and no concurrent investment. Instead, [Rampini and Viswanathan \(2010, 2013\)](#) impose the same constraints on both hedging and financing, thus linking them, and consider concurrent investment, implying a choice between committing internal funds to finance operations or risk management. The basic prediction of this theory is 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 for a given institution 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, not cash, liquid assets, or collateral per se. Financial institutions’ net worth determines their willingness to pledge collateral to back hedging positions, use it to raise additional funding, or keep it unencumbered. In other words, available cash or collateral are endogenous. Net worth is defined as total assets, including the current cash flow, net of liabilities. Thus, it includes unused debt capacity, such as unused credit lines and unencumbered assets.

[Vuillemeys \(2015\)](#) 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 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 by financial institutions. We use two measures of risk management, gross and net hedging. We also discuss the measurement of balance sheet interest rate exposures and relate these exposures to hedging patterns. Finally, we provide measures of net worth, 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 banks. We discuss the distinction between the two in the next subsection. All balance sheet data is from the call reports, obtained from the Federal Reserve Bank of Chicago at a quarterly frequency (forms FR Y-9C for BHCs and FFIEC 031 and FFIEC 041 for banks). The sample starts in 1995Q1, when derivatives data becomes available, and extends to 2013Q4.¹⁰ We drop the six main dealers, since they are much larger and engage in extensive market making in derivatives markets, but all our regression results regarding hedging are robust to the inclusion of these dealers.¹¹

To obtain several measures of net worth, the BHC-level balance sheet data is matched with market data. The market value of equity and credit ratings (from Standard & Poors) are retrieved from CRSP and Capital IQ, for 753 out of 2,102 BHCs. The resulting sample contains 22,723 BHC-quarter observations, that is, 301 observations per quarter on average, for 76 quarters. 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 bank-level dataset, which is not matched with market data, contains 627,219 bank-quarter observations (8,252 observations per quarter on average).

3.2 Unit of observation: BHCs versus banks

We conduct our empirical work both at the BHC and at the bank level. In the U.S., most banks 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. The BHC-level data consolidates balance sheets of all entities within a BHC (see [Avraham, Selvaggi, and Vickery, 2012](#), for details). For clarity of exposition, we use the term financial institutions whenever we mean both BHCs and banks and 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. Theoretically, risk management can be conducted at both levels.

¹⁰We drop U.S. branches of foreign banks, because a large part of their hedging activities is likely unobserved. We drop lower-tier BHCs, that is, BHCs which are subsidiaries of other BHCs that are in the sample. Finally, we drop a small number of observations corresponding to financial institutions with limited banking activity, defined by a ratio of total loans to total assets below 20%. In case of mergers and acquisitions, only one of two institutions remains after the event. We treat it as a single institution over the sample period, and check that regressions including fixed effects are robust to treating it as two separate entities before and after the merger or acquisition.

¹¹These institutions are Bank of America, Citigroup, Goldman Sachs, J.P. Morgan Chase, Morgan Stanley and Wells Fargo.

For liquidity management, Campello (2002) shows evidence on internal capital markets, which provide partial insurance to individual banks within a BHC against liquidity shortfalls. However, each individual bank in a BHC has its own managerial structure and can have its own derivatives trading desk. There can also be limits to intra-group transfers, which motivate risk management at the bank level.¹²

From a practical perspective, the BHC-level and bank-level datasets do not include an identical set of variables. Balance sheet data at the BHC level can be matched with market-based data on net worth (specifically data on market capitalization and credit rating). Bank-level data has the advantage that hedging can be more precisely measured, as 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 BHCs or banks when data availability forces us to.

3.3 Measurement: gross hedging

Our main measure of hedging is gross hedging. Gross hedging for institution i at time t is defined as

$$\text{Gross hedging}_{it} = \frac{\text{Gross notional amount of interest rate derivatives for hedging of } i \text{ at } t}{\text{Total assets}_{it}}, \quad (1)$$

and its construction, together with that of other variables, is detailed in Table 1. This variable is 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.

To identify derivatives used for risk management, as opposed to trading, we exploit a unique feature of BHC and bank reporting. Derivative exposures are broken down by contracts “held for trading” and “held for purposes other than trading.”¹³ We exclude all derivatives held for trading when measuring risk management and focus only on exposures held for other purposes, that is, hedging. In other industries, researchers are typically

¹²Our data shows that hedging occurs mostly at the bank level. Aggregating derivative exposures of individual banks within each top-tier BHC (that is, BHC that is not owned by another sample BHC), we find that these exposures represent on average 88.5% of the exposure reported by the BHC. Thus hedging by BHCs outside the banks they own is rather limited.

¹³Derivatives held for trading include (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 accommodation for customers and (iv) positions taken to hedge other trading activities.

forced to rely on indirect evidence to distinguish between hedging and trading (see, for example, [Chernenko and Faulkender, 2011](#)). 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 measurement concerns, which we address below.

Descriptive statistics for gross hedging and gross trading are provided in Table 2. Panel A shows that their distributions are skewed, with a large number of zeros. 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.

A potential concern about our data is whether derivative exposures for hedging are economically relevant when compared to exposures for trading. At an aggregate level, trading represents on average 93.8% of all derivatives in notional terms. These large exposures, however, are due almost exclusively to 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 large number of offsetting long and short positions. Residual exposures are also likely to be kept on the balance sheet for short periods of time only.

For the average sample bank, in contrast, the use of derivatives for trading is minimal, as can 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. 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 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 hedging may aggregate long and short positions. A potential 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. To address this concern, we construct a measure of net hedging for a subset of banks and show that gross and net hedging are highly correlated for these banks.

A measure of net hedging can be constructed for banks which report that they use only swaps and no other types of interest rate derivatives. No such measure can be obtained for BHCs. Banks report the notional amount of interest rate *derivatives* held for hedging as well as 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.¹⁴

Thus, for a bank i at time t which reports using only swaps and no other interest rate derivatives, we construct a measure of net hedging as

$$\text{Net hedging}_{it} = \frac{\text{Pay-fixed swaps}_{it} - \text{Pay-float swaps}_{it}}{\text{Total assets}_{it}}, \quad (2)$$

for which descriptive statistics are provided in Table 3. A positive (resp. negative) value of this ratio means that an institution is taking a net pay-fixed (pay-float) position, that is, hedges against increases (decreases) in the referenced interest rate. To our knowledge, this variable has not been constructed in previous research.

To document the relation between gross and net hedging, we use the absolute value of net hedging from Equation (2). Indeed, while net hedging can be both positive and negative, gross hedging is bounded from below by zero. Thus, we recognize that both net pay-fixed and pay-float swap positions can be used by banks to hedge, consistent with Vuillemeys (2015). The average ratio of (the absolute value of) net hedging to gross hedging is 90.9%. The percent of bank-quarter observations in which net hedging is larger than 80% of gross hedging is 89.2%. 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.¹⁵ This suggests that our main hedging variable, expressed in gross terms, is a good proxy for the underlying net hedging.

¹⁴Bank-quarter observations for which this ratio can be computed represent 28.7% of all bank-quarter observations for banks that use derivatives. Banks for which net hedging can be computed are relatively large and have a median size of 13.58 (in log assets), which is above the 90th percentile of the bank size distribution (see Table 5).

¹⁵A 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 Vuillemeys, 2014).

A final and related concern is whether net exposures are appropriately measured, given our reliance on notional amounts. Panel B 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 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, an increase in Libor results in a statistically significant increase (resp. decrease) in the market value of the derivatives portfolio. The estimated coefficients 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 its relation with derivatives hedging. Measuring balance sheet interest rate exposure 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. Moreover, it makes it possible to assess the accuracy of our measurement of net hedging, by showing that the joint pattern of net hedging and balance sheet exposures is consistent with risk management.

To measure the exposure to interest rate risk, we use the one-year *maturity gap*,

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

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.

The maturity gap (also called “income gap”) has been used in a number of earlier studies (see, for example, [Flannery and James \(1984\)](#), [Purnanandam \(2007\)](#), and [Landier, Sraer, and Thesmar \(2013\)](#)). It has been popularized in practitioners’ textbooks such as [Saunders and Cornett \(2008\)](#) and [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,

$$\Delta NII_{it} = \text{Maturity gap}_{it} \times \Delta r_t, \quad (4)$$

where ΔNII_{it} is the change in net interest income from assets and liabilities in the 1-year maturity bucket and Δr_t the change in interest rate at this maturity. A positive value of the maturity gap implies that increases in the short rate increase the institution's net interest income at the one-year horizon, because the institution 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.

Computing the maturity gap makes it possible to directly relate balance sheet exposures to derivatives hedging. A potential concern is whether derivatives reported for hedging are in fact used for risk management or for trading purposes instead. The existing literature has argued that reporting is likely truthful because all 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 (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, as banks with negative net hedging have a pay-float swap exposure, that is, gain when the short rate goes down, while a positive maturity gap implies that they gain when the short rate goes up. Figure 3 illustrates this by showing the distribution of net hedging conditional on the maturity gap being above the 75th percentile vs. below the 25th percentile; the shift in the distributions is evident.

Panel D of Table 3 provides further evidence using a regression approach. 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, consistent with risk management.

3.6 Measurement: net worth

Our main hypothesis pertains to the relation between hedging and net worth, the state variable in both [Froot, Scharfstein, and Stein \(1993\)](#) and [Rampini and Viswanathan \(2010, 2013\)](#). Net worth, however, is not directly observable in the data. We rely on the idea that net worth determines the tightness of financial constraints, and can thus be proxied by 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 \(2014\)](#), among others; 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 exclude institutions for which no rating information is available. We think that this net worth index may be of independent interest.

The evolution of the cross-sectional distribution of each measure of net worth at the quarterly frequency is plotted 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 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 hedging and net worth, both in the cross-section and in the time series. We also examine the dynamics of hedging for institutions approaching 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 isolate cross-sectional variation, we estimate BHC-mean specifications, where both dependent and independent variables are averaged for each BHC over the sample period. 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 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 the large number of zeros in the dependent variable (49% in the BHC sample), possibly biasing estimates downwards. Indeed, for BHCs that do not hedge, variation in net worth does not translate to any variation in hedging. We turn to several estimation methods which 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, *(iii)* quantile regressions in the upper percentiles (75th, 85th and 95th) of the distribution of gross hedging, and *(iv)* a Heckman selection model. In the first stage of the Heckman estimation, we predict whether a BHC hedges or not using the net worth index and size (orthogonalized on the net worth index) to capture the potential effect of fixed costs on the participation decision. In the second stage, the magnitude of hedging is predicted using the net worth index.

Estimates for these specifications are in Panel B of Table 6. With two exceptions, estimated coefficients are all positive and significant at the 1% level.¹⁶ 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 to previous work, we emphasize that cross-sectional patterns in hedging are not mainly driven by size, but by net worth, proxied by several measures.¹⁷

¹⁶We report only the estimate from the second stage of the Heckman estimation; in the first stage, both the net worth index and size, orthogonalized on the net worth index, are statistically significant.

¹⁷We obtain similar results at the bank-level, with net worth measured by size, net income, and dividends, but do not report these findings here.

4.2 Hedging and net worth within financial institutions

We now turn to the panel dimension and 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, fixed effects make it possible to difference out any time-invariant unobserved heterogeneity, such as differences in business models, sophistication, or the fixed costs of setting up a hedging desk, 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, and Panels B and C 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 regressions, but is still appreciable. Since theory predicts that the trade-off between hedging and financing is more acute for banks with low net worth, we provide an additional specification by excluding the 10% of institutions with the highest net worth. When these institutions are excluded (see the second specification in Panel A), all coefficients are positive and significant at the 1% level.

Further, we estimate two additional specifications to account for the large number of zeros. 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 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 is smaller.

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

We provide additional evidence of the relation between hedging and net worth within institutions by focusing on hedging by institutions that enter financial distress and thus

become severely constrained.¹⁸

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.¹⁹ 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 and 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. Of these events, 95.9% involve mergers or purchases before the entity actually fails, and the others 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

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

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 $\tau - j \in \{\tau - 8, \dots, \tau\}$ and 0 otherwise. The specification includes institution fixed effects (FE_i) and time fixed effects (FE_t), to isolate within-institution variation before distress.

Equation (5) is estimated both at the BHC and the bank level, using the whole sample of distressed and non-distressed institutions. At the bank level, we estimate it for both gross and net hedging. Regression coefficients are collected in Table 8. Both gross and net hedging decrease by a statistically significant amount several quarters before distress. Interestingly, both are reduced by comparable amounts at the bank level, again suggesting that gross and net hedging are relatively similar for most banks.

The economic magnitude of the pre-distress reduction in hedging is large. Financial institutions cut hedging by close to one half. Figure 4 illustrates this result by plotting mean and median hedging before distress for institutions for which all 8 observations

¹⁸While we focus on hedging before distress here, we emphasize that the positive relation between hedging and net worth is not just due to financial institutions that are close to distress. In fact, we obtain very similar results in our cross-sectional and within regressions after dropping the 10% of observations with the lowest net worth (as measured by the pertinent variable for each regression).

¹⁹There 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 [Granja, Matvos, and Seru, 2014](#)).

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 these cuts are explained by risk shifting before distress. We discuss this alternative hypothesis in Section 6. To anticipate our conclusion, we provide evidence on the trading behavior of these institutions that suggests that risk shifting is not a plausible interpretation of these findings.

5 Identification using house prices

We turn to our identification strategy next. We use changes in house prices to assess the effect of variation in net worth on hedging. First, we instrument net income with changes in local house prices. Second, we estimate the effect of a drop in net worth on hedging using a difference-in-differences estimation.

5.1 Instrumenting net income with changes in house prices

We use 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 house prices. We instrument net income by lagged changes in house prices at the local level. Because the instrument is likely stronger for 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 period do not also arise 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. 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 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 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.²⁰ 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, Chu, and Park \(2008\)](#), [Mayer, Pence, and Sherlund \(2009\)](#), [Demyanyk and Van Hemert \(2011\)](#), and [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.

²⁰The other important component of changes in net income is changes in non-interest income. Unreported results show that these changes are almost entirely attributable to goodwill impairments of a small subset of banks. For other banks, changes in provisions explain the bulk of changes in net income.

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 the 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

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

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 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 because data on loans at the ZIP-code level are not publicly available. 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 because 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 concentrated in 2009 and that losses faced by financial institutions over the period are 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 the *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

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

where ϵ_j is the housing supply elasticity in MSA j , and d_{ij} is the stock of deposits of institution i in MSA j , measured in 2008.²¹ 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 subject to larger 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 groups. 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

²¹The 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.

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.

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.

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’ 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 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’ 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, but because the exposures change. 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 risk 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. Hence, our difference-in-differences strategy identifies a negative causal effect of drops in financial institutions’ net worth on hedging.

6 Alternative hypotheses

So far, we have emphasized financial constraints as the main determinant of the positive relation between hedging and net worth. We now consider alternative explanations that might be consistent with this positive relation. Specifically, we first study whether the reduction in risk management by financially constrained institutions is evidence of risk shifting. Next we consider whether institutions that reduce financial hedging increase operational hedging by adjusting the maturity structure of their balance sheet instead. Finally, we ask whether the determinant of hedging is financial institutions’ regulatory capital rather than 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 hedging and net worth is risk shifting resulting from an agency conflict between debtholders 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 net income (see [Jensen and Meckling, 1976](#)). This may induce them to reduce hedging (see, for example, [Leland, 1998](#)).

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. In contrast, 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 by focusing on financial institutions' portfolio of derivatives for trading purposes.²²

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 around 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.²³ And we do not find

²²Recall that we exclude the six main broker-dealers in the results we report which is warranted for trading because most of the trading activities of these dealers arise from market making.

²³Indeed, one reason why it is not plausible that the basic pattern is due to risk shifting is that we 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.

6.2 Operational risk management

Another concern might be that financial institutions which have lower net worth cut financial hedging, but substitute it with operational risk management, that is, reduce their on-balance sheet exposure to interest rate risk (see [Petersen and Thiagarajan \(2000\)](#) and [Purnanandam \(2007\)](#)). 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.

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 they exit. These institutions thus do less operational risk management as they become more constrained, as also illustrated in

the same positive relation between hedging and net worth in our cross-sectional and within regressions even after dropping the 10% of observations with the lowest net worth (see footnote [18](#)), whereas risk shifting might predict such a pattern close to distress but not otherwise.

Panel B of Figure 8. Quantitatively, the drop is remarkably large, exceeding 10% of assets for both banks and BHCs. This pattern, which to the best of our knowledge has not been documented before, is of independent interest.

Overall, these results suggest that operational risk management cannot provide a satisfactory explanation for the positive relation between net worth and hedging. We find a remarkably strong pattern going the opposite way, as more financially constrained financial institutions have more net floating-rate liabilities, not less. 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 hedging and net worth is driven not by market measures of net worth, which we use, but by 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. If so, the positive relation which we document might spuriously arise from the positive correlation between market measures of net worth and 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 its role, we estimate the relation between hedging and 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. There is no significant and stable relation between hedging and regulatory capital, neither between institutions nor within institutions.

We further conduct the J -test proposed by Davidson and MacKinnon (1981) to test the specification with our (market-based) measures of net worth against the alternative specification with regulatory capital. 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 on regulatory capital as a determinant of financial institutions' risk exposures in much of the literature and policy debate may hence not be warranted.

7 Conclusion

The evidence that we present strongly suggest that the financing needs associated with hedging are a substantial barrier to risk management for financial institutions. 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 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 such drops in 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. 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.

We contend that financial constraints are a key impediment to risk management by financial institutions and firms, and to insurance by households, 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 activity may be significant. Limited interest rate risk management leaves financial institutions, especially financially constrained ones, exposed to changes in interest rates, which is an essential fact for both monetary and macro-prudential policy to consider.

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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 (<i>bhck8725</i>) over total assets; for the period 1995-2000, contracts not marked to market (<i>bhck8729</i>) are added; winsorized at the 99th percentile | Call reports |
| Net hedging | Interest rate swaps where the bank has agreed to pay a fixed rate (<i>rcon589</i>) 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 (<i>bhcka126</i>) | Call reports |
| Net worth and regulatory capital | | |
| Size | Log of total assets (<i>bhck2170</i>) | 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 (<i>bhck4340</i>) normalized by total assets; winsorized at the 1st and 99th percentiles | Call reports |
| Dividends / Assets | Cash dividends on common stock (<i>bhck4460</i>); 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 (<i>bhck3792</i>) normalized by risk-weighted assets (<i>bhcka223</i>); winsorized at the 1st and 99th percentiles | Call reports |
| Tier 1 capital / Assets | Tier 1 capital allowable under the risk-based capital guidelines (<i>bhck8274</i>) normalized by risk-weighted assets (<i>bhcka223</i>); 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 (<i>bhck4074</i>); annualized | Call reports |
| Noninterest income | Total noninterest income (<i>bhck4079</i>); annualized | Call reports |
| Noninterest expense | Total noninterest expense (<i>bhck4093</i>); annualized | Call reports |
| Net noninterest income | Total noninterest income (<i>bhck4079</i>) minus Total noninterest expense (<i>bhck4093</i>); annualized | Call reports |
| Provisions | Provision for loan and lease losses (<i>bhck4230</i>); annualized | Call reports |
| Other balance sheet variables | | |
| Total assets | Total assets (<i>bhck2170</i>) | Call reports |
| Maturity gap | Earning assets that are repriceable or mature within one year (<i>bhck3197</i>) minus interest-bearing deposits that mature or reprice within one year (<i>bhck3296</i>) minus long-term debt that reprices or matures within one year (<i>bhck3298</i> + <i>bhck3409</i>) minus variable rate preferred stock (<i>bhck3408</i>) minus other borrowed money with a maturity of one year or less (<i>bhck2332</i>) minus commercial paper (<i>bhck2309</i>) minus federal funds and repo liabilities (<i>bhdm6631</i> + <i>bhckb995</i>), normalized by total assets | Call reports |
| Noninterest bearing deposits | Noninterest-bearing deposits (<i>bhdm6631</i> + <i>bhfn6631</i>) | Call reports |
| Noninterest bearing assets | Noninterest-bearing balances and currency and coin (<i>bhck0081</i>) | Call reports |
| Total loans | Total loans and leases, net of unearned income (<i>bhck2122</i>) | Call reports |
| Total for real estate | Loans secured by real estate (<i>bhck1410</i>) | 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 the market value of banks' derivatives portfolios for hedging on interest rate changes conditional on a positive or negative net swap position. Panel C 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 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 C: 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 |
| <i>For reference (not incl. in maturity gap):</i> | | | | | | | | | |
| 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), quantile regressions at the 75th, 85th, and 95th percentile, and the second stage of a Heckman selection model using the net worth index and, in the first stage, also size as explanatory variables. 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*** (0.000) | 0.025*** (0.000) | 0.060 (0.313) | 0.962*** (0.000) | 15.884*** (0.004) | 0.014** (0.033) | 0.014*** (0.000) |
| Pooled OLS with time FE | 0.031*** (0.000) | 0.023*** (0.000) | 0.017 (0.143) | 0.344*** (0.000) | 3.304*** (0.000) | 0.013*** (0.000) | 0.010*** (0.000) |
| Panel B: Tobit, quantile regressions, and Heckman model | | | | | | | |
| BHC-mean Tobit | 0.052*** (0.000) | 0.040*** (0.000) | -0.059 (0.426) | 0.681* (0.098) | 17.631*** (0.005) | 0.013** (0.010) | 0.018*** (0.000) |
| Tobit with time FE | 0.055*** (0.000) | 0.043*** (0.000) | 0.130*** (0.000) | 0.695*** (0.000) | 11.958*** (0.000) | 0.014*** (0.000) | 0.022*** (0.000) |
| Quantile regres- sion 75th pctl | 0.031*** (0.000) | 0.019*** (0.000) | 0.112*** (0.000) | 0.338*** (0.000) | 16.142*** (0.000) | 0.016*** (0.000) | 0.008*** (0.000) |
| Quantile regres- sion 85th pctl | 0.049*** (0.000) | 0.029*** (0.000) | 0.131*** (0.000) | 0.599*** (0.000) | 22.791*** (0.000) | 0.021*** (0.000) | 0.014*** (0.000) |
| Quantile regres- sion 95th pctl | 0.086*** (0.000) | 0.053*** (0.000) | 0.096 (0.146) | 1.208*** (0.000) | 29.678*** (0.000) | 0.050*** (0.000) | 0.026*** (0.000) |
| Heckman selec- tion model | | | | | | | 0.005*** (0.000) |
| Panel C: With rating dummies | | | | | | | |
| | BBB- to BBB+ | BB- to BB+ | B- to B+ | CCC+ and below | | | |
| Pooled OLS | -0.078*** | -0.053*** | -0.124*** | -0.153*** | | | |
| BHC FE | 0.009*** | 0.024*** | -0.043*** | -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 pctl. | (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.

| Event time | BHC level | | Bank level | | | |
|----------------|---------------|------------|---------------|------------|-------------|------------|
| | 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 | |
| Within- 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 (19.05) | 0.091 (0.89) | | | 0.760 (18.57) |
| Δ Net noninterest income | 0.904 (34.94) | | 0.967 (36.39) | | |
| Δ Noninterest income | | | | | 0.807 (22.31) |
| Δ Noninterest expense | | | | | 0.918 (34.45) |
| Δ Provisions | -0.793 (-34.34) | | | -1.045 (-21.63) | -0.790 (-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** (0.037) | | 0.113** (0.033) |
| Within- R^2 | | 0.096 | | 0.053 |
| Net income | 0.185* (0.062) | 0.254** (0.049) | 0.049* (0.075) | 0.086** (0.044) |
| Within- 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** (0.042) | | | -0.040* (0.056) | | | -0.042* (0.051) | | |
| 2009 | | -0.020 (0.259) | -0.022** (0.025) | | -0.022 (0.246) | -0.026* (0.098) | | -0.027** (0.026) | -0.096** (0.037) |
| 2010 | | -0.039** (0.026) | -0.042*** (0.009) | | -0.022 (0.154) | -0.026 (0.111) | | -0.027** (0.035) | -0.092** (0.043) |
| 2011 | | -0.038** (0.037) | -0.035** (0.046) | | -0.044* (0.055) | -0.051** (0.049) | | -0.026** (0.041) | -0.059* (0.056) |
| 2012 | | -0.019 (0.263) | -0.020* (0.089) | | -0.042* (0.065) | -0.039* (0.085) | | -0.021* (0.054) | -0.055* (0.062) |
| 2013 | | -0.031* (0.099) | -0.033* (0.053) | | -0.025 (0.147) | -0.016 (0.326) | | -0.019* (0.096) | -0.047 (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*** (0.009) | | | -0.018* (0.068) | | | -0.005 (0.345) | | |
| 2009 | | -0.019** (0.042) | -0.017** (0.031) | | -0.014* (0.094) | -0.018* (0.087) | | -0.002 (0.756) | -0.003 (0.621) |
| 2010 | | -0.010 (0.181) | -0.017** (0.019) | | -0.014* (0.094) | -0.018* (0.087) | | -0.002 (0.756) | -0.003 (0.621) |
| 2011 | | 0.001 (0.910) | 0.006 (0.390) | | -0.022* (0.056) | -0.025* (0.064) | | -0.004 (0.458) | -0.003 (0.352) |
| 2012 | | -0.021*** (0.008) | -0.027*** (0.000) | | -0.019 (0.125) | -0.021 (0.100) | | -0.010 (0.555) | -0.006 (0.489) |
| 2013 | | -0.028*** (0.000) | -0.018** (0.017) | | -0.008 (0.341) | -0.010 (0.239) | | 0.002 (0.672) | 0.014 (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) |
| Within- R^2 | 0.009 | 0.042 | 0.049 | 0.044 | 0.042 | 0.096 | 0.134 |

| Panel B: Derivatives trading before distress | | | | |
|---|---------------|------------|---------------|------------|
| Event time | BHC level | | Bank level | |
| | 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 | |
| Within- 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*** (0.000) | 0.029*** (0.000) | 0.681*** (0.000) | 1.211*** (0.001) | -1.215 (0.794) | 0.090*** (0.000) | 0.022*** (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 | | | | | | | |
| Event time | BHC level | | Bank level | | | | |
| | 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 | | | | |
| Within- 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 (0.280) | 0.260 (0.114) | 0.192 (0.619) | 0.113 (0.318) |
| R^2 | 0.000 | 0.008 | 0.036 | 0.009 |
| Tier 1 cap. / Assets | 0.193 (0.529) | 0.086 (0.472) | -0.337 (0.259) | 0.247* (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: <i>Mkt. net worth explains residuals</i> | (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: <i>Reg. cap./Assets explains residuals</i> | (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: <i>Mkt. net worth explains residuals</i> | (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: <i>Tier 1 cap./Assets explains residuals</i> | (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.

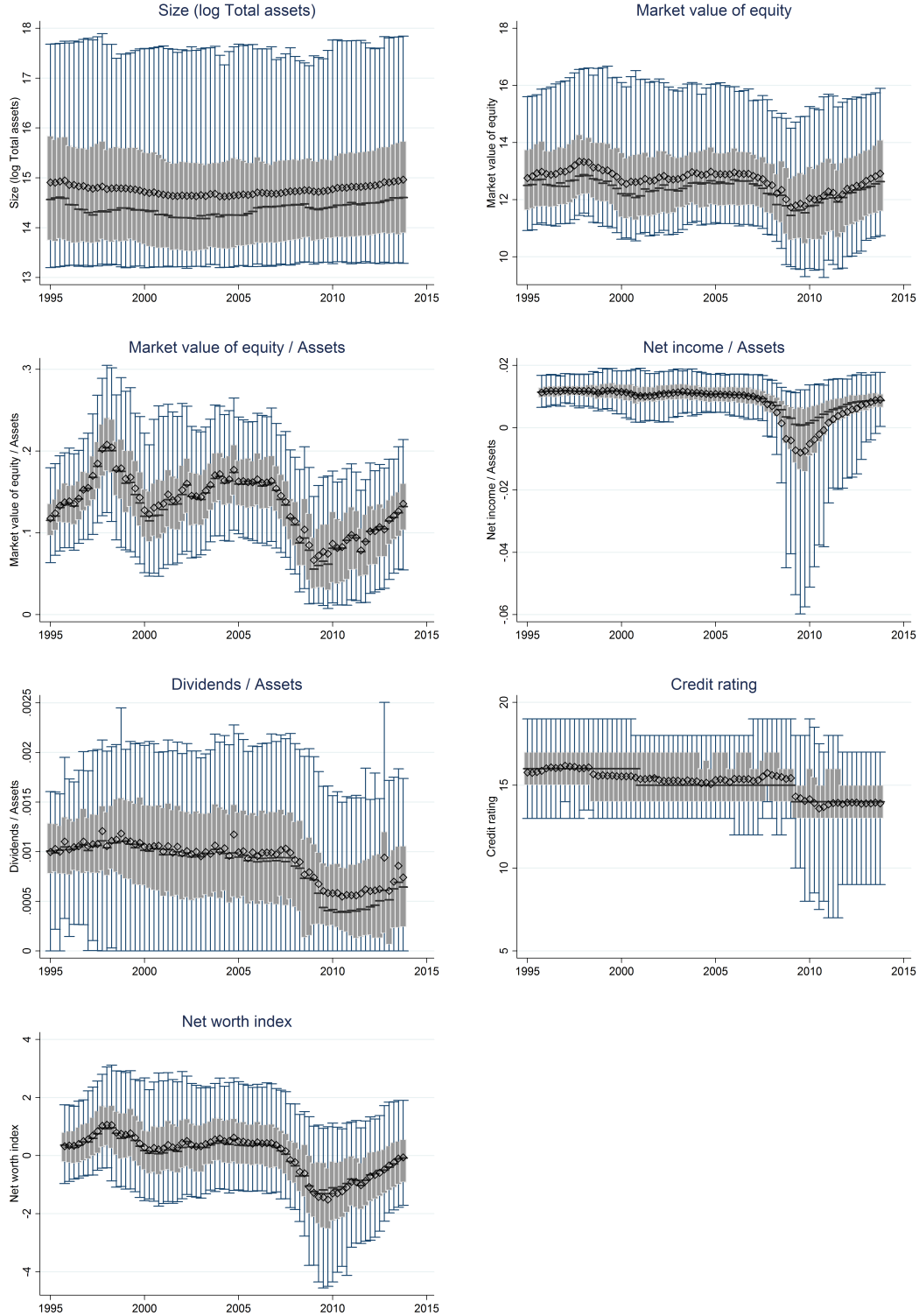


Figure 2: Distribution of measures of BHC regulatory capital

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.

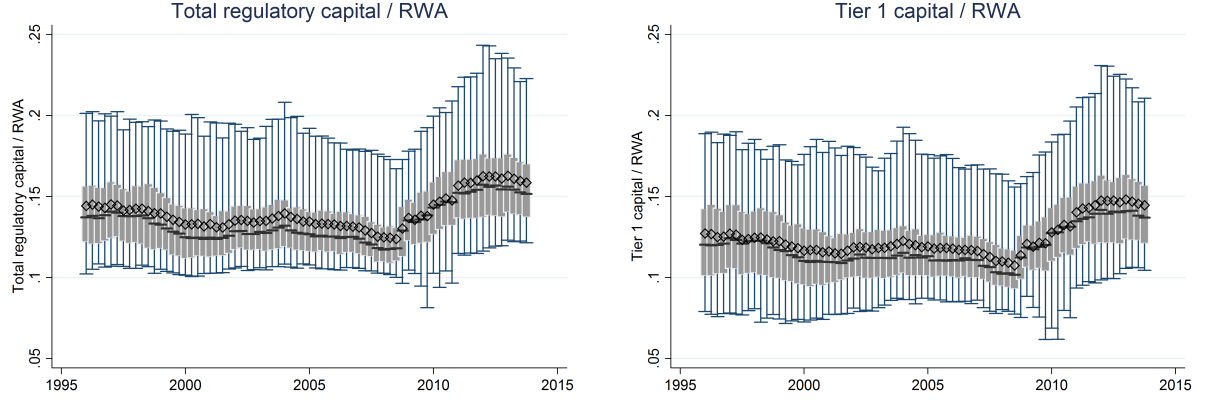


Figure 3: Net hedging conditional on maturity gap – Bank level

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.

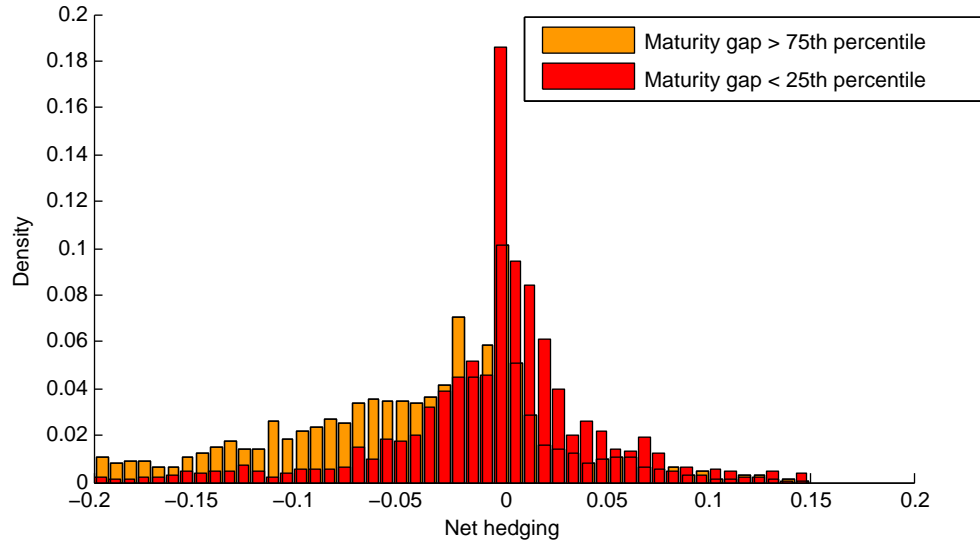
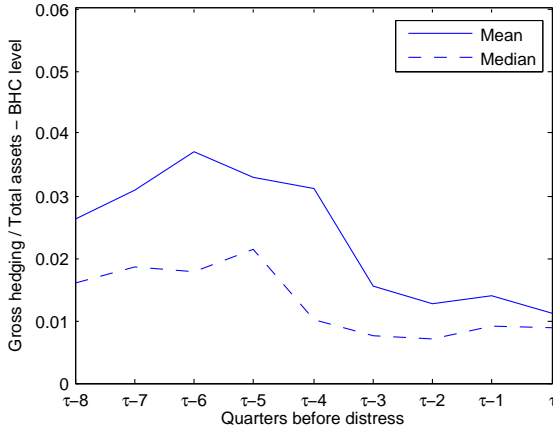


Figure 4: Hedging before distress events

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

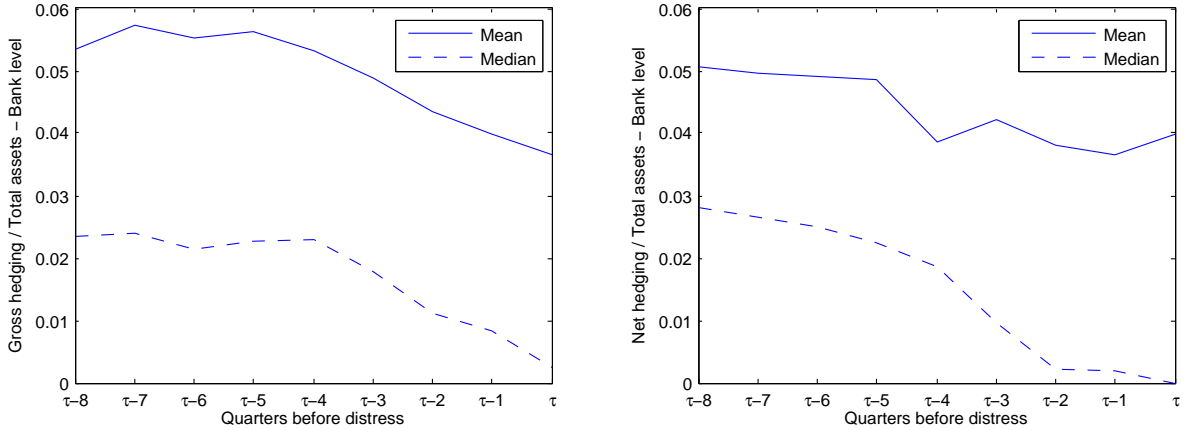


Figure 5: Decomposition of net income – BHC level

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.

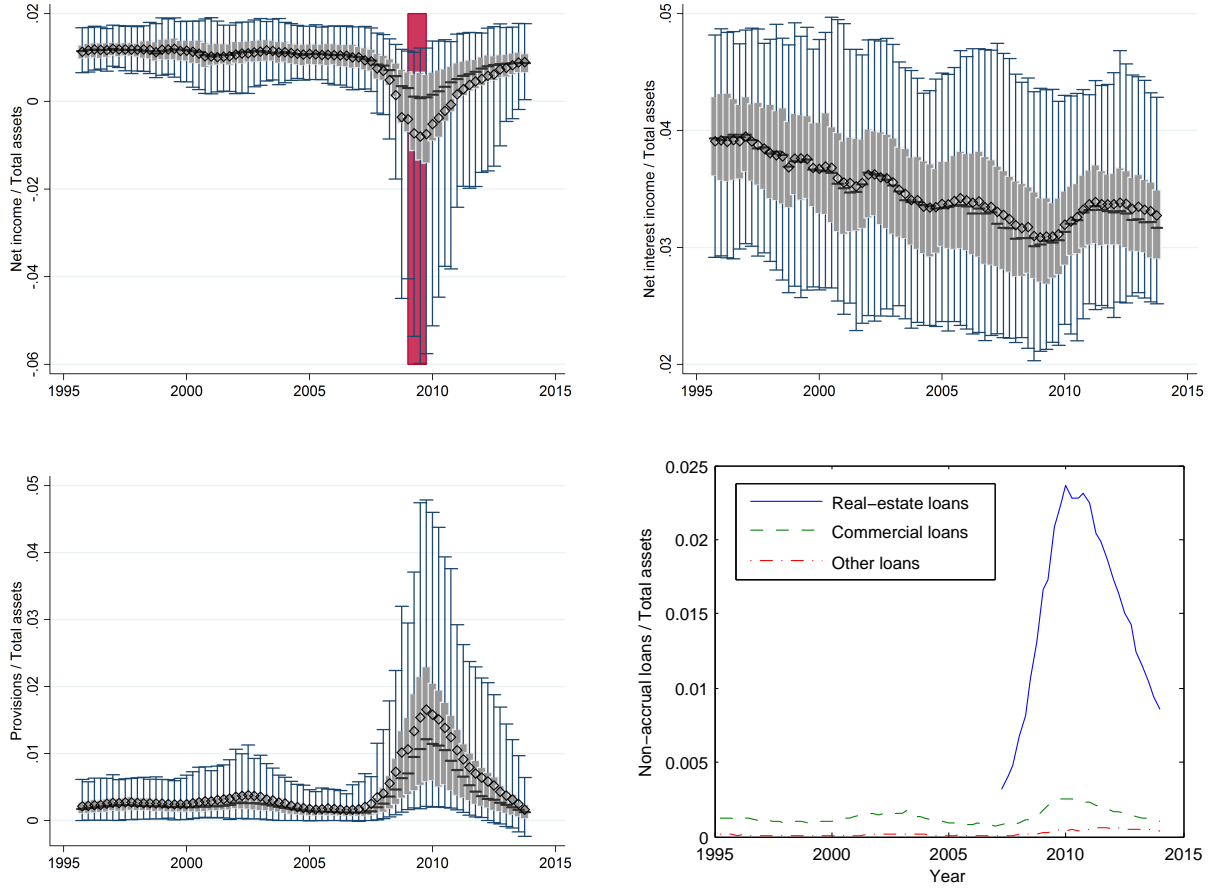


Figure 6: Effect of drop in net worth – Difference-in-differences – BHC level

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.

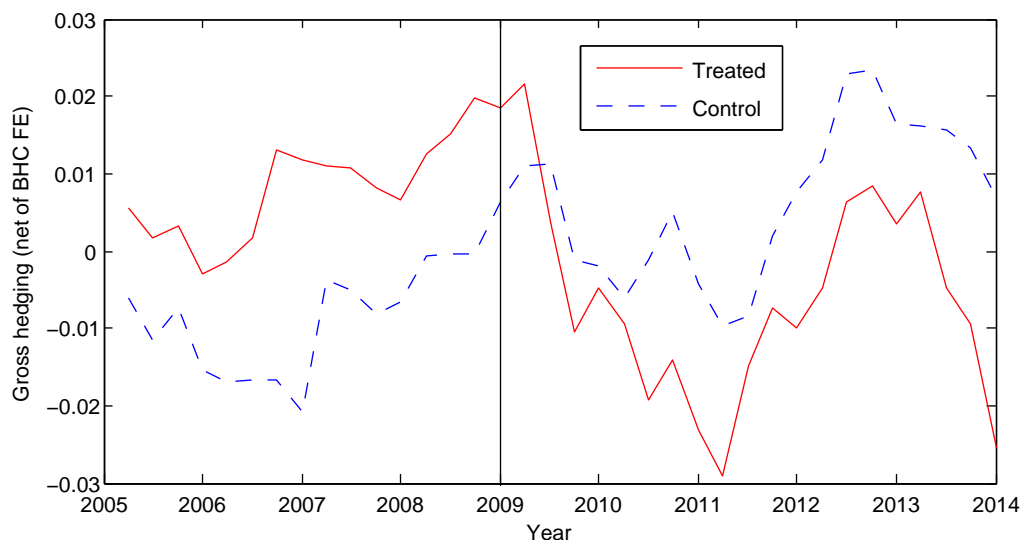


Figure 7: Maturity gap in treatment and control group – BHC level

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.

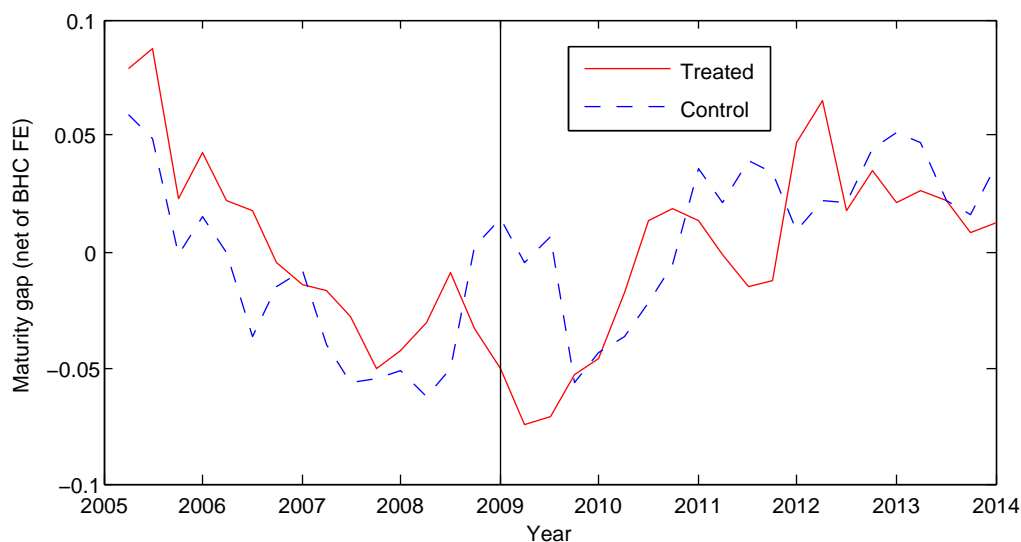
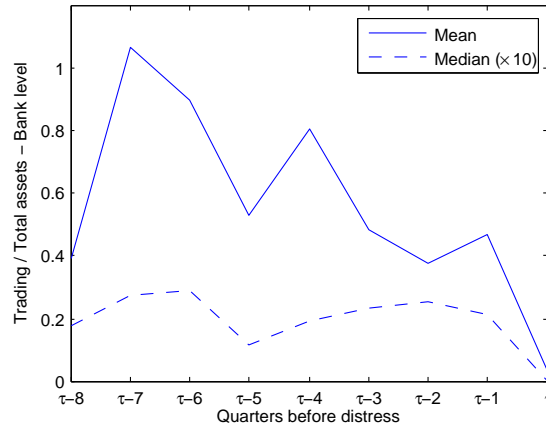


Figure 8: Trading and maturity gap before distress events

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

