## Essays in Financial Economics

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Essays in Financial Economics

A dissertation presented
by

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to

The Department of Economics

in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy
in the subject of
Economics

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Abstract

The chapters in this dissertation study the incidence of risk, risk taking, and the role of markets used to trade risk, with a focus on interest-rate risk. In Chapter 1, I ask why bank-dependent firms bear interest-rate risk. I argue that the short-term nature of banks’ own financing drives the extent to which bank-dependent firms bear interest-rate risk. In Chapter 2, I examine the implications of life insurers’ risk taking for theories of why financial institutions take risk. In Chapter 3, I argue that reference rates mitigate contractual incompleteness and facilitate risk sharing.
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Preface

The chapters in this dissertation study the incidence of risk, risk taking, and the role of markets used to trade risk, with a focus on interest-rate risk. I ask why certain kinds of institutions (for instance, certain types of non-financial firms) bear interest-rate risk. I ask what explains variation in financial institutions’ risk taking. I also study the transfer of risk through derivatives markets more broadly, asking how large these risk transfers are, what the limits to using derivatives to transfer risk are, and how derivatives markets should be designed.

In Chapter 1, I ask why bank-dependent firms bear interest-rate risk. Firms vary widely in the extent to which they are exposed to interest rates through floating-rate debt. I document that bank dependence is the key driver of this exposure: banks largely lend to firms at floating rates, which disproportionately affects firms that are more dependent on bank lending. In turn, I argue that banks lend to firms at floating rates because they themselves have floating-rate liabilities. Indeed, banks with more floating-rate liabilities make more floating-rate loans. To rule out the alternative interpretation that bank-dependent firms demand floating-rate loans, I show that banks with more floating-rate liabilities also hold more floating-rate securities (which would only add risk if banks found floating-rate loans risky), and quote lower prices for floating-rate loans relative to fixed-rate loans (which points to supply rather than demand, as these banks make more floating-rate loans). My results in this chapter establish an important link between the way financial intermediaries are funded and the types of contracts used by non-financial firms. They also highlight a role for banks in the Bernanke & Gertler (1995) balance-sheet channel of monetary policy.

In Chapter 2, I study risk taking by life insurers along two main dimensions: interest-rate risk and reaching for yield. Using detailed regulatory data, I construct comprehensive measures of risk taking along both dimensions. I document substantial heterogeneity in life insurer risk taking, and use it to shed light on different theories of risk taking. While I find evidence for risk shifting in aggregate, I show that it cannot fully explain insurer risk taking. In particular, I show that some of the largest and most levered insurers actually reduced
risk along both dimensions during and after the financial crisis. As these insurers heavily invested in private MBS pre-crisis and suffered large fair value losses during the crisis, this evidence suggests either that life insurers learned from the crisis, or that franchise value led them to reduce risk taking when in danger of failing. I also show that risk shifting was attenuated for insurers that had a poor crisis experience.

In Chapter 3, I ask what the precise role of reference rates is, and why it matters if they are manipulated. To address these questions, I analyze the use of reference rates in floating-rate loans and interest-rate derivatives in the context of lending relationships. I develop a simple framework combining maturity transformation with three key frictions which generate meaningful funding risk and a rationale for risk management. Reference rates like LIBOR mitigate contractual incompleteness, facilitating management of funding risk. As bank funding costs move with bank credit risk, in this context it makes sense for the reference rate to have a bank credit risk component. Manipulation can add noise, reducing the usefulness of reference rates for this purpose.
Chapter 1

Why do bank-dependent firms bear interest-rate risk?

1.1 Introduction

Firms vary widely in their exposure to interest-rate risk. I document that while some firms are largely financed with fixed-rate debt, others are primarily financed with floating-rate debt. The choice of interest-rate exposure matters in the presence of financial frictions: when rates rise, floating-rate debt creates cash-flow shocks that can have real effects on financially constrained firms’ investment (Fazzari, Hubbard & Petersen 1988, Froot, Scharfstein & Stein 1993, Stulz 2003). Why are some firms more exposed to floating rates than others? One view is that firms demand different levels of exposure to match the characteristics of their cash flows and assets. In this chapter, I focus on an alternative, supply-driven view that some firms – those that are dependent on banks for financing – borrow at floating rates because of the way banks themselves are financed. Banks offer floating-rate loans at lower cost because these loans help them match the interest-rate exposure of their own short-term liabilities.

Consistent with this supply-driven view, I document that bank dependence is the single dominant driver of firms’ use of floating debt. To show this, I combine detailed data
on firms’ debt structure from Capital IQ with manually collected data on their use of interest-rate swaps.\textsuperscript{1} Three facts point to bank dependence as the main driver of firms’ exposure to interest rates. First, the correlation between firms’ floating fraction of debt and the fraction of their debt from banks is high.\textsuperscript{2} Second, firms that borrow from banks appear bank dependent, rather than predisposed towards floating rates: they have poorer credit ratings and are smaller – and therefore are more likely to require bank monitoring (Rauh & Sufi 2010, Diamond 1984, Tirole 2006) – but they do not have more cyclical cash flows. Third, when these bank-dependent firms use interest-rate swaps, they use them to reduce exposure to short-term interest rate fluctuations, although only partially.

Why should bank dependence drive firms’ exposure to interest-rate risk? The answer lies in the observation that banking involves a fundamental maturity mismatch, as banks finance firms’ long-term projects with short-term, interest-bearing deposits.\textsuperscript{3} Because firms’ cash flows are only weakly correlated with interest rates, this leads to an interest-rate mismatch between firms’ output and banks’ liabilities.\textsuperscript{4} I use a simple model to show that banks prefer not to bear this mismatch themselves when external finance and hedging are both costly. Costly external finance makes banks effectively risk averse regarding asset-liability interest-rate mismatch (Froot et al. 1993, Stulz 2003).\textsuperscript{5} Moreover, as suggested in a growing literature (Rampini & Viswanathan 2010, Rampini, Viswanathan & Vuillemey 2015a, Rampini, Sufi &

\textsuperscript{1}I collect data on firms’ use of interest-rate swaps from SEC filings for a sample of almost 5,000 firm-years. Interest-rate swaps are the main derivative instrument non-financial firms use to hedge interest-rate risk.

\textsuperscript{2}In fact, most floating-rate debt is bank debt, and vice versa.

\textsuperscript{3}Bank lending to firms largely consists of term loans, which have similar maturities to corporate bonds, rather than short-term loans. Fixed interest rates on bank loans would therefore subject banks to interest-rate mismatch. Banks fund themselves with deposits despite this mismatch because deposits provide liquidity services, and are therefore cheap (Gorton & Pennacchi 1990, Gorton 2010, Diamond & Dybvig 1983, Stein 2012).

\textsuperscript{4}Floating rates also provide a way to write inflation-indexed contracts, which matters when inflation is volatile (one reason floating debt may be more common internationally). This is not relevant for the US where, at least in recent decades, inflation has been low and stable, and changes in nominal rates correspond with changes in real rates. I show that US firms’ cash flows, on average, are only slightly dependent on interest rates. Moreover, bank-dependent firms do not have more cyclical cash flows.

\textsuperscript{5}Banks behave as if they are highly risk averse: bank net interest margins have historically been very stable, despite significant leverage (Flannery 1981, English 2002, English, Van den Heuvel & Zakrajšek 2013). This literature focuses on commercial banks – the 1980s S&L crisis illustrates that interest-rate risk can matter for banking institutions.
Viswanathan 2014, Ivashina, Scharfstein & Stein 2015, Bolton & Oehmke 2015), collateral requirements make hedging costly, preventing banks from using derivatives to fully hedge exposure to interest rates.\textsuperscript{6} This combination of frictions pushes banks to manage risk, in part, by managing the interest-rate exposure of their loans. Firms more dependent on bank lending are thus disproportionately affected.

A key implication of this framework, in which banks’ liability structure drives the interest-rate exposure of their assets, is that banks with more floating-rate liabilities should make more floating-rate loans. I use variation in the degree to which banks pass through changes in short-term interest rates to depositors to test this hypothesis. Banks with greater deposit pass-through do indeed make more floating-rate loans; a bank with one standard deviation higher deposit pass-through extends four percentage points more of its loans at floating rates.\textsuperscript{7} One natural concern is that banks endogenously position their liabilities to match the characteristics of their assets. I partially address this concern by showing that my findings are robust to ‘instrumenting’ for deposit pass-through with measures of deposit competition; the component of deposit liabilities explained by competition also helps explain the extent to which banks make floating-rate loans.\textsuperscript{8,9}

Some identification concerns do remain, as banks with more floating liabilities might also make more floating-rate loans if they match with borrowers that demand them. My results

\textsuperscript{6}I model the opportunity cost of collateral as reduced investment in projects with concave returns, which leads to convex costs of hedging, following Ivashina et al. (2015). Convex collateral costs of hedging, which apply to firms as well as banks, explain why bank-dependent firms have more post-hedging exposure to interest rates than firms with better access to capital markets, even though both sets of firms use swaps. The chapter therefore connects with the empirical literature on how firms (Campbell & Kracaw 1993, Chernenko & Faulkender 2011, Bretscher, Mueller, Schmid & Vedolin 2015, Bicksler & Chen 1986, Tufano 1996, Guay & Kothari 2003, Bodnar, Graham, Harvey & Marston 2011) and banks (Begenau, Piazzesi & Schneider 2015, Rampini et al. 2015) use derivatives.

\textsuperscript{7}While I mostly focus on cross-sectional evidence, I also document time series evidence: within-bank variation in deposit pass-through also drives the interest-rate exposure of bank assets.

\textsuperscript{8}I use branch level data on bank deposits to calculate measures of deposit concentration, following Drechsler, Savov & Schnabl (2014), as well as an older literature (Berger & Hannan 1989, Neumark & Sharpe 1992).

\textsuperscript{9}I also show that when term spreads are high, a smaller fraction of bank deposits mature/reprice in one year, i.e. deposits become less floating. This is not consistent with the view that banks’ adjust their liabilities to match their assets: more ARMs than FRMs are issued when term spreads are high (Koijen, Van Hemert & Van Nieuwerburgh 2009), i.e. assets become more floating.
highlighting deposit competition as a source of variation in deposit pass-through may not fully address these concerns if, for example, firms demanding floating rates are concentrated in areas with more deposit competition. However, examining banks’ securities holdings allows me to rule out this alternative interpretation as the demand- and supply-driven views have opposing predictions regarding securities. In the supply-driven view, banks with higher deposit pass-through should hold more floating-rate securities, in addition to making floating-rate loans, to reduce asset-liability mismatch. In contrast, banks facing higher demand for floating-rate loans should hold more fixed-rate securities to reduce mismatch. With both OLS and IV regressions, I show that banks with more deposit pass-through hold more floating-rate securities. This fact is at odds with the view that banks with greater deposit pass-through match with firms demanding floating rates.\(^{10}\)

Variation in prices (interest rates on loans) further supports the supply-driven view: banks with more deposit pass-through quote larger interest-rate spreads between fixed-rate mortgages and adjustable-rate mortgages (larger FRM-ARM spreads).\(^{11}\) This means that banks with more floating liabilities hold higher quantities of floating-rate loans, at lower interest rates (lower prices), relative to fixed-rate loans. The cross-sectional combination of higher quantities and lower prices points to variation in supply rather than demand. In summary, evidence from three quite different parts of bank balance sheets (loans to firms, mortgages and securities) shows that the structure of bank liabilities drives floating-rate bank lending to firms.\(^{12}\)

Historical data provides additional evidence of the relationship between banks’ liabilities and the interest-rate exposure of their assets. Prior to about 1970, deposits were largely non-

\(^{10}\)I focus on securities not backed by standardized housing collateral, which largely consist of Treasury and Agency bonds, for which the US market is national.

\(^{11}\)A one standard deviation increase in deposit pass-through is associated with an eight basis point increase in FRM-ARM spreads. Banks may also use non-price channels (rationing or exclusion) to adjust their loan mix, as Foà, Gambacorta, Guiso & Mistrulli (2015) argue Italian banks do.

\(^{12}\)I show that supply shocks are more important than demand shocks in explaining cross-sectional variation in outcomes, analogously to the seminal work of Working (1927). In Appendix A.1.2, I outline a framework to think about the relative importance of supply and demand based on the correlation between the floating fractions of loans and securities, using equilibrium expressions for these fractions from the model.
interest-bearing, and hence also effectively fixed rate. In this period, floating-rate lending, and not fixed-rate lending, would have been risky for banks. If loans were nevertheless extended primarily at floating rates, this would suggest a different explanation for floating-rate bank lending more recently. Consistent with my argument, I show that in this period implied interest rates on loans were far less sensitive to short-term interest rates than they are today, suggesting that loans were effectively less floating.\footnote{I calculate implied loan interest rates as interest income on loans and leases scaled by net loans and leases.}

My results have implications for how monetary policy is transmitted to firms: bank-dependent firms’ exposure to floating rates is a component of the Bernanke & Gertler (1995) balance-sheet channel of monetary policy. Bernanke & Gertler (1995) show that firms’ financial health weakens when rates rise, as interest expense rises relative to cash flows, and connect this to the effect of monetary policy on business fixed investment. They focus on the interest expense of commercial paper issued by large investment-grade firms. I show that interest expense rises more directly for bank-dependent firms when rates rise, because of their floating-rate bank loans.\footnote{This does not necessarily imply that floating-rate loans are bad for bank-dependent firms in all circumstances. Floating-rate bank loans may provide a natural hedge for bank-dependent firms if they tend to be more financially constrained at times when central banks are likely to lower rates. Of course, when interest rates rise, these firms face higher interest expense. Bank-dependent firms do use derivatives to partially hedge their exposure, suggesting that they are concerned about the potential costs of floating-rate debt.} My results show that banks play a role in the transmission of monetary policy to firms beyond the usual bank-lending channel (Kashyap & Stein 1994, Kashyap & Stein 2000, Peek & Rosengren 2013) or the more recent deposits channel (Drechsler et al. 2014), as my effect is based on existing rather than new bank lending.\footnote{This channel is therefore more analogous to the role of ARMs documented by Di Maggio, Kermani & Ramcharan (2015), Keys, Piskorski, Seru & Yao (2014), Auclert (2015), Sufi (2015) and Calza, Monacelli & Stracca (2013).}

In complementary work, Ippolito, Ozdagli & Perez (2015) also connect floating-rate bank lending to monetary policy, but do not explain why bank debt is floating rate.

My argument that bank liabilities drive floating-rate bank lending to firms adds to the intermediation literature. It establishes an important link between intermediaries’ funding...
structure and the types of contracts used by non-financial firms. In aggregate, a significant fraction of bank assets are floating rate, and banks do not appear to face significant asset-liability interest-rate mismatch.\textsuperscript{16} I show that banks achieve this, at least in part, by passing interest-rate risk on to firms. Two recent papers advance related arguments: Ivashina et al. (2015) argue that hedging frictions make it advantageous for banks to lend in the same currency as their deposit financing.\textsuperscript{17} Hanson, Shleifer, Stein & Vishny (2014) argue that the types of assets intermediaries hold depend on the stability of their funding. More broadly, my argument is also connected with the view that there are synergies between deposits and commitments (Kashyap, Rajan & Stein 2002), and that intermediaries must themselves be incentivized to monitor (Diamond 1984, Holmström & Tirole 1998). This chapter highlights the impact of the interest-rate exposure of intermediaries’ funding structure on the types of contracts used by non-financial firms.

My results are of particular policy interest given renewed regulatory interest in banks’ exposure to interest rates.\textsuperscript{18} This chapter suggests that loans to firms reduce interest-rate risk for banks, at the cost of passing it on to bank-dependent firms. Tighter regulation of banks’ exposure to interest rates may have therefore unintended effects: it might lead banks to pass on more risk to bank-dependent firms than they do already.

The remainder of the chapter is organized as follows: Section 1.2 shows that bank-dependent firms are exposed to interest rates through floating-rate bank loans. Section 1.3 lays out the theoretical framework, and highlights testable implications for bank balance sheets. Section 1.4 presents the main empirical results. It shows that banks with more floating liabilities make more floating-rate loans, hold more floating-rate securities, and quote larger FRM-ARM spreads, establishing that the structure of banks’ liabilities affects

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\textsuperscript{16}About 40% of all loans and securities are reported to be floating rate as of 2014Q4, including instruments providing mortgage credit where long-term fixed-rate loans are common. Roughly 60% reprice or mature within three years.

\textsuperscript{17}Rajan (2012) argues that domestic banks passed currency risk on to firms during the asian financial crisis.

\textsuperscript{18}Central banks, particularly in the US and UK, are now considering raising interest rates for the first time in almost a decade, prompting regulatory concern about the possible effect of rate increases on banks. To take two examples, the Basel Committee on Banking Supervision is promulgating new regulations regarding interest-rate risk, and BIS argues in its Annual Report that banks’ exposure to interest-rate risk is growing.
the choices they make about interest-rate exposure on the asset side. It also presents several additional results supporting this supply-driven explanation of floating-rate bank lending to firms. Section 1.5 draws out the implications of my results for monetary policy. Section 1.6 concludes.

1.2 Firms’ exposure to interest-rate risk

This section describes variation in firms’ exposure to interest-rate risk through their debt. I show that firms with poorer credit ratings and smaller firms are more exposed, through bank debt. Several features of this variation suggest it is driven by bank dependence rather than preference for floating-rate debt, in particular that bank debt is the primary driver of variation in firms’ exposure. I begin by describing my data on firms’ capital structure, including manually collected data on firms’ use of interest-rate swaps, and then move on to the facts on firms’ exposure.

I construct a comprehensive data set on firms’ capital structure, augmenting standard balance sheet data from Compustat with detailed data on firms’ debt structure from Capital IQ and manually collected data on firms’ use of swaps. The novel aspect of Capital IQ data is that it provides information on whether debt is fixed or floating rate, at the instrument level. I aggregate instrument level information to the firm level to directly analyze sources of floating-rate debt. I restrict the analysis to firms headquartered in the United States. The data is annual, going from 2003-2013, with about 13,500 firm-year observations, for about 2,200 firms. Appendix A.2.1 describes the data construction process and variable definitions in detail. I also manually collect quantitative data on how firms use interest-rate swaps from SEC filings. The data on swaps covers almost 5,000 firm-year observations, for around 600 firms. Appendix A.2.2 describes the data collection process.

These sources do also provide data internationally. Internationally, however, floating-rate debt is also used because it is effectively inflation-indexed. This aspect of floating-rate debt is not the focus of this chapter. See Campbell (2013) for a discussion of the role of historical inflation patterns in shaping mortgage markets.

I thank Adi Sunderam and Sergey Chernenko for sharing their data, which constitutes a fraction of this sample. I collect additional data on usage of interest-rate swaps. Out of the 571 firms in my sample, 381 (two
I begin with summary statistics, showing the relevance of floating-rate debt and bank debt, and that firms’ cash flows are only weakly cyclical. Panel A of Table 1.1 shows summary statistics for the full sample. Floating-rate debt and bank debt are important parts of firms’ capital structure, comprising 38% and 43% of firms’ debt respectively. Leverage, measured by the ratio of debt to assets, is on average 33%.\textsuperscript{21} I measure the cyclicity of firms’ cash flows with a cash-flow beta.\textsuperscript{22} On average, firms have slightly positively cyclical cash flows.\textsuperscript{23} Panel B shows summary statistics for the sub-sample of firms for which I have information on derivatives. Firms in this sample are larger on average, and have slightly less bank debt.

While investment grade and large firms are primarily funded with fixed-rate corporate bonds, firms with poor credit ratings and smaller firms borrow more through floating-rate bank term loans. Figure 1.1 shows average debt capital structure as a fraction of debt. Panel A divides firms by credit rating. Investment grade firms borrow primarily via fixed-rate corporate bonds (this is the omitted category). They also borrow using short-term commercial paper to some extent, and are the only types of firms to do so.\textsuperscript{24} Firms rated as speculative, or unrated, borrow more from banks. Panel B shows firms by size tercile (assigned within year). Small firms also borrow more from banks. Importantly, this bank debt is largely extended at floating rates, with interest rates typically reset every three thirds) use interest-rate swaps at some point. Interest-rate swaps are the main instrument non-financial firms use to hedge interest-rate risk. Firms do also mention interest rate caps and, in rare instances, other instruments in their SEC filings. To my knowledge, Chernenko & Faulkender (2011) and Bretscher et al. (2015) are the only other authors to have collected a panel of this type, the former for a period for which Capital IQ data is not available, and the latter for S&P500 firms, which are less bank dependent. Several authors including Ippolito et al. (2015) have performed text searches to separate users of derivatives from non-users.

\textsuperscript{21}While this level of leverage is typical in recent years, Graham, Leary & Roberts (2014) document that corporate leverage was significantly lower up to the 1950s.

\textsuperscript{22}This is a coefficient from firm level regressions of operating income before depreciation, as a fraction of assets, on LIBOR. As is appropriate, I use a measure of cash flow before interest expense is taken into account. Estimating the beta with regressions in changes produces the same qualitative results.

\textsuperscript{23}On average, cash flows rise by about 20 basis points as a fraction of assets when LIBOR rises by 1 percentage point. The corresponding fraction for the median firm is 10 basis points.

\textsuperscript{24}Rauh & Sufi (2010) and Colla, Ippolito & Li (2013) also present facts about variation in firms’ debt structure: large firms with poor credit ratings tend to use several types of debt, while very well rated or unrated firms tend to use only corporate bonds and bank debt respectively.
Table 1.1: Summary statistics for sample of firms

Notes: The sample combines balance sheet data from Compustat for firms headquartered in the USA, debt capital structure details from Capital IQ and ratings from S&P. I exclude financial firms and utilities in the Fama & French (1997) 12 industry classification. The data is annual, and goes from 2003-2013. I require debt reported by Capital IQ and Compustat to be within 10% of each other, and variable and fixed-rate debt to total to within 10% of Capital IQ debt, for at least half of the observations at the firm level. I exclude observations where the fraction of floating or bank debt is greater than 110%, or where the debt/assets ratio is greater than 120%. Ratios to debt and assets and cash-flow beta are winsorized at the 1% level on both sides. See Appendices A.2.1 and A.2.2 for more details. Panel A shows summary statistics for the full sample. I also collect data on usage of interest-rate swaps for SEC filings. Panel B shows summary statistics for the sub-sample where this data is available.

Panel A: Full sample

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets (MM)</td>
<td>976.0</td>
<td>4,567.2</td>
<td>23,936.6</td>
</tr>
<tr>
<td>Floating Fraction</td>
<td>30.3</td>
<td>38.3</td>
<td>34.6</td>
</tr>
<tr>
<td>Bank Fraction</td>
<td>36.2</td>
<td>42.7</td>
<td>37.5</td>
</tr>
<tr>
<td>Debt/Assets</td>
<td>29.5</td>
<td>33.1</td>
<td>21.6</td>
</tr>
<tr>
<td>LTD/Debt</td>
<td>93.9</td>
<td>80.9</td>
<td>27.9</td>
</tr>
<tr>
<td>CAPX/Assets</td>
<td>3.4</td>
<td>5.8</td>
<td>7.0</td>
</tr>
<tr>
<td>RD/Assets</td>
<td>0.0</td>
<td>2.1</td>
<td>5.2</td>
</tr>
<tr>
<td>CF Beta</td>
<td>0.1</td>
<td>0.2</td>
<td>3.0</td>
</tr>
<tr>
<td>Firm-Years</td>
<td>13,400</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firms</td>
<td>2,186</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Derivatives sub-sample

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets (MM)</td>
<td>1,526.8</td>
<td>4,325.6</td>
<td>10,490.5</td>
</tr>
<tr>
<td>Floating Fraction</td>
<td>26.9</td>
<td>34.9</td>
<td>32.2</td>
</tr>
<tr>
<td>Bank Fraction</td>
<td>30.4</td>
<td>38.2</td>
<td>35.2</td>
</tr>
<tr>
<td>Net Pay Fixed</td>
<td>0.0</td>
<td>6.1</td>
<td>22.3</td>
</tr>
<tr>
<td>Post-Hedge Floating</td>
<td>22.9</td>
<td>28.8</td>
<td>31.1</td>
</tr>
<tr>
<td>Post-Hedge Floating/Assets</td>
<td>6.7</td>
<td>10.2</td>
<td>12.9</td>
</tr>
<tr>
<td>Firm-Years</td>
<td>4,846</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firms</td>
<td>571</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

months.25 This is not mechanical: bank lending substantially consists of term loans, which, unlike short-term debt, do not have to be floating rate. Indeed, bank loans and corporate

25Most floating-rate bank debt is indexed to the three month tenor of LIBOR, with rates actually resetting every three months. Occasionally, other tenors are used, and some loan contracts allow firms to choose the reset frequency (out to about one year).
Panel A: Debt by firm rating

Panel B: Debt by firm size

Notes: The data is annual, and goes from 2003-2013. See Appendix A.2.1 for more details. The figure shows types of debt (revolving loans, term loans, commercial paper and floating-rate bonds) as a fraction of debt (value weighted). Term loans are separated into fixed and floating rate. The remainder of the debt (not shown) is primarily fixed-rate bonds. Panel A shows capital structure by rating. Panel B shows capital structure for firms sorted into size tercile by year.

Figure 1.1: Debt structure by rating and size

Bank debt is the primary driver of firm level variation in firms’ exposure to interest rates through debt. I present results from firm level regressions in Table 1.2 to show this (Appendix A.2.1 provides variable definitions). I begin with cross-sectional analysis, collapsing the sample to means at the firm level. The outcome variable is the fraction of debt that is floating rate (including commercial paper). The single most important determinant of how much of a non-financial firm’s debt is floating rate is how much of its debt is bank debt. This variable alone leads to an $R^2$ of close to 50%.

Adding various other variables

---

26 In unreported analysis, I show that, in most years, the median dollar of a bank loan in my data is part of a five year term loan.

27 In my data, about 75-80% of bank loans to firms are floating rate. The Federal Reserve Board’s E2 survey, available on the Board’s website, provides another data point on this. It shows that in the past 15-20 years, about 70-80% of new C&I lending has maturity or repricing date less than one month, while the vast majority of such lending has maturity or repricing interval less than one year (Vickery 2005). Ippolito et al. (2015) also
leads to a negligible improvement in model fit. Table 1.2 also shows that bank debt is the primary driver of this variation in the time series, using regressions with firm fixed effects.28

Table 1.2: Determinants of floating debt

Notes: The data is annual, and goes from 2003-2013. See Appendix A.2.1 for more details. The outcome variable is the fraction of debt that is floating. Debt rated is a dummy variable for whether the firm has any rating (for long-term debt or short-term debt) in the year. Ratios with assets and debt are defined based on Compustat variables. Cash-flow beta is the regression coefficient of operating income before depreciation on LIBOR. Swap spread is the 5Y swap - Treasury spread, and the term spread is 5Y - 1Y treasury yield. Floating debt and bank fraction are in percentage points. ln(assets), ratios to debt and assets, and cash-flow beta are winsorized at the 1% level on both sides. These variables and interest rate conditions are normalized to have unit variance. ‘Collapsed’ specifications collapse the sample to means at the firm level. Specifications with firm fixed effects restrict to firms with at least 5 years of data, with standard errors double clustered by firm and year. t-statistics are shown in parentheses to the right.

<table>
<thead>
<tr>
<th></th>
<th>Collapsed Floating Fraction</th>
<th>Collapsed Floating Fraction</th>
<th>Firm FE Floating Fraction</th>
<th>Firm FE Floating Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank Fraction</td>
<td>0.60 (46.13)</td>
<td>0.57 (38.98)</td>
<td>0.73 (42.47)</td>
<td>0.71 (39.82)</td>
</tr>
<tr>
<td>Debt rated</td>
<td>-4.53 (-3.23)</td>
<td>-3.12 (-2.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Debt/Assets</td>
<td>2.21 (4.27)</td>
<td>-0.03 (-0.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intangible/Assets</td>
<td>2.04 (3.96)</td>
<td>1.16 (1.46)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RD/Assets</td>
<td>-0.84 (-2.21)</td>
<td>-0.87 (-0.74)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Assets)</td>
<td>0.03 (0.04)</td>
<td>1.68 (0.98)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPX/Assets</td>
<td>0.33 (0.60)</td>
<td>0.51 (1.16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LTD/Debt</td>
<td>-0.84 (-1.46)</td>
<td>-0.71 (-1.73)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CF Beta</td>
<td>-0.09 (-0.28)</td>
<td>-0.32 (-1.57)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Swap Spread</td>
<td>0.56 (2.88)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Term Spread</td>
<td></td>
<td>-0.32 (-1.57)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.49</td>
<td>0.51</td>
<td>0.74</td>
<td>0.75</td>
</tr>
<tr>
<td>Firm-Years</td>
<td>13,400</td>
<td>13,400</td>
<td>11,363</td>
<td>11,363</td>
</tr>
<tr>
<td>Firms</td>
<td>2,186</td>
<td>2,186</td>
<td>1,404</td>
<td>1,404</td>
</tr>
</tbody>
</table>

Firms’ use of floating-rate debt is not systematically related to the cyclicality of their cash flows. This is not consistent with the demand-driven view that firms take on exposure to interest rates to match the characteristics of their cash flows. If firms chose floating-rate debt to match greater cash-flow sensitivity to interest rates, cash-flow betas would be strongly

note that most bank debt is floating rate, while other forms of debt are largely fixed rate. This pattern likely also holds internationally: for instance Becker, Bos & Roszbach (2015) document that Swedish banks effectively lend largely at floating rates.

28In specifications with firm fixed effects, I double cluster standard errors by firm and year, following Thompson (2011). This accounts for correlation across years within firm, as well as correlation across firms within year.
positively related to the floating fraction of debt. However, as Table 1.2 shows, co-movement of firms’ cash flows with interest rates is not meaningfully related to the fraction of floating debt in the cross section. These firms are likely to have bank debt not because of its floating rate nature, but because they need bank financing.

1.2.1 Credit rating, firm size and hedging

Through a combination of greater initial exposure, partial hedging, and more leverage, firms with poor credit ratings and smaller firms are more exposed to interest-rate risk than investment grade and larger firms. There is a noticeable increase in exposure around the investment grade cutoff, supporting the idea that bank dependence is a key driver.

Firms with poorer credit ratings and smaller firms have more floating-rate debt, both as a fraction of debt and as a fraction of assets. I begin with the full sample of firms, initially focusing on exposure before hedging. Panel A of Table 1.3 first shows regressions for firms separated by credit rating, including dummies for high yield and unrated firm-years (investment grade firm-years are the omitted category). There are three outcome variables: floating-rate debt as a fraction of debt, the debt to assets ratio, and floating-rate debt as a fraction of assets. Relative to investment grade firms, high yield and unrated firms have more floating-rate exposure, both as a fraction of debt and as a fraction of assets. Panel A also shows that smaller firms have more exposure, in similar regressions separating firms into three categories by size.

I plot exposure for firms separated into credit rating groups, to visually depict the importance of credit rating. I categorize firms into six coarse rating groups ranging from GG to U. Groups labeled IG and HY combine the three closest ratings on either side of the investment grade/high yield cutoff. Figure 1.2 looks at exposure before the impact of hedging. Panels A and B show floating debt as a fraction of debt and assets respectively. By

29The relationship is also not statistically significant if I estimate a cash-flow beta based on operating income net of capital expenditure, following Chernenko & Faulkender (2011).

30I continue to double cluster standard errors by firm and year.
Table 1.3: Risky, small firms bear more interest-rate risk

Notes: The data is annual, and goes from 2003-2013. See Appendix A.2.1 for more details. The outcome variables are the floating fraction of debt (V/D), the debt/assets ratio (D/A) and floating debt as a fraction of assets (V/A). In Panel A, specifications on the left show firms separated by rating, where the omitted category is investment grade (IG) firms. Specifications on the right show firms separated by size, based on size terciles assigned within fiscal year, where the omitted category is large firms. Panel B shows regressions with the same outcome variables, but restricting the sample to the two ratings closest to the IG/HY cutoff, and including industry and year fixed effects. Standard errors are double clustered by firm and year. \( t \)-statistics are shown in parentheses.

### Panel A: Split by rating and size

<table>
<thead>
<tr>
<th>Rating</th>
<th>Size</th>
<th>V/D</th>
<th>D/A</th>
<th>V/A</th>
<th>V/D</th>
<th>D/A</th>
<th>V/A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td></td>
<td>18.33</td>
<td>26.27</td>
<td>4.91</td>
<td>25.98</td>
<td>33.65</td>
<td>9.77</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(10.52)</td>
<td>(37.09)</td>
<td>(10.47)</td>
<td>(14.22)</td>
<td>(39.56)</td>
<td>(12.10)</td>
</tr>
<tr>
<td>High Yield</td>
<td></td>
<td>14.43</td>
<td>19.01</td>
<td>10.78</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(8.23 )</td>
<td>(19.84)</td>
<td>(12.25)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unrated</td>
<td></td>
<td>29.74</td>
<td>1.67</td>
<td>8.87</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(20.20)</td>
<td>(1.75 )</td>
<td>(20.51)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>13.07</td>
<td>3.23</td>
<td>5.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(10.63)</td>
<td>(3.45 )</td>
<td>(8.46)</td>
</tr>
<tr>
<td>Small</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>23.81</td>
<td>-4.91</td>
<td>4.32</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(15.46)</td>
<td>(-4.82)</td>
<td>(5.58)</td>
</tr>
<tr>
<td>SE Clustered By</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
</tr>
<tr>
<td>R²</td>
<td></td>
<td>0.11</td>
<td>0.15</td>
<td>0.06</td>
<td>0.08</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Firm-Years</td>
<td></td>
<td>13,400</td>
<td>13,400</td>
<td>13,400</td>
<td>13,400</td>
<td>13,400</td>
<td>13,400</td>
</tr>
<tr>
<td>Firms</td>
<td></td>
<td>2,186</td>
<td>2,186</td>
<td>2,186</td>
<td>2,186</td>
<td>2,186</td>
<td>2,186</td>
</tr>
</tbody>
</table>

### Panel B: Restricted to BBB- and BB+ firms

<table>
<thead>
<tr>
<th></th>
<th>V/D</th>
<th>D/A</th>
<th>V/A</th>
</tr>
</thead>
<tbody>
<tr>
<td>BB+</td>
<td>7.28</td>
<td>3.78</td>
<td>3.15</td>
</tr>
<tr>
<td></td>
<td>(2.79)</td>
<td>(2.45)</td>
<td>(3.35)</td>
</tr>
<tr>
<td>Industry FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SE Clustered By</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
<td>Firm,Y</td>
</tr>
<tr>
<td>R²</td>
<td>0.07</td>
<td>0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>Firm-Years</td>
<td>1,057</td>
<td>1,057</td>
<td>1,057</td>
</tr>
<tr>
<td>Firms</td>
<td>273</td>
<td>273</td>
<td>273</td>
</tr>
</tbody>
</table>

both measures, there is a noticeable jump in exposure at the cutoff. Note that firms with the best credit ratings have exposure primarily through commercial paper.

Firms’ exposure to floating rates jumps significantly at the cutoff between investment
Panel A: Floating debt/Debt  
Panel B: Floating debt/Assets

Notes: The data is annual, and goes from 2003-2013. See Appendix A.2.1 for more details. This figure separates firms into 6 rating categories, going from ‘very good rating’ to unrated. IG combines the lowest three rating categories that fall within investment grade (BBB+, BBB, BBB-), and HY combines the highest three rating categories that fall within high yield (BB+, BB, BB-). Panel A shows the fraction of debt that is floating, in percentage points. Panel B shows floating debt as a fraction of assets, in percentage points. Standard errors are shown based on the standard deviation within each category.

Figure 1.2: Exposure to interest rates by credit rating

grade and high yield ratings. Panel B of Table 1.3 restricts the sample to firms with the lowest investment grade rating (BBB-) or the highest high yield rating (BB+). I include a dummy for BB+ firms; BBB- firms are the omitted category. Relative to BBB- firms, BB+ firms have more floating debt both as a fraction of debt and as a fraction of assets. They also have more leverage. These patterns are consistent across year and industry: indeed, these regressions include both industry and year fixed effects. This likely reflects that institutions such as insurance companies and pension funds frequently have requirements to invest in, or strong preferences for, investment grade bonds.31

While firms do hedge their exposure partially, firms with poorer credit ratings and smaller firms continue to have more exposure to floating rates even after taking hedging

31In addition to a preference for low credit-risk exposure, this institutions do of course have a preference for assets providing significant duration exposure.
into account. Table 1.4 shows how exposure to interest rates varies with rating and size post-hedging (Panel A splits firms by rating, and Panel B by size). These regressions show five outcome variables: the floating fraction of debt, net pay-fixed interest-rate swaps as a fraction of debt, post-hedging floating fraction of debt, the debt to assets ratio and post-hedging floating debt as a fraction of assets. Panel A of Table 1.4 shows that both high yield and unrated firms have more exposure to interest rates, through a combination of more floating debt, partial hedging, and for high yield firms, greater leverage. Investment grade firms use swaps to increase their exposure to interest rates. A comparison with Panel A of Table 1.3 shows that the post-hedging difference in net floating-rate debt as a fraction of assets is roughly half the pre-hedging difference. Panel B of Table 1.4 shows that, like poorly rated firms, smaller firms also have more exposure to interest rates than large firms.

I also plot firms’ exposure within the hedging sample to visually depict that firms do hedge, but only partially. Figure 1.3 shows firms separated into the same six ratings groups as in Figure 1.2. Panel A of Figure 1.3 shows floating debt as a fraction of debt (pre-hedging for comparability). Panel B shows floating-rate debt, post hedging, as a fraction of assets. A comparison with Panel B of Figure 1.2 shows again that firms with poorer credit ratings do hedge towards levels of exposure faced by better rated firms, but only partially. There is a noticeable jump in post hedging exposure for firms at the investment grade/high yield cutoff.

To summarize, bank-dependent firms, i.e. firms with poor credit ratings and small

---

32 Firms often use interest-rate derivatives to modify their exposure, principally interest-rate swaps. As discussed above, I manually collect data on usage of interest-rate swaps from SEC filings for about 40% of the relevant sample.

33 This pattern has been anecdotally discussed in the literature for some time, with varying interpretations (Bicksler & Chen 1986, Titman 1992). As Bretscher et al. (2015) focus on S&P 500 firms, they find that firms choose pay floating swaps in their sample.

34 This initial exposure is very similar to the full sample (Panel A of Figure 1.2), with the exception of firms with the best ratings – the derivatives sample contains fewer firms with significant commercial paper borrowings.
Table 1.4: Risky, small firms bear more interest-rate risk post-hedging

Notes: The data is annual, and goes from 2003-2013. These regressions are for the derivatives sub-sample. See Appendices A.2.1 and A.2.2 for more details. The outcome variables are the floating fraction of debt (V/D), net pay fixed swaps as a fraction of debt (NPF/D), post-hedging floating fraction of debt (V-NPF/D), the debt/assets ratio (D/A) and post-hedging floating debt as a fraction of assets (V-NPF/A). Panel A shows firms separated by rating, where the omitted category is investment grade (IG) firms. Panel B shows firms separated by size, based on size terciles within fiscal year, where the omitted category is large firms. Standard errors are double clustered by firm and year. t-statistics are shown in parentheses.

Panel A: Split by rating

<table>
<thead>
<tr>
<th></th>
<th>V/D</th>
<th>NPF/D</th>
<th>(V-NPF)/D</th>
<th>D/A</th>
<th>(V-NPF)/A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>18.28</td>
<td>-5.07</td>
<td>23.35</td>
<td>27.27</td>
<td>6.44</td>
</tr>
<tr>
<td></td>
<td>(10.77)</td>
<td>(-3.43)</td>
<td>(9.70)</td>
<td>(25.53)</td>
<td>(10.32)</td>
</tr>
<tr>
<td>High Yield</td>
<td>13.95</td>
<td>13.74</td>
<td>0.21</td>
<td>19.94</td>
<td>4.95</td>
</tr>
<tr>
<td></td>
<td>(5.95 )</td>
<td>(8.58 )</td>
<td>(0.09)</td>
<td>(13.43)</td>
<td>(6.37)</td>
</tr>
<tr>
<td>Unrated</td>
<td>28.42</td>
<td>13.58</td>
<td>14.84</td>
<td>0.69</td>
<td>4.07</td>
</tr>
<tr>
<td></td>
<td>(11.71)</td>
<td>(8.50)</td>
<td>(5.61)</td>
<td>(0.45)</td>
<td>(5.02)</td>
</tr>
</tbody>
</table>

SE Clustered By: Firm,Y Firm,Y Firm,Y Firm,Y Firm,Y
R²            | 0.10  | 0.06  | 0.05      | 0.20  | 0.02      |
Firm-Years    | 4,846 | 4,846 | 4,846     | 4,846 | 4,846     |
Firms         | 571   | 571   | 571       | 571   | 571       |

Panel B: Split by size

<table>
<thead>
<tr>
<th></th>
<th>V/D</th>
<th>NPF/D</th>
<th>(V-NPF)/D</th>
<th>D/A</th>
<th>(V-NPF)/A</th>
</tr>
</thead>
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<tr>
<td>Constant</td>
<td>25.22</td>
<td>1.38</td>
<td>23.83</td>
<td>37.09</td>
<td>8.95</td>
</tr>
<tr>
<td></td>
<td>(13.08)</td>
<td>(0.87 )</td>
<td>(13.78)</td>
<td>(28.79)</td>
<td>(14.46)</td>
</tr>
<tr>
<td>Medium</td>
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<td>7.06</td>
<td>3.85</td>
<td>1.08</td>
<td>1.73</td>
</tr>
<tr>
<td></td>
<td>(5.68 )</td>
<td>(5.34)</td>
<td>(2.36)</td>
<td>(0.67)</td>
<td>(2.27)</td>
</tr>
<tr>
<td>Small</td>
<td>18.18</td>
<td>7.04</td>
<td>11.14</td>
<td>-2.65</td>
<td>1.89</td>
</tr>
<tr>
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<td>(8.47)</td>
<td>(4.54)</td>
<td>(5.69)</td>
<td>(-1.45)</td>
<td>(2.47)</td>
</tr>
</tbody>
</table>

SE Clustered By: Firm,Y Firm,Y Firm,Y Firm,Y Firm,Y
R²            | 0.05  | 0.02  | 0.02      | 0.01  | 0.00      |
Firm-Years    | 4,846 | 4,846 | 4,846     | 4,846 | 4,846     |
Firms         | 571   | 571   | 571       | 571   | 571       |

firms, have more floating-rate bank debt.\textsuperscript{35} While they hedge the resulting interest-rate exposure with interest-rate swaps, they only do so partially. These firms are more exposed to interest rates through floating-rate debt than firms with better access to capital markets.

\textsuperscript{35}Bank-dependent firms are important: in my sample, firms with above-median fractions of bank debt account for around 20\% of total investment. This understates their importance, as my data only includes public firms. Private firms are also likely to be bank-dependent.
This exposure seems to be driven by a need for bank financing rather than a desire to be exposed: it consists primarily of bank debt, and is not matched by greater cash-flow sensitivity to interest rates.

1.3 Theoretical framework

This section presents a theoretical framework for understanding why banks pass interest-rate risk on to firms. I use the framework to make three main points regarding my argument that floating-rate bank liabilities drive floating-rate bank lending to firms. First, banks with more floating-rate liabilities should make more floating loans. Second, banks’ securities holdings allow me to rule out the idea that these banks have relationships with firms demanding
floating-rate loans. Third, collateral costs prevent firms and banks from hedging fully with derivatives.

I take the basic interest-rate mismatch involved in bank lending to firms as my starting point. Bank-dependent firms need to borrow from banks, because they need monitoring to raise sufficient external finance to invest (Diamond 1984, Holmström & Tirole 1998, Tirole 2006). Firms need external finance to fund long-term projects, requiring long-term finance. However, the banking system ultimately funds these long-term projects with short-term interest-bearing deposits. It does so despite the interest-rate risk involved because deposits provide liquidity services, and are therefore cheap (Diamond & Dybvig 1983, Gorton 2010, Stein 2012, Greenwood, Hanson & Stein 2015). In the model, banks are endowed with exogenous deposit franchises, and bank-dependent firms exogenously need to raise a portion of their external finance from banks.

This mismatch between banks’ assets and liabilities is relevant because future interest rates are uncertain. I take uncertainty regarding future interest rates as exogenous. To fix ideas, I interpret this uncertainty as arising from variation in future consumer discount rates, as in Greenwood et al. (2015). More broadly, monetary policy is a relevant source of variation in nominal interest rates. I focus on the US for recent decades: in this period, as inflation has been low and stable, changes in nominal rates closely correspond with changes in real rates. While I conceptualize firms’ output as being only weakly dependent on

---

36 Many long-term projects produce little cash flow in the interim, which would make interim repayment difficult. Short-term finance would expose firms to rollover risk in addition to interest-rate risk.

37 Krishnamurthy & Vissing-Jorgensen (2015) make a related argument: that the financial sector issues short-term bonds because they provide safety, which is in demand.

38 I take the existence of banks combining monitoring and lending on the asset side and liquidity provision through deposits as exogenous. In practice, investment grade firms sell their bonds to other institutions such as insurance companies and pension funds, which in turn provide insurance services to end consumers through contracts that do not strongly depend on interest rates. It is an ambitious research agenda for future work to understand why monitoring and deposit based liquidity provision are paired together, while arms-length investment and long-term insurance are paired together.

39 Eggertsson & Mehrotra (2014) provide an alternative way to think about uncertainty in ‘natural’ interest rates: they propose a life cycle model generating variation in the interest rate arising from supply and demand for saving across generations.

40 If real rates were instead essentially fixed, with variation in nominal rates largely coming from inflation,
interest rates, I do include some dependence in the model, capturing the extent to which floating-rate debt provides a natural hedge for firms’ asset exposure. This allows the model to capture the effects of variation in firms’ associated ‘demand’ for floating-rate debt.

Following Froot et al. (1993), both banks and firms are effectively risk averse due to financial frictions. Froot et al. (1993) show that, if external finance is costly, constrained firms become effectively risk averse as they cannot fully smooth shocks to internal funds. For simplicity, I capture this hedging motivation with mean-variance preferences for both banks and firms. Both banks and firms do appear to be at least somewhat risk averse in practice. Despite significant leverage, bank net interest margins have historically been very stable (Flannery 1981, English 2002, English et al. 2013). Firms also frequently use derivatives with the stated goal of risk management: indeed, as I show in Section 1.2, bank-dependent firms do attempt to reduce their exposure to interest rates with derivatives.

As collateral requirements make hedging costly, banks can only avoid bearing interest-rate risk by passing some of it on to firms. If hedging were frictionless, mismatch between firms’ output and banks’ short-term funding would not matter. Firms could borrow at floating rates and fully hedge the exposure, or banks could lend at fixed rates and hedge themselves. I follow a growing literature in arguing that collateral costs make hedging costly (Rampini & Viswanathan 2010, Rampini et al. 2015a, Rampini et al. 2014, Ivashina et al. 2015, Bolton & Oehmke 2015). Collateral requirements are relevant for banks: Rampini et al. (2015a) show that, consistent with collateral costs of hedging, banks reduce their use of floating-rate debt would provide a natural economic hedge to firms. In periods of high inflation with high nominal rates, the nominal value of firms’ output would also be higher. Internationally, floating-rate debt likely is commonly used as a way to inflation-index contracts.

41Froot & Stein (1998) show that these effectively risk averse preferences can approximately be captured in this manner, where the effective level of risk aversion depends on initial choices regarding capital structure. I do not model this initial stage here.

42Rajan (2012) notes that in the run up to the asian financial crisis, domestic banks passed interest-rate risk on to domestic firms. Domestic banks had obtained funding from foreign sources, denominated in foreign currency. To avoid bearing currency mismatch themselves, domestic banks then lent to domestic firms in loans denominated in foreign currency as well.

derivatives following a negative net worth shock. I model the opportunity cost of collateral as reduced investment in projects with concave returns, generating convex costs of hedging, following Ivashina et al. (2015).

The model includes a single period, which represents the entire term over which loans are made to firms. Uncertainty regarding interest rates is realized within the period. The difference between fixed-rate loans and floating-rate loans is that while for the former the interest rate is known at the beginning of the period, this is not the case for the latter. As I show in Section 1.2, floating-rate bank lending to firms largely consists of term loans. The question of why firms and banks negotiate floating-rate term loans instead of short-term debt is itself interesting, but outside the scope of the chapter. The model also incorporates interest-rate derivatives, which will also refer to instruments traded over the life of loans to firms.

In the remainder of this section, I begin by describing the set up of the model for banks and firms. I use the model to highlight how this combination of factors affects the equilibrium structure of banks’ loan and securities portfolios, building up to testable implications regarding bank balance sheets. The key testable implication is that banks with more floating liabilities should make more floating-rate loans. I also allow banks to adjust their securities portfolios in the model, and show that banks’ securities holdings allow me to distinguish the supply-driven view of floating-rate bank lending to firms from the demand-driven view.

44 Rampini et al. (2015a) find that banks roughly halve their use of interest-rate derivatives following a negative net worth shock. They exclude the largest banks (i.e. broker-dealers), focusing on smaller banks.

45 In unreported analysis, I show that maturity of term loans is typically similar to that of corporate bonds. This likely reflects that firms need to finance long-term projects, producing little cash-flow in the interim. Mian & Santos (2011) use confidential supervisory data to show that the effective maturity of bank loans ranges from 2-4 years, driven by the refinancing behavior of firms with good credit quality. They show that such firms choose to extend their debt maturity in good times; weaker firms do not do so.

46 As the model only includes one period, there is no formal difference between short-term debt rolled over and floating-rate debt here.
1.3.1 Banks

Consider a simple view of bank risk management. Banks make loans, and hold securities, funded by deposit liabilities and internal wealth. Deposit liabilities are short-term, and therefore floating. However, they are also cheap, in the sense that pass-through of short-term interest rates is only partial, leading to lower average interest rates than on alternative sources of funding. This creates the potential for exposure to interest-rate risk: if interest rates rise, causing deposit interest expense to rise, net income will fall if banks hold only fixed-rate assets. Banks’ effective risk aversion makes this exposure relevant.

Banks choose the floating fractions of their loan and securities holdings; for simplicity I hold the total size of these portfolios fixed. Banks are exogenously endowed with deposits $D$, a loan portfolio of size $L$, and a securities portfolio of size $S$. For simplicity, the total size of each portfolio is fixed. Internal net worth is the difference $L + S - D$. The future short-term interest rate is $r$, a random variable, with $E[r] = \bar{r}$ and $\text{Var}[r] = \sigma^2$. Deposit interest expense is $ar$, where $a < 1$: pass-through on deposits is not complete. Again, this is the sense in which deposits are associated with a money premium. Deposit pass-through, $a$, is also exogenous. Conceptually, I model bank loans as a single asset class with an endogenous characteristic, the floating fraction, determined in equilibrium. Let $f_L$ and $f_S$ be the floating fraction of loans and securities respectively.

Matching floating-rate liabilities with floating-rate assets involves a tradeoff, as floating-rate assets provide a lower yield. Both loan and security portfolios can be tilted towards being more floating-rate, at the cost of giving up a term premium. There is a second cost associated with floating-rate loans: firms are also effectively risk averse, and find bearing

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47 See Figure 1.4, which shows interest-expense on bank deposits in aggregate: while there is some pass-through, it is partial. In practice this is achieved at least in part by attracting transaction deposits on which no interest is paid. Here, I take deposit pass-through as exogenous. A more general model could also endogenize this process.

48 I refer to banks and, later, firms in the plural. In the model I explicitly include only one of each type of institution: I interpret this as a continuum of identical institutions of each type of measure one.

49 A positive term premium can exist in equilibrium if investors have limited wealth, and are risk averse about duration risk. See, for example, Greenwood, Hanson & Stein (2010).
interest-rate risk costly. A portfolio with more floating-rate loans must therefore have lower average interest rates. Let $\mu$ be the loan spread between the rate charged to firms and general interest rates. In Section 1.3.2, I describe bank-dependent firms’ objective function, and derive the equilibrium spread required for bank-dependent firms to continue to borrow the fixed amount, $L$, from banks.\footnote{To provide some intuition at this point: let the demand function for bank loans be $B(\mu, f)$, where $f$ is the floating fraction, and $\mu$ is the spread relative to general interest rates. Implicitly differentiating $L = B(\mu^*, f)$ provides}

The loan portfolio consists of a fraction $f_L$ of floating-rate loans, linked to the short-term interest rate $r$. The interest rate received on the loan portfolio is therefore

$$
(1 - f_L)(\bar{r} + \delta) + f_Lr + \mu^*(f_L)
$$

(1.2)

where $\delta > 0$ is the term premium. Recall that $E[r] = \bar{r}$. Let the interest rate on short-term securities be $r_S$, with the same mean and variance as $r$, and correlation $\rho$ with $r$.\footnote{This avoids a choice for banks between two assets with effectively identical cash flows but different prices, which would lead to corner solutions. I do not explicitly include constraints that these floating fractions are between 0 and 1, which would be required in this case.} The interest rate received on the securities portfolio is

$$
(1 - f_S)(\bar{r} + \delta) + f_S r_S
$$

(1.3)

This is similar to the interest rate on the loan portfolio, but does not include an equivalent to the loan spread, $\mu$. For simplicity, the term premium, $\delta$, is the same for loans and for securities.\footnote{I do not explicitly include monitoring costs or credit risk associated with bank loans in the model. This is one sense in which loan and securities portfolios of exogenous size simplify the model. A more general model including these features could also endogenize banks’ asset allocation across these broad asset classes.}

Banks can also use interest-rate swaps to manage interest-rate risk, subject to collateral costs. One positive unit of the swap involves making a fixed payment of $\bar{r} + \delta$, where $\delta$ is
the term premium, in return for receiving the short-term interest rate \( r \). Banks also face collateral costs of using interest-rate swaps. Following Ivashina et al. (2015), I model this cost as the opportunity cost of collateral. Hedging requires collateral: for each unit of the derivatives contract, \( \bar{q} \in (0, 1) \) units of collateral must be posted, reducing investment in outside opportunities. I model the cost of this collateral as

\[
\frac{q}{2} H_{Bank}^2
\]

(1.4)

where \( q = \bar{q}^2 \). This form for the opportunity cost of collateral can be derived from a production function where loss of output is quadratic from the optimum.\(^{53}\)

**Banks’ objective function**

Banks have mean-variance preferences regarding net income. Net income is the sum of interest income on loans and securities, as well as returns on hedging, net of interest expense on deposits and collateral costs of hedging.

\[
NI = L((1 - f_L)(\bar{r} + \delta) + f_L r + \mu^*(f_L)) + S((1 - f_S)(\bar{r} + \delta) + f_S r_S) + H_{Bank}(r - (\bar{r} + \delta)) - Dar - \frac{q}{2} H_{Bank}^2
\]

(1.5)

The objective is to maximize

\[
\Omega_{Bank} = E[NI] - \frac{\gamma}{2} Var[NI]
\]

(1.6)

\(^{53}\)Collateral costs as in Equation 1.4 can be justified as follow. Banks have concave outside investment opportunities. Absent any use of derivatives, they are able to invest in these outside opportunities at the optimal level. Define the production function as

\[
Z(w) = \begin{cases} 
\frac{1}{2} \bar{w}^2 - \frac{1}{2} (\bar{w} - w)^2 & w \leq \bar{w} \\
\frac{1}{2} w^2 & w > \bar{w}
\end{cases}
\]

The optimal level of investment is \( \bar{w} \), beyond which there are no further returns to investment. A derivatives position of \( H_{Bank} \) requires \( \bar{q} H_{Bank} \) to be provided as collateral and not invested in outside opportunities. The opportunity cost of doing so is \( \frac{q}{2} H_{Bank}^2 \). This assumes, of course, that the bank is collateral constrained at the optimal level of investment in outside opportunities, \( \bar{w} \).
where $\gamma$ captures the extent to which banks are effectively risk averse.\footnote{For simplicity, I ignore the role of deposit insurance or any implicit government backing. As Froot & Stein (1998) note, this effective risk aversion depends on the initial choice of capital structure. These authors frame the tradeoff at this initial stage as the ability to bear more risk in the future, balanced against tax costs of equity relative to debt.}

I proceed by differentiating banks’ objective function, as in Equation 1.6, to obtain first order conditions for $H_{\text{Bank}}$, $f_L$, and $f_S$. These first order conditions can be expressed as follows:

\begin{align*}
H_{\text{Bank}} &= \frac{\gamma \sigma^2}{q + \gamma \sigma^2} (D \alpha - f_L L - \rho f_S S) - \frac{\delta}{q + \gamma \sigma^2} \\
f_L L &= D \alpha - \rho f_S S - H_{\text{Bank}} + \frac{\partial \mu(f_L)}{\partial f_L} - \frac{\delta}{\gamma \sigma^2} \\
f_S S &= \rho(D \alpha - f_L L - H_{\text{Bank}}) - \frac{\delta}{\gamma \sigma^2}
\end{align*}

As Equation 1.7 shows, collateral requirements ($q > 0$) discourage banks from hedging fully.\footnote{Fully hedging would require $H_{\text{Bank}} = D \alpha - f_L L - \rho f_S S$. A positive term premium $\delta$ also discourages hedging.} Equations 1.8 and 1.9 show first order conditions for the floating fractions of loans and securities respectively. For loans, increasing the floating fraction reduces the loan spread.\footnote{See Lemma 1 for an equilibrium expression for $\frac{\partial \mu(f_L)}{\partial f_L}$, which depends on the extent to which floating-rate debt is a natural hedge for firms.} The expression for securities takes $\rho$, the correlation between the interest rate on securities $r_S$ and the general short-term rate $r$, into account. To solve the model, I substitute the expression for $H_{\text{Bank}}$ from Equation 1.7 back into the objective function. I then derive first order conditions for floating fractions of loans and securities again, this time anticipating subsequent optimal hedging. I discuss the properties of these fractions in equilibrium in Section 1.3.3. I now turn to describing the set up for firms.

### 1.3.2 Bank-dependent firms

In the baseline version of the model, I include only bank-dependent firms. These firms must finance some of their investment with bank debt. Firms have fixed-scale investment, and
have output that potentially co-moves with interest rates. They also have mean-variance preferences, as well as access to interest-rate swaps, subject to the same collateral costs as banks.\textsuperscript{57} Again, a positive unit of the swap contract is in the pay-fixed direction.

Bank-dependent firms invest an amount $I$, which must be financed with debt, and produce output $AI + Cr$. Potential dependence of output on interest rates, represented by $C$, captures the extent to which floating interest rates are an economic hedge for bank-dependent firms. This will affect the responsiveness of the equilibrium bank loan spread, $\mu$, to a higher floating fraction of lending. Firms borrow an amount $B$ in the form of bank debt, and finance the remainder, $I - B$, with bonds. As noted above, fixed-rate financing is associated with a term premium $\delta$: the cost of bonds is $\bar{r} + \delta$.\textsuperscript{58}

Bank-dependent firms’ net income is

\[
NI_{BD} = AI + Cr - (1 + \bar{r} + \delta)(I - B) - (1 + f_Lr + (1 - f_L)(\bar{r} + \delta) + \mu)B \\
+ (r - (\bar{r} + \delta))H_{BD} - \frac{q}{2}H_{BD}^2
\]

As firms have mean-variance preferences, the objective is to maximize

\[
\Omega_{BD} = E[NI_{BD}] - \frac{\gamma}{2}Var[NI_{BD}]
\]

For simplicity, I assume that firms have the same effective level of risk aversion as banks.\textsuperscript{59}

As with banks, I proceed by first finding the firm’s optimal hedging demand, and substituting this into the objective function. Then, I use the first order condition with respect

\textsuperscript{57}The implicit assumption here is that bank-dependent firms hedge with a swap counterparty that is different from their lender. It is more challenging to explain the necessity of collateral requirements from first principles if the lender is also the swap counterparty, as bank-dependent firms typically try to reduce the variability of their interest expense. Firms often do enter into swaps with entities other than their lenders (indeed, for firms with relationships with smaller banks there may be little choice in this regard). Moreover, within large banking organizations, client-facing swap desks often impose their own counterparty exposure limits.

\textsuperscript{58}Bond yields typically include an additional credit spread. I exclude this from the model for simplicity.

\textsuperscript{59}In practice, both orderings of risk aversion are possible. On one hand, banks are in the business of bearing certain types of financial risks. On the other hand, banks have greater leverage. A more general model could also endogenously determine the level of leverage chosen by banks and firms. Several forces would push banks towards choosing greater leverage: deposits are associated with a money premium, deposits are insured, and through diversification banks likely face lower asset risk.
to bank credit to find a credit demand curve from firms’ perspective. Using this demand curve, I find the equilibrium loan spread $\mu$ at which firms will demand a fixed quantity, $L$, of bank credit. The thought experiment, therefore, is that banks change the floating fraction of lending without changing the total size of the loan portfolio.

**Lemma 1.** The equilibrium spread responds to the floating fraction of lending as follows:

$$
\frac{\partial \mu^*(f_L)}{\partial f_L} = \frac{q((C - 2f_L L)\gamma \sigma^2 + \delta)}{q + \gamma \sigma^2}
$$

(1.12)

The proof is omitted. This derivative has a decreasing component, capturing the intuition that banks must accept a lower loan spread to increase the floating fraction. This is attenuated by three factors: first, to the extent that firms’ output is cyclical ($C$ is large), floating-rate loans may be an economic hedge for firms. Second, fixed-rate debt is more expensive due to the term premium ($\delta$). Third, firms can partially hedge the interest-rate risk associated with floating-rate loans, where the cost of doing so depends on the collateral requirement $q$.

### 1.3.3 Testable predictions

To summarize the set up, banks fund firms’ long-term projects with short-term interest-bearing deposits, creating interest-rate mismatch. Both banks and firms are effectively risk averse due to costly external finance. Anticipating optimal hedging, banks choose the floating fractions of loans and securities to manage interest-rate risk. In the presence of collateral costs of hedging, banks have an incentive to reduce interest-rate risk in part by making floating-rate loans, thereby engaging in operational hedging as well as financial hedging. I now lay out the main testable implications generated by this theoretical framework.

A key testable implication of this framework, in which floating-rate liabilities push banks to lend to firms at floating rates, is that banks with more floating liabilities should make more floating-rate loans. Specifically, banks with greater pass-through on deposits should make more floating-rate loans. Proposition 1 summarizes this result. Recall that $a$ represents the degree of pass-through on bank deposits.
**Proposition 1.** Banks with more floating-rate liabilities (greater deposit pass-through) should make more floating-rate loans:

\[
\frac{\partial f^*_{L}}{\partial a} > 0
\]  

(1.13)

**Proof.** See Appendix A.1.1.

Would showing that banks with more floating liabilities make more floating loans suffice to establish causality in this direction? Is it possible that banks that make more floating loans do so because they have lending relationships with firms that demand floating-rate loans? In terms of the model, such banks might match with firms with more positively cyclical cash flows (more positive \(C\)), for whom floating-rate loans would be a natural hedge.\(^{60}\)

I show that banks’ securities holdings can clearly distinguish the supply-driven view from firms’ demand for floating-rate debt. Proposition 1 shows that, under the supply-driven view, banks with more deposit pass-through should make more floating-rate loans. Such banks should also hold more floating-rate securities to match their liabilities. In contrast, if banks make floating-rate loans because their borrowers demand this interest-rate exposure, they should hold fewer floating-rate securities. While more floating-rate liabilities would reduce interest-rate risk, so would fixed-rate securities. Indeed, increasing pass-through on deposits would be an expensive way to manage interest-rate risk, particularly in comparison with holding more fixed-rate securities (earning the term premium to boot).\(^{61}\) Proposition 2 summarizes this discussion.

**Proposition 2.** Banks with more floating-rate liabilities should make more floating-rate loans and hold more floating-rate securities

\[
\frac{\partial f^*_{L}}{\partial a} > 0, \frac{\partial f^*_{S}}{\partial a} > 0
\]

(1.14)

\(^{60}\)The evidence I present in Section 1.2 does already suggest that this argument is not very plausible: firms with more bank debt do not in aggregate have more cyclical cash flows.

\(^{61}\)In the model, deposit pass-through is exogenous. A more general model could also endogenize deposit pass-through. For example, suppose that retail deposits with very low pass-through are costly to source. Then, banks facing more demand would put less effort into lowering deposit pass-through. This would also generate a negative correlation between deposit pass-through and the floating fraction of banks’ securities.
In contrast, banks responding to demand for floating-rate loans from their borrowers should make more floating-rate loans, but hold fewer floating-rate securities

\[
\frac{\partial f_L^*}{\partial C} > 0, \quad \frac{\partial f_S^*}{\partial C} < 0
\]

(1.15)

Proof. See Appendix A.1.1.

Hence, if banks with more floating liabilities hold more floating securities in addition to making more floating loans, this is consistent with the supply-driven view I argue for, but inconsistent with the idea that firms demand floating-rate loans. Recall that \( C \) parametrizes the extent to which firms' cash-flows are positively dependent on interest rates. Appendix A.1.2 shows how the correlation between the floating fractions of loans and securities is informative about the relative importance of cross-sectional variation in supply and demand.

1.3.4 Extensions

The baseline model highlights the main testable implication of the theoretical framework: banks should match the interest-rate exposure of their assets to that of their liabilities. It also shows that banks' securities holdings provide a way to exclude demand from firms for floating-rate loans. I now describe a fuller version of the model, which addresses additional features of variation in firms' exposure to interest rates and their use of interest-rate derivatives.

I incorporate three extensions into the model. First, I include a price of interest-rate swaps beyond the term premium, determined in equilibrium. Second, I explicitly include firms with better access to capital markets. To fix ideas, I refer to these firms as investment grade firms. For simplicity, they are identical to bank-dependent firms, except that they borrow only with fixed-rate corporate bonds. A positive equilibrium price of swaps will induce investment grade firms to bear some interest-rate risk with swaps. Third, to close the model I include a set of institutions that bears residual interest-rate risk that other institutions do not wish to bear. To fix ideas, I refer to these institutions as hedge funds, which are risk-neutral, but also face collateral costs of using derivatives. The price of swaps
is determined in equilibrium to clear the market.

Appendix A.1.3 shows that this fuller version of the model qualitatively matches the relative levels of interest rate risk that bank-dependent and investment grade firms bear, including the use of derivatives that I document in Section 1.2. Collateral costs of hedging prevent all institutions from using derivatives to fully arrive at the desired position. Bank-dependent firms hedge only partially, while investment grade firms actually take on some interest-rate risk with derivatives. Even though both types of firms use derivatives, the convexity of collateral costs of hedging mean that firms do not equate their levels of exposure. The main results, Propositions 1 and 2, continue to hold.

1.4 Empirics: main results

This section presents the main empirical results of this chapter. The evidence supports the supply-driven view of floating-rate bank lending to firms: banks with more floating liabilities make more floating-rate loans. These banks also hold more floating-rate securities, and quote lower prices for adjustable-rate mortgages relative to fixed-rate mortgages, ruling out alternative explanations based on firms’ demand for floating-rate debt. I present three types of further evidence of these empirical relationships: first, evidence using deposit competition as an instrument for the interest-rate exposure of bank liabilities, second, time series evidence, and third, historical evidence from periods when deposits were largely non-interest-bearing.

I construct empirical measures of the interest-rate exposure of bank assets and liabilities

---

62 The majority of firms in the sample I collect data for do use interest-rate swaps. Without convex costs of hedging, both types of firms would equate their exposure, following the principle of equal risk sharing. Many smaller firms do not use derivatives at all; this is better captured through fixed costs of using derivatives.

63 Two sets of institutional details are worth noting. First, bank loans are often prepayable. Firms might prefer floating-rate loans to the extent that stable market value facilitates repayment at par. Second, revolving loans and term loans are typically part of the same contractual agreement. Revolving loans need to be floating rate, given that firms have the option to draw down, potentially over a long period of time in which interest rates might fluctuate substantially. Revolving loans (or short-term credit) provided by banks likely pre-date term loans. It is possible that, at least initially, term loans were floating rate because they were governed by the same agreements as revolving loans.
using bank regulatory data. I measure the extent to which assets are floating in different categories with the fraction of assets that are floating. This approach is simpler than estimating duration or maturity weighting, as the maturity and repricing distribution of assets is reported directly. 64 The literature on bank risk management has also considered return attribution and regressions on short-term interest rates (Flannery 1981, Flannery & James 1984, English 2002, English et al. 2013). I use this latter approach to measure deposit pass-through, using co-movement of deposit rates with the federal funds rate (in changes) at the bank level.65

Figure 1.4 uses aggregate data to show that deposit interest expense broadly co-moves with short-term interest rates, with partial pass through. Panel A shows a time series from the late 1980s using bank holding company level data. Panel B shows time series of deposit pass-through and interest rates on C&I lending from the early 2000s, using call report level data (see Appendices A.2.3 and A.2.4 for more details on the data). Banks’ interest expense on deposits does fluctuate with general interest rates, but pass-through is not complete. In particular, as interest rates rise banks do not fully pass through interest rates, and are able to borrow more cheaply. Panel B also shows realized interest rates on C&I lending, which roughly track deposit interest expense with a spread.

1.4.1 Tests of primary hypotheses

In this subsection, I present my main results: tests of the hypotheses from Section 1.3. Consistent with Proposition 1, I show that banks with greater interest rate pass-through on deposits make more floating-rate loans. These banks also hold more floating-rate (short-term) securities. As Proposition 2 shows, the evidence regarding securities is consistent with the supply-driven view that bank liabilities drive floating-rate lending to firms, but

64 This is related to the approach of using maturity gaps to measure the net interest-rate exposure banks have (Rampini et al. 2015a, Landier, Sraer & Thesmar 2015). As discussed in Section 1.4.3, I find consistent results using this approach on the liability side as well, using regulatory data at the bank holding company level.

65 The literature on deposit pass-through has also used a variety of approaches, including panel regressions and structural partial adjustment models (Samuelson 1945, Berger & Hannan 1989, Neumark & Sharpe 1992, Drechsler et al. 2014).
Panel A: Deposit pass-through (BHC data)

Notes: This figure shows aggregate pass through on deposits and on C&I lending. Panel A uses BHC level call report data for 1986Q3-2014Q4, aggregated pro-forma based on mergers. The sample requires banks to have assets above quarterly reporting requirement limits. See Appendix A.2.4 for more details. Implied deposit rate is interest expense on deposits scaled by deposits, annualized and in percentage points. Effective Fed Funds is the quarterly average effective federal funds rate, in percentage points. Panel B uses commercial bank level call report data for 2001Q1-2014Q4, aggregated to the parent company level. The sample requires banks to have assets above 80% of quarterly holding company reporting requirement limits. See Appendix A.2.3 for more details. It shows these same variables, as well as the implied C&I rate: interest and fee income on C&I loans divided by C&I loans, annualized and in percentage points. It also shows the weighted average effective rate on C&I loans from the Fed’s Survey of Terms of Business Lending.

Figure 1.4: Aggregate deposit and C&I pass-through
inconsistent with the idea that firms demand floating-rate loans. I also show that banks with more pass through quote lower interest rates for adjustable-rate mortgages relative to fixed-rate mortgages. The combination of higher quantities of floating-rate loans and lower relative prices for them points to supply.

I begin with commercial bank level call report data, as it provides the most disaggregated information on the interest-rate exposure of bank assets. Table 1.5 shows summary statistics for the sample, which consists of almost 60,000 bank-quarters for about 1,500 banks (I aggregate the data to the parent bank holding company level). I define the floating fraction of loans and securities as the fraction of loans and securities with remaining maturity or repricing frequency of less than three months, capturing short-term as well as contractually floating-rate assets. I also define similar fractions for loans and, separately, securities not backed by standardized mortgages on single family residences. These fractions are in percentage points. On average, about 30% of banks’ non-residential loans are floating-rate, and about 10% of non-residential securities are floating-rate. Floating-rate securities are likely to primarily be short-term securities.

Call report data also allows me to construct a bank level estimate of deposit pass-through using the sensitivity of interest expense on deposits to the federal funds rate. I define an implied deposit interest rate by scaling interest expense on deposits by all deposits, including non-interest-bearing deposits. Subsequently, I estimate deposit pass-through at the bank level by regressing changes in the implied deposit rate on changes in the federal funds rate,

---

66 After the filters I apply, discussed in detail in Appendix A.2.3, in 2014Q4 the sample covers about 80% of total commercial bank assets.

67 Loans and securities make up the majority of commercial bank balance sheets. They comprise about 70% of commercial bank assets (based on aggregate data as of 2014Q4, compiled by SNL). Loans and securities not backed by standardized housing collateral comprise 40% and 10% of bank assets respectively.

68 This average floating-fraction of non-residential securities might seem low at first glance. The largest banks, which have more deposit pass-through, do hold more floating-rate securities. Floating-rate non-residential securities largely consist of short-term government or agency issued debt. While floating-rate bank loans provide banks comparatively high yield in current periods, short-term government bonds provide relatively little yield. If current period yield is particularly important for banks, as in Hanson & Stein (2015), this might push them away from holding floating-rate securities.

69 This methodology captures the overall cost structure of banks’ deposits.
Table 1.5: Summary statistics for Commercial Bank data

Notes: This table shows summary statistics of US Commercial bank assets for 2001Q1-2014Q4. I use commercial bank level call report data from the FFIEC’s website. I aggregate data to the parent holding company level on a pro-forma basis using current ownership from SNL. I include banks that are not owned by a holding company in the sample. I restrict to banks with assets at least 80% of the minimum requirements for quarterly reporting at the holding company level (150MM in assets prior to 2005Q4, and 500MM subsequently). I also require maturity data to be reported for at least 75% of loans and securities. See Appendix A.2.3 for more details. Floating fraction is the reported fraction of loans and securities with maturity or repricing frequency less than three months, in percentage points. Floating fraction (non-res loans) is the corresponding fraction of loans not backed by pass-through mortgages on 1-4 family residences, in percentage points. Floating fraction (non-res securities) is the corresponding fraction of securities not backed by pass-through mortgages on 1-4 family residences, in percentage points. Implied deposit rate is interest expense on deposits scaled by deposits, annualized and in percentage points. Deposit PT is the coefficient from quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate (using data for 2001Q1-2008Q4), in percentage points, winsorized at the 1% level. I require 20 quarters of data to estimate Deposit PT. Deposit HHI is measured at the county level using branch level deposit data from SNL, aggregated to the parent level weighted by deposits (pro-forma, based on current ownership), expressed as a fraction. Large banks are the largest 5% of banks by assets in each quarter. I report the standard deviation for each variable (for the full sample).

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Small Banks</th>
<th>Large Banks</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets (BN)</td>
<td>7.2</td>
<td>0.9</td>
<td>127.2</td>
<td>75.3</td>
</tr>
<tr>
<td>Floating fraction</td>
<td>24.7</td>
<td>24.0</td>
<td>37.9</td>
<td>14.9</td>
</tr>
<tr>
<td>Floating fraction (non-res loans)</td>
<td>34.1</td>
<td>33.2</td>
<td>51.4</td>
<td>17.9</td>
</tr>
<tr>
<td>Floating fraction (non-res securities)</td>
<td>9.0</td>
<td>8.5</td>
<td>19.3</td>
<td>14.6</td>
</tr>
<tr>
<td>Deposits/Liabilities</td>
<td>90.8</td>
<td>91.3</td>
<td>80.3</td>
<td>7.9</td>
</tr>
<tr>
<td>Implied Deposit Rate</td>
<td>1.8</td>
<td>1.8</td>
<td>1.4</td>
<td>1.1</td>
</tr>
<tr>
<td>Deposit PT</td>
<td>28.6</td>
<td>28.3</td>
<td>33.4</td>
<td>9.1</td>
</tr>
<tr>
<td>HHI</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Bank-Quarters 57,224
Banks 1,483

using data for 2001Q1-2008Q4.\textsuperscript{70} On average, deposit pass-through is about 30%: for each percentage point increase in the federal funds rate, deposit interest rates rise by about 30 basis points. I also estimate deposit competition, at the county level, in a manner similar to Drechsler et al. (2014) (see Appendix A.2.3 for more details). Deposits are an important part of bank capital structure: 90% of bank liabilities, on average, are deposits.\textsuperscript{71}

Turning to the results, I first show that banks with more deposit pass-through make

\textsuperscript{70}I restrict estimation of pass-through to the period before interest rates were constrained by the zero lower bound. Table 1.7 shows the results are robust to estimating pass-through over the full sample, extending to 2014Q4, instead.

\textsuperscript{71}This is an equal weighted average: an asset weighted average is closer to 60%, as the largest banks have more non-deposit funding.
more floating-rate loans. Panel A of Table 1.6 shows regressions of the floating fraction of loans and securities, and of non-residential loans, on deposit pass-through. The regressions collapse the sample to means at the bank level to focus on cross-sectional variation. They show that both measures are strongly positively related with deposit pass-through. As Proposition 1 shows, this is consistent with my argument that banks match the interest-rate exposure of their assets to the exposure of their liabilities. To provide a sense for the magnitudes, when deposit pass-through rises by one percentage point, these floating fractions rise by about half a percentage point. A one standard deviation increase in deposit pass-through is associated with a four to five percentage point increase in these floating fractions, or about a quarter of a standard deviation.

Banks achieve this asset-liability matching by adjusting loans both within and across asset classes. Panel A also shows regressions including controls for the fraction of lending related to C&I lending, consumer lending, and (primarily residential) real-estate related lending (see Appendix A.2.3 for more details). As these controls are available in detail only for quarters since 2009Q2, I first repeat the earlier regressions for the restricted sample. The relationship is still strong, although the magnitude is somewhat reduced. Finally, I show regressions including asset mix controls. The relationship continues to be present, though the magnitude drops further. This shows that banks adjust their portfolios both within and across asset classes.

Importantly, banks with more pass though also hold more floating-rate securities, establishing that bank liabilities drive banks’ floating-rate lending to firms, not borrowers’ demand for interest-rate exposure. Panel B of Table 1.6 looks at the relationship of deposit pass-through and the floating fraction of loans with the floating fraction of securities. In the cross section, the floating fraction of non-residential securities is positively related with deposit pass-through. Moreover, the floating fractions of loans and securities are positively correlated. As Proposition 2 shows, these patterns are consistent with the supply-driven view that floating-rate bank liabilities push banks to lend to firms at floating rates. However, they are inconsistent with the idea that firms demand floating-rate loans: if this were
Table 1.6: Floating fraction of bank assets and deposit pass-through (commercial bank data)

Notes: This table shows regressions of the floating mix of bank assets on deposit pass-through, using commercial bank level call report data for 2001Q1-2014Q4. See Appendix A.2.3 for more details. Panel A focuses on the aggregate balance sheet and on non-residential loans. The first dependent variable (Loans, Sec) is the reported fraction of loans and securities with maturity or repricing frequency less than three months, in percentage points. The second dependent variable (NR Loans) is the corresponding fraction of loans not backed by pass-through mortgages on 1-4 family residences, in percentage points. Deposit PT is the coefficient from quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate (using data for 2001Q1-2008Q4), in percentage points, winsorized at the 1% level. The first two columns show the regressions for the full sample. The third and fourth columns repeat these regressions for 2009Q2-2014Q4. The final two columns include controls for asset mix (fractions related to C&I, consumer and real estate lending), available in their present form beginning 2009Q2. Panel B looks at the floating fraction of non-residential securities. All specifications collapse to means at the bank level. $t$-statistics are shown in parentheses.

### Panel A: Deposit PT and floating fraction

<table>
<thead>
<tr>
<th></th>
<th>2001Q1-2014Q4</th>
<th></th>
<th>2009Q2-2014Q4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Loans, Sec</td>
<td>NR Loans</td>
<td>Loans, Sec</td>
<td>NR Loans</td>
</tr>
<tr>
<td>Deposit PT</td>
<td>0.48</td>
<td>0.47</td>
<td>0.39</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(14.40)</td>
<td>(11.88)</td>
<td>(9.33)</td>
<td>(7.28)</td>
</tr>
<tr>
<td>Collapsed</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Asset Mix Controls</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.12</td>
<td>0.09</td>
<td>0.08</td>
<td>0.05</td>
</tr>
<tr>
<td>Bank-Quarters</td>
<td>57,224</td>
<td>57,224</td>
<td>18,845</td>
<td>18,845</td>
</tr>
<tr>
<td>Banks</td>
<td>1,483</td>
<td>1,483</td>
<td>956</td>
<td>956</td>
</tr>
</tbody>
</table>

### Panel B: Floating fraction of securities

<table>
<thead>
<tr>
<th></th>
<th>NR Securities</th>
<th></th>
<th>NR Securities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deposit PT</td>
<td>0.13</td>
<td></td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>(4.72)</td>
<td></td>
<td>(10.05)</td>
</tr>
<tr>
<td>NR Loans (floating fraction)</td>
<td>0.16</td>
<td></td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>(4.72)</td>
<td></td>
<td>(10.05)</td>
</tr>
<tr>
<td>Collapsed</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.01</td>
<td>0.06</td>
<td>0.01</td>
</tr>
<tr>
<td>Bank-Quarters</td>
<td>57,224</td>
<td>57,224</td>
<td>57,224</td>
</tr>
<tr>
<td>Banks</td>
<td>1,483</td>
<td>1,483</td>
<td>1,483</td>
</tr>
</tbody>
</table>

the case, the floating fraction of securities would move in the opposite direction to bank liabilities and loans.\(^{72}\)

\(^{72}\)My results show that cross-sectional variation in supply is more important for explaining variation in equilibrium outcomes than variation in demand. Appendix A.1.2 presents a framework for using the regression coefficient of the floating fraction of securities on that of loans to think about the relative importance of supply and demand.
These results are robust to estimating deposit pass-through in different ways. The results presented in Table 1.6 are based on estimates of deposit pass-through as the sensitivity of implied deposit rates to changes in the effective federal funds rate, with bank level regressions estimated in changes for 2001Q1-2008Q4. Table 1.7 shows that my main results are robust to estimating pass-through for the full sample, as well as to using LIBOR as the proxy for short-term interest rates instead of the effective federal funds rate. Panel A of Table 1.7 begins by repeating the main regressions from Table 1.6, and shows that the results are essentially unchanged by expanding estimation of the pass-through period to 2001Q1-2014Q4. Panel B of Table 1.7 shows that they are also very similar if I use LIBOR instead of the effective federal funds rate, for both sample periods.

I also show that larger banks have greater deposit pass-through and hold more floating-rate loans and more floating-rate securities, suggesting that bank size is one source of variation in the interest-rate exposure of bank liabilities.\textsuperscript{73} I define large banks as the largest 5\% of banks by assets in each quarter. Table 1.5 shows summary statistics for banks separated by size in this manner. Large banks have greater deposit pass-through. By all measures of floating-rate assets, including securities, large banks also have more floating-rate assets. I discuss the relationship between bank size and deposit pass-through in more detail in Section 1.4.2.

While most of the analysis I present relates to the floating fractions of banks’ assets (quantities), I also present evidence supporting the supply-driven view based on mortgage interest rates (prices). In addition to making floating-rate loans to firms, holding floating-rate securities and using derivatives, making adjustable-rate mortgage loans is another margin of adjustment for banks.\textsuperscript{74} I find that banks with more deposit pass-through offer fixed-rate mortgages (FRMs) at a higher interest rate relative to adjustable-rate mortgages (ARMs).

\textsuperscript{73}Larger banks also have more non-deposit sources of funding (repo, federal funds, wholesale funding) which have much higher interest-rate pass-through than deposits.

\textsuperscript{74}Banks do make floating-rate loans beyond loans to firms. Commercial banks hold about $3.5TN in floating-rate loans in aggregate, and about $1.6TN in C&I loans (based on aggregate data as of 2014Q4, compiled by SNL). The difference likely largely consists of ARMs.
Table 1.7: Robustness of Table 1.6 to estimating deposit pass-through differently

Notes: This table shows regressions of the floating mix of bank assets on deposit pass-through, with pass-through estimated in different ways to verify that the results in Table 1.6 are robust. See Appendix A.2.3 for more details regarding the data. The first dependent variable (Loans, Sec) is the reported fraction of loans and securities with maturity or repricing frequency less than three months, in percentage points. The second dependent variable (NR Loans) is the corresponding fraction of loans not backed by pass-through mortgages on 1-4 family residences, in percentage points. The final dependent variable (NR Sec) is the corresponding fraction of securities, again not backed by pass-through mortgages on 1-4 family residences, in percentage points. Deposit PT is the coefficient from quarterly bank level regressions of changes in the implied deposit rate on changes in short-term interest rates, in percentage points, winsorized at the 1% level. While all specifications include data on floating fractions for 2001Q1-2014Q4, they use deposit pass-through measured in different ways. Panel A uses changes in the effective federal funds rate as the proxy for short-term interest rates, as in Table 1.6. It shows results from estimating pass-through for 2001Q1-2008Q4 as well as 2001Q1-2014Q4. Panel B repeats this exercise using LIBOR as the proxy for short-term interest rates. All specifications collapse to means at the bank level. t-statistics are shown in parentheses.

Panel A: Estimating deposit pass-through for different periods

<table>
<thead>
<tr>
<th>PT period: 2001Q1-2008Q4</th>
<th></th>
<th>PT period: 2001Q1-2014Q4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Loans, Sec</td>
<td>NR Loans</td>
<td>NR Sec</td>
<td>Loans, Sec</td>
</tr>
<tr>
<td>Deposit PT</td>
<td>0.48</td>
<td>0.47</td>
<td>0.13</td>
</tr>
<tr>
<td>(14.40)</td>
<td>(11.88)</td>
<td>(4.72)</td>
<td>(14.15)</td>
</tr>
<tr>
<td>Collapsed</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>R²</td>
<td>0.12</td>
<td>0.09</td>
<td>0.01</td>
</tr>
<tr>
<td>Bank-Quarters</td>
<td>57,224</td>
<td>57,224</td>
<td>57,224</td>
</tr>
<tr>
<td>Banks</td>
<td>1,483</td>
<td>1,483</td>
<td>1,483</td>
</tr>
</tbody>
</table>

Panel B: Estimating deposit pass-through with LIBOR, for different periods

<table>
<thead>
<tr>
<th>PT period: 2001Q1-2008Q4</th>
<th></th>
<th>PT period: 2001Q1-2014Q4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Loans, Sec</td>
<td>NR Loans</td>
<td>NR Sec</td>
<td>Loans, Sec</td>
</tr>
<tr>
<td>Deposit PT</td>
<td>0.47</td>
<td>0.44</td>
<td>0.13</td>
</tr>
<tr>
<td>(15.39)</td>
<td>(12.24)</td>
<td>(5.32)</td>
<td>(13.12)</td>
</tr>
<tr>
<td>Collapsed</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>R²</td>
<td>0.14</td>
<td>0.09</td>
<td>0.02</td>
</tr>
<tr>
<td>Bank-Quarters</td>
<td>57,224</td>
<td>57,224</td>
<td>57,224</td>
</tr>
<tr>
<td>Banks</td>
<td>1,483</td>
<td>1,483</td>
<td>1,483</td>
</tr>
</tbody>
</table>

Table 1.8 shows the results of this analysis, which uses data on interest rates on jumbo mortgages from SNL (see Appendix A.2.3 for more details). In terms of magnitudes, a one standard deviation move in deposit pass-through leads to FRM-ARM spreads that are

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75This analysis is more informative when conducted with interest rates on jumbo loans as banks are more likely to hold these on balance sheet (in comparison with conforming loans).
Table 1.8: Relationship of FRM-ARM spread to deposit pass-through

Notes: This table shows the relationship between the FRM-ARM spread at the bank level and deposit pass-through. I use branch level data on interest rates on jumbo mortgages for the end of 2014 from SNL, and aggregate it to the bank level weighting by the fraction of deposits at different branches. The data includes interest rates for FRMs with different maturities, as well as ARMs and hybrid ARMs (an N/1 ARM has a fixed rate for N years, followed by a floating rate, adjusted once a year). See Appendix A.2.3 for more details. Deposit PT is the coefficient from quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate (using data for 2001Q1-2008Q4), in percentage points, winsorized at the 1% level. Panel A shows regressions where the dependent variables are spreads between 15 year FRMs and different types of ARMs. Panel B instead uses spreads relative to 30 year FRMs. All spreads are in basis points. t-statistics are shown in parentheses. To provide a sense for data coverage, I also report the fraction of deposits accounted for by branches for which data is available for each regression, in percentage points (Frac deposits).

Panel A: Spread between 15 year FRM and different types of ARMs

<table>
<thead>
<tr>
<th>Deposit PT</th>
<th>FRM - ARM</th>
<th>FRM - ARM 3/1</th>
<th>FRM - ARM 5/1</th>
<th>FRM - ARM 7/1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.77</td>
<td>0.93</td>
<td>0.65</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>(0.82)</td>
<td>(2.11)</td>
<td>(1.80)</td>
<td>(1.51)</td>
</tr>
</tbody>
</table>

| R²          | 0.01       | 0.02           | 0.01          | 0.01          |
| Banks       | 104        | 265            | 419           | 296           |
| Frac deposits (%) | 4   | 22             | 65            | 63            |

Panel B: Spread between 30 year FRM and different types of ARMs

<table>
<thead>
<tr>
<th>Deposit PT</th>
<th>FRM - ARM</th>
<th>FRM - ARM 3/1</th>
<th>FRM - ARM 5/1</th>
<th>FRM - ARM 7/1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.46</td>
<td>0.76</td>
<td>0.67</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>(0.50)</td>
<td>(1.76)</td>
<td>(1.94)</td>
<td>(1.44)</td>
</tr>
</tbody>
</table>

| R²          | 0.00       | 0.01           | 0.01          | 0.01          |
| Banks       | 104        | 265            | 419           | 296           |
| Frac deposits (%) | 4   | 22             | 65            | 63            |

about 7-8 basis points larger (compared to a standard deviation of around 70 basis points). Variation in mortgage rates therefore points to the supply-driven view: in the cross-section, banks with more floating-rate liabilities hold more floating-rate loans, and charge a lower price for them (relative to fixed-rate loans).

The comparatively small magnitude is consistent with the literature: banks might also use non-price mechanisms (differences in quantity or rationing) to affect their asset mix. For example, Foà et al. (2015) argue that Italian banks funnel customers towards either fixed or floating-rate residential mortgages based on the nature of their own funding. These authors emphasize that pricing does not explain all of the variation in quantities that they document.

As discussed in Section 1.3, I model loans to firms as a single asset class, where the floating fraction is a characteristic that affects the equilibrium price. A more general model could separate fixed-rate and floating-rate loans, generating a theoretical counterpart to the variation in FRM-ARM spreads that I analyze here.
The evidence is therefore consistent with the main hypotheses put forth in Section 1.3.\textsuperscript{78} Variation in three quite different parts of bank balance sheets (loans to firms, mortgages, and securities) therefore points to the supply-driven view of floating-rate bank lending to firms. I provide additional evidence, beginning with deposit competition as an instrument for pass-through, in Section 1.4.2. I then turn to time series evidence in Section 1.4.3 and historical evidence in Section 1.4.4.

1.4.2 Deposit pass-through, competition and size

I show that deposit pass-through is partly driven by geographic variation in deposit competition, and continue to find my main results using competition as an instrument for deposit pass-through. The impact of deposit competition on deposit pass-through also helps address concerns that the interest-rate exposure of bank liabilities is chosen to match the characteristics of banks’ assets rather than dictated by external forces. This also highlights that increasing pass through on deposits would be an expensive way to reduce interest-rate risk for a bank facing such demand for floating-rate loans, particularly in comparison with holding more long-term securities.

As banks are likely to try to minimize deposit interest expense, the idea that banks increase pass through on deposits to reduce mismatch with assets is somewhat implausible. The results so far strongly suggest that banks match the floating mix of their assets to match the nature of their deposit franchise. Results regarding the floating fraction of securities and FRM-ARM spreads are helpful in cutting against the idea that some banks’ borrowers demand floating-rate loans, and banks respond by increasing pass through on deposits. Such an explanation would be implausible regardless: if a bank had too many borrowers demanding floating-rate lending, it could hold more long-term, fixed-rate securities. By doing so, it would benefit from the term premium, instead of having to pay more interest

\textsuperscript{78} The theoretical predictions do hold the structure of bank liabilities fixed. Evidence in Sections 1.4.2 and 1.4.3 supports the idea that banks’ liabilities are constrained by external forces. I show that deposit competition increases deposit pass-through for some banks. I also show that time series variation in banks’ deposit composition seems not to be driven by a desire to match banks’ asset mix.
on its deposits. In the other direction, if a bank could reduce pass through on deposits, presumably it would already have done so.

To emphasize this interpretation, I show that competition and bank size are two sources of variation in deposit pass-through. I then recover my main results using competition as an instrument for deposit pass-through. Following Drechsler et al. (2014), I measure competition at the bank level as a deposit-weighted average of county-level Herfindahl Indices of deposit concentration (see Appendix A.2.3 for more details). Table 1.9 shows cross-sectional regressions (with collapsed samples) of deposit pass-through on bank competition, and on competition and bank size. Focusing on the first regression, banks operating in counties with a Herfindahl Index (HHI) higher by 0.1 (one standard deviation) have deposit pass-through lower by one percentage point. HHI is higher in counties with more deposit concentration, where the market for bank deposits is less competitive. As the second regression shows, bigger banks have more deposit pass-through.
Table 1.9: Deposit pass-through, competition and bank size (commercial bank data)

Notes: This table shows the relationship between pass through, HHI, and bank size, using commercial bank level call report data for 2001Q1-2014Q4. See Appendix A.2.3 for more details. Panel regressions instead include quarter and bank fixed effects. Deposit PT is the coefficient from quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate (using data for 2001Q1-2008Q4), in percentage points, winsorized at the 1% level. Deposit HHI is measured at the county level using branch level deposit data from SNL, aggregated to the parent level weighted by deposits (pro-forma, based on current ownership), expressed as a fraction. Log(Assets) is the base-10 logarithm of assets. Δ Deposit rate is the quarterly change in the implied deposit rate. ΔFF is the change in the quarterly average effective federal funds rate. Standard errors are clustered by bank for panel regressions. t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th>Collapsed cross section</th>
<th>Panel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Deposit PT</td>
</tr>
<tr>
<td>HHI</td>
<td>-10.30</td>
</tr>
<tr>
<td></td>
<td>(-4.77)</td>
</tr>
<tr>
<td>Log(Assets)</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>(4.01)</td>
</tr>
<tr>
<td>Δ FF × HHI</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ FF × Log(Assets)</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(5.55)</td>
</tr>
</tbody>
</table>

| Collapsed | Y | Y | N | N |
| Quarter FE | N | N | Y | Y |
| Bank FE   | N | N | Y | Y |
| SE Clustered by | - | - | Bank | Bank |
| R²        | 0.02 | 0.03 | 0.33 | 0.33 |
| Bank-Quarters | 57,224 | 57,224 | 55,245 | 55,245 |
| Banks     | 1,483 | 1,483 | 1,483 | 1,483 |
Table 1.10: HHI as an instrument for deposit pass-through

Notes: This table uses HHI as an instrument for deposit pass-through, using commercial bank level call report data for 2001Q1-2014Q4. See Appendix A.2.3 for more details. Panel A focuses on the relationship between pass through, HHI, and bank size. Deposit PT is the coefficient from quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate (using data for 2001Q1-2008Q4), in percentage points, winsorized at the 1% level. Deposit HHI is measured at the county level using branch level deposit data from SNL, aggregated to the parent level weighted by deposits (pro-forma, based on current ownership), expressed as a fraction. The first three columns repeat OLS regressions from Table 1.6. The dependent variables are the floating fraction of all loans and securities, non-residential loans and non-residential securities respectively. The fourth column repeats the first stage from Table 1.9 and shows the $F$-statistic. The final three columns use HHI as an instrument for Deposit PT in 2SLS estimation. $t$-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th>OLS</th>
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</thead>
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<tr>
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<td>Loans, Sec</td>
<td>NR Loans</td>
</tr>
<tr>
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<td>0.47</td>
</tr>
<tr>
<td></td>
<td>(14.40)</td>
<td>(11.88)</td>
</tr>
<tr>
<td>HHI</td>
<td>-10.30</td>
<td>-10.30</td>
</tr>
<tr>
<td></td>
<td>(-4.77)</td>
<td>(-4.77)</td>
</tr>
<tr>
<td>Collapsed</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.12</td>
<td>0.09</td>
</tr>
<tr>
<td>$F$</td>
<td>22.77</td>
<td>22.77</td>
</tr>
<tr>
<td>Bank-Quarters</td>
<td>57,224</td>
<td>57,224</td>
</tr>
<tr>
<td>Banks</td>
<td>1,483</td>
<td>1,483</td>
</tr>
</tbody>
</table>
For robustness, I also show this dependence of deposit pass-through on competition and bank size using specifications similar to Drechsler et al. (2014). Table 1.9 also shows panel regressions of the quarterly change in deposit rates on the quarterly change in the federal funds rate, with quarter and bank fixed effects. They include an interaction of the change in the federal funds rate with HHI, and in the final regression, with size as well. In these specifications standard errors are clustered at the bank level. I recover the result that banks facing less competition have less deposit pass-through (the magnitudes are somewhat bigger than those found by Drechsler et al. (2014)). These specifications also show that larger banks have more pass-through.

My results regarding the floating fractions of loans and securities also hold when I use competition as an instrument for deposit pass-through. Table 1.10 shows regressions of the floating fraction of bank assets on deposit pass-through, using competition as an instrument for pass-through. The outcome variables are the floating fractions of loans and securities, non-residential loans, and non-residential securities. Table 1.10 first shows OLS specifications, repeated from Table 1.6. It then repeats the first stage from Table 1.9, reporting the $F$-statistic to show that the first stage is statistically strong. Finally, I show two-stage least-squared versions of these regressions. All regressions show a positive relationship, though the magnitude is somewhat stronger than that from OLS regressions. That this applies to securities as well helps argue against concerns that competition is related to loan opportunities. 79 In unreported regressions, I show that the component of bank liabilities explained by variation in competition also helps explain the extent to which banks with higher pass through quote higher FRM-ARM spreads. 80

These results help address concerns that deposit pass-through is a fully endogenous variable, chosen primarily to match the characteristics of banks’ assets. Contrary to the view

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79 One explanation for why instrumental-variable regressions lead to bigger magnitudes is that I estimate deposit pass-through with error. OLS regressions might then be subject to standard measurement-error attenuation bias. If deposit competition helps isolate variation in pass-through from measurement error, instrumental variable regressions might reduce attenuation bias.

80 See Table 1.8 for the OLS versions of this.
that the composition of banks’ liabilities shifts to match the characteristics of banks’ assets, I argue that banks match the interest-rate exposure of their assets with that of their liabilities. I take the structure of bank liabilities as a largely exogenous variable. Indeed, as noted in Section 1.3, assume that deposit pass-through is exogenous in the model. The importance of external forces like deposit competition supports this approach. I provide additional supporting evidence based on the response of the structure of banks’ deposits to variation in interest-rate conditions in Section 1.4.3.

While the results so far apply to banks’ loans in aggregate, I show that they apply to C&I lending in particular. Banks also match the interest-rate exposure of C&I loans with that of their liabilities. As call report data does not directly provide information on the floating fraction of C&I lending, I use implied interest rates on C&I loans by dividing interest and fee income on C&I lending by the volume of C&I loans. I estimate pass through of interest rates for C&I lending in a similar manner to deposit pass-through, and then examine how this is related to deposit pass-through. As Table 1.11 shows, banks with more deposit pass-through also have more pass through on their C&I lending. This result also holds when I instrument for deposit pass-through with competition.

### 1.4.3 Time series analysis

In this subsection, I analyze the relationship between deposit pass-through and bank assets in the time series. I find evidence that within-bank variation in deposit pass-through also helps explain variation in banks’ asset interest-rate exposure, using bank holding company level data. I also show the cross-sectional relationships presented thus far hold over a longer time period. Finally, I show that banks’ liabilities do not seem to adjust to match the structure of bank assets in the time series.

To explore the relationship between deposit pass-through and bank assets in the time

---

81 C&I loans are an important component of bank balance sheets: they comprise about 20% of commercial bank loans and about 10% of total commercial bank assets.

82 As with the baseline methodology to estimate deposit pass-through, I estimate C&I pass-through using data for 2001Q1-2008Q4.
Table 1.11: C&I pass-through, deposit pass-through and competition (commercial bank data)

Notes: This table shows the relationship between C&I pass-through, deposit pass-through and competition, using commercial bank level call report data. See Appendix A.2.3 for more details. C&I PT is the coefficient from quarterly bank level regressions of changes in the implied rate on C&I Loans on changes in the effective fed funds rate, in percentage points. I require C&I PT to be positive and smaller than 110. Deposit PT is the coefficient from quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate, in percentage points, winsorized at the 1% level. Both types of pass-through are estimated using data for 2001Q1-2008Q4. Deposit HHI is measured at the county level using branch level deposit data from SNL, aggregated to the parent level weighted by deposits (pro-forma, based on current ownership), expressed as a fraction. All specifications collapse the sample to means at the bank level. t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>First Stage</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>C&amp;I PT</td>
<td>0.44 (5.16)</td>
<td></td>
<td>2.05 (2.77)</td>
</tr>
<tr>
<td>Deposit PT</td>
<td></td>
<td>-10.76 (4.55)</td>
<td></td>
</tr>
<tr>
<td>HHI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Collapsed</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>R²</td>
<td>0.02</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td></td>
<td>20.73</td>
<td></td>
</tr>
<tr>
<td>Bank-Quarters</td>
<td>47,029</td>
<td>47,029</td>
<td>47,029</td>
</tr>
<tr>
<td>Banks</td>
<td>1,168</td>
<td>1,168</td>
<td>1,168</td>
</tr>
</tbody>
</table>

series, I turn to bank holding company level data (from form FR-Y9C). While this data provides less detailed information on bank assets, consistent time series can be constructed for a longer sample period (this data is available for 1986Q3-2014Q4). I aggregate this data pro-forma based on present ownership, adjusting for mergers. I restrict the sample to holding companies that meet the requirements for quarterly reporting. The sample consists of about 80,000 bank quarters for close to 2,000 banks. See Appendix A.2.4 for more details regarding the data.

While a longer time series is available for bank holding company data, floating fractions within categories of assets are not directly reported, and have to be estimated. Here, I define the floating fraction as the fraction of assets with remaining maturity or repricing frequency less than one year. For the entire balance sheet, this information is reported directly. I construct estimates of the floating fraction of loans and securities, and of loans only, by progressively adjusting for federal funds and repo assets, and floating securities. Due to
the longer time series, here I am able to estimate a time series of deposit pass-through for each bank. I do so using lagged data for 8-20 quarters, as available. Table 1.12 shows similar summary statistics to the call report sample (Table 1.5). It shows again that larger banks have greater deposit pass-through and more floating-rate assets.

Table 1.12: Summary statistics for Bank Holding Company data

| Notes: This table shows summary statistics of US Bank Holding Company balance sheets for 1986Q3-2014Q4. I use BHC level call report data from the Chicago Fed’s website. I aggregate data pro-forma to present ownership using data on BHC mergers from the Chicago Fed’s website. I restrict to BHCs with assets above the minimum requirements for quarterly reporting (150MM in assets prior to 2005Q4, and 500MM subsequently). See Appendix A.2.4 for more details. Total assets ≤ 1 Yr is the fraction of assets with maturity or repricing frequency less than one year, in percentage points. Loans and securities ≤ 1 Yr is the corresponding inferred fraction of loans and securities (i.e. net of interest-bearing cash and federal fund and repo assets), in percentage points. Loans ≤ 1 Yr is the corresponding inferred fraction of loans (i.e. net of interest-bearing cash, federal funds, and repo assets and debt securities with maturity or repricing frequency less than one year), in percentage points. I require these ratios to be positive and less than 110%. Implied deposit rate is interest expense on deposits scaled by deposits, annualized and in percentage points. Deposit PT is the coefficient from rolling quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate (using data from the previous 8-20 quarters, as available), in percentage points, winsorized at the 1% level. Large banks are the largest 5% of banks by assets in each quarter. I report the standard deviation for each variable for the full sample. |
|---|---|---|---|---|
| | Full Sample | Small Banks | Large Banks | Std. Dev. |
| Assets (BN) | 4.2 | 1.2 | 51.8 | 23.1 |
| Total ≤ 1 Yr (%) | 43.3 | 42.9 | 49.7 | 16.0 |
| Loans and securities ≤ 1 Yr (%) | 40.8 | 40.5 | 47.2 | 16.2 |
| Loans ≤ 1 Yr (%) | 50.9 | 50.2 | 61.2 | 25.4 |
| Deposits/Liabilities | 89.1 | 89.9 | 76.9 | 9.9 |
| Implied Deposit Rate | 2.6 | 2.6 | 2.5 | 1.5 |
| Deposit PT | 26.9 | 26.5 | 33.7 | 21.5 |
| Bank-Quarters | 78,160 |
| Banks | 1,912 |

I find the cross sectional relationship between deposit pass-through and floating-rate assets in this longer panel, as well as some evidence of a time series relationship. Table 1.13 looks at the relationship between deposit pass-through and floating assets for this sample. Panel A shows regressions of the three measures of floating assets on deposit pass-through. The first three regressions include only quarter fixed effects. I double cluster standard errors by quarter and bank here. These regressions show that the floating fraction of banks’ assets is positively related with deposit pass-through in a sample going back to the late 1980s. Panel A also shows regressions including both quarter and bank fixed effects. While
much of the relationship is in the cross section, with this second set of regressions, I do find evidence that within-bank variation in deposit pass-through also helps explain the interest-rate exposure of bank assets.\textsuperscript{83}

In unreported analysis, I find similar results using the floating fraction of liabilities as the extent to which bank liabilities are floating. I use deposit pass-through as my main measure of the extent to which bank liabilities are floating rate. This directly measures the extent to which deposits are sticky and hence the extent to which bank liabilities are actually floating. It is also possible to construct measures of the floating fraction of bank liabilities (similar to the manner in which I construct the floating fraction of assets). This measure provides a different way to exploit time series variation in the extent to which banks’ liabilities are floating.\textsuperscript{84} In unreported analysis, I find similar results to those in Panel A of Table 1.13 using this alternative measure on the liability side. As might be expected, the results are stronger in the time series with this alternative measure.

Finally, I show that the time series response of banks’ liabilities to market conditions is not consistent with the idea that banks adjust their liabilities to match shifts in their assets. Table 1.14 shows that when term spreads are high, banks tend to have a smaller fraction of deposits maturing or repricing in less than one year, using regressions including bank fixed effects. This also applies to deposits combined with long-term debt. To provide a sense for magnitudes: a one standard deviation move in term spreads leads to variation in deposits of about a sixth of a standard deviation.\textsuperscript{85} This variation is likely driven by depositors’ desire to ‘lock in’ comparatively high fixed rates on CDs. Importantly, to match changes in asset composition, bank liabilities would need to co-move with term spreads in

\textsuperscript{83}Panel B of Table 1.13 looks at the relationship between deposit pass-through and bank size in this sample. The first regression, with quarter fixed effects, shows again that the positive relationship between these variables is clear in the cross section. The second, also including bank fixed effects, has a positive but statistically insignificant coefficient.

\textsuperscript{84}It is straightforward to construct this measure with regulatory data reported at the bank holding company level. This is the liability component of the maturity gap, as in Rampini et al. (2015a). The corresponding exercise with data at the commercial bank level would be less straightforward.

\textsuperscript{85}I scale the shift in deposit composition by the standard deviation in the maturing/repricing fraction of deposits across quarters, which provides a more appropriate comparison. There are larger differences across banks, which variation in term spreads is unlikely to generate.
Table 1.13: Floating mix of bank assets and deposit pass-through (BHC data)

Notes: This table shows regressions of the floating mix of bank assets on deposit pass-through, using bank holding company level call report data for 1986Q3-2014Q4. See Appendix A.2.4 for more details. Panel A shows the relationship between the floating fraction of assets and deposit pass-through. The first dependent variable (All) is the fraction of total assets with maturity or repricing frequency less than one year, in percentage points. The second dependent variable (Loans) is the corresponding inferred fraction of loans, in percentage points. The third dependent variable (Loans) is the corresponding inferred fraction of loans (i.e. net of interest-bearing cash, federal fund and repo assets, and debt securities with maturity or repricing frequency less than one year), in percentage points. Deposit PT is the coefficient from rolling quarterly bank level regressions of changes in the implied deposit rate on changes in the effective fed funds rate (using data from the previous 8-20 quarters, as available), in percentage points, winsorized at the 1% level. Panel B shows the relationship between deposit pass-through and bank size. Log(Assets) is the base-10 logarithm of assets. Standard errors are double clustered by Quarter and Bank. *-statistics are shown in parentheses.

Panel A: Variation of floating mix within Quarter and Bank

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Loans, Sec</th>
<th>Loans</th>
<th>All</th>
<th>Loans, Sec</th>
<th>Loans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deposit PT</td>
<td>0.10</td>
<td>0.10</td>
<td>0.13</td>
<td>0.02</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(6.75)</td>
<td>(6.75)</td>
<td>(5.82)</td>
<td>(2.59)</td>
<td>(2.50)</td>
<td>(0.29)</td>
</tr>
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<td>Quarter FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Bank FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SE Clustered by</td>
<td>Q, Bank</td>
<td>Q, Bank</td>
<td>Q, Bank</td>
<td>Q, Bank</td>
<td>Q, Bank</td>
<td>Q, Bank</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.15</td>
<td>0.17</td>
<td>0.11</td>
<td>0.72</td>
<td>0.71</td>
<td>0.61</td>
</tr>
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<td>BHC-Quarters</td>
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<td>78,160</td>
<td>78,160</td>
<td>78,160</td>
<td>78,160</td>
<td>78,160</td>
</tr>
<tr>
<td>BHCs</td>
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<td>1,912</td>
<td>1,912</td>
<td>1,912</td>
<td>1,912</td>
<td>1,912</td>
</tr>
</tbody>
</table>

Panel B: Deposit pass-through and bank size

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Log(Assets)</td>
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<tr>
<td></td>
<td>(6.57)</td>
<td>(1.42)</td>
</tr>
<tr>
<td>Quarter FE</td>
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<td>Y</td>
</tr>
<tr>
<td>Bank FE</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>SE Clustered by</td>
<td>Q, Bank</td>
<td>Q, Bank</td>
</tr>
<tr>
<td>$R^2$</td>
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<td>0.46</td>
</tr>
<tr>
<td>Bank-Quarters</td>
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</tr>
<tr>
<td>Banks</td>
<td>1,912</td>
<td>1,912</td>
</tr>
</tbody>
</table>

the opposite direction: it is well known that when term spreads are high, mortgages are much more likely to be made at floating rates (Koijen et al. 2009).
Table 1.14: Repricing fraction of bank liabilities and term spreads (BHC data)

Notes: This table shows regressions of the repricing/maturing fraction of bank liabilities on term spreads, using BHC level call report data for 1986Q3-2014Q4. The two dependent variables are the fraction of deposits that mature or reprice in less than one year, and a corresponding fraction of deposits and long-term debt (other borrowed money and subordinated debt). Both fractions are in percentage points. See Appendix A.2.4 for more details. I obtain constant maturity yields on government bonds from FRED. The term spread is the difference between the five year constant maturity yield and the one year constant maturity yield, in percentage points. I show specifications with standard errors clustered only by Quarter, as well as specifications with standard errors double clustered by Quarter and Bank. t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th>Term Spread</th>
<th>Deposits</th>
<th>Deposits+LTD</th>
<th>Deposits</th>
<th>Deposits+LTD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1.18</td>
<td>-0.99</td>
<td>-1.18</td>
<td>-0.99</td>
</tr>
<tr>
<td></td>
<td>(-2.13)</td>
<td>(-1.87)</td>
<td>(-2.09)</td>
<td>(-1.83)</td>
</tr>
<tr>
<td>Bank FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SE Clustered by</td>
<td>Q</td>
<td>Q</td>
<td>Q, Bank</td>
<td>Q, Bank</td>
</tr>
<tr>
<td>R^2</td>
<td>0.56</td>
<td>0.55</td>
<td>0.56</td>
<td>0.55</td>
</tr>
<tr>
<td>BHC-Quarters</td>
<td>78,160</td>
<td>78,160</td>
<td>78,160</td>
<td>78,160</td>
</tr>
<tr>
<td>BHCs</td>
<td>1,912</td>
<td>1,912</td>
<td>1,912</td>
<td>1,912</td>
</tr>
</tbody>
</table>

1.4.4 Historical analysis

I argue that banks’ floating-rate liabilities, i.e. short-term, interest-bearing deposits, drive floating-rate bank lending to firms. While this does describe the structure of bank liabilities over the past forty years, bank liabilities have not always been floating. Prior to about 1970, deposits were effectively fixed-rate liabilities, as they were largely non-interest-bearing. In this period realized interest rates on loans were also much less sensitive to short-term interest rates, supporting the supply-driven view that bank liabilities drive the interest-rate exposure of their lending.

I use the FDIC’s Historical Statistics on Banking to show that, historically, deposits were largely non-interest-bearing and loan rates were less sensitive to short-term rates. Before about 1970, bank liabilities were largely non-interest-bearing demand deposits. I show that during this period, interest rates on loans did not co-move strongly with short-term rates. While loans were likely extended at floating rates in contractual terms, perhaps during this period banks did not frequently adjust the rates they charged, effectively making the loans

86 The FDIC’s Historical Statistics on Banking (HSOB) go back to 1934. Appendix A.2.5 describes the data and definitions of variables.
fixed rate.\(^{87}\) This provides further evidence that the structure of bank liabilities is important for the interest-rate exposure banks pass on to borrowers.

Panel A of Figure 1.5 shows that primarily interest-bearing bank liabilities are a relatively recent phenomenon.\(^{88}\) Variation in the interest-bearing fraction of bank liabilities is primarily driven by the fraction of deposits on which banks pay interest. A few observations stand out: up until the late 1950s, bank liabilities were predominantly non interest-bearing, and hence effectively fixed rate.\(^{89}\) During this period, Regulation Q ceilings on interest rates on saving and time deposits were above market rates and hence not binding (Gilbert 1986). Beginning in the mid 1960s, interest was paid on a growing fraction of liabilities, a trend which accelerated in the 1970s, facilitated by the introduction of interest-bearing checking accounts.\(^{90}\) This change was also driven by a shift in composition of deposits from demand deposits to saving and time deposits.\(^{91}\) Since the mid 1980s, commercial banks have primarily been funded with interest-bearing liabilities.\(^{92}\)

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\(^{87}\)This can happen when loans make reference to a benchmark rate set by the bank, such as a prime rate. In contrast, when the benchmark is something like LIBOR, loan rates largely move with market conditions. Following the crisis, it has become common for loan contracts linking the interest rate to benchmarks like LIBOR to include interest-rate floors - in this case, loan rates move with market conditions only when the floor is not binding.

\(^{88}\)Payment of interest on deposits was restricted starting with the National Banking Acts of 1933 and 1935. These acts prohibited payment of interest on demand deposits (in effect until 2011), and allowed the Federal Reserve to restrict rates that could be paid on savings and time deposits (phased out in 1986). The original motivation for doing so was to prevent banks from competing ‘too much’ on deposits, leading to high deposit rates, in turn requiring risky investments (Gilbert 1986).

\(^{89}\)The falling fraction of interest-bearing liabilities through to the mid 1940s and subsequent rise are likely driven by WWII. In the early period savers were probably shifting money from savings accounts at banks to war bonds; later they were moving it back as these bonds matured. However, even excluding this feature of the data, the majority of bank liabilities did not pay interest.

\(^{90}\)This includes NOW accounts, and innovations facilitating automated transfers between checking and savings accounts.

\(^{91}\)See Appendix A.2.5 for a table showing the fraction of deposits held in these different types of accounts from 1950 to 2010 in twenty year intervals.

\(^{92}\)During this period uncertainty regarding exchange rates following the end of Bretton Woods, as well as uncertainty regarding monetary policy and inflation, kicked off a focus on managing these risks. Indeed, this is the period in which many types of derivatives were first traded (Campbell & Kracaw 1993).
Panel A: Interest-bearing fraction of liabilities

Panel B: Effective loan and deposit rates

Notes: I use historical data on bank balance sheets from 1934-2013 from the FDIC. The data contains annual aggregate information for all US commercial banks with deposit insurance over this period. See Appendix A.2.5 for more details. Panel A shows the interest-bearing fraction of liabilities. The implied loan rate is the ratio of interest income on loans and leases to net loans and leases. The implied deposit rate is the ratio of interest expense on deposits to interest-bearing deposits. I use the yield on three month Treasury Bills (from FRED) as a proxy for the short-term rate. Panel B shows these rates. The statistical analysis looks at sub-samples before and after 1970, marked by a vertical dashed line here. All variables are in percentage points.

Figure 1.5: Historical balance sheets of FDIC insured commercial banks (1934-2013)

Prior to 1970, when bank liabilities were mostly non interest-bearing and effectively
fixed rate, floating-rate lending, not fixed-rate lending, would have been risky for banks. As data is not available on the floating fraction of lending for this period, I use sensitivity of interest income on loans to short-term interest rates to assess the extent to which loans were floating rate. I infer average realized interest rates on bank loans on an annual level by dividing interest income on loans and leases by net outstanding loans and leases.\textsuperscript{93} Panel B of Figure 1.5 shows this inferred interest rate. It also shows a similarly inferred deposit rate for comparison. Interest-bearing deposits were subject to (binding) rate ceilings below market rates beginning in 1966. After June 1970, at least some types of time deposits in excess of $100,000 were exempt from Regulation Q ceilings on interest rates (Gilbert 1986).\textsuperscript{94} It is clear from Panel B of Figure 1.5 that there is substantially more volatility in both deposit rates and loan rates after about 1970.

Having constructed a time series of realized interest rates on loans, I now assess how sensitive these loan rates were to short-term interest rates. If loans are made at floating rates, realized loan rates should strongly co-move with short-term interest rates. In contrast, if loans are made at fixed rates, this should not be the case.\textsuperscript{95} Denote the inferred loan rate by $y_t$, and the short-term interest rate by $r_t$. I use the yield on three month Treasury Bills (from the Federal Reserve) as a proxy for short-term interest rates. I regress changes in loan rates on changes in short-term rates and compare the results for different periods.

$$\Delta y_t = \alpha + \beta \Delta r_t + \rho \Delta y_{t-1}$$

(1.16)

I include an autoregressive term to allow loan yields to shift slowly.

Interest rates on loans were much less sensitive to short-term rates prior to 1970, suggesting that loans were effectively made at fixed rates in this period. Table 1.15 shows the results of regressions following Equation 1.16 in different periods. Prior to 1970, loan rates

\textsuperscript{93}See Appendix A.2.5 for details. The results are very similar if I scale by gross loans and leases instead.

\textsuperscript{94}One of the roles of money market mutual funds was to pool smaller deposits into larger amounts above the limit. Also see Friedman (1986) for more on this period.

\textsuperscript{95}If bank loans were always short term, this distinction would not be meaningful. In the period for which I have Capital IQ data, I show in unreported analysis that the bank loans are typically extended at five year terms, although maturities do fluctuate with market conditions.
Table 1.15: Sensitivity of implied loan rates to short-term interest rates

Notes: I use historical data on bank balance sheets from 1934-2013 from the FDIC. The data contains annual aggregate information for all US commercial banks with deposit insurance over this period. I calculate an inferred loan rate, $y_t$, as the ratio of interest income on loans and leases to net loans and leases. I use the yield on three month Treasury Bills (from the Federal Reserve) as a proxy for the short-term rate $r_t$. See Appendix A.2.5 for more details. I run regressions of the form

$$\Delta y_t = \alpha + \beta \Delta r_t + \rho \Delta y_{t-1}$$

for different sub-samples: 1934-1969 and 1970-2013. The table also shows the long term response of loan rates, $\beta/(1 - \rho)$. The table shows t-statistics based on Newey-West standard errors, allowing autocorrelation up to five lags.

<table>
<thead>
<tr>
<th></th>
<th>1934-1969</th>
<th>1970-2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta r_t$</td>
<td>0.24</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>(3.08)</td>
<td>(11.25)</td>
</tr>
<tr>
<td>$\Delta y_{t-1}$</td>
<td>0.37</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>(3.14)</td>
<td>(4.17)</td>
</tr>
<tr>
<td>$\beta/(1 - \rho)$</td>
<td>0.37</td>
<td>0.67</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.27</td>
<td>0.79</td>
</tr>
<tr>
<td>N</td>
<td>34</td>
<td>44</td>
</tr>
</tbody>
</table>

were not very responsive to short-term interest rates: they rose only about 20 basis points for a 100 basis point increase in short-term rates. The long term response, $\beta/(1 - \rho)$, was about 40 basis points. The $R^2$ from the regression is small: only 27%. In contrast, after 1970, loan rates co-moved more strongly with short-term interest rates. They rose almost 50 basis points for a 100 basis point increase in short-term rates. The long term response was almost 70 basis points. The $R^2$ from the regression also rises substantially, to 79%. I use simulations to show that these results imply that only about 10% of loans were floating-rate before 1970, while around 25-40% were floating-rate subsequently.

I choose the year 1970 as the cutoff because this is approximately when the majority of bank liabilities became interest bearing (judged visually). As noted above, after 1970, at least the largest denominated accounts were exempt from interest-rate ceilings. However, they were only binding after 1966. For robustness, I repeat this exercise using each other year from 1965-1975 as the cutoff instead of 1970, and confirm that the results remain similar whichever cutoff is used.

I simulate an AR(1) process for short-term rates and credit spreads. I use these to simulate paths of loan rates for different floating fractions of lending, taking maturing and new loans into account. Fixed-rate loans have an average rate that is a weighted average of recent short-term rates and loan spreads, while changes in interest rates on floating-rate loans track changes in the short term rate. I simulate regressions similar to Equation 1.16, but for simplicity exclude the autoregressive term (the results in Table 1.15 are similar without the autoregressive term). A coefficient $\beta$ of about 0.25 corresponds to a floating fraction of loans of about 10%.

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97 I simulate an AR(1) process for short-term rates and credit spreads. I use these to simulate paths of loan rates for different floating fractions of lending, taking maturing and new loans into account. Fixed-rate loans have an average rate that is a weighted average of recent short-term rates and loan spreads, while changes in interest rates on floating-rate loans track changes in the short term rate. I simulate regressions similar to Equation 1.16, but for simplicity exclude the autoregressive term (the results in Table 1.15 are similar without the autoregressive term). A coefficient $\beta$ of about 0.25 corresponds to a floating fraction of loans of about 10%.
In summary, the evidence strongly supports the supply-driven view that bank liabilities drive floating-rate bank lending to firms. Consistent with Proposition 1, banks with more floating-rate liabilities make more floating-rate loans. They also hold more floating-rate securities. As Proposition 2 shows, this allows me to rule out the idea that firms demand floating-rate loans. These results also hold when I instrument for pass through with deposit competition, and also apply to pass through on C&I lending in particular. I also show that banks with more floating liabilities quote lower interest rates for ARMs, relative to FRMs. In addition to the historical evidence presented in this subsection, I also find some evidence of time-series versions of these relationships.

1.5 Implications for transmission of monetary policy

In this section I draw out the implications of floating-rate bank lending for monetary policy. I interpret the effect of floating-rate bank lending as a component of the Bernanke & Gertler (1995) balance-sheet channel of transmission of monetary policy. I also use the sensitivity of investment to non-interest expense related components of cash flow to impute the size of the effect of investment for bank-dependent firms. Finally, I show that this imputed effect can account for a significant portion of the greater relative interest rate sensitivity of bank-dependent firms’ investment.

1.5.1 Relevance for balance-sheet channel

Banks play a role in the transmission of monetary policy to firms by lending to them at floating rates; this is distinct from the usual bank lending channel, and is an important

while $\beta$ of roughly 0.50 corresponds to a floating fraction of around 25-40%, based on the 10th-90th percentile of coefficients for 1,000 simulations for each floating fraction. The range of simulated coefficients is larger (i.e. this process leads to less certain inference) for higher floating fractions.
component of the Bernanke & Gertler (1995) balance-sheet channel. Under the traditional bank lending channel, firms are adversely affected by tighter monetary policy because less new bank lending is available (Kashyap & Stein 1994, Kashyap & Stein 2000, Peek & Rosengren 2013).\textsuperscript{98} I emphasize that bank-dependent firms are more directly affected by changes in interest rates: as bank lending is largely floating rate, the cost of these firms’ existing debt responds to changes in interest rates. This is a version of the Bernanke & Gertler (1995) balance-sheet channel, in which firms’ financial health deteriorates as interest rates rise, both because interest expense rises and because cash flows fall as aggregate demand falls.\textsuperscript{99} Bernanke & Gertler (1995) focus on the importance of short-term debt (commercial paper); here I show the relevance of floating-rate debt.\textsuperscript{100}

Bank-dependent firms’ financial condition, as measured by interest coverage ratios, is more sensitive to interest rates than that of firms with better access to capital markets. To show this, I use a sample containing capital structure and balance sheet data, as before, as well as data on total interest expense. As with the analysis in Section 1.2, the data covers 2003-2013. I calculate firms’ interest coverage ratios, defined as the ratio of interest expense to operating income before depreciation.\textsuperscript{101} I identify bank-dependent firms as firms with a high average fraction of bank debt, within industry. Figure 1.6 shows that bank-dependent firms’ interest coverage ratios are more sensitive to short-term interest rates.\textsuperscript{102}

\textsuperscript{98}This channel is based on changes in reserve requirements, which may be less relevant in the current environment of significant excess reserves. The Drechsler et al. (2014) deposits channel, in which banks exercise market power by changing the quantity of deposits supplied, is an alternative channel under which the quantity of new bank lending is sensitive to interest rates.

\textsuperscript{99}These authors also emphasize that residential investment responds earlier and more sharply to interest rates than business fixed investment.

\textsuperscript{100}The classic discount rate channel is another important way in which monetary policy is relevant for firms. As the interest rate (and discount rate) changes, which projects are found to have positive NPV also changes (Keynes 1936).

\textsuperscript{101}This is the inverse of the usual definition, following Bernanke & Gertler (1995).

\textsuperscript{102}Interest coverage ratios jump for both types of firms in 2009 because cash flows dropped substantially. See Panel B of Figure 1.7.
Notes: The data is annual, and goes from 2003-2013. See Appendices A.2.1 and A.2.2 for more details. I restrict the sample to firms with at least five observations on interest expense data. I calculate the average bank fraction of debt for firms over the sample, and separate firms into high bank and low bank based on this average fraction within Fama & French (1997) 12 industries. The interest coverage ratio is the ratio of interest expense to operating income before depreciation, in percentage points (inverted from the normal definition following Bernanke & Gertler (1995)). The ratio is value weighted within each category. LIBOR is shown on the right axis, and is also in percentage points.

Figure 1.6: Interest coverage ratios by bank dependence

Floating-rate bank lending is a significant contributor to this greater sensitivity. In this sample, bank-dependent firms obtain two thirds of their debt finance from banks, largely at floating rates, while firms with better access to capital markets obtain only one sixth of their debt from banks. As discussed in Section 1.2, firms only partially hedge away these differences: for the subsample where I have information on hedging, bank-dependent firms have twice as much floating-rate debt as a fraction of assets after taking hedging into account.\textsuperscript{103} Indeed, as Panel A of Figure 1.7 shows, bank-dependent firms’ realized interest rates are more sensitive to interest rates. While Bernanke & Gertler (1995) focus on the importance of short-term debt (commercial paper), which does play a role for larger, better rated firms, floating-rate bank debt is the driver here.\textsuperscript{104} Floating-rate bank debt largely

\textsuperscript{103}Going forward, the prominence of interest-rate floors in loan contracts may mean that firms are not exposed to initial increases in short term interest rates.

\textsuperscript{104}This literature emphasizes that larger firms borrow more with commercial paper to finance inventories as
Panel A: Realized interest rates

Panel B: Cash flow scaled by lagged assets

Notes: The data is annual, and goes from 2003-2013. See Appendices A.2.1 and A.2.2 for more details. I restrict the sample to firms with at least five observations on interest expense data. I calculate the average bank fraction of debt for firms over the sample, and separate firms into high bank and low bank based on this average fraction within Fama & French (1997) 12 industries. Panel A shows realized interest rates: interest expense scaled by total debt, in percentage points (value weighted within each category). Panel B shows firms’ cash flows: operating income before depreciation scaled by lagged assets, in percentage points (value weighted within each category). Both panels show LIBOR on the right axis, also in percentage points.

Figure 1.7: Components of interest coverage by bank dependence

interest rates rise. Consistent with this observation, leverage does rise somewhat for firms I classify as low bank in 2006-2007.
consists of term loans, which have similar maturities to corporate bonds.

Bank-dependent firms have similar aggregate cash flows as firms with better access to capital markets. Bank-dependent firms are present in every industry; indeed, I identify bank-dependent firms based on the fraction of bank debt within industry. As shown in Section 1.2, bank-dependent firms do not have more cyclical cash flows to offset floating-rate bank debt. Panel B of Figure 1.7 shows that both types of firms had similar cash flows over the recent business cycle and crisis. While bank-dependent firms did experience a sharper response during the financial crisis, their cash flows are not markedly more sensitive to interest rates.

To the extent that bank-dependent firms are more financially constrained at times when central banks are likely to lower interest rates, floating-rate bank loans might provide a natural hedge. Bank-dependent firms do not have more cyclical cash-flows, and do partially hedge their exposure to rates. Evidence from the cross-section of bank-balance sheets presented in Section 1.4 shows that most variation in floating-rate debt is driven by variation in bank credit supply. However, it may be the case that bank-dependent firms tend to be more financially constrained in poor macroeconomic environments, which is when central banks are likely to lower rates. Then, floating-rate bank loans allow the benefits of looser monetary policy to flow to bank-dependent firms.

1.5.2 Implied effect of cash-flow shocks on investment

As interest rates vary, bank-dependent firms face cash-flow shocks through changes in interest expense on floating-rate debt. To quantify the effect these shocks have on investment, I use the methodology of the investment cash-flow sensitivity literature (Fazzari et al. 1988, Baker, Stein & Wurgler 2003, Greenwood 2003). This literature argues that investment responds to cash-flow shocks of any kind, as external finance is costly. I produce similar estimates using variation in cash flow unrelated to interest expense and use them to impute the effect of cash-flow shocks from floating-rate debt on investment. I then show that

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105 Panel A of Figure 1.7 suggests that spreads did rise for bank-dependent firms in 2009.
this channel can account for a significant portion of the greater interest-rate sensitivity of bank-dependent firms’ investment.

I begin by imputing the effect on investment for the sample of firms where I have balance sheet and capital structure data, as well as information on hedging, as this provides detailed information on the size of the shock. As above, I separate firms into bank-dependent and non-bank-dependent firms based on the bank fraction of debt, within industry. Bank-dependent firms’ floating-rate debt amounts to 13% of their assets on average, implying that a 1% change in interest rates would lead to a cash-flow shock of 13 bps as a fraction of assets.\footnote{This is roughly double the exposure of firms with better access to capital markets.} Next, I regress investment on market-book ratios and operating income within the set of bank-dependent firms, finding that a $1 cash-flow shock translates to a 17 cent effect on investment.\footnote{This estimate is comparable to results found in this literature. I define variables following Baker et al. (2003), with the exception of cash flow: I define this as operating income before depreciation, scaled by lagged assets, to exclude the effect of interest expense from cash-flow shocks.} Combining these estimates suggests that a one percent rise interest rates leads to a 2 basis point reduction in investment. Over the course of a business cycle, when interest rates might shift by as much as 5%, this amounts to an effect around 2% of the mean and 4% of the standard deviation.

This channel can account for a significant portion of the greater interest-rate sensitivity of bank-dependent firms’ investment. To show this, I present a simple calculation using a larger sample constructed only from Compustat data, which allows me to extend the analysis back to the late 80s. I identify bank-dependent firms based on the sensitivity of their interest expense to interest rates.\footnote{I identify high floating firms by estimating firm level interest expense betas, regressing changes in implied interest rates on debt on changes in LIBOR. I separate firms on this basis within industry. This sorting works well: high floating firms have interest rate betas around 0.7-0.8, while low floating firms exhibit little interest-rate sensitivity for the cost of debt.} I also combine this split with a sort by interest expense volatility scaled by overall cash-flow volatility. Within the subset of firms I label both high floating and high interest expense volatility, a simple calculation along the lines outlined in the previous paragraph suggests that a 1% rise in interest rates leads to investment being...
lower by 6 basis points as a fraction of assets.\textsuperscript{109}

This imputed effect through floating-rate debt can account for about 20% of the differential interest-rate sensitivity of bank-dependent firms. To estimate the differential effect of interest rates on bank-dependent firms’ investment through all channels of transmission of monetary policy, I regress investment on interest rates interacted with sub-group indicator dummies. In unreported regressions, I show that, relative to firms with good access to capital markets, firms that are both high floating and have high interest expense volatility invest about 30 bps less as a fraction of their assets, when interest rates rise by 1%.\textsuperscript{110} Hence, the total difference in investment sensitivity is about 5 times the effect imputed through the floating-rate channel above. Equivalently, the floating-rate channel can account for about 20% of the total difference in interest-rate sensitivity. These back of the envelope calculations suggest that floating-rate bank lending plays an important role in the transmission of monetary policy to firms.

1.6 Conclusion

Bank lending is in large part funded with floating-rate deposits. As hedging is costly, banks avoid mismatch with the interest-rate exposure of their liabilities, in part, by making floating-rate loans to firms. To establish this link between the structure of bank liabilities and the floating-rate nature of bank lending, I examine the cross section of banks. Banks with greater interest rate pass-through on their deposits hold more floating-rate assets: both loans and securities. In the cross section, these floating fractions are positively correlated with each other. I show that if banks were responding to demand for floating-rate debt

\textsuperscript{109}These firms have a debt-assets ratio of 39% on average, interest expense betas averaging 0.73, and investment cash-flow sensitivity of 20 cents on the dollar. Combining these estimates, a 1% interest rate shock has an investment effect of 6 bps.

\textsuperscript{110}In unreported analysis, I separate firms into low, medium and high relevance for this effect. Firms in the low category are both low floating and low interest expense volatility. Firms in the high category are high along both dimensions; medium captures the remaining firms. I then regress investment on market to book ratios, cash flow and LIBOR, and include interactions of these variables with dummies for medium and high firms. The number reported in the text, 30 bps, is the coefficient on the interaction of high relevance and LIBOR.
from firms instead of their own liabilities, this correlation would be negative. Moreover, while banks with more deposit pass-through hold more floating-rate loans, they quote lower interest rates for ARMs relative to FRMs. The combination of higher quantities and lower prices points to variation in supply rather than demand. I also present time series and historical evidence supporting the supply-driven view of floating-rate bank lending to firms.

This chapter therefore highlights an important consequence of banks’ short-term funding: the potential for interest-rate mismatch. While standard models do analyze maturity mismatch created by short-term funding, they typically do not consider uncertainty in interest rates and interest-rate mismatch. This chapter shows that the structure of banks’ funding has important implications for the choices banks make about interest-rate risk on the asset side of their balance sheets. More broadly, my results establish an important link between intermediaries’ funding structure and the types of contracts used by non-financial firms. My results suggest that tighter regulation of banks’ exposure to interest rates might lead banks to pass on more risk to firms, which is particularly relevant given renewed regulatory focus on banks’ exposure to rates.

Bank-dependent firms, i.e. poorly rated firms and smaller firms, are more exposed to interest rates than firms with better access to capital markets. While these firms do use interest-rate derivatives to hedge this exposure, they do so only partially. I show that this exposure is a component of the Bernanke & Gertler (1995) balance-sheet channel of transmission of monetary policy. Banks therefore play a role in the transmission of monetary policy to firms beyond the usual bank lending channel; here the effect is based on existing rather than new bank lending.
Chapter 2

Understanding risk taking by life insurers

2.1 Introduction

Understanding why financial institutions take risk is central to our understanding of financial intermediation. In this chapter, I study risk taking in a large sector facing increased attention and scrutiny since the financial crisis: life insurance. I construct detailed measures of risk in two key dimensions, net interest-rate risk and asset risk, at the insurer level. Using both measures, I document considerable heterogeneity in risk taking by life insurers, both in the cross section and in the time series. Intriguingly, I find that some of the largest, most sophisticated life insurers reduced risk on both dimensions, relative to other insurers, during and subsequent to the financial crisis.

This heterogeneity in insurer risk taking sheds light on why financial institutions take risk. Risk shifting (Jensen & Meckling 1976), one of the standard ways to think about risk taking, posits that leverage creates incentives for institutions to take risk, exploiting the option-like payoff to equity. While I do find evidence that more levered insurers take more risk on both dimensions, risk shifting cannot explain all variation in insurer risk taking. Indeed, the group of insurers that reduced risk had more leverage than even other large
insurers. The evidence points to explanations in which these insurers’ crisis experience drove their risk taking behavior, as they insurers invested in asset classes that turned out to be risky during the crisis and faced substantial fair value losses. These explanations include learning about risk from the crisis, whether previously neglected (Gennaioli, Shleifer & Vishny 2012) or not, and preserving franchise value. I also address an alternative view that insurer risk taking is driven primarily by institution specific preferences and circumstances.

Life insurance is particularly suited to studying why financial institutions take risk for both conceptual and data-related reasons. On the conceptual side, the dimensions of insurer risk taking, which include interest-rate risk and asset risk (or reaching for yield) are well understood (Koijen & Yogo 2015b, Becker & Ivashina 2015). On the data side, detailed regulatory data is available to researchers regarding insurers’ assets (far more detailed, for instance, than bank regulatory data). I obtain this data for 2005-2014, covering the crisis as well as periods before and after. I construct quarterly and daily views of all bonds held and transacted (in the general account), at the bond level. The ability to construct similarly detailed views of insurers’ derivatives positions and transactions allows me to obtain a comprehensive view of interest-rate risk.

I construct two main measures of insurer risk taking: net interest-rate risk, and reaching for yield. As life insurers have very long-term liabilities (annuities are essentially long-dated fixed-rate bonds), they face interest-rate risk to the extent that the market value of their liabilities fluctuates in a manner not offset by the assets they hold (Koijen & Yogo 2015b). I construct a detailed measure of the exposure to interest rates insurers obtain through their

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1This is not to suggest that life insurers do not take risk in complicated ways: see, for example, McDonald & Paulson (2015) on the behavior of AIG during the crisis, and Koijen & Yogo (forthcoming) on the phenomenon of shadow reinsurance. I focus on the life insurance subsidiaries of insurers here (which excludes much of AIG’s problematic behavior during the crisis), and account for shadow reinsurance in parts of my analysis.


3As noted earlier, I focus on the life insurance subsidiaries of insurance groups here. Within interest-rate derivatives, I focus on insurers’ single-currency interest-rate swaps. As is typical, less detailed data is available on the liability side.

4Re-investment risk is another aspect interest-rate risk for life insurers. If they are unable to invest in assets with maturities as long as their liabilities, they may be forced to reinvest at lower interest rates in the future.
assets (bonds as well as derivatives). Due to data limitations, I estimate the interest-rate exposure on the liability side in a simple manner.\(^5\) I show that insurers do not fully offset interest-rate exposure on the liability side with their assets, and I refer to the remaining gap as net interest-rate risk. Following Becker & Ivashina (2015), I use average yields to maturity on bonds purchased on a quarterly basis to measure reaching for yield.\(^6\)

While some aspects of heterogeneity in insurer risk taking in these two dimensions are very consistent with risk shifting, it is difficult to fully explain insurers’ risk taking through a risk shifting framework. By both measures of risk-taking (interest-rate risk and reaching for yield), insurers with more equity take less risk over the full sample.\(^7\) Evidence for reaching for yield persists even after including insurer fixed effects, addressing the view that institution specific risk-taking preferences drive most important variation. I even find evidence for a key prediction of risk shifting, that risk shifting incentives should have steepened during the crisis, when the option of default was likely to be particularly valuable. However, this steepening was concentrated among smaller insurers, which have substantially less leverage overall. The extent to which large insurers with more leverage reach for yield actually fell during, and post-crisis.

I therefore turn to investigating whether there is evidence for alternative theories of insurer risk taking, particularly those placing emphasis on insurers’ crisis experience. While risk shifting would suggest increased incentives for risk taking during the crisis, other views might suggest reduced risk taking during the crisis. In particular, insurers that had invested in asset classes in which there was particular turmoil during the crisis could learn from the experience and actually take less risk going forward.\(^8\) Insurers with significant franchise value, if faced with the possibility of bankruptcy, might also reduce risk taking to ensure

\(^5\)I suggest that insurer liabilities quite plausibly have a modified duration of 15 years, and use this to estimate interest-rate risk on the liability side. See Section 2.4 for more details.

\(^6\)I also present some analysis focusing on purchases of newly issued bonds only.

\(^7\)Becker & Ivashina (2015) also report this relationship for reaching for yield.

\(^8\)A behavioral version of this would emphasize that little new information was revealed, arguing instead that certain types of risks merely became salient again (Shleifer 2011, Gennaioli et al. 2012).
survival as a going concern.\textsuperscript{9} Consistent with this, I find that risk shifting was attenuated during the crisis for insurers that had invested in private MBS pre-crisis or faced fair value losses during the crisis.

Within the largest insurers, it is helpful to separate those that used interest-derivatives in a significant way from those that did not. The use of derivatives is highly skewed, and a small subset of large insurers account for almost all significant use of interest-rate swaps by the sector.\textsuperscript{10} These insurers, which I term ‘heavy users’ of interest-rate derivatives, had substantially more leverage prior to the crisis, even relative to other large insurers.\textsuperscript{11} They also invested heavily in private MBS prior to the crisis, and faced large fair value losses during the crisis. Heavy users of derivatives therefore present a clean contrast between risk shifting and crisis experience-based theories of risk taking: the former predicts that heavy users should have increased risk taking, particularly during the crisis, while the latter predict reduced risk taking.

Heavy users of derivatives reduced their risk taking during and after the crisis, relative to other insurers. This strengthens the conclusion that risk shifting cannot fully explain insurers’ risk taking, and lends credence to the relevance of insurers’ crisis experience. During and after the crisis, heavy users reduced their net interest-rate risk, even relative to other large insurers. Before the crisis their net interest-rate exposure was about half a standard deviation larger than other large insurers; by the end of the sample period it was no longer statistically different.\textsuperscript{12} Similarly, heavy users also reached for yield less than other large insurers during and post-crisis. The average yields of bonds bought by heavy

\textsuperscript{9}Koijen & Yogo (2015a) document that many insurers faced serious trouble during the crisis. Chodorow-Reich (2014) presents the time series of CDS rates for large insurers during the crisis.

\textsuperscript{10}Life insurers’ use of interest-rate derivatives is informative about the market for interest-rate risk more broadly. Anecdotally, insurers are amongst the largest end-users of derivatives for hedging purposes. I show that insurers use interest-rate swaps to reduce interest-rate risk (at least the swaps held within life insurance subsidiaries). I also show that, subsequent to the crisis, some life insurers use interest-rate swaps as an asset class on par with corporate bonds.

\textsuperscript{11}These heavy users of derivatives are also roughly similar in size to all other life insurers combined.

\textsuperscript{12}Heavy users of derivatives lowered their interest-rate risk in part by ceding reserves through shadow reinsurance (Koijen & Yogo forthcoming). However, even after adjusting for shadow reinsurance, heavy users became safer post-crisis.
users were about a quarter of a standard deviation lower than those bought by other large insurers. All of these results are robust to including insurer fixed effects, addressing the alternative view that insurer-specific risk preferences drive most important variation.

The two views in which insurers’ crisis experience could lead them to reduce risk taking during the crisis, learning from the crisis and franchise value, are difficult to separate empirically, as they have similar implications for risk taking in this period. To the extent that they make predictions that are subtly different, I find evidence supporting aspects of both possibilities. For instance, a key feature of the neglected risk view of the crisis is that changes in risk taking should be concentrated in asset classes that performed poorly in the crisis. Consistent with this, I show that heavy users of derivatives reached for yield less during the crisis in part because they bought fewer privately issued structured bonds. Equally, an important aspect of the view that franchise value led some insurers to reduce risk taking during the crisis is that once bankruptcy was no longer a danger after the crisis, risk taking should have returned back to normal. Consistent with this, I present evidence that risk shifting was amplified post-crisis (but not during the crisis) for insurers that invested in private MBS prior to the crisis.\(^{\text{13}}\)

I highlight the implications of life insurers’ trading in three further broad areas. First, life insurers tend to trade very smoothly, with very little net selling.\(^{\text{14}}\) This is true even during periods with large price and quantity shocks such as those associated with quantitative easing. Particularly if other institutional investors behave similarly, this raises questions about standard frameworks in finance, in which capital is reallocated in response to shocks. Moreover, it is not clear whether slow, smooth behavior by all agents is equivalent to models of slow-moving capital in which individual agents only trade periodically (Duffie 2010). Second, gross trading is much larger than net trading, particularly for US government bonds. This is related to broader questions about why there is so much trading. Third, the prices at

\(^{\text{13}}\)An examination of risk taking behavior going forward may be useful here.

\(^{\text{14}}\)Indeed, even during the depth of the crisis life insurers largely traded smoothly and engaged in little net selling.
which life insurers transact may be of interest in and of themselves. For instance, they might suggest a different view of market conditions during key periods such as the announcement phase of quantitative easing.

I build on and connect with three main strands of literature. First, and most closely related, there is a literature on risk taking by insurers, both during the crisis and more broadly (Koijen & Yogo 2015a, Koijen & Yogo 2015b, Koijen & Yogo forthcoming, Becker & Ivashina 2015, Ellul, Jotikasthira, Lundblad & Wang 2015, Merrill, Nadauld, Stulz & Sherlund 2012). I present new evidence on the extent to which life insurers take risk in two important dimensions, and emphasize heterogeneity in risk taking within life insurers. Second, there is large literature documenting risk taking by financial institutions, particularly around the crisis, and trying to understand why this occurred, for example: Shleifer (2011), Gennaioli et al. (2012), Rajan (2006), French, Baily, Campbell, Cochrane, Diamond, Duffie, Kashyap, Mishkin, Rajan, Scharfstein et al. (2010), Brunnermeier (2009), Chodorow-Reich (2014), and Chernenko, Hanson & Sunderam (forthcoming). I present evidence consistent with risk shifting in aggregate, particularly in pre-crisis behavior. I show that risk shifting cannot fully explain insurer risk taking, and highlight the relevance of insurers’ experience during the crisis. Third, there is a literature on the use of derivatives by financial institutions, investigating whether derivatives are used for hedging or not and presenting mixed evidence (Begenau et al. 2015, Rampini, Viswanathan & Vuillemey 2015b). I show that life insurers use interest-rate swaps to reduce their net interest-rate exposure.

The remainder of this chapter is structured as follows. In Section 2.2, I lay out four main theories of risk taking by financial institutions and discuss their implications. I then discuss the data in Section 2.3. I develop my main measures of risk taking and present some initial tests of risk shifting in Section 2.4. In Section 2.5, I turn to presenting evidence for theories of risk taking emphasizing the relevance of insurers’ experience during the crisis, focusing on the experience of heavy derivatives users. I highlight the implications of insurer behavior

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15 Begenau et al. (2015) conclude that large banks use derivatives to add exposure in the same direction as their bond holdings. Rampini et al. (2015b) conclude that small banks use derivatives to hedge interest-rate risk.
in other domains in Section 2.6. Section 2.7 concludes.

### 2.2 Theories of risk taking

In this section, I outline four main theories of risk taking and their implications. First, risk shifting, according to which equity holders have incentives to take risk due to the option-like payoff of equity. Second, that insurers might learn from crises and reduce (at least certain kinds of) risk taking. Third, that insurers have significant franchise value as going concerns, and try to avoid failure. Fourth, that institution-specific factors and preferences drive most interesting variation. While these theories are not mutually exclusive at all times, there are circumstances under which they make different predictions.\(^{16}\)

Risk shifting (Jensen & Meckling 1976) is a classic view of why financial institutions might take on risk. This view typically highlights a conflict between shareholders and other claimants of firm value, particularly holders of debt.\(^{17}\) As equity holders own an option – to default on debt owed – taking risk can be beneficial in some circumstances. Particularly when a firm is close to defaulting on debt, increasing risk can allow shareholders the possibility of upside while debt holders bear the downside. This perspective suggests that firms with more leverage should take more risk (because the option of default is more valuable for such firms), and that the incentives to do so should be stronger during a crisis and after losses have occurred (because the option to default becomes more valuable at these times).

A second view is that financial institutions learn from crises, and that the occurrence of serious turbulence in financial markets actually leads them to reduce risk. This view includes ‘rational’ behavior along the lines of learning that certain kinds of securities are

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\(^{16}\) It should be acknowledged that risk taking is an essential part of financial intermediation. These theories relate to situations in which financial institutions may take too much risk, and, importantly, in which risk taking incentives materially change over time.

\(^{17}\) Rajan (2006) points out that conflicts of interest of this nature can occur on many levels within a financial firm. For example, they may even arise between traders and senior management.
risky. It also includes a more behavioral view that certain kinds of risks are neglected in the run up to crises, and then suddenly recognized, and that this occurs frequently (Shleifer 2011, Gennaioli et al. 2012). On a broad level, this view suggests that insurers, particularly those which faced trouble during the crisis, should reduce risk, having in some sense learned about risk. The more behavioral version suggests that reduced risk taking should be driven by the special kinds of securities that were viewed as safe before the crisis, but not after (in this crisis, particularly private MBS). Depending on which version of the argument one makes, this view might also suggest that risk taking should be reduced for some time, and not just very temporarily.

A third view is based on the idea that financial institutions have significant franchise value which they retain only if they survive as going concerns. Central to this view is the idea that bankruptcy does not preserve franchise value. For financial institutions that rely heavily on reputation to obtain customers (and life insurers certainly qualify in this regard), this is very plausible. This view suggests that risk taking should be reduced as the possibility of failure approaches, with induced risk aversion near bankruptcy. The key prediction that distinguishes this view from the second view is that the motivation for reducing risk taking only lasts while the prospect of failure is imminent.

A fourth view is that institution specific concerns drive most important variation with regards to risk taking (and other corporate behavior). For example, some institutions may have the sophistication needed to use certain kinds of instruments, whereas others do not. Managers of certain institutions may have a lot of effective control and very particular levels of risk tolerance. Certain institutions may have a culture for tolerating risk, whereas others do not. Some institutions may have historically invested in certain kinds of assets or entered business, while others have not. This view is certainly not mutually exclusive with the previous views, but if considerations like these are very important, institution fixed

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18 A variant is that specific people, such as senior risk managers, learn from crises.

19 The view that managers obtain private benefits from continued operation of the firm (and their continued employment) would have very similar implications.

20 See, for example, Bertrand & Schoar (2003) and Bloom & Van Reenen (2010).
effects should explain most interesting variation.

I now turn to describing the data I obtain regarding life insurers, which I use to construct detailed measures of risk taking to shed light on which of these views hold water.

2.3 Data

Life insurance in the US is a good setting to study and understand risk taking by financial institutions for two reasons. First, some of the primary dimensions of risk taking, interest-rate risk and asset risk are well understood.\footnote{See Section 2.4 for a more detailed discussion.} Second, rich regulatory data is available to researchers, covering these main dimensions of risk taking. I obtain this data from SNL Financial, and use it to construct a view of life insurers’ holdings on a quarterly basis based on position level data on all bonds in the general account, as well as a daily view of transactions, again at the position level. As the same data is available for derivatives at the transaction level, I include derivatives (focusing on interest-rate swaps) as well.\footnote{This data is much more detailed than US bank regulatory available to researchers, which is only available in aggregate, only at the quarterly frequency, and provides far less detail on derivatives.} As is typical, less detailed data is available on the liability side. I obtain the data for 2005-2014, therefore covering the crisis as well as periods before and after.

I focus on the life insurance subsidiaries of insurance groups, excluding subsidiaries involved in P&C insurance or any other business.\footnote{SNL separates insurance entities by type, and makes this classification available. Note that this also excludes any other financial line of business. For example, much of AIG’s extraordinary risk taking during the crisis documented by McDonald & Paulson (2015) was housed in AIG Financial Products, and is excluded here.} I restrict the sample to insurers with at least $10M in assets, and positive life reserves. Panels A and B of Figure 2.1 show total assets and liabilities of all life insurers meeting these restrictions in the US. Detailed data is only available for assets held by insurers in the general account, which comprise around half of insurers’ total assets. These assets roughly correspond with insurers’ life insurance liabilities (as opposed to, for example, accident and health insurance).\footnote{The remaining assets are held in separate accounts and correspond to separate account liabilities. This is not the case for credit risk, which is correspondingly measured as the difference between all assets and liabilities.} Within this category,
most of the investment is in bonds.

Panel A: Assets

Panel B: Liabilities

Notes: This figure shows total assets and liabilities for all US life insurers. The data is based on insurance regulatory filings submitted to the NAIC. I obtain this data from SNL Financial. The data includes only life insurance subsidiaries of insurance companies. I aggregate the data pro-forma to insurance groups based on present ownership, as reported by SNL. The data is quarterly, from 2005Q1-2014Q4. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. Panel A shows the composition of total assets (in $TN). Detailed data is available for assets held in the general account. Stock and other assets shown separately from the separate account are also held in the general account. Panel B shows the composition of total liabilities (in $TN).

Figure 2.1: Total assets and liabilities of US Life Insurers (2005-2014)

where variable annuities are typically housed (Chodorow-Reich 2014).
Using this data, I construct a detailed view of life insurers’ assets, beginning with their quarterly holdings. I summarize the approach to processing the data in brief here - see Appendix B.1 for more details. I aggregate the data to the insurer group level, pro-forma based on current ownership structures. This leads to a sample of 340 insurers, with almost 11,000 insurer-quarters. Quarterly data is available on all bonds held, at the CUSIP level (reported on Schedule D) and all on interest-rate derivatives outstanding, at the transaction level (reported on Schedule DB). Within this, I identify and restrict attention to standard single-currency interest-rate swaps.

I summarize insurers’ asset exposure to interest rates by DV01 to treat bonds and derivatives in a comparable way. DV01 refers to the change in value of an instrument when interest rates increase by one basis point. Bonds held by insurers tend to have duration around 8 years. To get a simple sense for magnitudes, consider the case of modified duration of 10 years: this means that when rates rise by 1%, bond values fall by 10%: a multiplication by 0.1. The corresponding change for a basis point shift in rates is a hundredth of this, or a multiplication by 0.001. Therefore, when total bond fair values are in trillions of dollars, DV01 tends to be in billions of dollars. To calculate DV01 for derivatives, I price them using a log-linearly interpolated swap curve (for which I obtain data from Bloomberg). Sometimes I also report the ‘duration equivalent notional’ of swaps: the amount in bonds that an insurer would need to hold to obtain the same DV01 as with a given portfolio in swaps, if holding bonds of the same duration as their bond portfolio.

I partition life insurers’ duration exposure on the asset side into several distinct asset classes to facilitate granular analysis. First, I identify corporate bonds, issued by entities that are not government bodies or financial issuers. I separate these by their credit rating,

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25I use information on ownership reported by SNL and the NAIC. I aggregate insurance groups owned by the same ultimate parent.

26The reporting requirements for derivatives changed at the beginning of 2010, prior to which certain kinds of options were reported differently. I focus on interest-rate swaps, a subset of all swaps, which were consistently reported during the sample period.

27I refer to a parallel shift in the yield curve across all maturities and credit quality. DV01 is negative for fixed-rate bonds, as they lose value when rates rise.
separating ‘safe’ corporate bonds (NAIC category 1) and ‘risky’ corporate bonds (NAIC category greater than 1). I keep track of bonds issued by financial issuers separately. Next, I identify government bonds, which include local or foreign government bonds, but exclude structured bonds. Finally, I identify structured bonds issued either by government agencies (typically Agency MBS) or private issuers (typically privately issued MBS). Derivatives are a separate asset class.

Notes: This figure shows total duration exposure for all US life insurers. The data is quarterly, from 2005Q1-2014Q4. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. I show DV01 (in $BN) by asset class: DV01 is the change in value of these assets given a parallel one basis point shift upwards in the yield curve. I scale DV01 by -1 here: bonds have negative DV01. Corporate bonds are separated into safe (NAIC category 1) and risk (NAIC category higher than 1). Financial issuers are identified by Fama & French (1997) industries. See Section 2.3 and Appendix B.1 for details.

**Figure 2.2: Composition of life insurers’ duration exposure by asset class (2005-2014)**

Figure 2.2 shows the composition of life insurers’ duration exposure by asset class over time. Particularly in the early part of the sample period, most of insurers’ duration exposure was obtained from corporate bonds of various kinds, as well as MBS, both privately issued and structured. Government bonds accounted for a comparatively small portion of

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28The residual category of all other bonds is very small.

29Note that I scale DV01 to be positive here. Bonds in general have negative DV01.
insurers’ portfolios. Insurer portfolios, in aggregate, tend to evolve smoothly over time.\textsuperscript{30} It is notable that during the later part of the sample period, the use of derivatives as an asset class substantially increased.\textsuperscript{31}

Insurance regulatory data also allows me to construct a daily view of transactions in bonds and derivatives. Both acquisitions and disposals of bonds are reported with transaction dates. For derivatives, all positions are reported with an initiation date, and terminations are reported separately. I undertake a similar exercise as with the quarterly view to price bonds and derivatives as of the transaction dates, which I summarize by the change in DV01 effected by the transaction. Importantly, the transaction view only includes changes directly resulting from transactions, and excludes mark to market changes. Mark to market changes are reflected in the quarterly view.

Figure 2.3 shows life insurers’ cumulative trading by asset class over the sample period. Several aggregate trends are clear. Towards the beginning of the sample, life insurers bought more private MBS, whereas in the later period of the sample, insurers shifted away from MBS and towards corporate bonds, government bonds, and derivatives. Insurers’ balance sheets tend to evolve very smoothly. Net purchases themselves shift slowly in composition, and therefore the aggregate balance sheet shifts even more slowly.\textsuperscript{32}

I also collect data on shadow reinsurance, at an annual frequency. Following Koijen & Yogo (forthcoming), I classify reinsurance contracts with reinsurers that are either affiliates or unauthorized with no AM Best rating as shadow reinsurance.\textsuperscript{33} As I focus on general account bonds, I also separate shadow reinsurance based on whether it pertains to the

\textsuperscript{30}One important exception in this is the drop in DV01 from 2008Q3-2008Q4. This drop occurs because the reported fair value of bonds drops in 2008Q4. Fair values of bonds are reported (marking to market) annually. In intermediate quarters, fair values are based on a blend of what was reported at year-end and transactional prices. See Appendix B.1 for details.

\textsuperscript{31}Aggregate data does not make clear that these derivatives were only held by a small group of insurers, for which derivatives constitute a substantial portion of duration exposure at times. See Section 2.5.

\textsuperscript{32}See Section 2.6 for a more detailed discussion of these facts and their implications. Note that the sharp drops visible for MBS (both Agency and private MBS) reflect paydowns rather than active selling.

\textsuperscript{33}I include life reserve credits taken as well as modified coinsurance reserves. See Appendix B.1 for more details.
Notes: This figure shows cumulative transactions for all US life insurers. The data is daily, from 2005-2014. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. I show cumulative changes in DV01 (in $MM) due to trading, by asset class. DV01 is the change in value of these assets given a parallel one basis point shift upwards in the yield curve. I scale DV01 by -1 here: bonds have negative DV01. Corporate bonds are separated into safe (NAIC category 1) and risk (NAIC category higher than 1). These changes in DV01 are purely based on trading, and exclude any mark to market changes in DV01. Transactions of bonds issued by financial issuers are not shown here. See Section 2.3 and Appendix B.1 for details.

Figure 2.3: Cumulative change in DV01 by asset class (2005-2014)

general account or separate account. Figure 2.4 shows shadow reinsurance in aggregate over the sample period. It also shows insurers’ life and separate account reserves, as well as all other reinsurance for comparison. Most shadow reinsurance pertains to the general account.
Notes: This figure shows total reserves, shadow reinsurance and other reinsurance (in $TN) for all US life insurers. The data is quarterly, from 2005Q1-2014Q4. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. I obtain data on all cedent reported reinsurance relationships. Relationships with either an affiliate or with an unauthorized reinsurer with no AM Best rating are classified as shadow reinsurance (Koijen & Yogo forthcoming). Shadow reinsurance is separated by whether it applies to the general account or separate account. See Section 2.3 and Appendix B.1 for details.

Figure 2.4: Life reserves and shadow reinsurance (2005-2014)

I use this data to construct measures of risk taking in two main dimensions: interest-rate risk and asset risk in the form of reaching for yield. Section 2.4 describes these measures and presents some initial evidence on risk shifting.

2.4 Risk and risk shifting

In this section, I construct measures of life insurers’ risk taking on two main dimensions: interest-rate risk and reaching for yield. I then present some initial evidence for risk shifting in aggregate. I also present some initial evidence that risk shifting cannot fully account for insurers’ risk taking behavior.

I construct measures of the two primary measurable dimensions of life insurer risk taking: interest-rate risk and reaching for yield. Life insurers are exposed to interest-rate risk because their liabilities are very long-term, and largely fixed rate. If market interest rates fall, the market value of their liabilities rises. If this is not fully offset by duration
exposure on the asset side of the balance sheet through long-term bonds or derivatives, life insurers are exposed to interest-rate risk (Koijen & Yogo 2015b).\textsuperscript{34} I use detailed data on insurer’ assets and derivatives positions and a simple approximation on the liability side to measure insurers’ net interest-rate exposure. I show that insurers do not fully offset the liability-side exposure to interest rates through their assets. Asset risk in the form of reaching for yield is a second key dimension of life insurer risk taking. Becker & Ivashina (2015) highlight that insurers have incentives to invest in higher yielding bonds, particularly within rating categories. I measure reaching for yield with the average yields to maturity on bonds purchased by insurers, based on transaction level data.\textsuperscript{35}

I use these measures of risk taking to present evidence for risk shifting in aggregate; however, I also begin to show that risk shifting alone cannot explain everything. On both dimensions, interest-rate risk and reaching for yield, insurers with more equity take less risk. Equivalently, insurers with more leverage take more risk. A key prediction of the risk shifting framework is that risk shifting incentives should have steepened during the crisis, when the option to default was more valuable. Consistent with this, I find that the relationship between equity and risk taking became stronger in aggregate during the crisis.\textsuperscript{36} I also present some initial evidence that risk shifting cannot fully explain insurers’ risk taking. The steepening of risk-shifting is concentrated within small insurers. Moreover, the relationship between leverage and reaching for yield is actually weaker during the crisis for large insurers.

\textsuperscript{34}Reinvestment risk is another aspect of interest-rate risk for insurers. As insurers’ liabilities are long-term with fixed rates, if they are unable to hold assets with comparable maturities, they face the risk of having to reinvest at lower interest rates in the future.

\textsuperscript{35}Koijen & Yogo (2015b) note that mortality risk and policy holder behavior are two further dimensions of risk for life insurers. Mortality risk, or longevity risk, refers to the risk that insurers’ policy holders on average live longer than expected, requiring insurers to pay out life annuities for longer than expected. Policy holder behavior is also a source of uncertainty and risk for insurers (for instance, policy holders may try to withdraw lump sums at a higher frequency than expected). Both types of risk are harder to measure than interest-rate risk and reaching for yield.

\textsuperscript{36}I also begin to present evidence against the view that insurer-specific preferences drive most risk taking behavior: these results are robust to including insurer fixed effects.
2.4.1 Net interest-rate risk

In this subsection, I construct my main measures of net interest-rate risk for life insurers. Doing so requires measuring the duration exposure of the bonds held by these insurers, understanding and measuring the duration exposure of their derivatives portfolios, as well as estimating the duration exposure on the liability side. I use detailed data on the asset side, and simple estimates on the liability side (due to data limitations). I show that insurers do not fully offset the duration exposure arising from their liabilities.

As discussed above, life insurers have interest-rate exposure on the liability side of their balance sheet in the form of long-term, fixed-rate liabilities. To offset this exposure, they need to hold duration exposure on the asset side of their balance sheet. One way insurers do so is by holding long-term, fixed-rate bonds. Insurers hold long-term bonds issued by corporations, various forms of asset backed securities, as well as government bonds. Overall, their bonds have duration of around eight years. Another way insurers can obtain duration exposure is by holding receive-fixed interest-rate swaps. These provide cash flows equivalent to ownership of long-term fixed-rate bonds, funded by borrowing at a short-term, floating rate, and therefore also provide the duration exposure from this strategy. I measure duration exposure of insurers’ bonds and derivatives using DV01 to treat them in a comparable manner.\footnote{See Section 2.3 for more details.}

In order to get a sense for magnitudes, it is also helpful to look at the ‘duration equivalent notional’ for a swaps portfolio. This refers to the amount in bonds that would have to be held (with duration similar to other bonds held) in order to obtain the duration exposure from a swaps portfolio.

Figure 2.5 summarizes life insurers’ aggregate holdings of interest-rate swaps, for three different quarters in the sample period. As insurers substantially increased the size of their derivatives positions during and after the crisis, these quarters are in the later part of the sample. Life insurers have large offsetting positions of pay-fixed and receive-fixed interest-rate swaps. Their net position is typically in the receive-fixed direction. For example, in 2012 Q2, a total portfolio with notional $600BN corresponded to a net receive-fixed position...
with notional less than $100BN.\textsuperscript{38} Net receive-fixed positions add duration exposure on the asset side for insures. As insurers typically do not fully offset the liability-side exposure, this means that derivatives are used to reduce net interest-rate risk. To provide a sense for magnitude, Figure 2.5 also shows the duration equivalent notional in each quarter. In 2012 Q2, the duration equivalent notional was around $200BN (in comparison, these insurers held bonds valued at around $2TN in their general accounts).\textsuperscript{39}

![Figure 2.5: Interest-rate swaps: total, net receive-fixed, and duration-equivalent notional]

Notes: This figure shows measures of the size of interest-rate swap portfolios (in $BN) held by all US life insurers for 2010Q2, 2012Q2 and 2014Q4. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. In each quarter, the figure first shows total notional amounts separated by whether the swaps are pay-fixed or receive-fixed. Next the figure shows the net receive-fixed notional amount. Finally, the figure shows the duration-equivalent notional. This is the amount of bonds that insurers would need to hold (with the same duration as their bond portfolio) to obtain equivalent duration exposure. See Section 2.3 and Appendix B.1 for details.

Parenthetically, I note that this is one of the few settings in which detailed data is available on derivatives positions, including not only notional amounts, but also contractual terms that allow some estimate of the exposure involved. For example, BIS statistics show that, as of the first half of 2015, interest-rate derivatives with notional amounts of $430TN

\textsuperscript{38}Begenau et al. (2015) document that gross-net ratios are larger for the biggest dealer banks.

\textsuperscript{39}Also see Figure 2.2 for a DV01-based view of insurers’ duration exposure across bonds and derivatives.
were outstanding, with a gross market value of $11TN.\textsuperscript{40} These statistics would suggest that the market for interest-rate risk is one of the biggest in the world – flow of funds data shows that the total market value of corporate and foreign bonds is $12TN. The life insurer view of derivatives suggests a different outlook - in terms of equivalent exposure, derivatives account for about 10% of the exposure of life insurers’ general account bonds. Anecdotally, insurers are among the largest end-users of derivatives. While this data is only for insurers in the US, and within that only life insurance subsidiaries, it helps in understanding what derivatives are for, and how big they really are.\textsuperscript{41}

As less detailed data is available about life insurers’ liabilities, I use a simple approximation to estimate the duration exposure of insurers’ liabilities. The only information I can use to construct an estimate of duration on the liability side is the market value of insurers’ liabilities.\textsuperscript{42} I therefore use a simple assumption about the average modified duration of these liabilities. Figure 2.6 shows the modified duration of bond portfolios with maturities evenly distributed between 10 and 50 years, with a coupon of 5%, under different scenarios for the yield. It suggests that a modified duration of 15 years is a reasonable estimate.

<table>
<thead>
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<th>Maturity/Yield</th>
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<th>4%</th>
<th>2%</th>
</tr>
</thead>
<tbody>
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<td>10</td>
<td>7.6</td>
<td>7.9</td>
<td>8.2</td>
</tr>
<tr>
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<td><strong>13.1</strong></td>
<td><strong>15.4</strong></td>
<td><strong>18.1</strong></td>
</tr>
</tbody>
</table>

**Figure 2.6:** Modified duration for bonds with 5% coupon: maturity and yield scenarios

\textsuperscript{40}See the BIS semiannual OTC derivatives statistics release.

\textsuperscript{41}The small notional amounts used by life insurers actually suggest a puzzle as to which counterparties account for the large notional volumes of derivatives reported globally. In unreported analysis, I show that derivatives positions that correspond to financial institutions other than dealers are far larger than those held by US life insurers.

\textsuperscript{42}Ideally, I would use information about maturities and coupons at the instrument level, as I can on the asset side.
This assumption translates into a simple estimate for the duration exposure of life insurers’ liabilities. Given a bond portfolio with modified duration of 15 years, a 1% increase in rates leads to a reduction in market value of 15%. As DV01 refers to the absolute change in value for a one basis point shift in rates, this translates to a 15 basis point multiplier to convert market value to DV01.

I construct two measures of net interest-rate risk: one including only insurers’ bond portfolios, and one taking account of derivatives as well. Given that the duration of insurers’ liabilities is likely substantially higher than the average duration of their bonds, and that insurers’ bond holdings and life reserves are comparable in size (see Panels A and B of Figure 2.1), insurers do not fully offset duration exposure on the liability side with their assets. I define the Bond DV01 Gap as the gap between liability-side DV01 and bond DV01, as a fraction of liability-side DV01, in percentage points. The Net DV01 gap is similar, but also takes into account insurers’ derivatives portfolios. Table 2.1 shows summary statistics for the full sample. DV01 gaps are roughly 35% on average.

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43This is consistent with the conventional wisdom on the composition of life insurers’ assets and liabilities: see, for example, Chodorow-Reich (2014).

44See Figure 2.11 for a visual depiction of the components of the DV01 gap. This figure separates insurers based on whether they use derivatives heavily, as described in Section 2.5.
Table 2.1: Summary statistics of insurer characteristics (separated by size)

Notes: This table shows summary statistics of key variables for all US life insurers, separated by size. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Assets are reported in $BN. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. (E-Required E)/A is surplus in excess of required surplus, scaled by assets, in basis points. Public is a dummy for whether the insurer was ever owned by a public company. Bond DV01 Gap is (Liability DV01 - Bond DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. YTM (Purchases) is the fair value value weighted average yield to maturity of all bonds purchased in the insurer-quarter, winsorized at the 5th and 95th percentiles. VA share of assets is separate accounts as a share of total assets, in percentage points. Deposit reserve share is the share of deposit like reserves as a fraction of deposit like reserves, life reserves and accident and health reserves, in percentage points. See Appendix B.1 for details. The first column shows the mean for each variable in the full sample. The second column shows the mean for small insurers (bottom eight asset deciles by quarter). The third column shows the mean for large insurers (top two asset deciles by quarter). The final column shows the standard deviation in the full sample.

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Small</th>
<th>Large</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets (BN)</td>
<td>19.2</td>
<td>1.5</td>
<td>90.3</td>
<td>59.2</td>
</tr>
<tr>
<td>Equity/Assets</td>
<td>22.0</td>
<td>25.4</td>
<td>7.9</td>
<td>19.4</td>
</tr>
<tr>
<td>(E-Required E)/A</td>
<td>209.3</td>
<td>258.5</td>
<td>10.7</td>
<td>380.3</td>
</tr>
<tr>
<td>Public</td>
<td>0.3</td>
<td>0.2</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>Bond DV01 Gap</td>
<td>34.3</td>
<td>32.2</td>
<td>43.0</td>
<td>27.0</td>
</tr>
<tr>
<td>Net DV01 Gap</td>
<td>34.0</td>
<td>32.1</td>
<td>41.5</td>
<td>27.0</td>
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<tr>
<td>YTM (Purchases)</td>
<td>4.6</td>
<td>4.5</td>
<td>4.7</td>
<td>1.2</td>
</tr>
<tr>
<td>VA share of assets</td>
<td>10.2</td>
<td>4.0</td>
<td>34.9</td>
<td>21.4</td>
</tr>
<tr>
<td>Deposit-like reserve share</td>
<td>5.5</td>
<td>4.6</td>
<td>9.4</td>
<td>10.3</td>
</tr>
<tr>
<td>Insurer-Quarters</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.4.2 Asset risk: reaching for yield

I measure reaching for yield using the average yield to maturity on bonds purchased by insurers in a given quarter. Following Becker & Ivashina (2015), I focus on the yields to maturity only of purchased bonds.\(^{45}\) I calculate the average yield to maturity of all bonds purchased by an insurer group in each quarter. This measures risk taking on an ongoing basis, rather than for the balance sheet in aggregate.\(^{46}\) As discussed in Section 2.3, I use detailed transaction level data in this calculation. See Appendix B.1 for more details. Table

\(^{45}\)For corporate bonds, gross trading is not much larger than net purchases. As discussed in Section 2.6, gross trading is substantially larger than net purchases for government bonds.

\(^{46}\)This is appropriate given that insurers adjust their balance sheets slowly, as I highlight in Section 2.6.
1.1 shows that the average yield of bonds purchased by insurers over the sample period is 4.6%.

2.4.3 Initial tests of theory

In this subsection, I present some initial tests of the alternative theoretical views of risk taking by financial institutions laid out in Section 2.2. I find evidence consistent with risk shifting in aggregate: insurers with more equity take less risk on both dimensions of risk taking. I also find some evidence that risk shifting incentives became stronger during the crisis. As these results hold even after including insurer fixed effects, I suggest that insurer specific preferences are not crucial for understanding risk taking in these domains. I also present some initial evidence that risk shifting cannot explain all variation in life insurers’ risk taking behavior.

Table 2.1 shows summary statistics of key variables for the full sample, and for insurers separated by size. Here large insurers are those in the top two asset deciles, and small insurers are all other insurers. Size is highly skewed. The size cutoff for large insurers is around $10-15BN, depending on the quarter. I measure leverage as the ratio of equity (surplus as reported in insurance regulatory filings) to assets, in percentage points. In the full sample, a one standard deviation shift in leverage is quite large: almost 20 percentage points. Large insurers tend to have significantly more leverage than small insurers.\(^{47}\) Larger insurers tend to take more risk on both dimensions: they have bigger DV01 gaps and buy higher yielding bonds on average.

The overall analytical approach here is to regress risk taking along the two dimensions discussed earlier on leverage. As time variation in risk taking is important for distinguishing the theoretical approaches that can be used to understand risk taking, I also examine time variation in the relationship between leverage and risk taking. Following Becker & Ivashina (2015), I define the pre-crisis period as 2005Q1-2007Q2. I define the crisis period as 2007Q3-

\(^{47}\)This is due to a combination lower required equity ratios and smaller buffers kept between actual and required equity.
2010Q4, and the post-crisis period as 2011Q1-2014Q4. I use coefficients between interactions between leverage and time period dummies to assess time variation. Most regressions I present include time period (quarter) fixed effects.\(^48\) I also include insurer fixed effects in many specifications. I control for size using the logarithm of assets in most specifications. I double-cluster standard errors by insurer and quarter (Thompson 2011).

I begin by presenting evidence consistent with risk shifting on the dimension of interest-rate risk. I use the Net DV01 gap (including derivatives) as the measure of interest-rate risk here. Table 2.2 presents the results. The first column shows that, consistent with risk shifting, insurers with more leverage take more risk in the full sample (the coefficient on the equity ratio is negative). The second column shows that this finding is attenuated by, but nevertheless robust to, including insurer fixed effects.\(^49\) The third column includes interactions of leverage with the crisis and post-crisis period, therefore showing the change in the coefficient on leverage using the pre-crisis period as a baseline. Consistent with one of the key predictions of risk shifting, the relationship between leverage and risk taking is steepened during the crisis (the coefficient on the interaction of leverage and the crisis period dummy is negative).

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\(^{48}\)This is evidently important when looking at the average yield of bonds purchased.

\(^{49}\)Regression \(R^2\) does of course rise substantially when insurer fixed effects are included.
Table 2.2: Regressions of Net DV01 gap on insurer characteristics

Notes: This table shows regressions of Net DV01 Gap (dependent variable) on leverage by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. See Appendix B.1 for details. Some specifications include interactions of leverage with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. The first three columns show regressions run in the full sample. The fourth column restricts the sample to small insurers (bottom eight asset deciles by quarter), and the fifth column restricts the sample to large insurers (top two asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
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<th>AssetD ≥ 9</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NDV01Gap</td>
<td>NDV01Gap</td>
<td>NDV01Gap</td>
</tr>
<tr>
<td>E/A</td>
<td>-0.66</td>
<td>-0.41</td>
<td>-0.41</td>
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<tr>
<td></td>
<td>(-9.65)</td>
<td>(-3.53)</td>
<td>(-3.34)</td>
</tr>
<tr>
<td>E/A × 2007Q3-2010Q4</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>-0.06</td>
<td>-0.04</td>
<td>-0.03</td>
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<tr>
<td></td>
<td>(-1.85)</td>
<td>(-1.39)</td>
<td>(-0.15)</td>
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<tr>
<td>E/A × 2011Q1-2014Q4</td>
<td>0.05</td>
<td>0.02</td>
<td>0.04</td>
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<td>(-3.14)</td>
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<td>Y</td>
<td>Y</td>
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<tr>
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<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SE clustered by</td>
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<td>I,Q</td>
<td>I,Q</td>
</tr>
<tr>
<td>R²</td>
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<td>0.84</td>
<td>0.85</td>
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<td>Insurer-Quarters</td>
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<td>10,747</td>
<td>10,747</td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>340</td>
<td>340</td>
</tr>
</tbody>
</table>

Next, I present evidence similarly consistent with risk shifting in the domain of reaching for yield. Table 2.3 presents the results. The dependent variable here is the average yield to maturity on bonds purchased at the insurer-quarter level, in bases points. Again, the first column shows that, consistent with risk shifting, insurers with more leverage take more risk. Here, though, the coefficient in the full sample is no longer statistically different from zero once insurer fixed effects are included. However, the third column shows that during, and subsequent to the crisis, risk shifting incentives were steepened (even after including insurer fixed effects). Overall, this evidence points away from the view that insurer specific

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⁵⁰The sample for these regressions is restricted to insurer-quarters in which some bonds were purchased.
preferences and circumstances drive most important variation.\textsuperscript{51}

Table 2.3: Regressions of VW YTM (bps) of bond purchases on insurer characteristics

Notes: This table shows regressions of the average yield to maturity on bonds purchased (dependent variable) on leverage by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. YTM is the fair value value weighted average yield to maturity of all bonds purchased in the insurer-quarter, winsorized at the 5th and 95th percentiles, in basis points. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. See Appendix B.1 for details. Some specifications include interactions of leverage with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. The first three columns show regressions run in the full sample. The fourth column restricts the sample to small insurers (bottom eight asset deciles by quarter), and the fifth column restricts the sample to large insurers (top two asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. \(t\)-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
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<th>AssetD ≥ 9</th>
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</thead>
<tbody>
<tr>
<td></td>
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<td>YTM</td>
<td>YTM</td>
</tr>
<tr>
<td>E/A</td>
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<td></td>
<td>(-10.60)</td>
<td>(-1.55)</td>
<td>(0.71)</td>
</tr>
<tr>
<td>E/A × 2007Q3-2010Q4</td>
<td>-1.12</td>
<td>-1.37</td>
<td>3.48</td>
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<tr>
<td></td>
<td>(-5.99)</td>
<td>(-6.72)</td>
<td>(2.86)</td>
</tr>
<tr>
<td>E/A × 2011Q1-2014Q4</td>
<td>-0.93</td>
<td>-1.30</td>
<td>3.71</td>
</tr>
<tr>
<td></td>
<td>(-5.01)</td>
<td>(-6.51)</td>
<td>(2.62)</td>
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<td>Log(Assets)</td>
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<td>17.40</td>
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<tr>
<td></td>
<td>(-1.36)</td>
<td>(2.74)</td>
<td>(2.43)</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Insurer FE</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SE clustered by</td>
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<td>1Q</td>
<td>1Q</td>
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<td></td>
<td>0.51</td>
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<td>0.73</td>
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<td>Insurer-Quarters</td>
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</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>340</td>
<td>340</td>
</tr>
</tbody>
</table>

While I do find evidence for risk shifting in aggregate, evidence within size sub-samples begins to suggest that risk shifting cannot explain all variation in insurers’ risk taking. The evidence presented so far is quite consistent with risk shifting. Insurers with more leverage take more risk on both dimensions: they have bigger DV01 gaps, and they reach for yield more. There is even evidence in aggregate for a key prediction of risk shifting, that risk taking incentives for levered insurers should have steepened during the crisis. However, risk

\textsuperscript{51}Results presented in Section 2.5 are also robust to including insurer fixed effects, strengthening this conclusion.
shifting cannot explain all the variation observed during and after the crisis. In particular, this steepening during the crisis is concentrated within small insurers, not within more levered large insurers (fourth and fifth columns of Tables 2.2 and Table 2.3). Intriguingly, the final column of Table 2.3 shows that large insurers with more leverage actually reached for yield less during and post-crisis.

To summarize the evidence presented so far, I find some evidence consistent with risk shifting, but also show that it cannot explain all variation in risk taking observed during the crisis. In Section 2.5, I explore whether there is evidence for other views of insurer risk taking, in particular those that provide a role for insurers’ experience during the crisis. I identify a sub-group of insurers within large insurers (those that use derivatives in a substantial manner) whose risk taking behavior is helpful in understanding the results for large insurers.

2.5 Alternative views of risk taking

Section 2.4 shows that while there is some evidence for risk shifting in variation in life insurer risk taking, risk shifting provides incomplete understanding. I now present evidence that risk shifting was actually mitigated for insurers that suffered during the crisis. I also show that large insurers that began to heavily use interest derivatives drive interesting variation within large insurers. Collectively, this evidence provides some support for the idea that insurers learn from crisis, or that franchise value matters. As discussed in Section 2.2, these two views have similar implications for risk taking during this period, and as such are hard to separate. To the extent that they make subtly different predictions, I find evidence for both.

Using two measures of crisis experience, I present evidence that risk shifting was mitigated for insurers with a poor crisis experience. These measures are based on investment strategies prior to the crisis, as well as portfolio concentration in asset classes where prices fell substantially during the crisis. I show that these measures help understand variation in risk taking that is difficult to understand through the risk shifting lens.
Within large insurers, I separate heavy users of derivatives from other insurers: this presents a division of the data that is helpful in separating different views of risk taking. These heavy users of derivatives are some of the most levered large insurers. However, they also suffered more during the crisis. Risk shifting, on one hand, and learning from the crisis and franchise value on the other therefore point in opposite directions for this subgroup of insurers. Risk shifting suggests that these insurers should have increased risk taking, relative to other insurers, during the crisis. Learning from the crisis and franchise value suggest the opposite. As this group of insurers actually reduced risk taking on both dimensions, I find evidence pointing towards this latter set of theories. My results here are also robust to including insurer fixed effects, again pointing away from the view that insurer specific preferences drive most important variation in risk taking.

2.5.1 Relevance of crisis experience

In this subsection, I present some initial evidence pointing towards theories of risk taking that place emphasis on insurers’ experience during the crisis. As discussed in Section 2.2, both learning from the crisis and franchise value predict reduced risk taking during the crisis. I construct two measures of insurers’ experience in the crisis, and present some evidence that risk shifting was mitigated for insurers that suffered during the crisis.

To proxy for insurers’ experience during the crisis, I use measures relating to insurers’ investment strategy prior to the crisis and the extent to which they faced losses during the crisis. The first measure is based on the extent to which insurers invested in private MBS prior to the crisis. Figure 2.3 shows that insurers in aggregate invested in private MBS prior to the crisis, and then shifted away from this asset class. As private MBS were very much at the center of the financial crisis, insurers that invested heavily in private MBS prior to the crisis must have suffered during the crisis. On this measure, I identify insurers that obtained more than 25% of their total DV01 exposure prior to the crisis through private MBS with a dummy: a private MBS flag. I also examine whether insurers invested in asset classes with falling market prices more directly. On this measure, I select insurers that reported a
fair value loss greater than 10% for their bonds from 2008Q3-2008Q4 with a Crisis FV drop flag.\textsuperscript{52}

I now present evidence that risk shifting was mitigated for insurers that suffered during the crisis. I present regressions with triple interactions: interactions of leverage, time period dummies, and dummies for crisis experience. Tables 2.4, 2.5, 2.6 and 2.7 present the results. Tables 2.4 and 2.5 focus on interest-rate risk (the dependent variable is Net DV01 Gap), while Tables 2.6 and 2.7 focus on reaching for yield (the dependent variable is average yield to maturity on bond purchases). Tables 2.4 and 2.6 use investment in private MBS as the measure of crisis experience, while Tables 2.5 and 2.7 drop in fair value as the measure of crisis experience. In all specifications the crisis experience dummy itself is absorbed by insurer fixed effects.

Taken as a whole, Tables 2.4, 2.5, 2.6 and 2.7 present evidence pointing towards learning from crises and franchise value. The first column in all panels shows regressions for the full sample. There is some evidence that insurers risk shifting was attenuated for insurers that suffered during the crisis: the interaction of leverage, crisis experience flags and a crisis dummy is generally positive, and statistically significantly so in at least some specifications. This evidence is broadly consistent with theories emphasizing insurers’ crisis experience, including learning from the crisis and franchise value. Between these theories, the relevance of private MBS in particular might be taken as evidence pointing to the neglected risk version of learning from the crisis. On the other hand, Table 2.6 shows that with the MBS measure of crisis experience, reaching for yield actually strengthened in the reaching for yield domain. This points to the franchise value view of risk taking.\textsuperscript{53} Again, these specifications include insurer fixed effects, pointing away from insurer-specific preferences.

\textsuperscript{52}As discussed in Section 2.3 and Appendix B.1, fair values are reported for bonds on an annual basis. Fair values in intermediate quarters are blended: they are based on fair values reported at the previous year end, adjusted for subsequent transactions at their market prices. The drop in fair value from 2008Q3-2008Q4 therefore does not necessarily reflect price changes that happened within just one quarter, but more broadly during the crisis period from 2007-2008. Also note that life insurers did not generally need to recognize these mark-to-market losses (see Panel A of Figure 2.1), even though they reported them to regulators.

\textsuperscript{53}This evidence could also be interpreted as consistent with the neglected risk view of the crisis. With this interpretation, either the same or different risks are neglected post-crisis.
Table 2.4: Regressions of Net DV01 gap on insurer crisis experience (private MBS)

Notes: This table shows regressions of Net DV01 Gap (dependent variable) on leverage and measures of crisis experience by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. See Appendix B.1 for details. All specifications include interactions of leverage with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. All specifications include triple interactions of leverage, period dummies and crisis experience as well. This table uses Private Structured Flag as the measure of crisis experience: this is a dummy for whether the average fraction of DV01 in private structured assets prior to the crisis was more than 25%. The first column shows the regression in the full sample. The second column restricts the sample to small insurers (bottom eight asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>AssetD ≤ 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Net DV01 Gap</td>
<td>Net DV01 Gap</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------</td>
<td>-------------</td>
</tr>
<tr>
<td>E/A</td>
<td>-0.40</td>
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<tr>
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<td>E/A × Priv Struc Flag × 2007Q3-2010Q4</td>
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<td>0.08</td>
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<tr>
<td></td>
<td>(2.02)</td>
<td>(2.01)</td>
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<tr>
<td>E/A × 2011Q1-2014Q4</td>
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<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>E/A × Priv Struc Flag × 2011Q1-2014Q4</td>
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<td></td>
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<td>Insurers</td>
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<td>297</td>
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</table>
Table 2.5: Regressions of Net DV01 gap on insurer crisis experience (FV drop)

Notes: This table shows regressions of Net DV01 Gap (dependent variable) on leverage and measures of crisis experience by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. See Appendix B.1 for details. All specifications include interactions of leverage with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. All specifications include triple interactions of leverage, period dummies and crisis experience as well. This table uses Crisis Drop Flag as the measure of crisis experience: this is a dummy for whether the insurer reported a drop in fair value of bonds from 2008Q3-2008Q4 greater than 10%. The first column shows the regression in the full sample. The second column restricts the sample to small insurers (bottom eight asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. t-statistics are shown in parentheses.

Crisis experience measured by drops in bond fair values

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>AssetD ≤ 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Net DV01 Gap</td>
<td>Net DV01 Gap</td>
</tr>
<tr>
<td>E/A</td>
<td>-0.41</td>
<td>-0.40</td>
</tr>
<tr>
<td></td>
<td>(-3.37)</td>
<td>(-3.29)</td>
</tr>
<tr>
<td>E/A × 2007Q3-2010Q4</td>
<td>-0.06</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>(-1.56)</td>
<td>(-1.15)</td>
</tr>
<tr>
<td>E/A × Crisis Drop Flag × 2007Q3-2010Q4</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(-0.13)</td>
<td>(-0.15)</td>
</tr>
<tr>
<td>E/A × 2011Q1-2014Q4</td>
<td>0.07</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(1.13)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>E/A × Crisis Drop Flag × 2011Q1-2014Q4</td>
<td>-0.06</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>(-0.70)</td>
<td>(-0.64)</td>
</tr>
<tr>
<td>Log(Assets)</td>
<td>-0.25</td>
<td>-0.31</td>
</tr>
<tr>
<td></td>
<td>(-0.11)</td>
<td>(-0.13)</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Insurer FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SE clustered by</td>
<td>I,Q</td>
<td>I,Q</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>Insurer-Quarters</td>
<td>10,747</td>
<td>8,611</td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>297</td>
</tr>
</tbody>
</table>
Table 2.6: Regressions of VW YTM (bps) of bond purchases on insurer crisis experience (private MBS)

Notes: This table shows regressions of the average yield to maturity on bonds purchased (dependent variable) on leverage by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. YTM is the fair value value weighted average yield to maturity of all bonds purchased in the insurer-quarter, winsorized at the 5th and 95th percentiles, in basis points. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. See Appendix B.1 for details. All specifications include interactions of leverage with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. All specifications include triple interactions of leverage, period dummies and crisis experience as well. This table uses Private Structured Flag as the measure of crisis experience: this is a dummy for whether the average fraction of DV01 in private structured assets prior to the crisis was more than 25%. The first column shows the regression in the full sample. The second column restricts the sample to small insurers (bottom eight asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. $t$-statistics are shown in parentheses.

Crisis experience measured by investment in private MBS

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>AssetD ≤ 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>YTM</td>
<td>YTM</td>
</tr>
<tr>
<td>E/A</td>
<td>0.16</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>(0.55)</td>
<td>(1.55)</td>
</tr>
<tr>
<td>E/A × 2007Q3-2010Q4</td>
<td>-1.17</td>
<td>-1.42</td>
</tr>
<tr>
<td></td>
<td>(-6.04)</td>
<td>(-6.69)</td>
</tr>
<tr>
<td>E/A × Priv Struc Flag × 2007Q3-2010Q4</td>
<td>0.21</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(0.72)</td>
</tr>
<tr>
<td>E/A × 2011Q1-2014Q4</td>
<td>-0.85</td>
<td>-1.21</td>
</tr>
<tr>
<td></td>
<td>(-4.52)</td>
<td>(-5.98)</td>
</tr>
<tr>
<td>E/A × Priv Struc Flag × 2011Q1-2014Q4</td>
<td>-0.51</td>
<td>-0.56</td>
</tr>
<tr>
<td></td>
<td>(-1.61)</td>
<td>(-1.69)</td>
</tr>
<tr>
<td>Log(Assets)</td>
<td>13.91</td>
<td>14.77</td>
</tr>
<tr>
<td></td>
<td>(2.27)</td>
<td>(2.31)</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Insurer FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>SE clustered by</td>
<td>1Q</td>
<td>1Q</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.74</td>
<td>0.73</td>
</tr>
<tr>
<td>Insurer-Quarters</td>
<td>9,865</td>
<td>7,729</td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>297</td>
</tr>
</tbody>
</table>
Table 2.7: Regressions of VW YTM (bps) of bond purchases on insurer crisis experience (FV drop)

Notes: This table shows regressions of the average yield to maturity on bonds purchased (dependent variable) on leverage by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. YTM is the fair value value weighted average yield to maturity of all bonds purchased in the insurer-quarter, winsorized at the 5th and 95th percentiles, in basis points. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. See Appendix B.1 for details. All specifications include interactions of leverage with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. All specifications include triple interactions of leverage, period dummies and crisis experience as well. This table uses Crisis Drop Flag as the measure of crisis experience: this is a dummy for whether the insurer reported a drop in fair value of bonds from 2008Q3-2008Q4 greater than 10%. The first column shows the regression in the full sample. The second column restricts the sample to small insurers (bottom eight asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. $t$-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>AssetD ≤ 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>YTM</td>
<td>YTM</td>
</tr>
<tr>
<td>E/A</td>
<td>0.22</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>(0.73)</td>
<td>(1.74)</td>
</tr>
<tr>
<td>E/A × 2007Q3-2010Q4</td>
<td>-1.22</td>
<td>-1.51</td>
</tr>
<tr>
<td></td>
<td>(-6.19)</td>
<td>(-6.96)</td>
</tr>
<tr>
<td>E/A × Crisis Drop Flag × 2007Q3-2010Q4</td>
<td>0.31</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>(1.47)</td>
<td>(1.81)</td>
</tr>
<tr>
<td>E/A × 2011Q1-2014Q4</td>
<td>-0.93</td>
<td>-1.32</td>
</tr>
<tr>
<td></td>
<td>(-4.58)</td>
<td>(-6.19)</td>
</tr>
<tr>
<td>E/A × Crisis Drop Flag × 2011Q1-2014Q4</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>Log(Assets)</td>
<td>15.18</td>
<td>16.27</td>
</tr>
<tr>
<td></td>
<td>(2.40)</td>
<td>(2.47)</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Insurer FE</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td>SE clustered by</td>
<td>I,Q</td>
<td>I,Q</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.73</td>
<td>0.73</td>
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<tr>
<td>Insurer-Quarters</td>
<td>9,865</td>
<td>7,729</td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>297</td>
</tr>
</tbody>
</table>

I now turn to understanding these patterns in more detail within large insurers, with a focus on those insurers that used derivatives heavily.
2.5.2 Heavy users of derivatives

It is helpful to separate insurers that use derivatives heavily, from those that do not, to understand heterogeneity in insurer risk. As these heavy users of derivatives both have more leverage and suffered more during the crisis, risk shifting and theories of risk taking with a role for these insurers’ crisis experience make opposing predictions. Heavy users of derivatives reduced risk taking relative to other insurers on both dimensions of risk taking, providing further evidence for learning from crises or franchise value. This separation also helps illustrate the widely varying investment strategies within the life insurance sector.

Heavy users’ actions are in stark contrast to other insurers, even other large insurers. Heavy users are roughly the same size as all other insurers, and engage in very different investment strategies. They invested more heavily in private MBS pre-crisis, and faced larger fair value losses during the crisis. By both measures of crisis experience, they had more to learn from and more to lose from the crisis. They also had more leverage than other insurers, even other large insurers. During and after the crisis, they reduced risk taking relative to other insurers, both in terms of interest-rate risk and in terms of reaching for yield. In conjunction with evidence presented in earlier sections, this evidence points towards the view that insurers learned from the crisis or had franchise value-driven concerns.

Identifying heavy users of derivatives

I now describe how I separate heavy users of derivatives from other insurers, as well as how heavy users differ in their investment behavior from other insurers. These insurers account for essentially all use of derivatives by the sector. They are large and more levered, even within large insurers. They invested more in private MBS prior to the crisis, and faced larger losses during the crisis. I also show that they exhibited different trading patterns during the crisis.

The use of derivatives is highly skewed, and heavy derivatives users account for almost

\[54\] I also assess whether these insurers increase risk in more subtle ways, in particular through shadow reinsurance (Koijen & Yogo forthcoming).
all use of derivatives by life insurers in aggregate. I identify heavy users as those for which
derivatives are an important part of their investment strategy. As discussed earlier, insurers
generally use receive-fixed swaps as a way to add duration exposure (see Figure 2.5). I
classify insurers for which derivatives account for at least 5% (in absolute value) of their total
DV01 exposure and have DV01 exposure greater than $1MM in absolute value for at least
one quarter as heavy users of derivatives. 21 insurers are heavy users of derivatives by this
definition. Figure 2.7 shows that the distribution of derivatives use and heavy derivatives
use is highly skewed, depicting the fraction of insurers in these categories by asset decile.
Insurers in the bottom six asset deciles of the sample never use derivatives, and all heavy
users of derivatives are in the top two asset deciles. Given this last observation, I often
compare heavy users of derivatives to other large insurers; i.e. other insurers in the top two
asset deciles. Table 2.8 shows summary statistics for insurers separating out heavy users,
which highlight these points further.55

Heavy users of derivatives had more leverage prior to the crisis, and also suffered more
during the crisis. This group of insurers therefore presents a good test to separate risk
shifting and the relevance of crisis experience: for this group of insurers these theories make
opposing predictions. Table 2.9 presents regressions of eventual heavy derivatives use on
pre-crisis characteristics, at the insurer level. I collapse the sample to the insurer level to
focus on cross-sectional variation here. Table 2.9 shows that heavy users had more leverage,
and suffered more during the crisis (both based on facing losses and having invested more
in private MBS), even within large insurers.56 Table 2.10 shows that these conclusions are
largely robust to controlling for size directly.

55 In principle, the fact that very large insurers are the only ones to use derivatives in a significant way might
seem favorable for the idea that insurer-specific circumstances drive risk taking behavior. However, time series
variation in risk-taking behavior by this group is substantial even after including insurer fixed effects, as I show
below.

56 As noted earlier, the cutoff for the top two asset deciles is roughly $10-15BN in assets depending on the
quarter.
Notes: This figure shows the distribution of derivatives use by asset decile. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. I separate insurers by asset decile separately in each quarter. The horizontal axis for this figure is the mean asset decile by insurer across the sample period. Derivatives user is a dummy for whether the derivatives DV01 is ever different from 0. Heavy user is a dummy for whether derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in a quarter. The figure shows the percentage of insurers that are derivatives users and heavy users by asset decile.

Figure 2.7: Fraction of users and heavy users of derivatives by asset decile
Table 2.8: Summary statistics of insurer characteristics (separated by heavy user status)

Notes: This table shows summary statistics of key variables for all US life insurers, separated by heavy user status. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Assets are reported in $BN. Equity/Assets is surplus reported in regulatory filings scaled by assets, in percentage points and winsorized at the 5th and 95th percentiles. (E-Required E)/A is surplus in excess of required surplus, scaled by assets, in basis points. Public is a dummy for whether the insurer was ever owned by a public company. Bond DV01 Gap is (Liability DV01 - Bond DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. YTM (Purchases) is the fair value value weighted average yield to maturity of all bonds purchased in the insurer-quarter, winsorized at the 5th and 95th percentiles. VA share of assets is separate accounts as a share of total assets, in percentage points. Deposit reserve share is the share of deposit like reserves as a fraction of deposit like reserves, life reserves and accident and health reserves, in percentage points. See Appendix B.1 for details. The first column shows the mean for each variable in the full sample. The second column shows the mean excluding heavy users of derivatives. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. The third column shows the mean for heavy users of derivatives. The final column shows the standard deviation in the full sample.

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Non-users</th>
<th>Users</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>7.6</td>
<td>155.9</td>
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</tr>
<tr>
<td>Equity / Assets</td>
<td>22.0</td>
<td>23.3</td>
<td>5.7</td>
<td>19.4</td>
</tr>
<tr>
<td>(E-Required E)/A (bps)</td>
<td>209.3</td>
<td>226.8</td>
<td>2.9</td>
<td>380.3</td>
</tr>
<tr>
<td>Public</td>
<td>0.3</td>
<td>0.2</td>
<td>0.7</td>
<td>0.4</td>
</tr>
<tr>
<td>Bond DV01 Gap</td>
<td>34.3</td>
<td>33.2</td>
<td>47.5</td>
<td>27.0</td>
</tr>
<tr>
<td>Net DV01 Gap</td>
<td>34.0</td>
<td>33.2</td>
<td>43.4</td>
<td>27.0</td>
</tr>
<tr>
<td>YTM (Purchases)</td>
<td>4.6</td>
<td>4.6</td>
<td>4.5</td>
<td>1.2</td>
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<tr>
<td>VA share of assets</td>
<td>10.2</td>
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<tr>
<td>Deposit-like reserve share</td>
<td>5.5</td>
<td>4.9</td>
<td>13.0</td>
<td>10.3</td>
</tr>
</tbody>
</table>

Insurer-Quarters: 10,747
Insurers: 340
Table 2.9: Regressions of heavy user indicator on insurer characteristics

Notes: This figure shows regressions of heavy user status (dependent variable) on insurer characteristics. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. The dependent variable is a dummy for whether the insurer is a heavy user of derivatives multiplied by 100. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. I collapse the sample to means at the insurer level for all specifications shown here. Equity/Assets is average surplus scaled by assets in quarters prior to the crisis (2005Q1-2007Q2), winsorized at the 5th and 95th percentiles, and scaled to have unit standard deviation in the relevant sample. Crisis Drop Flag is a dummy for whether the insurer reported a drop in fair value of bonds from 2008Q3-2008Q4 greater than 10%. Private Structured Flag is a dummy for whether the average fraction of DV01 in private structured assets prior to the crisis was more than 25%. Public is a dummy for whether the insurer was ever owned by a public company. Shadow Reinsurance Flag is the average of dummies for whether more than 10% of general account reserves were ceded to shadow reinsurers in quarters prior to the crisis. The first two columns show regressions for the full sample, and the final two columns restrict the sample to large insurers (top two asset deciles by quarter). t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Top two asset deciles only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Huser×100</td>
<td>Huser×100</td>
</tr>
<tr>
<td>Equity/Assets</td>
<td>-4.35</td>
<td>-4.81</td>
</tr>
<tr>
<td></td>
<td>(-3.57)</td>
<td>(-3.92)</td>
</tr>
<tr>
<td>Crisis FV Drop Flag</td>
<td>10.07</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.69)</td>
<td></td>
</tr>
<tr>
<td>Private Structured Flag</td>
<td>6.42</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.99)</td>
<td></td>
</tr>
<tr>
<td>Public</td>
<td>11.27</td>
<td>13.17</td>
</tr>
<tr>
<td></td>
<td>(3.71)</td>
<td>(4.31)</td>
</tr>
<tr>
<td>Shadow Reinsurance Flag</td>
<td>11.28</td>
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</tr>
<tr>
<td></td>
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<tr>
<td>$R^2$</td>
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</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>340</td>
</tr>
</tbody>
</table>
Table 2.10: Regressions of heavy user indicator on insurer characteristics (including size)

Notes: This figure shows regressions of heavy user status (dependent variable) on insurer characteristics. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. The dependent variable is a dummy for whether the insurer is a heavy user of derivatives multiplied by 100. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. I collapse the sample to means at the insurer level for all specifications shown here. Equity/Assets is average surplus scaled by assets in quarters prior to the crisis (2005Q1-2007Q2), winsorized at the 5th and 95th percentiles, and scaled to have unit standard deviation in the relevant sample. Crisis Drop Flag is a dummy for whether the insurer reported a drop in fair value of bonds from 2008Q3-2008Q4 greater than 10%. Private Structured Flag is a dummy for whether the average fraction of DV01 in private structured assets prior to the crisis was more than 25%. Public is a dummy for whether the insurer was ever owned by a public company. Shadow Reinsurance Flag is the average of dummies for whether more than 10% of general account reserves were ceded to shadow reinsurers in quarters prior to the crisis. This table includes Log(Assets), the natural logarithm of total assets, as a control for size. The first two columns show regressions for the full sample, and the final two columns restrict the sample to large insurers (top two asset deciles by quarter). t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Top two asset deciles only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Huser×100</td>
<td>Huser×100</td>
</tr>
<tr>
<td>Equity/Assets</td>
<td>1.76</td>
<td>1.91</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
<td>(1.34)</td>
</tr>
<tr>
<td>Crisis FV Drop Flag</td>
<td>5.25</td>
<td>16.67</td>
</tr>
<tr>
<td></td>
<td>(2.01)</td>
<td>(1.79)</td>
</tr>
<tr>
<td>Private Structured Flag</td>
<td>-0.46</td>
<td>1.47</td>
</tr>
<tr>
<td></td>
<td>(-0.15)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Public</td>
<td>2.24</td>
<td>2.33</td>
</tr>
<tr>
<td></td>
<td>(0.73)</td>
<td>(0.74)</td>
</tr>
<tr>
<td>Shadow Reinsurance Flag</td>
<td>9.72</td>
<td>10.44</td>
</tr>
<tr>
<td></td>
<td>(2.12)</td>
<td>(2.19)</td>
</tr>
<tr>
<td>Log(Assets)</td>
<td>4.42</td>
<td>23.09</td>
</tr>
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<td></td>
<td>(7.34)</td>
<td>(7.76)</td>
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<td>Collapsed</td>
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<td>Y</td>
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<tr>
<td>R²</td>
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<td>0.49</td>
</tr>
<tr>
<td>Insurer-Quarters</td>
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<td>546</td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>64</td>
</tr>
</tbody>
</table>

99
Heavy users had markedly different investment strategies from other insurers. Figure 2.8 summarizes the annual changes in DV01 by asset class for the pre-crisis period (2005-2007H1) and subsequently (2007H2-2014). It divides the total changes in DV01 in each period by the number of years in each period to facilitate comparison. Figure 2.9 shows trading over the full sample period, separating heavy users (Panel B) from other insurers (Panel A). Prior to the crisis, heavy users bought more private MBS. Subsequent to the crisis, the shifted away from government bonds and private MBS, and towards using derivatives as a source of duration exposure. Heavy users also shifted away more from Agency MBS, suggesting that they had acquired more of it prior to the sample period.

![Figure 2.8: Annual changes in DV01 ($MM) by asset class and use of derivatives](image)

Heavy users’ trading in derivatives is informative about the derivatives market more broadly as well. As discussed above, life insurers’ use of derivatives helps illustrate the scale of the interest-rate derivatives market, as well as the typical uses of interest-rate derivatives. Panel B of Figure 2.9 shows that life insurers really did not use interest-rate swaps in a significant way prior to the middle of 2006. Subsequently, they shifted towards interest-rate swaps quite dramatically (when this trading is compared to trading in other asset classes). Indeed, in the later part of the sample, swaps are the primary asset class through which heavy users obtained duration exposure. On the other hand, the use of swaps remains very much on the same order of magnitude as other asset classes.
Panel A: Excluding heavy users of derivatives

Panel B: Heavy users of derivatives only

Notes: This figure shows cumulative transactions for all US life insurers separated by derivatives use. The data is daily, from 2005-2014. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. I show cumulative changes in DV01 (in $MM) due to trading by asset class: DV01 is the change in value of these assets given a parallel one basis point shift upwards in the yield curve. I scale DV01 by -1 here: bonds have negative DV01. Corporate bonds are separated into safe (NAIC category 1) and risk (NAIC category higher than 1). These changes in DV01 are purely based on trading, and exclude any mark to market changes in DV01. Transactions of bonds issued by financial issuers are not shown here. See Section 2.3 and Appendix B.1 for details. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. Panel A excludes heavy users of derivatives, and Panel B shows heavy users of derivatives only.

Figure 2.9: Cumulative change in DV01 by asset class (2005-2014)
Insurer trading during the crisis is also informative regarding market conditions. Figure 2.10 shows daily transactions by asset class during the depth of the crisis, again separating heavy users of derivatives from other insurers. Although heavy users and all other insurers are roughly the same size in aggregate, heavy users were much more active during the crisis period. Consistent with the idea that there was a buyers’ strike in private MBS rather than a fire sale (Chernenko, Hanson & Sunderam 2014), there is little discrete activity in private MBS. There was some selling of Agency MBS during the crisis, although as discussed in Section 2.6, this largely reflects the trading activity of MetLife.

Having described how I identify heavy users of derivatives, I now turn to evolution of their risk taking behavior over time. As discussed above, risk shifting and theories of risk taking emphasizing crisis experience make opposing predictions for this group of insurers. I show that they reduced risk taking, relative to other insurers, during and after the crisis, consistent with learning from the crisis or the importance of franchise value.

**Evolution of risk taking by heavy users over time**

Heavy users of derivatives reduced risk taking on both dimensions: interest-rate risk and reaching for yield. As these insurers had more leverage, these results highlight that risk shifting cannot fully explain insurers’ risk taking behavior. These results also provide evidence that insurers’ crisis experience mattered: these insurers had invested more in private MBS prior to the crisis, and also faced larger fair value losses during the crisis. The evidence is therefore consistent with the idea that insurers learned from the crisis, as well as the idea that franchise value mattered, leading to induced risk aversion for these insurers. It is difficult to separate these two theories, and I find evidence consistent with key predictions of both theories. As these results are robust to including insurer fixed effects, these results continue to point away from the view that insurer-specific preferences and characteristics drive the most important risk taking behavior.

57Note that the discrete drops on December 1st in private and Agency MBS reflect paydowns rather than active selling by insurers. They occur regularly on the 1st of December and (to a lesser degree) on the 1st of the last month of each quarter.
Panel A: Excluding heavy users of derivatives

Panel B: Heavy users of derivatives only

Notes: This figure shows cumulative transactions for all US life insurers separated by derivatives use, during the depth of the crisis (July 2008-February 2009). I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. I show cumulative changes in DV01 (in $MM) due to trading by asset class: DV01 is the change in value of these assets given a parallel one basis point shift upwards in the yield curve. I scale DV01 by -1 here: bonds have negative DV01. Corporate bonds are separated into safe (NAIC category 1) and risk (NAIC category higher than 1). These changes in DV01 are purely based on trading, and exclude any mark to market changes in DV01. Transactions of bonds issued by financial issuers are not shown here. See Section 2.3 and Appendix B.1 for details. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. Panel A excludes heavy users of derivatives, and Panel B shows heavy users of derivatives only.

Figure 2.10: Cumulative change in DV01 by asset class during the crisis (July 2008-February 2009)
I begin with interest-rate risk. Prior to the crisis, heavy users faced greater interest rate risk, and had larger DV01 gaps. During and subsequent to the crisis, they reduced their exposure to interest rates, in part by holding larger derivatives positions. Figure 2.11 shows the composition of the DV01 gap for insurers, separating out heavy users from all other insurers (Panels B and A respectively). Heavy users reduced their DV01 gap both by adding derivatives, and by growing liabilities slower. Figure 2.12 plots the average net DV01 gaps for heavy users and other large insurers over the sample period. It shows that heavy users had bigger DV01 gaps prior to the crisis, but reduced their DV01 gaps closer to other large insurers during and post-crisis.
Panel A: Excluding heavy users of derivatives

Panel B: Heavy users of derivatives only

Notes: This figure shows the composition of the DV01 gap for all US life insurers separated by derivatives use. The data is quarterly, from 2005Q1-2014Q4. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Bond DV01, Derivatives DV01 and the gap to Liability DV01 are shown stacked (all in $BN). Bond and derivatives DV01 are shown scaled as positive even though they are negative numbers. The total height of the bars in each quarter is the total Liability DV01. Bond and derivatives DV01 are calculated based on detailed position level data. Liability DV01 is estimated assuming a constant modified duration of 15 years. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. Panel A excludes heavy users of derivatives, and Panel B shows heavy users of derivatives only. See Sections 2.3 and 2.4 and Appendix B.1 for details.

Figure 2.11: Composition of DV01 gap (2005-2014)
Notes: This figure shows the time series of Net DV01 Gap for heavy users and other large insurers (insurers in the top two asset deciles that are not heavy users of derivatives). Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. The figure shows equal weighted averages of Net DV01 Gap within each subgroup. See Sections 2.3 and 2.4 and Appendix B.1 for details. Cutoffs between the pre-crisis and crisis period (2007Q2) and crisis and post-crisis period (2010Q4) are also shown.

Figure 2.12: Net DV01 gap for heavy users and other large insurers

Tables 2.11 and 2.11 present these findings in a regression setting. The dependent variable here is either the Bond DV01 Gap (excluding derivatives) or the Net DV01 Gap (including derivatives). Regressions include dummies for heavy user status as well as interactions of this dummy with crisis and post-crisis dummies. I also report specifications restricting the sample to insurers in the top two asset deciles. All specifications include controls for size. Tables 2.11 includes only quarter fixed effects. Heavy users reduced their interest-rate risk, relative to other insurers, during and after the crisis (coefficients on the interactions of the heavy user dummy and crisis and post-crisis dummies are negative). Derivatives are an important part of this trend (coefficients are larger when the dependent variable is the Net DV01 Gap). The results are stronger post-crisis. To provide a sense for magnitudes, heavy users reduced their exposure by about a third of a standard deviation over the sample period. Table 2.11 shows that these results are robust to including insurer

---

58 The standard deviation of the DV01 gap variables is about 20 percentage points within large insurers.
fixed effects.

**Table 2.11: Regressions of DV01 gap on insurer characteristics**

*Notes:* This table shows regressions of Net DV01 Gap (dependent variable) on heavy user status by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Net DV01 Gap is \((\text{Liability DV01} - \text{Bond DV01} - \text{Derivatives DV01})/(\text{Liability DV01})\), in percentage points with a cap at 100 and floor at 0. Heavy user (Huser) is a dummy for whether derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in a quarter. See Appendix B.1 for details. All specifications include interactions of heavy user status with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. The first two columns show regressions in the full sample, and the final two columns restrict the sample to large insurers (top two asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. *t*-statistics are shown in parentheses.

### Quarter fixed effects only

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<th></th>
<th>All insurers</th>
<th>Top two asset deciles</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Bond DV01 Dap</td>
<td>Net DV01 Gap</td>
</tr>
<tr>
<td>Huser</td>
<td>10.03 (2.30)</td>
<td>9.97 (2.33)</td>
</tr>
<tr>
<td>Huser × 2007Q3-2010Q4</td>
<td>2.95 (-2.99)</td>
<td>-0.53 (-0.37)</td>
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<tr>
<td>Huser × 2011Q1-2014Q4</td>
<td>-4.46 (-1.60)</td>
<td>-11.55 (-3.87)</td>
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<tr>
<td>Log(Assets)</td>
<td>0.96 (1.62)</td>
<td>0.96 (1.62)</td>
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<tr>
<td>Quarter FE</td>
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<td>Y</td>
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<tr>
<td>SE clustered by</td>
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<td>I,Q</td>
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<td>(R^2)</td>
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<tr>
<td>Insurers</td>
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</table>

107
Table 2.12: Regressions of DV01 gap on insurer characteristics (insurer FE)

Notes: This table shows regressions of Net DV01 Gap (dependent variable) on heavy user status by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), in percentage points with a cap at 100 and floor at 0. Heavy user (Huser) is a dummy for whether derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in a quarter. See Appendix B.1 for details. All specifications include interactions of heavy user status with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. The first two columns show regressions in the full sample, and the final two columns restrict the sample to large insurers (top two asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. Standard errors are double-clustered by insurer and quarter. t-statistics are shown in parentheses.

Insurer and quarter fixed effects

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<th>All insurers</th>
<th>Top two asset deciles</th>
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<td></td>
<td>Bond DV01 Gap</td>
<td>Net DV01 Gap</td>
</tr>
<tr>
<td>Huser × 2007Q3-2010Q4</td>
<td>3.35</td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td>(2.23)</td>
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<td>Huser × 2011Q1-2014Q4</td>
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<td>(-0.91)</td>
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<td>Insurer FE</td>
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<td>R²</td>
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<td>10,747</td>
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<tr>
<td>Insurers</td>
<td>340</td>
<td>340</td>
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</tbody>
</table>

I find consistent results in the reaching for yield domain: heavy users reduced risk during and post-crisis, relative to other insurers. Figure 2.13 shows this visually: it plots average yield to maturity of bonds purchased by heavy users and by other large insurers over the sample period. There are two differences relative to the interest-rate risk domain. First, heavy users bought bonds with very comparable yields prior to the crisis, and second, heavy users started reaching for yield less than other large insurers quite early on in the crisis period. Table 2.13 presents these findings in a regression setting. Heavy users reached for yield less than other insurers during and post crisis. In terms of magnitudes, heavy users
reduced reaching for yield by about a fifth of a standard deviation during and post-crisis.\textsuperscript{59} These results are robust to restricting the sample to large insurers, as well as to including insurer fixed effects.

Notes: This figure shows the time series of the average yield to maturity on bonds purchased for heavy users and other large insurers (insurers in the top two asset deciles that are not heavy users of derivatives). Heavy users are insurers with derivatives DV01 is at least 5\% of total DV01 (in absolute value) and greater than $1\text{MM}$ (in absolute value) in at least one quarter. YTM of purchases is the fair value value weighted average yield to maturity of all bonds purchased in the insurer-quarter, winsorized at the 5th and 95th percentiles. The figure shows equal weighted averages of this average yield to maturity within each subgroup. See Sections 2.3 and 2.4 and Appendix B.1 for details. Cutoffs between the pre-crisis and crisis period (2007Q2) and crisis and post-crisis period (2010Q4) are also shown.

Figure 2.13: Average YTM of bond purchases for heavy users and other large insurers

\textsuperscript{59}The standard deviation of the average YTM of bonds purchased is around 110 basis points within large insurers.
Table 2.13: Regressions of VW YTM (bps) of bond purchases on insurer characteristics

Notes: This table shows regressions of the average yield to maturity on bonds purchased (dependent variable) on heavy user status by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. YTM is the fair value value weighted average yield to maturity of all bonds purchased in the insurer-quarter, winsorized at the 5th and 95th percentiles, in basis points. Heavy user (Huser) is a dummy for whether derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in a quarter. See Appendix B.1 for details. All specifications include interactions of heavy user status with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. The first two columns show regressions in the full sample, and the final two columns restrict the sample to large insurers (top two asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. The first and third columns include only quarter fixed effects, while the second and fourth columns include quarter and insurer fixed effects. Standard errors are double-clustered by insurer and quarter. \( t \)-statistics are shown in parentheses.

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<td></td>
<td>YTM</td>
<td>YTM</td>
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<tr>
<td>Huser</td>
<td>-33.28</td>
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<td></td>
<td>(-3.13)</td>
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<td>Huser × 2007Q3-2010Q4</td>
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<td>Huser × 2011Q1-2014Q4</td>
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Variation in which newly issued bonds heavy users bought over different periods within the sample is also informative. The results so far in the reaching for yield domain include all purchased bonds. I also present some results focusing on purchases of newly issued bonds, analyzing determinants of the fraction of new issuance purchases that heavy users account for. Becker & Ivashina (2015) use similar analysis focusing on the insurance share of purchases, relative to other institutions (mutual funds and pension funds). Table 2.14 presents the results. I show separate regressions for each part of the sample period. All specifications include month and issuer fixed effects, with standard errors clustered by both month and issuer. During the crisis period, heavy users bought a substantially smaller fraction of issues of structured bonds. Post-crisis, heavy users reached for yield less in general, and were also less likely to buy bonds not rated as NAIC Category 1.
Table 2.14: Regressions of heavy user share of insurance issue purchases on issue characteristics

Notes: This table shows regressions of the fraction of new issues of bonds purchased by heavy users of derivatives on bond characteristics by subsample. The underlying data for this is daily transaction transaction data from 2005-2014. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. I restrict the sample to newly issued bonds. See Appendix B.1 for details. The regression is at the issue level. The sample is restricted to investment grade (NAIC category 1 or 2) bonds issued by private issuers. The dependent variable is the fraction of the purchases accounted for by heavy users of derivatives, in percentage points. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. YTM is the fair value weighted yield to maturity of the bond based on purchases by all life insurers (during the issuance period), winsorized at the 5th and 95th percentiles. NAIC 2 is a dummy for whether the NAIC category of the bond is 2. Structured is a dummy for whether the bond is a structured bond. Duration is the duration of the bond in years, rounded to half years. Total insurer purchases are the natural logarithm of total issuance purchases reported by life insurers. I identify issuers based on the first six digits of bond CUSIPs (using versions reported by SNL and Mergent FISD) and issuer names (as reported by SNL). All specifications include (origination) month and issuer fixed effects. The columns show the pre-crisis, crisis and post-crisis periods. Standard errors are double-clustered by issuer and month. t-statistics are shown in parentheses.

<table>
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<tr>
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<tr>
<td></td>
<td>Huser fraction</td>
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<td></td>
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<td>(0.13)</td>
<td>(3.08)</td>
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<td>Tot insurer purchases</td>
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<td>2.19</td>
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<tr>
<td></td>
<td>(6.05)</td>
<td>(2.92)</td>
<td>(3.63)</td>
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</tbody>
</table>

|                  |            |            |
| Month FE         | Y          | Y          |
| Issuer FE        | Y          | Y          |
| SE clustered by  | Iss,M      | Iss,M      |
| R²               | 0.63       | 0.58       |
| Issues           | 1,877      | 2,773      |
| Issuers          | 827        | 1,087      |

Heavy users’ risk taking behavior shows that risk shifting alone cannot explain all variation in risk taking. These insurers reduced risk on both dimensions of risk taking during and post-crisis, even though they had higher leverage. They also suffered more during the crisis, providing further evidence for the view that some insurers learned from the crisis, or that franchise value led to greater induced risk aversion.

It is difficult to separate learning from the crisis from franchise value, and to the extent
that these views make subtly different predictions, I find evidence for both. For example, a key prediction of the neglected risk version of learning from the crisis is that behavioral change should be driven private MBS – the asset class viewed as safe prior to the crisis, and discovered as unsafe during the crisis. Results based on issuance fractions do suggest that during the crisis heavy users reached for yield less largely because they stayed away from structured bonds. However, heavy users of derivatives did also substantially reduce interest rate risk. Turning to franchise value, a key prediction of this view is that the incentives to reduce risk taking should be short lived. There is some evidence along these lines: the strength of the results that heavy users reduced risk taking is lower in some specifications post-crisis. As discussed earlier, I find some evidence that risk shifting was magnified post-crisis for insurers that bought MBS prior to the crisis.

Other dimensions of risk taking for heavy users of derivatives

I show that heavy users reduced risk, relative to other insurers, during and post-crisis. While these insurers reduced risk in these primary domains, it is possible that they merely shifted their risk taking to domains that are harder to observe. I show that while heavy users did engage in more shadow reinsurance, they reduced interest-rate risk even after adjusting for this. I also raise the possibility that derivatives are a way for insurers to obtain more leverage. Increased derivatives positions are not accompanied by bigger cash positions, and they are not recognized as assets in a way that comparable bond positions would be.

Heavy users reduced interest-rate risk in part by reducing reserves declared on-balance-sheet through shadow reinsurance. However, they reduced interest-rate risk even after adjusting for this. Table 2.15 shows regressions where the dependent variable is the fraction of total life reserves reinsured through shadow reinsurers. These reserves are not declared on balance sheet, and the motivation for reinsurance here is not risk sharing but merely capital conservation (Koijen & Yogo forthcoming). Shadow reinsurance may also have the effect of reducing net interest-rate risk, by reducing the value of liabilities reported on the balance sheet. While heavy users did reduce interest-rate risk in part in this manner,
Figure 2.14 shows that heavy users reduced interest-rate risk even after adjusting for shadow reinsurance. Table 2.16 confirms this in regression form. Particularly post-crisis, heavy users reduced their DV01 gap relative to other large insurers even after adjusting for shadow reinsurance.

Table 2.15: Regressions of fraction of liabilities reinsured through shadow reinsurers on insurer characteristics

Notes: This table shows regressions of the fraction of liabilities ceded to shadow reinsurers on heavy derivatives user status by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. The dependent variable is fraction shadow reinsurance: general account reserves ceded to shadow reinsurers as a fraction of life reserves and shadow reinsurance, in percentage points. Heavy user (Huser) is a dummy for whether derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in a quarter. See Appendix B.1 for details. All specifications include interactions of heavy user status with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. The first two columns show regressions in the full sample, and the final two columns restrict the sample to large insurers (top two asset deciles by quarter). The first and third columns include only quarter fixed effects, while the second and fourth columns include quarter and insurer fixed effects. Standard errors are double-clustered by insurer and quarter. t-statistics are shown in parentheses.
Notes: This figure shows the time series of Adjusted Net DV01 Gap for heavy users and other large insurers (insurers in the top two asset deciles that are not heavy users of derivatives). Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. Adjusted Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), where Liability DV01 uses life reserves adjusted for shadow reinsurance, in percentage points with a cap at 100 and floor at 0. The figure shows equal weighted averages of Adjusted Net DV01 Gap within each subgroup. Cutoffs between the pre-crisis and crisis period (2007Q2) and crisis and post-crisis period (2010Q4) are also shown.

Figure 2.14: Adjusted Net DV01 gap for heavy users and other large insurers
Table 2.16: Regressions of adjusted DV01 gap on insurer characteristics

**Notes:** This table shows regressions of Adjusted Net DV01 Gap (dependent variable) on heavy user status by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Adjusted Net DV01 Gap is (Liability DV01 - Bond DV01 - Derivatives DV01)/(Liability DV01), where Liability DV01 uses life reserves adjusted for shadow reinsurance, in percentage points with a cap at 100 and floor at 0. Heavy user (Huser) is a dummy for whether derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in a quarter. See Appendix B.1 for details. All specifications include interactions of heavy user status with dummies for the crisis (2007Q3-2010Q4) and post-crisis (2011Q1-2014Q4) periods. The first two columns show regressions in the full sample, and the final two columns restrict the sample to large insurers (top two asset deciles by quarter). All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. The first and third columns include only quarter fixed effects, while the second and fourth columns include quarter and insurer fixed effects. Standard errors are double-clustered by insurer and quarter. \( t \)-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>All insurers</th>
<th>Top two asset deciles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj DV01 Gap</td>
<td>Adj DV01 Gap</td>
</tr>
<tr>
<td>Huser</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>20.28</td>
<td>8.37</td>
</tr>
<tr>
<td></td>
<td>(3.78)</td>
<td>(1.27)</td>
</tr>
<tr>
<td>Huser × 2007Q3-2010Q4</td>
<td>1.29</td>
<td>-2.77</td>
</tr>
<tr>
<td></td>
<td>(1.39)</td>
<td>(-4.03)</td>
</tr>
<tr>
<td>Huser × 2011Q1-2014Q4</td>
<td>-4.47</td>
<td>-6.72</td>
</tr>
<tr>
<td></td>
<td>(-1.78)</td>
<td>(-2.18)</td>
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<tr>
<td>Log(Assets)</td>
<td>-2.48</td>
<td>4.30</td>
</tr>
<tr>
<td></td>
<td>(-3.51)</td>
<td>(1.43)</td>
</tr>
<tr>
<td>Quarter FE</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Insurer FE</td>
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<td>N</td>
</tr>
<tr>
<td>SE clustered by</td>
<td>I,Q</td>
<td>I,Q</td>
</tr>
<tr>
<td>R²</td>
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<tr>
<td>Insurer-Quarters</td>
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<td>2,136</td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>64</td>
</tr>
</tbody>
</table>

It is possible that insurers use their derivatives positions as a source of leverage: larger derivatives positions are not accompanied by bigger cash positions, and derivatives positions are not recognized on balance sheet in a commensurate manner to the way a corresponding bond portfolio would be. Figure 2.15 plots heavy users’ derivatives portfolio in the form of duration equivalent notional: the size of the bond portfolio that would have to be held to obtain comparable duration exposure. It also plots heavy users’ cash holdings, which are far smaller. Table 2.17 makes this point in regression form. Larger derivatives positions are largely unmatched by increased cash holdings. Derivatives are also not fully recognized.
on balance sheet. Figure 2.16 compares the duration equivalent notional of insurers’ swap positions to net derivative assets reported on balance sheet (available after 2010). Duration equivalent notional is much larger than net derivative assets recognized.

Notes: This figure shows total duration equivalent notional of swaps held and cash holdings, both in $BN for heavy users of derivatives. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. The data is quarterly, from 2005Q1-2014Q4. Duration-equivalent notional is the amount of bonds that insurers would need to hold (with the same duration as their bond portfolio) to obtain equivalent duration exposure. See Section 2.3 and Appendix B.1 for details.

Figure 2.15: Duration equivalent derivatives and cash holdings for heavy users of derivatives
Table 2.17: Regressions of cash held on derivatives DEN and insurer characteristics

Notes: This table shows regressions of cash held (dependent variable) on insurer characteristics by sub-sample. The data is quarterly, from 2005Q1-2014Q4. I aggregate the data to the insurance group level, pro-forma based on current ownership, as reported by SNL. I restrict the sample to insurance group-quarters where insurers have at least $10M in assets, and positive life insurance reserves. Der DEN/Assets is duration equivalent notional scaled by assets, in percentage points. Duration-equivalent notional is the amount of bonds that insurers would need to hold (with the same duration as their bond portfolio) to obtain equivalent duration exposure. See Section 2.3 and Appendix B.1 for details. All specifications include Log(Assets), the natural logarithm of total assets, as a control for size. The first two columns show regressions in the full sample, and the final two columns restrict the sample to heavy users of derivatives only. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. The first and third columns include only quarter fixed effects, while the second and fourth columns include quarter and insurer fixed effects. Standard errors are double-clustered by insurer and quarter. t-statistics are shown in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
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<th>Heavy users only</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Cash/Assets</td>
<td>Cash/Assets</td>
<td>Cash/Assets</td>
<td>Cash/Assets</td>
</tr>
<tr>
<td>Der DEN/Assets</td>
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<td>0.03</td>
<td>0.02</td>
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<tr>
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<td>(-4.06)</td>
<td>(-1.82)</td>
<td>(-2.40)</td>
</tr>
<tr>
<td>Quarter FE</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Insurer FE</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>SE clustered by</td>
<td>1,Q</td>
<td>1,Q</td>
<td>1,Q</td>
<td>1,Q</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.19</td>
<td>0.71</td>
<td>0.22</td>
<td>0.42</td>
</tr>
<tr>
<td>Insurer-Quarters</td>
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<td>10,747</td>
<td>840</td>
<td>840</td>
</tr>
<tr>
<td>Insurers</td>
<td>340</td>
<td>340</td>
<td>21</td>
<td>21</td>
</tr>
</tbody>
</table>
Notes: This figure shows total duration equivalent notional of swaps held and net derivative assets, both in $BN for heavy users of derivatives. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. The data is quarterly, from 2005Q1-2014Q4. Duration-equivalent notional is the amount of bonds that insurers would need to hold (with the same duration as their bond portfolio) to obtain equivalent duration exposure. Net derivative assets are derivative assets net of derivative liabilities (reported starting in 2010Q1). See Section 2.3 and Appendix B.1 for details.

Figure 2.16: Duration equivalent derivatives and net derivative assets for heavy users of derivatives

2.5.3 Summary of evidence

The evidence presented in this section shows that risk shifting cannot fully explain insurers’ risk taking behavior during and post-crisis. In a direct sense I show that insurers that risk shifting was mitigated during the crisis for insurers that had relevant experience. I also show that heavy users reduced risk taking, relative to other insurers, during and post-crisis. As heavy users were both more levered than other large insurers and had invested in private MBS pre-crisis and faced fair value losses during the crisis, this evidence allows a clear contrast between risk shifting and other explanations of risk taking behavior.

Collectively these results suggest that insurers either learned from the crisis or that franchise value was an important motivation during this period. It is difficult to distinguish between these alternative explanations under which crisis experience is relevant for these insurers’ risk taking behavior. To the extent that they make subtly different predictions, I
find evidence for both theories. As most results are robust to including insurer fixed effects, it does not seem to be the case that insurer-specific preferences or circumstances explain most interest risk taking behavior.

2.6 Other stylized facts

In this section, I outline additional stylized facts about insurers’ trading behavior and their implications in three other areas. First, I point out that insurers trade slowly and smoothly, which raises questions about frameworks in which capital actively moves. Second, I show that gross trading can be much larger than net buying, particularly for treasuries, which is related to broader questions about why there is so much trading. Third, I suggest that prices from insurer trading may add information to standard indices.

2.6.1 Movement of capital and QE

Standard theories of allocation of capital suggest that capital shifts dramatically and rapidly across domains. While there are circumstances under which this occurs, it is well known that capital often does not shift dramatically or rapidly. A prominent theoretical explanation for why capital moves slowly is that not all agents make decisions in all periods (Duffie 2010). Even this theoretical approach predicts that capital moves eventually. Indeed, in this framework agents rebalance their entire portfolio in the periods in which they do make decisions, in a forward looking manner.

Insurers’ trading behavior does not seem to fit within this framework. A good example of this is the response (or lack thereof) of insurer trading behavior to large supply shocks during quantitative easing in the US. As discussed in Section 2.3, insurance regulatory data allows detailed views of insurer trading to be constructed. I construct daily measures of both purchases and sales in specific sub-asset classes (for example, US treasury bonds or corporate bonds with maturity greater than 25 years). I also construct price indices within
these asset classes based on daily prices reported by insurers.\footnote{See Appendix B.1 for more details.} Insurers trade smoothly, in a manner that does not obviously respond to large supply shocks and movements in prices. While the flow of purchases does adjust from time to time, the aggregate balance sheet adjusts very slowly.

Figure 2.17 shows insurer purchases and sales in long-term US government bonds along with the prices at which these transactions occur, on a daily basis.\footnote{Insurers trade most frequently in long-dated bonds.} It also shows all expansionary dates during the various phases of QE (including the maturity extension program) reported by Greenwood et al. (2015). While prices, at this scale, are largely consistent with broader price indices (such as the constant maturity series prepared by the Fed), insurers continued trading smoothly. There is no obvious response at the daily frequency to announcements of large supply shocks in the future. Figure 2.18 (Panel A) zooms in on the period in which QE1 was announced. Again, it shows that trading evolves smoothly.

Figure 2.19 shows very similar patterns in the space of long-term corporate bonds. Treasuries form a comparatively small part of insurer holdings, whereas corporate bonds are a larger asset class for insurers. However, even with corporate bonds, there is no clear indication that responded to large supply shocks. It should be emphasized that these patterns relate to insurers’ trading, not changes to the balance sheet in aggregate. When trading evolves smoothly, and is small relative to the balance sheet, the aggregate balance sheet can only adjust slower.

Another interesting feature of insurer trading is that there is generally little net selling of assets (with one notable exception). All views of insurer trading over time show that there is very little net selling (see Figures 2.3, 2.9, 2.10, 2.17, 2.18 and 2.19).\footnote{Note that changes in holdings of MBS (both private and Agency) reflected in these Figures reflect paydowns rather than active selling.} There is one notable exception to this: MetLife. Panel B of Figure 2.18 shows that heavy users sold Agency MBS during the crisis. Panel A of Figure 2.20 shows that MetLife accounted for all
Notes: This figure shows insurer trading in US treasuries and prices at which trades occur, using daily trading data for all US life insurers from 2005-2014. I restrict the sample to trading by insurers with at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. The sample is restricted to US Federal government bonds with maturity greater than 25 years as of the date of trading (maturity rounded to the nearest half year). Yield to maturity is the fair value value weighted average using both purchases and sales of trades, calculated on a daily basis (left axis, in percentage points). I exclude changes of more than 50 basis points that are reversed to within [80%,120%] by the next observations from the data. Purchases and sales are shown (right axis, in $BN) on a cumulative basis, at a daily frequency. All QE expansionary dates (including MEP) from Greenwood et al. (2015) are marked as well.

Figure 2.17: VW YTM on treasury bonds with maturity >25 years and insurer trading (2005-2014)

of this net selling. Panel B of Figure 2.20 shows that MetLife acquired a portfolio of foreign government bonds starting late 2008, and then sold heavily on a single day (May 31st 2012). This exposure included a substantial portfolio of Japanese JGB and local government bonds.
Panel A: Insurer trading and prices

Panel B: Insurer trading, prices and Treasury CMS series

Notes: This figure shows insurer trading in US treasuries and prices at which trades occur, using daily trading data for all US life insurers during the period in which QE1 was announced. I restrict the sample to trading by insurers with at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. The sample is restricted to US Federal government bonds with maturity greater than 25 years as of the date of trading (maturity rounded to the nearest half year). Yield to maturity is the fair value value weighted average using both purchases and sales of trades, calculated on a daily basis (left axis, in percentage points). I exclude changes of more than 50 basis points that are reversed to within [80%,120%] by the next observations from the data. Purchases and sales are shown (right axis, in $BN) on a cumulative basis, at a daily frequency. All QE1 expansionary dates from Greenwood et al. (2015) are marked as well. Panel B also includes the 30Y CMS series from the Fed (left axis).

Figure 2.18: VW YTM on treasury bonds with maturity >25 years and insurer trading (QE1 announcement period)
Notes: This figure shows insurer trading in corporate bonds and prices at which trades occur, using daily trading data for all US life insurers from 2005-2014. I restrict the sample to trading by insurers with at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. The sample is restricted to corporate bonds (excluding structured bonds and financial issuers) with maturity greater than 25 years as of the date of trading (maturity rounded to the nearest half year). Yield to maturity is the fair value value weighted average using both purchases and sales of trades, calculated on a daily basis (left axis, in percentage points). I exclude changes of more than 50 basis points that are reversed to within [80%,120%] by the next observations from the data. Purchases and sales are shown (right axis, in $BN) on a cumulative basis, at a daily frequency. All QE expansionary dates (including MEP) from Greenwood et al. (2015) are marked as well.

Figure 2.19: VW YTM on corporate bonds with maturity >25 years and insurer trading (2005-2014)
Panel A: Net purchases of Agency MBS by MetLife and all other heavy derivatives users

Panel B: Net purchases of foreign government bonds by Metlife

Notes: This figure shows trading behavior of MetLife during two incidents where substantial net selling occurred. Panel A shows cumulative net purchases of Agency MBS (in $BN) during the crisis (July 2008-February 2009), separately showing MetLife and all other heavy users of derivatives. Heavy users are insurers with derivatives DV01 is at least 5% of total DV01 (in absolute value) and greater than $1MM (in absolute value) in at least one quarter. See Figure 2.10 for aggregate trading patterns during this period. Panel B shows cumulative net purchases of foreign government bonds for MetLife from late 2008 to mid 2012. The discrete selling all occurred on May 31st 2012. There is little activity by other insurers in foreign government bonds during this period.

Figure 2.20: The MetLife incidents
Collectively, these stylized facts suggest a more mechanical view of trading than that implied by models in which capital shifts. It is not clear that insurers’ trading responds to substantial supply shocks and movements in prices. As trading moves slowly, insurer balance sheets evolve extremely slowly. If all major institutions behave in this way, perhaps prices are determined by the behavior of a small group of agents that account for a small part of the overall market.\textsuperscript{63}

2.6.2 Other implications

Insurer trading has implications in two further areas. First, gross trading is sometimes much larger than net trading, which relates to a broader puzzle about why there is so much trading. Second, I suggest that the prices at which insurers trade may themselves be informative.

Gross trading is much larger than net trading for long-term treasuries, but less so for long-term corporate bonds. Figure 2.17 shows that over 2005-2015, insurers bought $300BN of long-term treasuries and sold $270BN, with net purchases of only about $30BN. This corresponds to a gross-net trading ratio of 19:1. Figure 2.19 shows that over the same period, insurers bought $380BN in long-term corporate bonds and sold roughly $140BN, with net purchases of $240BN, corresponding to a gross-net ratio of roughly 2:1.\textsuperscript{64} Gross trading may be much larger than net trading for treasuries because life insurers use treasuries as the equivalent of transactional bank accounts. In this case, insurers’ trading activity could allow the size of liquidity shocks and their spillovers to be measured.\textsuperscript{65}

Prices at which insurers trade may also be of interest and informative on their own. For

\textsuperscript{63}Institutions that primarily invest in short-term assets are one likely exception to the hypothesis that institutions’ balance sheets generally evolve slowly. Their balance sheets must evolve faster because most of their assets mature in months rather than decades. Chodorow-Reich (2014) documents that aggregate yields of their holdings shift rapidly.

\textsuperscript{64}The gross-net ratio for Agency MBS is 5:1.

\textsuperscript{65}Another possibility is that institutions trade in treasuries to hedge the changing duration of holdings of MBS as the likelihood of prepayment changes. However, there is no particular response of trading in treasuries to large, discrete changes in the size of MBS portfolios in the form of paydowns.
Notes: This figure shows price indices for long-term US Treasuries and corporate bonds, using daily trading data for all US life insurers from 2005-2014. I restrict the sample to trading by insurers with at least $10M in assets, and positive life insurance reserves. See Appendix B.1 for details. Yield to maturity is the fair value value weighted average using both purchases and sales of trades, calculated on a daily basis (left axis, in percentage points). I exclude changes of more than 50 basis points that are reversed to within [80%,120%] by the next observations from the data. Corporate bonds trades (excluding structured bonds and financial issuers) are restricted to those with maturity greater than 25 years as of the date of trading (maturity rounded to the nearest half year). US Federal government bonds trades are also restricted to those with maturity greater than 25 years as of the date of trading (maturity rounded to the nearest half year). Price indices are monthly equal weighted averages of these daily trading prices. All QE expansionary dates (including MEP) from Greenwood et al. (2015) are marked as well.

**Figure 2.21:** VW YTM on corporate and treasury bonds with maturity >25 years (2005-2014)

Example, Panel B of Figure 2.18 shows the prices at which insurers traded long-term bonds and the 30Y Constant Maturity Series released by the Fed. During the period when QE1 was being announced, insurers traded in treasuries at much higher yields, and therefore lower prices, than those indicated in the CMS series.\(^6\) Several prominent event studies studying the short-term impact of QE announcements on yields use standard indices (Gagnon, Raskin, Remache, Sack et al. 2011, Krishnamurthy & Vissing-Jorgensen 2011). In unreported analysis, I show that the gap between yields at which insurers traded Agency MBS and current coupon yields was larger and more persistent.\(^7\) Figure 2.21 shows price indices for treasuries and corporate bonds based on insurer trading at a monthly frequency over the

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\(^6\) Perhaps this reflects that insurers bought different treasuries than those priced in the CMS series. For example, this may reflect a jump in the on-the-run to off-the-run spread.

\(^7\) D’Amico & King (2013) show that yields fell more for treasuries actually bought by the Fed during QE.
sample period.

2.7 Conclusion

In this chapter, I construct measures of risk taking by life insurers across two main dimensions: interest-rate risk, and asset risk, in the form of reaching for yield. I use rich insurance regulatory data for US life insurers to construct these measures of risk taking. I use them to document considerable heterogeneity in risk taking across insurers and across time. I use this heterogeneity shed light on different theories of risk taking. I focus on four main views of risk taking: risk shifting, views in which insurers might learn from crises, the importance of franchise value, and the view that most important risk taking behavior is driven by insurer specific preferences and circumstances.

While I find evidence consistent with risk shifting in aggregate, risk shifting cannot explain all variation in insurers’ risk taking behavior. In aggregate, consistent with risk shifting, insurers with more leverage do take more risk, on both dimensions of risk taking. I even find evidence for one of the key predictions of risk shifting: that risk taking incentives for insurers with more leverage should have steepened during the crisis. As these results are robust to including insurer fixed effects, the evidence points away from a view that puts primary emphasis on insurer specific preferences. While the evidence is consistent with risk shifting in aggregate, risk shifting cannot explain all variation. The steepening of risk shifting during the crisis is concentrated within small insurers. Within large insurers, risk shifting seems to have abated somewhat during the crisis, particularly in the domain of reaching for yield.

I use variation in the extent to which insurers suffered during the crisis and the behavior of insurers that used derivatives heavily to provide evidence for theories in which there is a role for insurers’ crisis experience. I measure insurers’ experience during the crisis with two proxies: the extent to which they invested in private MBS prior to the crisis, and the extent to which they faced fair value losses during the crisis. I find evidence that risk shifting was attenuated for insurers that suffered during the crisis on both dimensions of
risk taking. I also point to the behavior of heavy users of derivatives. As these insurers were more levered (even relative to other large insurers) and ‘suffered’ more during the crisis, they provide a clean test between risk shifting and crisis experience. On both dimensions of risk taking, heavy users of derivatives reduced risk taking during and after the crisis. This points towards the relevance of views in which insurers learn from crises or are concerned about ongoing franchise value.

The results are broadly consistent with many views in which insurers’ crisis experience might matter for risk taking behavior. Indeed, these theories make quite similar predictions about risk taking over this period. To the extent that they make subtly different predictions, I find evidence pointing towards both learning in some form and franchise value. For example, a neglected risk view of the crisis (Shleifer 2011, Gennaioli et al. 2012) suggests a crucial role for private MBS. Consistent with this, reduced risk taking during the crisis is to some extent driven by a shift away from private MBS. Equally, there is some evidence for an important prediction of the franchise value view: that incentives to reduce risk taking have started to wear off since the crisis.

I also highlight the implications of insurers’ trading behavior in three further areas. First, insurers trade smoothly, even in periods with large supply shocks such as those associated with quantitative easing. This suggests that models in which capital moves dramatically, even if slowly, may not be consistent with the data. Second, I document that gross trading can be much larger than net trading, particularly for treasuries. Finally, I suggest that the prices at which insurers trade may be informative in addition to standard price indices.
Chapter 3

What are reference rates for?

3.1 Introduction

Contingent financial contracts allow parties to agree to payments which are determined in the future, depending on how circumstances evolve. In a broad sense contract theory has studied their role in providing incentives and facilitating risk sharing. An important class of contingent contracts, including loans and related derivatives, involves interest rates. These contracts provide for payments that are contingent on reference rates: frequently determined and readily available interest rates. The stated aim for using these contracts is typically risk management. Contingent versions of contracts are also sometimes thought to be cheaper (for instance the interest rate may be perceived to be lower, in expectation, with a variable rate loan compared to a fixed-rate loan). The characteristics of the reference rate determine the ways in which these contracts can be used for risk management.

Many interest-rate-dependent contracts, particularly those denominated in dollars, refer to the London Interbank Offered Rate, LIBOR, which provides a daily measure of interest rates in interbank transactions in major currencies between large banks. Loans and derivatives are large asset classes, and LIBOR is quite dominant: consequently, contracts with a total notional value of as much as $300TN are estimated to refer to LIBOR (FSA 2012).

1Contracts denominated in Euros typically refer to EURIBOR, which is similar but subtly different; see Section 3.2 and Footnote 12.
Reference rates have attracted significant attention in recent years due to allegations of their manipulation. In April and May 2008, the Wall Street Journal ran articles suggesting that LIBOR was being manipulated. Global banks have since been fined billions of dollars by regulators from several countries for attempting to manipulate LIBOR. Numerous lawsuits have been filed against banks by US municipalities and GSEs; Fannie Mae recently sued 9 banks claiming damages of $800MN. Belying the importance of well functioning reference rates, an alphabet soup of regulators and official bodies has responded (FSA 2012, BIS 2013, IOSCO 2013, FSOC 2013). LIBOR even merits a dictionary entry providing a timeline of the various allegations of misconduct (Hou & Skeie 2013). Most recently, individual traders have been prosecuted for their role in manipulating LIBOR.

The small, but growing, academic literature on LIBOR has mainly addressed two issues: detection and quantification of manipulation, and ways LIBOR could be replaced or determined differently. However, relatively little attention has been paid to the purpose that reference rates serve. In light of the new policy relevance of reference rates, this is an important topic to study. In particular, in order to contemplate modifying or replacing LIBOR, it is important to understand how and why it is used. As many have noted, floating interest rates and interest-rate derivatives allow institutions to manage exposure to short-term interest rates. However, it is important to understand which specific risks are being managed and why. For example, as discussed in Section 3.2, LIBOR has a bank credit risk component. Alternatives that have been considered, including market rates for Overnight Indexed Swaps (OIS) or repurchase (repo) agreements, do not. Is it important for the reference rate to capture bank credit risk? More generally, how do the properties of

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4One trader convicted in connection with manipulation of LIBOR has been handed a long jail sentence (eight years) and a personal monetary penalty in excess of one million dollars. See USA Today, Trader ordered to pay $1.24M for Libor rigging, March 2016.

5I discuss this literature further in Section 3.2.

6See Duffie & Stein (2015) for a broad discussion of the roles reference rates can play.
reference rates affect how useful linked contracts are for hedging?

In this chapter I focus on the role reference rates play in the market they originated from: bank lending to firms. I analyze the use of reference rates in floating-rate loans and in the associated use of interest-rate derivatives using a simple model of maturity transformation. Three key frictions generate a framework in which the use of reference rates makes sense. First, I assume that the lender must use short-term liabilities to fund long-term loans, generating maturity mismatch. This is best thought of as a stronger version of the assumption that short-term funding is cheaper. Certainly lenders do use short-term funding, and much of the instability of the financial crisis of 2007-08 can be traced to excessive dependence on short-term funding. Stein (2012), for example, argues that a preference for safe assets drove this.

Next, I assume that the bank’s own cost of funding is not contractible. This is a natural way to capture the difficulty borrowers have with observing borrowing costs directly and the skepticism they are likely to have about banks’ incentives to reveal them truthfully. Reference rates serve the purpose of mitigating this contractual incompleteness. These first two assumptions generate funding risk that, in the absence of a contingent contract, the lender must bear. Finally, I argue that financial frictions lead to effective risk aversion by making firm profit functions concave, following Froot et al. (1993) and Froot & Stein (1998). These three frictions combine to produce a setting in which reference rates facilitate hedging of meaningful funding risk.

This framework permits analysis of how the availability of floating-rate loans and interest-rate derivatives affects credit markets. In their absence, lenders can only offer fixed interest rates and must bear funding risk themselves. When floating rates are available, this risk can be transferred to borrowers, lowering the cost of borrowing. However, whether welfare increases depends on how risk averse firms are. Interest-rate swaps permit this risk to be sold to the market for a price, which depends on how well the market is positioned to bear interest-rate risk. As long as aggregate risk aversion is not too high, it would be better for lenders to use swaps for risk management than to transfer risk to borrowers through
floating-rate loans.\(^7\)

In practice, firms typically borrow at floating rates and subsequently manage the risk, at least partially, with swaps.\(^8\) Why might this be better than lenders managing the risk directly? One advantage of this more complicated arrangement is that firms can join the set of institutions bearing interest-rate risk, reducing aggregate risk aversion and the cost of hedging this risk. It may be easier for firms to justify retaining more floating-rate exposure from a floating-rate loan by not hedging it than acquiring such exposure through ‘naked’ swaps. Alternatively, if derivatives markets are concentrated and lenders provide floating loans and derivatives as a package this arrangement could just be a way for lenders to channel volume to high margin activities. As contracts linked to the reference rate serve to insulate the lender against funding risk, it makes sense in this context for the reference rate to be linked to bank funding costs, which are related to bank credit risk. Manipulation which simply makes the reference rate more volatile reduces welfare by diminishing its usefulness for hedging.

The analysis relates to themes considered in several literatures. Brousseau, Chailloux & Durré (2013) propose that reference rates should capture bank funding costs across instruments, informally arguing that reference rates should be related to bank funding costs. Detragiache (1992) argues that floating-rate loans optimally insure developing countries against fundamental shocks in an incomplete contracting framework given the empirical correlation between LIBOR and these fundamentals. The framework demonstrates conclusions made by Barzel (1982) that good standards are accurate and low cost. I also use the idea that hedging need not be a zero NPV proposition if there is aggregate risk aversion, as suggested by Demsetz (1969). The effects of frictions in financial intermediation have also attracted attention recently. Gabaix & Maggiori (2015) build up effective risk aversion for

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\(^7\)This assumes that there are no other costs associated with using interest-rate swaps. Collateral requirements and associated implicit costs can change the nature of the cost of hedging substantially (Rampini & Viswanathan 2010, Rampini et al. 2014, Rampini et al. 2015, Ivashina et al. 2015). Also see Chapter 1.

\(^8\)In Chapter 1, I document that firms only hedge interest-rate risk partially with swaps, and argue that collateral requirements limit the use of swaps. Here I explore other potential explanations.
financial institutions from a commitment problem, studying how this affects exchange rates when intermediaries have to bear exchange rate risk. Shin (2012) constructs a demand curve for risk by modeling risk management as a constraint (either self- or regulator-imposed) on the probability of large losses, arguing that the resulting fluctuations in leverage for global banks transmit financial conditions across borders.

The remainder of this chapter is organized as follows. Section 3.2 provides more background on LIBOR and related literature. Section 3.3 details the set up and the three key frictions described above. Section 3.4 analyzes the basic uses of reference rates. Section 3.5 considers derivatives in more detail, and discusses interpretation and welfare loss from manipulation. Section 3.6 concludes.

### 3.2 Background on LIBOR

Growth in the magnitude of contractual payments affected by LIBOR has primarily been driven by the explosive growth in volumes of interest-rate derivatives over recent decades. These derivatives were introduced as part of the wave of financial innovation which responded to the uncertain environment and restrictions firms faced in the 1970s and 1980s. The breakdown of Bretton Woods and the resulting fluctuations in exchange rates, in addition to high inflation during this period, led firms to try to actively manage risk. Currency swaps, first introduced in 1979, were a more efficient version of agreements that allowed firms to skirt British foreign exchange controls in the 1970s. Interest-rate swaps were a natural extension in which different interest rates in the same currency were exchanged, introduced in London in 1981 and first used in the US in 1982 by Sallie Mae.\(^9\)

One of the drivers of the early growth of the interest-rate swap market was a coincidence of mutual need. In the early 1980s, financial institutions in the US funded long-term, fixed-rate loans such as mortgages with short-term deposits such as CDs. The interest rates on these short-term deposits fluctuated, moving around with T-bill rates or CD rates. Financial

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Institutions were exposed to the risk that their cost of borrowing could substantially rise due to this mismatch between assets and liabilities. At the same time, banks in Europe typically funded themselves through long-term, fixed-rate Eurobonds, but extended variable-rate loans. These opposite problems meant that interest-rate swaps could allow both sets of institutions to manage interest-rate risk. The reason these swaps referenced LIBOR seems to have been that variable-rate loans made to households in Europe referred to LIBOR during this period.\(^\text{10}\)

LIBOR is now widely used as a reference rate for interest-rate derivatives as well as for loans to firms and households. The name was first used to label an arrangement created to define payments on a $80MN loan to the Shah of Iran in 1969 by a syndicate of banks led by Manufacturer’s Hanover. Shortly before agreed dates at which the interest rate would be updated, large banks in the syndicate reported their funding costs, an average of which became the new interest rate. As the use of LIBOR became more popular, banks’ funding costs started to be tied LIBOR, providing an incentive for banks to underreport. A more formal version of LIBOR was introduced in 1986 to address this issue, administered by the British Bankers’ Association.\(^\text{11}\) LIBOR is determined as a trimmed average of submissions from a panel of large banks: each bank submits one number to a calculating agent, which reports an average after discarding some high and low outliers. Each bank is asked to estimate the rate at which it could borrow on the interbank market ‘in reasonable market size’ in the morning London time.\(^\text{12}\) LIBOR is calculated for several currencies and maturities, though the three month dollar LIBOR is the most commonly used rate.

Informally, the interest rate for any transaction can be considered to be the sum of several

\(^{10}\)See Campbell & Kracaw (1993). Note that it is typical for swaps to be intermediated, so that these institutions may not have faced each other directly.

\(^{11}\)This is essentially the present version of LIBOR. See Business Insider, A Greek Banker on the Early Days of the LIBOR, August 2012 for an account of this first loan. This account argues that demand for these floating loans was driven by a desire for firms and countries to avoid domestic regulation and taxes. As of February 2014, ICE administers LIBOR (the FSA (2012) recommended that the BBA no longer administer LIBOR).

\(^{12}\)No transactions are required to have taken place at the rates reported, nor are submissions interpreted as quoted rates at which banks are committing themselves to borrow or lend (Gyntelberg & Wooldridge 2008). Note that EURIBOR is subtly different; banks are asked to estimate the rate offered ‘by one prime bank to another.’
components, including a risk-free rate, a term premium and a credit risk premium. LIBOR can be thought of as containing the risk free rate, the term premium, and a component pertaining to the credit risk of the panel of banks that submit rates for it. As banks are asked to estimate the cost they would be able to borrow at, some measure of their own credit risk must appear (BIS 2013, Hou & Skeie 2013). Such a rate makes sense in credit markets, where the risk being hedged is that bank funding costs, which have a credit risk component, change.

The interbank lending market is an over-the-counter market. Transactions and interest rates are not publicly announced, and this is why a survey based measure like LIBOR is necessary to create a reference rate tied to the interbank market. At the time LIBOR and interest-rate swaps were first introduced, interbank markets were a liquid market banks used to fund themselves. However, since then savers have shifted away from bank deposits, forcing banks to fund themselves through CDs or secured financing arrangements like repurchase agreements (Brousseau et al. 2013, BIS 2013). The interbank market, particularly at maturities beyond weeks, is therefore now quite thin. Indeed, even if transactions were collected over a ten day window, only a handful might occur at the three month maturity (Duffie, Skeie & Vickery 2013).

At the same time that the interbank market has thinned, the volume of assets that reference LIBOR has substantially grown, driven by explosive growth in derivatives volumes. Outstanding notional amounts of interest-rate derivatives have grown to hundreds of trillions of dollars.\textsuperscript{13} The Wheatley Review conducted by the FSA estimates that $300TN of assets reference LIBOR, including $10TN in syndicated loans.\textsuperscript{14} The unfortunate combination of a large volume of transactions related to LIBOR and an opaque and sparse underlying interbank market permitted the recent scandal as banks attempted to manipulate LIBOR.

\textsuperscript{13}The BIS published statistics on derivative notional amounts semi-annually. Notional amounts have fallen somewhat in recent years due to compression.

\textsuperscript{14}This estimate may be high as it appears to include derivatives denominated in Euros, which are likely to reference EURIBOR (for example, most euro denominated exchange traded derivatives are linked to EURIBOR). However, the broader point is that the volume of assets which require a reference rate is increasing dramatically.
As settlements with regulators make clear, banks’ incentives were driven by direct exposure to LIBOR through interest rate derivatives as well as reputational concerns.¹⁵

Several regulatory bodies have produced reports commenting on LIBOR. The FSOC identifies the continued use of LIBOR as one of its seven themes for concern about the financial system in its latest annual report (FSOC 2013). The FSA’s Wheatley review and the International Organization of Security Commissions (IOSCO) suggest improved regulatory frameworks and audit trails (FSA 2012, IOSCO 2013). The Bank for International Settlements’ Economic Consultative Committee emphasizes that network effects and logistics significantly complicate choosing a replacement (BIS 2013). Duffie & Stein (2015) summarize the recommendations put forward by the many groups convened by the Financial Stability Board to address the issue of reference rates. A key recommendation is to reduce reliance on reference rates with a credit risk component.

There is also a growing academic literature on LIBOR. One question of interest has been to identify manipulation using submissions and data on other short-term interest rates. Hou & Skeie (2013) summarize the early papers, arguing that they did not find clear cut evidence of manipulation. More recently, Eisl, Jankowitsch & Subrahmanyam (2013) use the distribution of bids to estimate the maximum amount LIBOR could have been manipulated by a perfectly informed bank. Youle (2015) estimates the magnitude of manipulation by analyzing how bids responded to changes in how much the bank expected to be able to affect LIBOR, estimating that since the crisis LIBOR is about 8 basis points lower than it would be absent portfolio incentives to manipulate. Both of these papers use the fact that as outliers are removed, how much any bank can shift LIBOR by changing its submission depends on the distribution of the remaining bids. Gandhi, Golez, Jackwerth & Plazzi (2015) instead estimate bank exposures to interest rates by regressing stock returns on changes in the reference rate, implicitly assuming that the market can estimate these exposures. They

¹⁵See, for example, Barclays’ settlement with the FSA. Barclays was the first bank to settle with regulators. Bank submissions were, until recently publicly disclosed. They are now disseminated after a three month delay, to reduce reputational concerns for banks reporting higher borrowing costs than the rest of the panel. Hou & Skeie (2013) provide a timeline of the various accusations and actions taken in recent years.
label correlation between submissions and these estimated exposures as manipulation, and estimate that absent this correlation panel banks’ market value would have been more than $20 BN lower.

Another question of interest has been whether LIBOR can be calculated differently or replaced. Taking a mechanism design approach, Coulter & Shapiro (2013) propose a generalization of the Moore-Repullo mechanism, and Chen (2013) suggests the AGV mechanism. These papers construct mechanisms that work because some of the issues of private information are not considered. If bank funding costs and exposures to the reference rate are private information, it does not seem possible to construct a mechanism that eliminates manipulation. This does not mean, of course, that mechanisms cannot be designed to reduce manipulability.16

Consider the issues arising from portfolio driven incentives to manipulate. Let $X_{it}$ refer to bank $i$’s exposure to the reference rate at time $t$, for instance through swaps. As swaps settle based on the level of the reference rate on specific days (based on days the swap payments are to be made, typically at six month frequencies), this exposure can vary significantly at short horizons. Bank settlements with regulators show that traders requested submitters to manipulate on days when exposures were large.

If manipulation is costly (for instance due to ex post punishments if the bank is caught), the bank’s payoff might be represented as

$$X_{it}R(r_{it}, r_{-it}) - C(r_{i} - \bar{r}_{i})$$

where $\bar{r}_{i}$ is the bank’s true cost of funding, $r_{it}$ is what it reports, and other banks in the panel report $r_{-it}$. The first order condition implies that the bank should choose its report to satisfy

$$C'(r_{i} - \bar{r}_{i}) = X_{it} \frac{\partial R(r_{it}, r_{-it})}{\partial r_{it}}$$

As long as the right hand side of this equation is not identically zero, manipulation occurs. Can a mechanism eliminate this problem? Suppose the mechanism outputs $R(r_{it}, r_{-it})$, and assign transfers $T_{i}(r_{it}, r_{-it})$. The first order condition now becomes

$$C'(r_{it} - \bar{r}_{it}) = X_{it} \frac{\partial R(r_{it}, r_{-it})}{\partial r_{it}} + \frac{\partial T_{i}(r_{it}, r_{-it})}{\partial r_{it}}$$

It is clearly not possible to set the bank’s effect on LIBOR to always be zero. Similarly, as long as $X_{it}$ and the bank’s true cost of funding, $r_{it}$ are private information, it is not possible to set transfers to eliminate manipulation. This argument is related to an impossibility result in (Hurwicz 1972) driven by private endowments. As noted in the text, this does not mean that mechanisms cannot reduce manipulation.

In contrast, Coulter & Shapiro (2013) assume that each bank’s funding costs are known to two other banks, which allows these banks to play the role of a whistleblower if reports are not truthful, in a generalization of the Moore-Repullo multi-stage mechanism. Chen (2013) argues that bank funding costs are tied to LIBOR, and that banks therefore have an incentive to shift LIBOR down. It is assumed that the strength of this incentive relative to the cost of manipulation is the same across banks and constant over time, allowing a version of the AGV mechanism to be applicable.

Note that Youle (2015) aims to identify manipulation based on changes in how much the bank expects to affect LIBOR, and not changes in the exposure. I construct a mechanism based on trading which reduces manipulation in (Kirti 2013). Duffie & Dworczak (2014) characterize the optimal weights to place on reports

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The FSA (2012) considers but rejects alternatives such as a random bid or the median bid using historical bid data to assess their impact. Youle (2015) simulates how bids would change if a median bid was used. Under the distribution of banks’ costs of funding which he infers from historical bids, any particular bank would be uncertain whether it would be the median bank, both before and after attempted manipulation, and would therefore find it much less attractive to manipulate. Abrantes-Metz & Evans (2012) propose requiring banks to commit to trade in a ‘committed quote’ range. Duffie et al. (2013) examine the practicality of using past transactions over extended windows and express concerns that this would lead to a stale reference rate. Brousseau et al. (2013) propose a trade-weighted average across bank wholesale funding operations. If this ideal cannot be achieved, they suggest using rates from overnight indexed swaps (OIS), an alternative that has also been considered by by policy makers (BIS 2013).

In this chapter I take a step back and analyze the rationale behind contracts linked to reference rates. What is the precise role of the reference rate? Indeed, why does it matter if LIBOR was manipulated? This analysis should inform how reference rates should be thought about. For example, Brousseau et al. (2013) suggest that the ideal reference rate should more accurately reflect bank borrowing costs across different types of funding operations. Why might this make sense? The framework I construct demonstrates that in the context of bank lending, as the role of the reference rate is to facilitate hedging funding risk, reference rates without such content may be less useful.

### 3.3 The basic framework

In order to understand the role of reference rates, I develop a simple model of maturity transformation incorporating uncertainty regarding future short-term financing costs. As discussed below, these costs are not contractible. Therefore, in the absence of reference rates, lenders must bear the associated funding risk. Reference rates are estimates of current

from different participants to minimize distortion.
short-term funding costs. Their existence permits contracts to refer to their levels in future, mitigating contractual incompleteness. In Section 3.3.1 I set up the model. Section 3.3.2 discusses key frictions in the presence of which managing funding risk is desirable. I analyze the use of floating-rate loans and derivatives to do this in Sections 3.4 and 3.5.

What is funding risk? The crisis provided one prominent example. Figure 3.1 shows the outstanding volume of C&I Loans and LIBOR. Of particular interest is the month (shaded) when the crisis was in its acute phase. Suppose that loans had to have fixed interest rates, and that banks borrowed short term to make the loans. In this case, banks would have to bear the risk that their cost of funding might rise, as it did in this period. In contrast, with floating rates, this risk is transferred to borrowers. I ask what incidence of risk makes sense and why institutions might care about this risk.17

Notes: Series sourced from FRED and Bloomberg.

Figure 3.1: Interest rate risk in the crisis

17Note that the reported jump in loan volume occurred because firms drew down on commitments (Ivashina & Scharfstein 2010). In the analysis that follows, I focus on loans for simplicity.
3.3.1 Set up

In general banks take on several forms of risk when they provide loans at a different interest rate and maturity than the liabilities that fund them. I focus on funding, or interest-rate, risk, which arises from uncertainty regarding the cost of short-term financing. Term premium, which is related to the opportunity cost of locking up a given amount of resources and being unable to invest them in better opportunities that may arise subsequently, is perhaps on a basic level the risk that banks are compensated for bearing. Credit risk due to uncertainty about how much the borrower will be able to or willing to repay is often an important consideration. I abstract away from the latter two sources of risk.

I analyze a model with three periods: $t_0, t_1, t_2$. I will consider a transaction between a single firm and a single bank, though as will become clear soon, the analysis will apply more generally. The bank lends $L$ to a firm at $t_0$ for a project with cash flows $L(1 + P)$ at $t_2$ (and no intermediate cash flows). In return, the firm promises to pay $L(1 + \mu)$ at $t_2$. Thus $\mu$ is the (fixed) interest rate. The quantity of credit, $L$, and the interest rate $\mu$, will be determined in equilibrium.

The bank finances itself with a sequence of two short-term loans from investors. It borrows $L$ from investors at $t_0$, and must pay $L(1 + S_0)$ back at $t_1$ (I make the normalization $S_0 = 0$ to simplify notation). It finances its repayment at $t_1$ by borrowing $L$ again at $t_1$, promising to pay $L(1 + S_1)$ at $t_2$. Figure 3.2 illustrates the timeline. Vertical arrows indicate payments and their directions, in the periods that they occur.

![Timeline](image)

**Figure 3.2:** Timeline (per dollar of lending)
Project outcomes, $P$, and short-term funding costs, $S_1$, are assumed to be Normally distributed (for a generic random variable $X$, I use the notation $X \sim N(\mu_X, \sigma^2_X)$, where $\mu_X$ and $\sigma^2_X$ are the mean and variance). I assume $\mu_P > \mu_S$ so that in expectation the project is worth funding.

The publicly determined reference rate, denoted $R_1$, will also be Normally distributed. To simplify notation, I assume that the reference rate has mean zero ($\mu_R = 0$). I denote the covariances with short-term funding costs and project outcomes $\text{Cov}(S_1, R_1) = \rho > 0$ and $\text{Cov}(P, R_1) = \pi$ respectively. Clearly the reference rate should be positively correlated with funding costs: this is its basic role. I note assumptions regarding these covariances as used. A baseline case to keep in mind is $\pi = 0$, i.e. that project outcomes are not correlated with funding costs.

### 3.3.2 Frictions

Three key frictions generate meaningful funding risk and a desire to reduce it. First, short-term funding must be used. This assumption reflects the fact that maturity transformation is central to bank intermediation. While in practice some longer term financing is used, banks do not entirely match the maturities of their assets and liabilities. A substantial majority of commercial bank liabilities continue to be in the form of interest-bearing deposits. In their seminal paper, Diamond & Dybvig (1983) model banks as transformers of maturity: investing in long-term illiquid assets, while providing liquidity insurance through short-term or demand deposits. More recently, Stein (2012) argues that a preference for the safety associated with short-term assets makes it cheaper for banks to fund themselves with shorter term liabilities.

Second, $S_1$ is not contractible. A contract that referred directly to an individual bank’s funding cost would likely be viewed with suspicion. For example, some retail mortgages

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18 See the FDIC’s website for data on commercial bank balance sheets.

19 The literature on banking, e.g. (Diamond & Rajan 2001), has also argued that short-term financing provides financial intermediaries the necessary incentives to monitor.
in the UK are pegged to discretionary rates. During the crisis banks lowered these rates slowly while policy rates were drastically lowered. Since the crisis banks have been raising their rates even as policy rates have stayed low.\footnote{These rates are known as ‘Standard Variable Rates’. See, for example, \textit{The Telegraph}, Mortgage borrowers locked into high rates, January 2013.} One interpretation is that large corporate borrowers have sufficient bargaining power to insist on a formal index. As discussed in Section 3.2, LIBOR began as a syndicate specific survey for a specific loan. The current formal version was introduced due to concerns with such an arrangement. Reference rates can thus be viewed as the standardized, publicly available and hence contractible version of bank funding costs.\footnote{As a theoretical matter, any contractible quantity which is correlated with bank funding costs could, in principle, be used to write contracts related to bank funding costs. Reference rates can be viewed as an example of such a quantity.}

Finally, \( S_1 \) is not known until \( t_1 \), and financial frictions prevent the bank from being risk neutral. In practice, banks in particular and firms in general do pay attention to hedging risks. However, while short-term financing costs are volatile and unpredictable (for example, Figure 3.3 shows the one year swap curve),\footnote{The one year swap rate is the fixed rate that must be paid today in order to receive the three month dollar LIBOR in a year.} uncertainty regarding profits per se does not invalidate the standard view that firms should maximize expected profits (Modigliani & Miller 1958). As I argue that contracts linked to reference rates exist in order to facilitate this hedging, it is important to understand why hedging is necessary in the first place.

The Modigliani-Miller view is that shareholders can replicate any hedging strategy the firm may follow, where the firm’s actions are treated as independent of financial transactions. In contrast, Campbell & Kracaw (1993) argue that the prospect of losses might prevent firms from executing their strategy. Froot et al. (1993) formalize a similar argument. I follow Froot et al. (1993) and Froot & Stein (1998), and assume financial frictions, in the presence of which banks and firms are effectively risk averse.\footnote{As discussed in Section 3.1, there other approaches to understanding why risk management is relevant. Gabaix & Maggiori (2015) build up effective risk aversion for financial institutions from a commitment problem. Shin (2012) constructs a demand curve for risk by assuming a constraint on the probability of large losses (a VaR constraint).}

The crux of the argument is that if today’s
risky payoffs affect how much can be invested in the following period when investment opportunities are concave, the profit function inherits this concavity. This concavity creates effective risk aversion. To understand the intuition, suppose that following the three periods that are modeled above, the bank has concave investment opportunities $F(I)$. Denote the internal funds that depend on risky payoffs by $w$. If the firm can raise no external funds, the profit function inherits this concavity: $P(w) = F(w)$. A firm maximizing expected profits when the profit function is concave is effectively risk averse.

Froot et al. (1993) point out that even if external financing is available, the profit function is still concave if external financing is costly. Denote the difference between investment and internal funds by $e = I - w$. If this external financing is associated with a convex cost $C(e)$, the profit function continues to be concave.

$$P_{ww} = F_{II} \frac{dI^*(w)}{dw} \propto -F_{II}C_{ee} \tag{3.1}$$

What financial frictions generate a convex cost of external finance? I follow Froot et al.
(1993) and use a version of the costly state verification model of Townsend (1979). More precisely, the output of production denoted by $F(I)$ cannot be used as collateral to borrow (for instance because the project has no liquidation value). Instead all borrowing must be collateralized by risky cash flows $y$, distributed $g(y)$, generated by existing assets. The only action external financiers can take to force repayment is to liquidate the assets generating these risky cash flows, at a cost. As Appendix C.1 shows, under general conditions this setup generates concavity of the production function.\(^{24}\)

I use a simplified version of the framework employed by Froot & Stein (1998) to generate a tractable form for the risk aversion arising from the concavity of the profit function. Suppose the bank has earlier chosen some level of capital $K$, and can currently add $\theta$ units of a Normally distributed payoff $X$ to its balance sheet. The funds available to be invested next period are then $w = w_0 + \theta X + K(1 - \tau)$. $\tau$ is a deadweight cost of cash held on the firm’s balance sheet so that the unmodeled choice of capital structure is meaningful.\(^{25}\)

Now the firm’s optimal allocation to the payoff $X$ can be chosen to maximize expected profits. The first order condition provides

$$
\frac{dEP(w)}{d\theta} = E\left(P_w \frac{dw}{d\theta}\right) = \text{Cov}\left(P_w, \frac{dw}{d\theta}\right) + EP_w E\frac{dw}{d\theta}
$$

$$
= EP_{ww} \text{Cov}(w, X) + EP_w EX
$$

$$
= \theta EP_{ww} \sigma_X^2 + EP_w \mu_X = 0
$$

where the third equality uses the fact that for $x, y$ normally distributed, $\text{Cov}(f(x), y) = E(f(x)) \text{Cov}(x, y)$ and that $\frac{dw}{d\theta} = X$. Solving for the optimal allocation

$$
\theta^* = \frac{\mu_X}{A \sigma_X^2} \quad \Rightarrow \quad A = -\frac{EP_{ww}}{EP_w}
$$

the allocation is the same as what would arise from a CARA utility function. The endogenous coefficient $A$ is similar to the standard coefficient of risk aversion, except that the level of

\(^{24}\)It is also necessary that $g$ has sufficient weight on the right tail. See Appendix C.1.

\(^{25}\)Froot & Stein (1998) motivate this as the tax disadvantage of not issuing debt.
curvature of the profit function depends on the earlier level of capital chosen by the bank.\textsuperscript{26} I make the argument with reference to banks, but it evidently applies to firms more generally.

In the remainder of this chapter I directly view the bank and firm as maximizing CARA utility functions, with exogenous coefficients of risk aversion $A_B$ and $A_F$ respectively. The usual first order conditions provide

$$\arg \max_{\theta} -E\exp(-A(W_0 + \theta X)) = \frac{\mu_X}{A\sigma_X^2}$$

(3.3)

The correspondence with Equation 3.2 is clear. I refer to $A\sigma_X^2$ as the utility cost of risk. This optimal allocation trades off expected return against the utility cost of risk. If there are $N$ participants with CARA preferences, their aggregate behavior is equivalent to that of a single agent with risk aversion $\bar{A}_N$, where $\bar{A}$ is the harmonic mean of individual risk aversion. In this sense the analysis is not specific to the case of a single bank dealing with a single firm.

### 3.4 Basic uses of reference rates

In the absence of a reference rate, a fixed-rate loan is the only contract available. As illustrated in Figure 3.2, per unit borrowed, the firm’s payoff is $P - \mu$. Similarly, the bank’s payoff is $\mu - S_1$. The equilibrium interest rate, $\mu^*$, equates the quantity of credit demanded by the firm and supplied by the bank based on the optimal allocation in Equation 3.3.

$$D(\mu^*) = \frac{\mu_P - \mu^*}{A_F\sigma_P^2} = \frac{\mu^* - \mu_S}{A_B\sigma_S^2} = L(\mu^*)$$

(3.4)

For example, the bank might lend $10$ MM to the firm at an interest rate of 500 basis points, or 5%. I refer to the sum of the utility costs of risk, $\Phi = A_F\sigma_P^2 + A_B\sigma_S^2$, as the total utility cost of risk.

When reference rates are available, there are two ways the lender can reallocate funding risk: floating interest rates and interest-rate derivatives. Both types of contracts are

\textsuperscript{26}Financial frictions generate a positive coefficient of risk aversion as the profit function is concave.
derivatives in the sense that the payments they require are not known in advance, but are determined based on the realized reference rate ($R_1$). Facilitating the existence of these contracts is the basic purpose of reference rates. Floating rates shift the incidence of funding risk from the bank to the firm. Interest-rate derivatives shift them to the broader market, at an explicit cost. Sections 3.4.1 and 3.4.2 show that if these contracts must be used independently, derivatives are better in welfare terms.

### 3.4.1 Floating rates

I denote the interest rate on floating-rate loans by $R_1 + v$. This corresponds to an interest rate of, for example, LIBOR + 300 bps. $R_1$ is the reference rate, and $v$ is the fixed premium, agreed in advance, charged over the realized reference rate. Recall that I assume the reference rate has zero mean, though the numerical example reflects the more realistic case of a positive mean. I assume that when a reference rate is available, there is no direct cost to writing a floating-rate contract, reflecting the public availability of the reference rate. Figure 3.4 shows the modified timeline.

![Timeline for floating rate](image.png)

As the reference rate has positive covariance with funding costs, the floating-rate loan shifts some funding risk from the bank to the firm. However both the bank and the firm now bear risk due to volatility of the reference rate. As long as the reference rate is not too volatile, and $\rho > \frac{\sigma_S^2}{2}$, the bank reduces its risk from $\text{Var}(S_1)$ to $\text{Var}(R_1 - S_1) = \sigma_S^2 + \sigma_R^2 - 2\rho$. This is achieved by increasing risk for the firm from $\text{Var}(P)$ to $\text{Var}(P - R_1) = \sigma_P^2 + \sigma_R^2 - 2\pi$. 

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I retain $\pi$ in the notation here, but the baseline case is $\pi = 0$. The new equilibrium interest rate is

$$D'(v^*) = \frac{\mu_P - v^*}{A_F(\sigma_P^2 + \sigma_R^2 - 2\pi)} = \frac{v^* - \mu_S}{A_B(\sigma_S^2 + \sigma_R^2 - 2\rho)} = L'(v^*)$$ (3.5)

Relative to Equation 3.4, the credit supply and demand curves effectively rotate downwards. I refer to $\Phi(R_1) = A_F(\sigma_P^2 + \sigma_R^2 - 2\pi) + A_B(\sigma_S^2 + \sigma_R^2 - 2\rho)$ as the total utility cost of risk when floating rates are used.\(^{27}\)

Figure 3.5: Fixed and floating rates

Figure 3.5 illustrates the comparison. $D$ and $L$ are the baseline credit demand and supply curves. $D'$ and $L'$ are the demand and supply curves when a reference rate is introduced. Interest rates ($L' = D'$) fall relative to the baseline case ($L = D$) both because the bank bears less risk and the firm bears more risk. In this framework, welfare is proportional to quantity transacted.\(^{28}\) Floating rates are therefore welfare improving as long as borrowers are not too risk averse and not too much risk is transferred to them.

However, if the risk transfer is one-for-one, floating rates only improve welfare compared

\(^{27}\)The floating-rate loan can reduce the overall risk faced by the firm if reference rates are sufficiently correlated with firm firm outcomes, i.e. $\pi > \frac{\rho}{2}$. However, as discussed in Section 3.3.1, firms frequently borrow at floating rates but then swap away the floating-rate exposure. This suggests that the level of exposure to floating rates provided by a floating loan is too high, and the relevant case is the one discussed in the text here. I discuss how firms can use swaps in Section 3.5.2.

\(^{28}\)Unit surplus $\mu_P - \mu_S$, and quantity of credit are the welfare triangle’s base and height respectively.
to fixed rates if firms are less risk averse than banks. Floating rates involve the transfer of risk from the bank to the firm, with the constraint that the reference rate as a percentage of the loan amount is transferred. While standard risk sharing arguments imply that a small amount of risk transfer from the bank to the firm should be optimal, floating rates do not necessarily provide the necessary flexibility. As discussed in Section 3.4.2, derivatives do provide this flexibility. Proposition 3 formalizes these observations.

**Proposition 3.** Floating rates transfer funding risk from the bank to the firm. If $\rho > \frac{s^2}{2}$ and $\pi < \frac{s^2}{2}$:

- **Interest rates fall**
  \[ \mu^* > v^* \iff \frac{2\rho - \sigma^2_R}{\sigma^2_S} + \frac{s^2 - 2\pi}{s^2 - p} > 0 \] (3.6)

- **However, welfare increases only if the utility benefit of reduced funding risk for banks outweighs the utility cost of increased risk for firms**
  \[ \Omega(R_1) > \Omega \iff A_B(2\rho - \sigma^2_R) > A_F(s^2_R - 2\pi) \] (3.7)

**Proof.** See Appendix C.2.1.

### 3.4.2 Interest-rate derivatives

Interest-rate swaps provide a natural alternative strategy for the bank to reallocate funding risk. There are three important differences between swaps and floating rates. First, the risk no longer needs to be shifted to the firm; it can be transferred on the market for swaps to any party willing to take the other side. I model swaps, denoted $R_1$, as a contract agreed to at $t_0$ which (per dollar of notional value) obligates the buyer to pay a fixed rate $\lambda$ in return for $R_1$, where all payments are made at $t_2$.

This highlights the remaining differences. The bank can choose a hedging ratio in this case (the notional value chosen need not be the

---

29 As the exchange only occurs once this is really a Forward Rate Agreement similar to the contract referred to in the Swap Curve shown in Figure 3.3.

30 I do not consider indirect costs of hedging here. In particular, I assume collateral costs of hedging away here.
loan amount) and there is a direct cost associated with using swaps, to the extent that they are not zero NPV transactions. I begin by taking the unit cost of hedging, $\lambda$, as exogenous and defer endogenizing it until Section 3.5.

How does the use of swaps compare with floating interest rates? For now I consider a return to fixed interest rates, and consider the bank’s joint choice of credit supply and hedging with swaps. Denote the fixed rate charged here with $\kappa$. The bank’s problem is

$$
\max_{\theta,\alpha} EU[\theta(\kappa - S_1 + \alpha R_1)]
$$

(3.8)

where $\alpha$ is the hedge ratio: the notional value of swaps purchased per unit of lending. With the use of swaps, the bank can construct a contract with payments according to any linear function of the reference rate $R_1$. Figure 3.6 shows the modified timeline.

![Timeline when swaps are available](image)

**Figure 3.6:** Timeline when swaps are available

First order conditions provide

$$
L''(\kappa) = \theta^* = \frac{\kappa - \mu S - \lambda \alpha^*}{A_R \left( \sigma_S^2 - \frac{\rho^2}{\sigma_R^2} \right)}
$$

(3.9)

$$
\alpha^*(\kappa, \lambda) = \frac{\rho}{\sigma_R^2} \alpha^* - \frac{\lambda}{A_R \theta^* \sigma_R^2}
$$

(3.10)

If the swap is zero NPV ($\lambda = 0$), the resulting optimal hedging ratio is $\alpha^* = \alpha^*(\kappa, 0) = \frac{\rho}{\sigma_R^2}$. This optimal hedging ratio is the beta of $S_1$ with respect to $R_1$. The bank is willing to

---

31 If non-linear derivatives on the reference rate were available, it might be optimal to use them. See Appendix C.3.2 for a discussion of the limited set of situations in which the optimal contract is likely to be linear.
supply more because it faces less funding risk: \( \text{Var}(-S_1 + \alpha^* R_1) = \sigma^2_S - \frac{\rho^2}{\sigma^2_R} \) is the residual funding risk after optimal hedging. The optimal level of risk reduction is therefore the beta of funding costs with the reference rate multiplied by their covariance.

When the derivative is costly, the bank reduces its position size in the derivative: \( \alpha^*(k, \lambda) \leq \alpha^* \). However, its demand for loans is the same as when the optimal hedge portfolio is purchased (see Appendix C.3.1). Equivalently, starting from its optimal hedging position, the bank is willing to bear some of the risk itself in exchange for the expected return of \( \lambda \). Regardless of how volatile the reference rate is, the principle of participation means that the bank is willing to keep some of the risk.

The equilibrium condition \( L''(\kappa) = D(\kappa) \) now allows \( \kappa \) to be determined. Figure 3.7 illustrates what happens. As before, \( D \) and \( L \) are the baseline credit demand and supply curves, and \( D' \) and \( L' \) are the demand and supply curves when a reference rate is introduced. When derivatives are used for optimal hedging, interest rates \( (L'' = D) \) are lower than the baseline case \( (L = D) \) but potentially higher than with reference rates \( (L' = D') \).

![Figure 3.7: The effect of reference rates](image)

As long as hedging with derivatives is not too expensive welfare is improved relative to both fixed rates and floating rates. The total cost of hedging, \( \lambda \alpha^* \), is best thought of as a fraction of the initial surplus, \( \mu_P - \mu_S \) (the interest-rate-intercepts of the original demand and supply curves, \( D \) and \( L \) in Figure 3.7). Relative to a fixed rate, as long as this cost is
not to high, the reduction in funding risk for the bank lowers interest rates and increases welfare. The effect on interest rates relative to floating rates is ambiguous: optimal hedging means that the risk is lower than with floating rates (strictly, unless $\alpha^* = 1$), pushing rates lower. On the other hand, the firm no longer has to bear risk, which pushes rates higher. Both of these effects raise welfare relative to floating rates. Proposition 4 formalizes these observations.

\textbf{Proposition 4.} If interest rate swaps are zero NPV transactions ($\lambda = 0$)

- The effect on interest rates relative to floating rates is ambiguous
  \[ \nu^* > \kappa^* \iff \frac{\sigma_R^2 (\alpha^* - 1)^2}{\sigma_S^2 - \frac{\nu^2}{\sigma_R^2}} > \frac{\sigma_R^2 - 2\pi}{\sigma_P^2} \]  
  \hfill (3.11)

- Welfare is improved relative to floating rates
  \[ \Omega(\mathcal{R}_1, \lambda = 0) > \Omega(R_1) \iff A_B \sigma_R^2 (\alpha^* - 1)^2 + A_F (\sigma_R^2 - 2\pi) > 0 \]  
  \hfill (3.12)

If interest rate swaps are costly, welfare is still increased as long as

\[ \lambda \alpha^* \leq \bar{C} = (\mu_P - \mu_S) \left( 1 - \sqrt{\frac{\Phi(\mathcal{R}_1)}{\Phi(R_1)}} \right) \]  
  \hfill (3.13)

where $\Phi(\cdot)$ is the total utility cost of risk.

\textit{Proof.} See Appendix C.2.2.

\begin{flushright} \Box \end{flushright}

\section*{3.5 Derivatives, interpretation and welfare}

The analysis in Section 3.4 shows that swaps are a more effective method than floating rates for banks to reduce funding risk, as long as they are not too costly. However, floating rates are widely used, particularly in the syndicated lending market.\footnote{See Chapter 1.} Moreover, borrowing firms often hedge the interest rate risk they acquire in this manner with swap positions of their own. To understand this behavior it is important to consider how firms would like to
use derivatives. I begin by connecting the cost of hedging to aggregate risk tolerance for funding risk in Section 3.5.1. Section 3.5.2 then shows that the combined use of floating rates and firm swaps positions broadens the set of market participants bearing funding risk, lowering the cost of hedging. Section 3.5.3 cautions that this analysis requires derivatives markets to be sufficiently competitive. Section 3.5.4 shows that manipulation which makes the reference rate more volatile reduces welfare when swaps are not too costly.

### 3.5.1 Cost of hedging

If hedging with swaps is a zero NPV transaction, there is no reason for floating rates to be used, since they transfer funding risk to effectively risk averse firms. But why should swaps be costly in the first place? Standard models of swap pricing begin with the assumption that initial contractual terms are set in a way such that they are zero NPV transactions. However, if the market in aggregate is risk averse about funding risk, insuring it should not be a zero NPV proposition, a point made for example by Demsetz (1969). Indeed, all that is required is that both parties should be indifferent between taking either side of the trade, but if both are risk averse, hedging should be costly.

Suppose, then, that the other side of swap transactions the bank makes its taken up by a set of dealers with aggregate risk aversion $A_D$. These dealers provide a supply function for swaps according to Equation 3.3. The equilibrium cost of hedging, $\lambda^*$, is how much these dealers need to be paid to satisfy the bank’s hedging demand (hedging demand per unit of credit extended is shown in Equation 3.10). This condition requires

$$L''(\kappa)\alpha^* - \frac{\lambda^*}{A_B\sigma_R^2} = \frac{\lambda^*}{A_D\sigma_R^2}$$ (3.14)

Recall that $L''(\kappa)$ is the amount of credit supplied, and $\alpha^*$ is the optimal hedging ratio.

As discussed in Section 3.4.2, the bank does not try to shift as much risk to the swap market as implied by the optimal hedging ratio when $\lambda > 0$. Instead, it keeps some of the risk, taking into account that transferring it is costly. Effectively, ‘market’ risk tolerance
combines the risk tolerance of swap dealers and the bank. Define this tolerance, as $T_{D,B}$:

$$T_{D,B} = \frac{1}{A_D} + \frac{1}{A_B}$$

(3.15)

With this notation, Equation 3.14 can be rearranged to show that the equilibrium cost of hedging is

$$\lambda^* \alpha^* = \frac{1}{T_{D,B}} L''(\kappa) \frac{\rho^2}{\sigma_R^2}$$

(3.16)

Intuitively, the cost of hedging depends on how much risk tolerance there is, how big underlying credit markets are, and how much swaps reduce risk with optimal hedging. Thus Proposition 4 implies that swaps are more effective than floating rates when $T_{D,B}$ is high enough ($\lambda \alpha^* < \bar{C}$).

### 3.5.2 Complementarity between floating rates and swaps

The argument leading to Equation 3.15 makes clear that aggregate risk tolerance, and therefore the cost of hedging, depends on how broadly funding risk is borne. If firms were to enter swap markets as well, they would have hedging demand of their own, similar to the bank demand shown in Equation 3.10.

$$\beta^*(\kappa, \lambda) = \frac{\pi}{\sigma_R^2} - \frac{\lambda}{A_F D(\kappa) \sigma_R^2}$$

(3.17)

Note that $\pi$ enters in the opposite direction given that the firm’s problem is a mirror image. This would lead to more risk tolerance for funding risk. However, firms directly holding swaps positions would likely be labeled speculators.

In contrast, if firms have floating-rate obligations, it is a more legitimate transaction for them to (partially) hedge the risk this comes with. This is a potential advantage of floating interest rates: they can draw firms into the market for swaps. Per unit of credit, the floating-rate transfers one unit of exposure to the reference rate from the bank to the firm. This increases the firm’s desired hedging ratio by one, and correspondingly decreases the bank’s desired hedging ratio by one. Figure 3.8 shows the modified timeline.
Recall that the baseline case is that $\pi = 0$: that the firm has no initial desire to use reference rates to reduce cash flow risk. In this case $\beta^* = 0$. With floating rates, then, the firm’s desired hedging ratio is one, and the bank would like $\alpha^* - 1$. Effectively the firm moves back to the situation with a fixed interest rate: it has no exposure to the reference rate. In this case the total demand for swaps would be the same as in Equation 3.14 except that the firm is also willing to bear some risk. The cost of hedging is now determined by

$$L''(\omega)[1 + (\alpha^* - 1)] = \frac{\lambda^*}{A_B \sigma^2_R} - \frac{\lambda^*}{A_F \sigma^2_R} = \frac{\lambda^*}{A_D \sigma^2_R}$$

(3.18)

As the firm absorbs some risk, market risk tolerance is now larger

$$T_{D,B,F} = \frac{1}{A_D} + \frac{1}{A_B} + \frac{1}{A_F} > T_{D,B}$$

(3.19)

This means hedging is cheaper and derivatives are more effective

$$\lambda^* \alpha^* = \frac{1}{T_{D,B,F}} L''(\kappa) \frac{\sigma^2}{\sigma^2_R}$$

(3.20)

Note that if reference rates are positively correlated with project outcomes, the exposure the firm obtains through floating rates insures it against cash-flow risks. The firm would then elect to keep even more of the exposure, further reducing the cost of hedging. Proposition 5 formalizes these observations.
Proposition 5. If $T_D = \infty$ ($\implies \lambda = 0$) and $\pi = 0$:

- Fixed rates with bank hedging and floating rates with hedging on both sides are equivalent.

- Compared to fixed rates without hedging, both lower interest rates in proportion to the reduction in risk $\left( \frac{r^2}{s^2} \right)$ and increase welfare in proportion to the utility benefit of this reduction in risk $\left( A_R \frac{r^2}{s^2} \right)$.

If $T_D < \infty$:

- Welfare is higher with floating rates than with fixed rates as firms can bear some of the risk.

- If $\pi \in (0, \rho)$, as firms’ optimal hedging ratio is $1 - \frac{\pi}{s^2} < 1$, the cost of hedging is decreasing in $\pi$ and welfare is increasing in $\pi$.

Proof. See Appendix C.2.3.

3.5.3 Competition in derivatives markets

I have argued that floating rates, when firms optimally hedge the risk this transfers to them, are a better contractual arrangement than swaps alone. This draws firms into the market for swaps written on the reference rate, broadening the set of players that bear funding risk, and lowering the cost of hedging. However, this argument relies on the competitiveness of derivatives markets. If, as is the case, a small set of dealers dominates the market for swaps, hedging may be sufficiently costly that a floating rate or even a fixed rate with no hedging would be better. This is important to consider as derivatives markets are very concentrated. Data from call reports shows that the top five bank holding companies account for about 96% of the total for swaps and for derivatives overall.\textsuperscript{33}

\textsuperscript{33}The OCC releases quarterly reports on bank trading and derivatives activities based on call report data. The text refers to the total notional value held by JP Morgan, Citigroup, Bank of America, Goldman Sachs and Morgan Stanley as a fraction of the total held by the top 25 bank holding companies in Q3 2013 (which is approximately the total held by US bank holding companies; the 25th, Principal Financial, accounts for 0.01%). Swaps here include currency swaps. However, the majority of derivatives volume is tied to interest rates. Moreover, currency swaps can also exchange variable rate payments (in different currencies).
Suppose that there are $N$ oligopolistic dealers in the swap market, each symmetrically contributing risk tolerance $\frac{T_D}{N}$. In a symmetric Cournot equilibrium, the cost of hedging is

$$\lambda' \alpha^* = \frac{1 + \frac{T_D}{NT_D F}}{T_{D,B,F} + \frac{T_D}{N}}L''(\omega) \frac{\rho^2}{\sigma_R^2} > \lambda^* \alpha^*$$  \hspace{1cm} (3.21)

In comparison with the competitive case, shown in Equation 3.20, the cost of hedging is higher (see Appendix C.3.3 for details). For instance, if these five large dealers account for even 80% of the total risk tolerance in the market for swaps, Equation 3.21 implies a cost of hedging 55% higher than the competitive situation described in Equation 3.20. If the market for swaps is sufficiently concentrated, even with the addition of firms to the set of players that bear funding risk, the cost of hedging may be above the threshold at which they are useful, discussed in Proposition 4.

Why might floating rates and swaps still be used? It is possible that the effect of firms being drawn in to swaps markets is useful for a different reason than wider risk sharing. If universal banks both lend to large clients and act as dealers writing derivatives contracts with them, this arrangement may be a way for banks to generate business with derivatives. If lending is a much more competitive business than derivatives, banks may be willing to lose money while lending to achieve this.

### 3.5.4 Welfare and the cost of manipulation

Contracts linked to reference rates facilitate hedging. Intuitively, their usefulness for this purpose is increased if the covariance between the reference rate and the underlying risk, $\text{Cov}(R_1, S_1) = \rho$, increases. Similarly, their use requires institutions to bear risk as the reference rate itself is volatile. As discussed in Section 3.2 and Footnote 16, manipulation of LIBOR was driven by both portfolio incentives and reputational concerns. Portfolio incentives fluctuated significantly over time, as they were particularly strong on days when banks had significant amounts of swaps contracts settling. These were the days submitters to the process were asked to modify their submissions. Manipulation due to this can be thought of as adding pure noise to the reference rate, which intuitively makes associated
hedging less useful. Reputational concerns could lead to manipulation which just changes
the level of the rate. However, if the intensity of reputational concerns also changes over
time, such manipulation can also add noise.

In this framework, the hedging properties of contracts of reference rates are determined
by their covariance with risks and with their volatility. A change in their level does not affect
welfare. Of course, if LIBOR were to be shifted down by 200 bps and remain otherwise
unchanged this might not be welfare neutral as reference rates are used for purposes other
than risk sharing. In particular, reference rates are used as a gauge for the health of the
financial sector, and an artificially low rate may have played a role in delaying recognition
of the crisis. Reference rates are also used to discount streams of payments, and changes in
the level might distort investment decisions.

Here I focus on understanding the effect of manipulation which adds pure noise to
the reference rate. I parametrize the results of such manipulation by considering a post-
manipulation reference rate

\[ \tilde{R}_1 = R_1 + \sqrt{K - 1}Z \]  

(3.22)

where \( Z \) is a normally distributed variable independent of \( R_1 \) as well as risks including \( S \)
and \( P \), with \( \sigma^2_Z = \sigma^2_{R_1} \). \( K \) is a parameter which captures the extent of manipulation. Now
\( \text{Cov}(\tilde{R}_1, S_1) = \text{Cov}(R_1, S_1) \) and \( \text{Cov}(\tilde{R}_1, P) = \text{Cov}(R_1, P) \), while \( \text{Var}(\tilde{R}_1) = K\sigma^2_{R_1} \). I consider
the effect of adding a small amount of manipulation, i.e. slightly increasing \( K \) from 1.

Intuitively, if hedging is a zero NPV activity, such manipulation must reduce welfare
as institutions now have to bear more risk as the reference rate moves. However, it is less
clear what happens when hedging is costly, as institutions will choose to bear more of the
underlying risk themselves as contracts linked to reference rates become less useful for
hedging. This, in turn, can lower the cost of hedging. As Proposition 6 formalizes, this
effect is not important when the market in aggregate is not too risk averse about risk related
to the reference rate.
Proposition 6. For aggregate risk tolerance $T$ high enough, welfare is decreasing in added noise, i.e.

$$
\lim_{T \to \infty} \frac{\partial \Omega(K)}{\partial K} = -\frac{(\mu_P - \mu_S)^2 \Phi'(K)}{2\Phi^2(K)} < 0
$$

(3.23)

where $\Phi'(K)$ is the added utility cost of risk participants bear as the reference rate becomes more volatile.

Proof. See Appendix C.2.4.

3.6 Conclusion

The growing literature on LIBOR has not focused on what purpose reference rates serve. This is an important question to consider as markets and regulators consider how LIBOR might be modified or replaced. In this chapter, I construct a simple model of credit markets with three key frictions, in the presence of which reference rates can be understood to be useful to hedge funding risk. Constraining lenders to using short-term funding generates maturity mismatch. As bank funding costs are not contractible, lenders, in their absence, bear funding risk. Due to financial frictions, profit functions become concave, implying that bearing this risk is costly. Reference rates mitigate contractual incompleteness and facilitate risk management.

Floating-rate loans transfer funding risk from lenders to borrowers. While this transfer may lower the cost of borrowing, whether it improves welfare depends on how costly it is for borrowers to bear funding risk. Indeed, if the cost of hedging through swaps is sufficiently low, it would be better for lenders to manage risk through swaps. In practice, firms borrow at floating rates and swap some of the exposure away. If firms find it easier to take exposure to interest rates when they have taken floating-rate loans, this more complicated arrangement may be a way to include firms in the set of institutions bearing interest rate risk, lowering the cost of hedging it. In concentrated derivatives markets, it may also be a way for banks to generate profitable activity.

I focus on understanding the uses of reference rates in credit markets and associated
derivatives markets; as discussed in Section 3.2, this is the market reference rates emerged from. While understanding the broader use of reference rates is important, this analysis clarifies the purpose of reference rates and should facilitate a clearer discussion of issues with manipulation and potential replacements. As the risk being managed in credit markets is uncertainty regarding the bank’s cost of funding, reference rates that better capture bank funding costs across instruments should be given more consideration (Brousseau et al. 2013). A good reference rate for use in credit markets is highly correlated with bank funding costs and stable, corresponding to the old idea that standards should be accurate and low cost (Barzel 1982). Manipulation driven by varying exposure of banks to interest rate derivatives can add noise, making reference rates less useful for hedging. However, in credit markets, it makes sense for reference rates to capture bank credit risk. Alternatives being considered to LIBOR may be less manipulable, but also less useful for hedging risks in credit markets.

As Duffie & Stein (2015) note, the various groups convened by the FSB have recommended that markets be steered away from reference rates incorporate credit risk. To the extent that reference rates with credit risk are needed, the suggestion is that the two separate reference rates should be used. This chapter suggests that there is demand from lenders relying on short-term funding to use pay-fixed interest-rate swaps to reduce funding risk. This raises a broader question about the extent to which demand and supply would be naturally balanced if interest-rate derivative markets are split into two separate markets (one set with reference rates incorporating credit risk, the other with reference rates not incorporating credit risk).
References


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Appendix A

Appendix to Chapter 1

A.1 Theory

A.1.1 Proofs

As discussed in Section 1.3.1, I first use first order conditions with respect to hedging to find optimal hedging as a function of assets held. Then, I substitute this optimal hedging into the objective function. I use first order conditions with respect to this modified objective function, anticipating hedging, to find asset demand. I use bank-dependent firms’ credit demand function to derive the loan spread required for bank-dependent firms to demand the fixed quantity of bank lending, $L$. I substitute the response of the loan spread to the floating fraction of loans (see Lemma 1) into the bank first order conditions to find the equilibrium floating fractions of loans and securities.
Proof of Proposition 1

I derive explicit expressions for the equilibrium floating fractions of loans and securities. I find that

\[ f^*_L = \frac{D\alpha(q + \gamma\sigma^2)(1 - \rho^2) + C(q + \gamma\sigma^2(1 - \rho^2)) + \left(1 + \frac{q}{\sigma^2} - \rho\right)\delta\rho}{L(q(3 - \rho^2) + 3\gamma\sigma^2(1 - \rho^2))} \]  
(A.1)

\[ f^*_S = \frac{(2D\alpha - C)q\rho - 3\delta\left(1 - \rho - \frac{q}{\sigma^2}\right)}{S(q(3 - \rho^2) + 3\gamma\sigma^2(1 - \rho^2))} \]  
(A.2)

The expression for \( f^*_L \) shows that

\[ \frac{\partial f^*_L}{\partial \alpha} = D\frac{(q + \gamma\sigma^2)(1 - \rho^2)}{L(q(3 - \rho^2) + 3\gamma\sigma^2(1 - \rho^2))} > 0 \]  
(A.3)

as \( \rho \in (0, 1) \), establishing Proposition 1.

Proof of Proposition 2

Proposition 1 shows that \( \frac{\partial f^*_L}{\partial \alpha} > 0 \). Similarly,

\[ \frac{\partial f^*_S}{\partial \alpha} = \frac{2Dq\rho}{S(q(3 - \rho^2) + 3\gamma\sigma^2(1 - \rho^2))} > 0 \]  
(A.4)

In contrast,

\[ \frac{\partial f^*_L}{\partial C} = \frac{q + \gamma\sigma^2(1 - \rho^2)}{L(q(3 - \rho^2) + 3\gamma\sigma^2(1 - \rho^2))} > 0 \]  
(A.5)

while

\[ \frac{\partial f^*_S}{\partial C} = -\frac{q\rho}{S(q(3 - \rho^2) + 3\gamma\sigma^2(1 - \rho^2))} < 0 \]  
(A.6)

establishing Proposition 2.

A.1.2 Relative importance of supply and demand

The model shows that banks’ securities holdings allow me to separate the supply-driven view of floating-rate bank lending to firms from the demand-driven view. Proposition 2 shows that if supply was the only cross-sectional source of variation, the correlation between the floating-fractions of loans and securities would be positive. In contrast, if demand was
the only source of variation, this correlation would be negative. Section 1.4 shows that, empirically, this correlation is positive. Specifically, it shows that the coefficient from a regression of the floating-fraction of securities on the floating-fraction of loans is positive, and statistically significantly so. Here I present a framework to show that this means supply is more important than demand for explaining cross-sectional variation in equilibrium outcomes.

I conduct an exercise analogous to Working (1927). Working (1927) argues that regressions of equilibrium prices on equilibrium quantities recover demand curves when variation in supply is more important (e.g. agriculture), but recover supply curves when variation in demand is more important (e.g. manufacturing). While I do not directly regress prices on quantities, an analogous argument can be made. The model incorporates both the supply-driven view of floating-rate bank lending to firms as well as the demand-driven view (as firms’ cash flows can depend on interest rates). When variation in supply is more important in the cross-section, this will drive the correlation between the floating-fractions of loans and securities.

Equations A.1 and A.2 show that equilibrium floating fractions of loans and securities can be represented as follows:

\[
\begin{align*}
    f_{L,i}^* &= \frac{1}{L \Gamma} (D \alpha_i \mu_L + C_i v_L + \zeta_L) \\
    f_{S,i}^* &= \frac{1}{S \Gamma} (D \alpha_i \mu_S - C_i v_S + \zeta_S)
\end{align*}
\]

(A.7)

(A.8)

where \( \Gamma, \mu_L, \mu_S, v_L, v_S \) are positive constants. Variation in pass-through across banks is captured by \( \alpha_i \) (variation in supply), while variation in firms’ demand for floating-rate loans is captured by \( C_i \) (variation in demand). Suppose both of these are random variables (independent from each other and from \( \zeta_L, \zeta_S \)), varying across banks, with variance \( \sigma^2_{\alpha} \) and \( \sigma^2_C \) respectively. Then the regression coefficient of the floating fraction of securities on that of loans is

\[
\frac{\text{Cov}(f_{L,i}^*, f_{S,i}^*)}{\text{Var}(f_{L,i}^*)} = \frac{L \sigma^2_{\alpha} D^2 \mu_L \mu_S - \sigma^2_C v_L v_S}{S \sigma^2_{\alpha} D^2 \mu_L^2 + \sigma^2_C v_L^2}
\]

(A.9)

The regression coefficient is therefore jointly informative about the relative importance of
supply shocks \((\sigma_s^2 D^2)\) and demand shocks \((\sigma_c^2)\) and the elasticities of the floating fractions of loans and securities to supply and demand variation.\(^1\)

**A.1.3 Extensions**

In this subsection, I describe a fuller version of the model incorporating three extensions. First, interest rate swaps have an equilibrium price, \(\theta\) (in addition to the term premium \(\delta\)).\(^2\) Second, I incorporate investment-grade firms that raise external finance only through fixed-rate bonds, but are otherwise identical to bank-dependent firms. Third, to close out the model, I include hedge funds which bear residual interest rate risk, to determine the equilibrium price of swaps. The main results, Propositions 1 and 2, continue to hold in this more developed model.

**Investment grade firms**

Investment grade firms’ net income is

\[
NI_{IG} = AI + Cr_A - (1 + \bar{r} + \delta)I + (r - (\bar{r} + \delta + \theta))H_{IG} - \frac{q}{2}H_{IG}^2 \tag{A.10}
\]

For simplicity, other than the debt capital structure, I assume that investment grade firms have the same balance sheet as bank dependent firms. This includes the sensitivity of output to interest rates. Investment grade firms also have mean variance preferences, so the objective is to maximize

\[
\Omega_{IG} = E[NI_{IG}] - \frac{\gamma}{2} \text{Var}[NI_{IG}] \tag{A.11}
\]

In equilibrium, as hedging will have a positive price, investment grade firms will choose a negative \(H_{IG}\). Effectively they will supply some risk bearing capacity with respect to

\(^1\)Equation A.9 treats \(x_L\) as a constant. Equation A.1 shows that \(x_L\) depends on parameters that I have assumed to be constants here. To the extent that there is cross-sectional variation (or any other noise) pertaining to this, the variance of \(x_L\) would also enter in the denominator in Equation A.9, akin to measurement error attenuation bias.

\(^2\)In practice, as modeled here, the fixed rate payable on the fixed leg of the swap is typically quoted as a spread relative to the yield on the government bond of comparable maturity.
interest-rate risk, and get paid for doing so. Lemma 2 illustrates the basic features of firms’
equilibrium exposures to interest-rate risk.

Lemma 2. **Bank-dependent firms bear more interest rate risk in equilibrium than investment grade firms**, even though both types of firms use derivatives to modify exposure.

Proof. Define a positive unit of exposure as a unit of pay-floating liabilities. Bank-dependent firms’ net exposure before hedging is \( L_f - C \) (in equilibrium bank-dependent firms borrow \( L \)). Recall that a positive unit of hedging is a pay-fixed swap, which reduces exposure. The final level of bank-dependent firms’ exposure to interest rate risk is therefore

\[
(L_f - C) - H_{BD} = \frac{q}{q + \gamma \sigma^2} (L_f - C) + \frac{\gamma + \theta}{q + \gamma \sigma^2} \tag{A.12}
\]

In contrast, the final exposure of investment grade firms is

\[
-C - H_{IG} = -\frac{q}{q + \gamma \sigma^2} C + \frac{\gamma + \theta}{q + \gamma \sigma^2} \tag{A.13}
\]

Bank-dependent firms have more exposure than investment grade firms \( (L > 0) \). For the benchmark case of \( C = 0 \), or for \( C \) small, both types of firms have positive exposure. Note that in the absence of collateral costs \( (q = 0) \), both types of firms would have the same final exposure \( \left( \frac{\gamma + \theta}{q + \gamma \sigma^2} \right) \).

Equilibrium cost of hedging

To close out the model, I also include a final type of institution: hedge funds that bear the residual interest rate risk that banks and firms do not want to bear at the equilibrium price. Hedge funds are risk neutral, but also face collateral costs of using derivatives.\(^3\) To keep notation consistent, I continue to use the convention that a positive unit of the derivative is

\[^3\text{It would not complicate the model if hedge funds were risk averse as well, but this set up clarifies that collateral costs are sufficient to generate a positive equilibrium price of hedging. Note that an equilibrium price of hedging alone, without collateral costs, would not generate a difference in post-hedging exposure for different types of firms. Lemma 2 shows that, in the model, bank-dependent firms and investment grade firms would have the same final exposure if } q = 0, \text{ despite starting with different initial levels of exposure.}\]
in the pay fixed direction. The objective function of the hedge fund is therefore

$$\Omega_{HF} = -(\delta + \theta)H_{HF} - \frac{q}{2}H_{HF}^2$$  \quad (A.14)$$

The first order condition with respect to this objective condition defines hedge funds’ supply of risk bearing capacity. The equilibrium price of hedging is determined by the condition that interest-rate swaps are in zero net supply:

$$H_{Bank} + H_{BD} + H_{IG} + H_{HF} = 0$$ \quad (A.15)$$

The resulting equilibrium price is a function of the floating fraction of loans and securities chosen by banks. I show that the price of hedging, including the term premium, is

$$\delta + \theta = \frac{q\gamma \sigma^2(D\alpha - fS - 2C\beta)}{4q + \gamma \sigma^2}$$ \quad (A.16)$$

Intuitively, the price of hedging depends on the quantity of effective interest-rate mismatch pooled across banks and firms.

Banks take the price of hedging as given when they choose hedging demand as well as floating fractions of loans and securities. I substitute this price into expressions for these floating fractions to determine final equilibrium outcomes. Propositions 1 and 2 continue to hold in this fuller version of the model.

### A.2 Data

#### A.2.1 Capital structure

I use balance sheet data from Compustat, debt capital structure details from Capital IQ, and ratings from S&P. Capital IQ provides data on whether debt is fixed rate or floating rate. I obtain this data from WRDS. I also use data on interest rates from the Federal Reserve (FRED) and Bloomberg. The data is annual, and goes from 2003-2013.

WRDS provides a crosswalk between Capital IQ and Compustat data pairing Capital IQ companyid to Compustat gvkey. I drop cases where the match is not unique. Capital IQ
provides capital structure details with frequent updates. To allow the data from different sources to be as comparable as possible, I match the Compustat data date to the closest available Capital IQ period end date. If there are multiple matches (e.g., one quarter before and after), I use the most recent Capital IQ data.

For Compustat data, I require the firm to be headquartered in the USA. I also require assets and current and long-term debt to not be missing. I require a positive level of assets and debt. I treat missing research expenditure as a zero. For Capital IQ data (capital structure summary), I require data on variable-rate debt, fixed-rate debt, and total principal amount to be reported. I use the most recent filing date for each firm and period end date (if there are multiple entries I take the most recent one). I treat missing values for several components of debt as zeros. I require the sum of reported variable- and fixed-rate debt to be positive. Total debt in Capital IQ is the sum of principal outstanding, unamortized premium or discount, minus total adjustment. I exclude firms where the sum of reported variable- and fixed-rate debt is not within 10% of total debt within Capital IQ for at least half of the years present. I also exclude firms where reported debt in Capital IQ and Compustat are not within 10% of each other for at least half the years present.

Capital IQ also provides data on whether individual debt instruments are fixed-rate or floating-rate (capital structure debt). I aggregate this back up to the firm level. I use financial collection ID and period end date to match individual items to firm level reporting dates. Within financial collection ID and period end date, I keep the most recent filing date. I drop items where description text contains either ‘facility’ or ‘Facility’ (these items refer to undrawn amounts). If multiple entries remain for an instrument (component ID) I choose the largest principal. Sometimes instrument level data is in different units: if scaling by one thousand or one million provides a total within 70% of the total by debt type, I keep the data. If variable- and fixed-rate debt of a particular type are more than 1% higher than the total in the summary data, I set the components to zero. If variable- and fixed-rate debt then sum to less than 25% of the summary total, I replace them with industry-year averages. I match SIC codes to industries based on the Fama & French (1997) classification with 12 categories.
I drop financial firms and utilities according to this classification. I treat commercial paper as floating-rate debt (as it is short-term), and add it to contractually floating-rate debt to calculate effective floating-rate debt. I drop firms where the fraction of floating or bank debt is higher than 110%, or where the debt/assets ratio is greater than 120%.

**Table A.1: Variable definitions**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floating fraction</td>
<td>(Variable rate debt + fixed rate CP)/Capital IQ Debt</td>
</tr>
<tr>
<td>Post-hedging floating fraction</td>
<td>(Floating fraction + net pay fixed swaps)/Capital IQ Debt</td>
</tr>
<tr>
<td>Bank fraction</td>
<td>Bank debt/Capital IQ Debt</td>
</tr>
<tr>
<td>ln(Assets)</td>
<td>Natural logarithm of Assets</td>
</tr>
<tr>
<td>Debt rated</td>
<td>Either long term debt or short-term debt rated by S&amp;P in year</td>
</tr>
<tr>
<td>Debt/Assets</td>
<td>Compustat debt/Compustat Assets</td>
</tr>
<tr>
<td>LTD/Debt</td>
<td>Compustat Long Term Debt/Compustat Debt</td>
</tr>
<tr>
<td>Invest/Assets</td>
<td>Investment Expenditure/Compustat Assets</td>
</tr>
<tr>
<td>R&amp;D/Assets</td>
<td>R&amp;D Expenditure/Compustat Assets (missing values for R&amp;D treated as zeros, following Chernenko &amp; Faulkender (2011))</td>
</tr>
<tr>
<td>CF Beta</td>
<td>Slope from regression of cash flow on LIBOR. Cash flow is operating income before depreciation as a fraction of assets, in percentage points (following Chernenko &amp; Faulkender (2011), requires 5 years of cash-flow data, based on average value of LIBOR for firm’s fiscal year)</td>
</tr>
<tr>
<td>Swap spread</td>
<td>Difference between 5Y swap pay fixed rates and treasury yields (from Bloomberg) - average matched for firm’s fiscal year</td>
</tr>
<tr>
<td>Term spread</td>
<td>Difference in constant maturity 5 year and 1 year treasury yields (FRED) - average matched for firm’s fiscal year</td>
</tr>
</tbody>
</table>
A.2.2 Hedging

I manually collect data on how firms use interest-rate swaps from annual SEC filings.\textsuperscript{4} I collect the notional amounts of pay-fixed and pay-floating interest-rate swaps in each fiscal year, from 2003-2013. While firms are not currently required to report the notional amounts of interest-rate derivatives, the vast majority of users nevertheless do disclose this information. Adi Sunderam and Sergey Chernenko graciously shared data that constitutes a portion of this sample.\textsuperscript{5} Beyond the sample provided by them, I randomly select firms from the capital structure sample within rating groups, allocating more weight to high yield and unrated firms.

Table A.2 shows the number of firms within each rating category, including firms for which information on notional amounts was not available. The majority of firms (381) use interest-rate swaps at some point in the sample.

<table>
<thead>
<tr>
<th>Rating</th>
<th>Data available</th>
<th>Data not available</th>
</tr>
</thead>
<tbody>
<tr>
<td>IG</td>
<td>141</td>
<td>5</td>
</tr>
<tr>
<td>HY</td>
<td>263</td>
<td>9</td>
</tr>
<tr>
<td>U</td>
<td>167</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>571</td>
<td>19</td>
</tr>
</tbody>
</table>

Information on the usage of swaps is often provided in a section of the annual report titled “Quantitative and Qualitative Disclosures About Market Risk” (some firms instead provide this information in sections providing details about their debt or derivatives). For example, Regal Entertainment Group disclosed the following information in their 2013 10-K: ‘Under the terms of the Company’s two effective interest-rate swap agreements (which hedge an aggregate of $300.0 million of variable rate debt obligations as of December 26, 2013) . . . [the company] pays interest at fixed rates ranging from 1.325% to 1.820% and receives interest at a

\textsuperscript{4}I thank Frederik Bruggink, Nicholas Gutmann, Craig Slater, and Milly Wang for their help with collecting this data.

\textsuperscript{5}I also thank Sergey Chernenko for discussing reporting requirements with me.
variable rate.' This information is classified as a notional amount of $300M pay-fixed swaps for the year 2013.

If no such information is provided, and the annual filing does not mention keywords ‘swap, hedg, or derivative’, I classify the firm as not using interest-rate swaps in that year. In determining the direction of swaps, it is occasionally helpful that pay-fixed swaps (if accounted for as hedges) are typically accounted for as cash-flow hedges, while pay-floating swaps are typically accounted for as fair value hedges.6

A.2.3 Banks (call reports)

Data on bank balance sheets based on call reports at the commercial bank level is for 2001Q1-2014Q4. I obtain this data from the FFIEC’s website. I aggregate all information to the parent holding company level on a pro-forma basis using current ownership, as reported by SNL. The sample includes banks not owned by a holding company. As my analysis is at the parent company level, I restrict the sample to banks with assets close to sufficient to meet quarterly reporting requirements at the holding company level. This also helps make the sample comparable to the one I use to show results based on holding company level data. After aggregating data to the parent level, I require banks to have at least 80% of the holding company requirement in assets: this requirement was 150MM prior to 2005Q4, and 500MM from 2006Q1 to 2014Q4.7

At the commercial bank level, maturity breakdowns are provided separately for loans and securities. The main component of interest here is loans and securities with remaining maturity or repricing interval less than three months. For both loans and securities, information is reported separately for assets backed by closed end first liens on 1-4 residential

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6The accounting difference is that changes in the market value of the swaps do not directly enter earnings for cash-flow hedges, but enter OCI instead, and can be added or subtracted from interest expense in a smooth manner. Changes in the market value of swaps accounted for as fair value hedges do directly enter earnings. However, this is usually offset by also adding the changes in the market value of the fixed-rate debt being converted to floating rates. See the summary of Statement No. 133 on the FASB’s website.

7Subsequent to the end of the sample period, only banks with assets greater than 1BN are required to report quarterly.
family mortgages. I require maturity information to be reported for at least 75% of loans and securities on the balance sheet. There are three main dependent variables: the floating fraction of all loans and securities, the floating fraction of ‘non-residential’ loans and the floating fraction of ‘non-residential’ securities. All fractions have the total reported amount in the relevant category as the denominator, and are in percentage points. ‘Non-residential’ refers to loans or securities not backed by closed-end first-liens on 1-4 residential family mortgages. This is a useful separation as, in the US, residential mortgages of this type are primarily long term and fixed rate. Most of the variation in maturity and floating fraction is in other categories.

I calculate an implied deposit rate as total interest expense on deposits divided by deposits, annualized and in percentage points. Note that the denominator includes non-interest-bearing deposits. This allows the measure of deposit interest expense to include the effect of cheaper non-interest-bearing deposits. I use a quarterly average of the daily effective federal funds rate from FRED, in percentage points, as the proxy for the short-term interest rate. I estimate a single measure of interest-rate pass through on deposits for each bank by regressing changes in the implied deposit rate on changes in the effective federal funds rate, also in percentage points. For the main results, I estimate this pass-through using data for 2001Q1-2008Q4. I require data for at least 20 quarters to estimate this relationship. I winsorize deposit pass-through on both sides at the 1% level.

I control for the mix of assets in some regressions. In these regressions, I include controls for fractions of lending related to C&I, consumer, and (primarily residential) real estate lending. These controls can be more precise after 2009Q2: starting in this quarter, mortgage-backed securities are separated by whether the collateral pertains to residential or commercial real estate. Therefore, I restrict regressions with these controls to using data starting in 2009Q2. For loans, the fraction of C&I lending is C&I lending divided by loans, in percentage points. The fraction of consumer lending combines credit card lending, auto loans and other consumer loans (revolving or otherwise) as a fraction of loans, in percentage points. The fraction of real estate lending refers to loans pertaining to residential real estate
loans, including 1-4 family loans, multifamily loans, HELOCs, junior liens and non-farm non-residential real estate lending as a fraction of loans, in percentage points. For loans and securities, I also take asset-backed securities backed by C&I lending and residential mortgage-backed securities into account.\textsuperscript{8}

I also analyze the effect of deposit competition. I measure deposit competition in a similar manner to Drechsler et al. (2014). I use branch level data on deposits from SNL. This data provides deposits outstanding for all branches of commercial banks on an annual level, as of June 30th of each year.\textsuperscript{9} I calculate a Herfindahl index (HHI) to measure the concentration of deposits for each county and year, as a fraction. I match this to banks and aggregate up to the parent level, weighting by deposits in each county. This is also pro-forma, based on present ownership.

SNL also provides data on branch level interest rates on jumbo mortgage loans.\textsuperscript{10} I use this data to calculate spreads between FRMs of different maturities and different types of ARMs. I obtain interest rate data for the final Friday of 2014 (12/26/2014) for all branches of commercial banks that report an interest rate for a 30 year FRM. I aggregate spreads to the parent level weighting by the fraction of deposits in corresponding branches as of June 2014. Data coverage is not very extensive for pure ARMs, but better for hybrid ARMs (hybrid N/1 ARMs have a fixed rate for the first N years, followed by a floating rate, adjusted once a year). In regressions with a particular spread as a dependent variable, I also report the fraction of deposits covered. This refers to the fraction of deposits held in branches for which components of the spread in question are reported.

Finally, I estimate pass through of interest rates for C&I lending. I calculate an implied interest rate on C&I lending as interest and fee income on C&I lending scaled by C&I loans, in percentage points. I estimate pass through by regressing changes in the C&I rate

\begin{itemize}
\item \textsuperscript{8}For securities, I take the total of book value of held-to-maturity securities and fair value of available-for-sale securities within the relevant categories. The primary type of lending not included here is commercial real estate lending (including CMBS). This can be thought of as the omitted category.
\item \textsuperscript{9}SNL provides this data from 1998. It is available from the FDIC from 1994.
\item \textsuperscript{10}SNL collects this data directly from banks.
\end{itemize}
on changes in the effective federal funds rate. I estimate this pass-through using data for 2001Q1-2008Q4. I require data for at least 20 quarters, and restrict C&I pass-through to be in between 0 and 110.

A.2.4 Banks (bank holding companies)

Data on banks at the holding company level is from form FR-Y9C, for 1986Q3-2014Q4. The main advantage of using this data in addition to commercial bank data is that consistent time series can be constructed for a longer sample period. I obtain this data from the Chicago Federal Reserve’s website. I aggregate data pro-forma to present ownership using data on bank holding company mergers, also provided by the Chicago Federal Reserve. I match banks to present ownership and check for chains of mergers or acquisitions. I restrict the sample to bank holding companies with assets above minimum requirements for quarterly reporting. This requirement was $150MM prior to 2005Q4, and $500MM from 2006Q1 to 2014Q4.

I report regressions with three dependent variables at the holding company level. These are the floating fraction of assets, loans and securities, and loans. I define floating fraction at the holding company level as the fraction of assets with remaining maturity or repricing frequency less than one year. The volume of total floating assets is reported directly: the floating fraction of assets scales this by total assets, in percentage points. To estimate the floating fraction of loans and securities, I estimate the volume of floating loans and securities by subtracting interest-bearing cash, federal funds sold, and securities purchased under repo agreements from floating assets. I then divide by loans and securities. The floating fraction of loans is similarly calculated, but also removes floating-rate debt securities (which are reported separately as a memo item). I require all three floating fractions to be positive.

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11 There are some chains of length two. In a given quarter, I drop holding companies with a top level owner that are not acquired later, or after they are acquired. I also drop holding companies for which, in that quarter, the acquirer is also the high holder.

12 Subsequent to the end of the sample period, as of 2015Q1, only banks with assets greater than $1BN are required to report quarterly.
and not greater than 110%.

I calculate an implied deposit rate as total interest expense on deposits divided by deposits, annualized and in percentage points. The denominator includes non-interest-bearing deposits. As a longer time series is available here, I estimate deposit pass-through using rolling data, allowing the estimate to change over time for each bank. I regress changes in the implied deposit rate on changes in the effective federal funds rate using data from the previous 8 to 20 quarters, as available.

I also analyze the sensitivity of banks’ deposit structure to interest rate conditions. To do so, I calculate the fraction of deposits that mature or reprice in less than one year. I also calculate a similar fraction for deposits and long-term debt (primarily subordinated debt and other borrowed money) combined. I regress these floating fractions on the term spread, which is a quarterly average of the difference between constant maturity 5 year and 1 year treasury yields (data from FRED).

A.2.5 Banks (historical)

The FDIC’s Historical Statistics on Banking (available on the FDIC’s website) provide annual data on US Commercial Banks with deposit insurance from 1934-2013. Call Reports (Reports of Income and Condition) are the underlying source. I use data on whether liabilities were interest-bearing or not, loans outstanding, interest income on loans and interest expense on deposits. The FDIC includes only domestic interest-bearing deposits until 1973. From 1974 to 1983, it includes all foreign deposits as interest bearing. From 1984, data is available on whether foreign deposits were interest bearing.

Table A.3 shows fractions of deposits in domestic offices in different types of accounts during the sample period.
Table A.3: Composition of US Commercial Bank domestic deposits (FDIC historical statistics)

<table>
<thead>
<tr>
<th>Year</th>
<th>Demand (%)</th>
<th>Savings (%)</th>
<th>Time (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1950</td>
<td>76</td>
<td>24</td>
<td>NA</td>
</tr>
<tr>
<td>1970</td>
<td>51</td>
<td>20</td>
<td>28</td>
</tr>
<tr>
<td>1990</td>
<td>20</td>
<td>34</td>
<td>46</td>
</tr>
<tr>
<td>2010</td>
<td>10</td>
<td>66</td>
<td>24</td>
</tr>
</tbody>
</table>

The FDIC does not classify any deposits as time deposits from 1942-1960.

To calculate an implied interest rate on loans, I divide total interest income on loans and leases (Table CB05) by net loans and leases (Table CB11). Net loans and leases are gross loans and leases less unearned income and allowances for losses. No estimates of unearned income are available before 1973, and no estimates of allowances for losses are available before 1948. Reserves for bad debt losses are used as estimates of allowances for losses before 1976. The results are essentially unchanged if I scale by gross loans and leases instead. To calculate an implied deposit rate, I divide total interest expense on deposits (Table CB06) by interest-bearing deposits (Table CB15).

The short-term interest rate is the three month T-bill rate from the Federal Reserve. I use the average of monthly reported yields in a year as the proxy for short-term interest rates in that year. This corresponds to the period over which interest income and expense accumulate.
Appendix B

Appendix to Chapter 2

B.1 Data

I obtain insurance regulatory data from SNL Financial. The data is ultimately sourced from insurance regulatory filings submitted to the NAIC: bonds in the general account are reported on Schedule D, and derivatives are reported on Schedule DB. Aggregate data is also based on insurance regulatory filings (as opposed to SEC filings or annual reports). I also obtain data on bond and issuer characteristics from Mergent FISD and data on interest rates and swap rates from Bloomberg. I restrict attention to life insurance subsidiaries, and largely focus on bonds held in the general account. I obtain data from 2005-2014. Depending on the setting, the data is either daily, quarterly, or annual.

I aggregate the data up to the group level pro-forma based on current ownership relationships, as reported by SNL. I identify individual companies based on NAIC Company Codes, and groups based on NAIC Group Numbers. I retain insurers that are not part of any insurance group in the sample, and identify them based on NAIC Company Codes. I restrict the sample to insurance group-quarters by this definition with at least $10M in assets and positive life insurance reserves. I identify insurers as part of a public company if they are ever owned by a public company.
B.1.1 General account bonds

Data on holdings of bonds is reported on Schedule D – Part 1. I obtain data on all bonds held in the general account. SNL provides this data with an identifier titled company investment key. Both the fair value and par value of bonds are reported, allowing prices to be calculated. The fair value is reported for each bond at the end of each year when held. For interim quarters, the fair value is a blended value, based on the fair value reported at the end of the previous year, and price paid for bonds bought and consideration received for bonds sold since the end of the previous year. I drop observations where the fair value is 0, missing or negative, or where the par value is 0. I calculate the price as the ratio of fair value scaled by par value, and drop observations where the price is outside of the interval [0.5, 2].

I match bonds to their owners (based on NAIC Company Code) and characteristics using the company investment key. Bond characteristics include CUSIP, asset type, issuer type, maturity, coupon, rate type (fixed or floating). For each company investment key these characteristics are collected from various sources and cleaned by SNL. I drop bonds that are hybrid securities, or bonds with maturity date before the relevant quarter (i.e. negative maturity). If no rate type is reported, I assume the bond is fixed rate. I also collect NAIC categories as reported by each company in each quarter. I collect supplemental information on bond characteristics from Mergent FISD. Using the issuer’s SIC code from Mergent FISD, I identify financial issuers based on their corresponding Fama & French (1997) industry. I also obtain the bond offering date from Mergent FISD.

I calculate DV01 at the bond identifier level (Company Investment Key) based on prices reported by each insurer by quarter. I round bond maturity in a given quarter (as of the reporting date at the end of the quarter) to the nearest half year. I drop observations with missing coupon information, or if the bond has 0 maturity and a fixed rate. I only calculate DV01 for fixed-rate bonds, and set it to 0 when the bond is floating rate, or reported exactly at par value. I calculate the yield to maturity of each bond observation numerically. The price of a bond with Maturity of $N$ years, coupon $C$, payment frequency $f$, and yield to
maturity $Y$ is

$$
P[N, C, f, Y] = \sum_{i=1}^{fN} \frac{C/f}{(1 + Y/f)^i} + \frac{1}{(1 + Y/f)^{fN}}
$$

$$
= (1 + Y/f)^{-fN} + \frac{C}{Y} \left[ 1 - (1 + Y/f)^{-fN} \right]
$$

$$
= \frac{C}{Y} + \frac{Y - C}{(1 + Y/f)^{fN}}
$$

(B.1)

Assuming semi-annual payment ($f = 2$), I use a bisection search to calculate the yield to maturity (all information other than the YTM is available). I run 20 iterations of a bisection search, and use the final midpoint as the yield to maturity. I match the estimated price of the bond using the calculated yield to maturity to the reported fair value, and drop the observation if the reported fair value is not within 1% of the estimated fair value. I then calculate DV01 numerically as the difference in price given a 1% shift in yield to maturity.\(^1\)

I classify bonds into separate asset classes. I identify bonds as corporate bonds when the issuer is reported by SNL as either an industrial or utility company, where the issuer is not in the Fama & French (1997) finance industry, and the bond is not a structured bond. I separate corporate bonds into safe (NAIC Category 1) and risky (NAIC Category higher than 1 or missing). I identify government bonds as bonds issued by the federal US government, a government agency, US states, local governments or foreign governments, excluding any structured bonds. I identify bonds issued by financial firms (in the Fama & French (1997) finance industry) excluding structured bonds. Private structured bonds are bonds issued by an industrial or utility issuer and are structured (this includes RMBS, CMBS, MBS, ABS and other structured bonds). Agency bonds are structured bonds issued by any type of government issuer. I classify all remaining bonds as ‘other’: this category is very small.

B.1.2 Derivatives outstanding

I collect data on interest-rate derivatives for 2005-2014 on a quarterly basis, and filter for standard single-currency interest-rate swaps. Reporting requirements for derivatives

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\(^1\)I also calculate duration bond, assuming annual payment of the coupon.
changed in 2010, but swaps were consistently reported. Prior to 2010, this data was reported on Schedule DB – Part C Section 1 (all collars, swaps and forwards open as of reporting date). After 2010, this data was reported on Schedule DB – Part A Section 1 (all options, caps, floors, collars, swaps and forwards open as of reporting date). Information is reported on the NAIC Company code, a text description, information on the terms or strike (also a text field), the notional amount and fair value. Data is at the transaction level. Initiation and maturity dates are also reported for all transactions.

I filter derivatives to retain only observations likely to pertain to standard single-currency interest-rate swaps. I use row numbers to perform an initial screen to do so. I drop observations when row numbers are not in ranges corresponding to a designated interest-rate swap type. Prior to 2010, this includes hedging (500000-599999) and other (700000-799999). After 2010, this includes hedging effective (850000-859999), hedging other (910000-919999), replication (970000-979999), income generation (1030000-1039999) and other (1090000-1099999). After 2010, risk type is also reported, and I only keep observations for which the risk type matches interest-rate risk. Using information in the description and strike fields, I exclude transactions that are likely to refer to CDS, currency swaps, total return swaps, inflation swaps or other miscellaneous swaps. I also drop observations where initiation or maturity are not reported. For some insurers, the two legs of swaps are reported as separate line items. I match these legs based on row numbers and terms (counterparty, notional, initiation and maturity) and combine them.

I parse the direction and fixed rate on the fixed leg of the swap from text fields describing the transaction and terms (description and strike).\(^2\) I merge in data on LIBOR and the maturity appropriate swap rate (both from Bloomberg) for both the initiation and the reporting date. I log-linearly interpolate the swap curve using the largest subset of maturities available from the set \{2,3,5,7,10,20,30\}. This allows me to determine the likely sign of the fair value of a fixed-rate swap initiated on the initiation date as of the maturity date. I then

\(^2\)Some swaps also have an adjustment on the floating leg (e.g. LIBOR + 50bps). I subtract the index adjustment from the fixed leg and treat the swap as otherwise standard.
proceed to identify the direction and fixed rate as follows:

1. In the best case, the direction of the swap (e.g. receive fixed, pay LIBOR) is identified clearly, and two separate interest rates can be identified from information on the strike. Before categorizing swaps as this type, I check whether the sign of the swap fair value matches what would be expected given general market rates, unless the fixed rate of the swap was more than 1% different from the swap rate at initiation, or the direction is very clearly reported.

2. In the next case, the direction is identified clearly, but only a single rate can be identified from information on swap terms. Before using the single rate as the fixed rate, I check whether it is closer to LIBOR as of the reporting date than the swap rate at initiation. Before categorizing swaps as this type, I check whether the sign of the swap fair value matches what would be expected given general market rates, unless the fixed rate of the swap was more than 1% different from the swap rate at initiation, or the direction is very clearly reported.

3. When information on the direction is available, but no information is available on the rate, I use the swap curve at initiation to determine the fixed rate.

4. When two rates are not available and the swap is not matched to this point, I identify the direction from the sign of the swap’s fair value in combination with changes in market conditions, and the fixed rate from the swap curve at initiation.

5. When two rates are available (in formats designating which rate is paid and which is received) and the swap is not matched to this point, I check which rate is closer to LIBOR at the reporting date and which leg is closer to the swap curve at initiation.

Table B.1 shows that the majority of swaps are classified based on the first step, but that the remaining steps are important.
Table B.1: Summary of swap sample by identification type

<table>
<thead>
<tr>
<th>Type</th>
<th># of swaps (000's)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>399</td>
</tr>
<tr>
<td>2</td>
<td>11</td>
</tr>
<tr>
<td>3</td>
<td>17</td>
</tr>
<tr>
<td>4</td>
<td>21</td>
</tr>
<tr>
<td>5</td>
<td>0.2</td>
</tr>
<tr>
<td>Total</td>
<td>448</td>
</tr>
</tbody>
</table>

Having identified the direction and fixed rate on the fixed leg of the swap, I proceed to price it and calculate DV01. The fair value of a pay-fixed and receive-floating swap is

\[
\text{Notional} \times (1 - P[N, C, f, Y])
\]  

(B.2)

as the floating leg is always valued at par, where the price of the bond is defined by Equation B.1. The price of a pay-floating swap is this value multiplied by -1. I use the log-linearly interpolated swap curve as of the reporting date as the yield to price swaps, and assume semi-annual payment of coupons. Finally, I calculate DV01 numerically as the change in fair value given a one basis point shift in the swap curve.

B.1.3 Bond and derivatives transactions

Data is also available to construct a view of bond transactions on a daily level for bonds in the general account. Bond acquisitions are reported on Schedule D – Part 3, and disposals are reported on Schedule D – Part 4, all providing transaction dates. Data is reported on the purchase price for acquisitions and consideration received for disposals, as well as par value. Entity identifiers (NAIC Company Code) and bond CUSIP are also reported. I collect this data for 2005-2014.

I match transaction level information to bond characteristics as reported by SNL at the NAIC Company Code and CUSIP level. I then identify asset types as above. I also identify transactions pertaining to new bond issues or passive sales. To do so, I find the number of insurance companies buying or selling a particular CUSIP on a given day. I identify issuance
purchases as one of the three following cases:

- Purchases within one week of offering date, as reported in Mergent FISD

- Purchases on the first reported transaction date for CUSIP, with more than five buyers and no sellers on that date

- Purchases within one week of the first reported transaction date, with the number of buyers at least 10 greater than the number of sellers on that date

I also identify passive sales (regular repayments that might be coupon payments or paydowns and prepayments). MBS paydowns happen regularly on the 1st of December of each year as well as (to a lesser degree) the 1st of the last month of each other quarter, so I classify any sales of structured bonds on those days as paydowns. I also identify regular cycles of frequent sales for other kinds of bonds. To do so, I first find the mode sale month (e.g. December) and the mode sale day (e.g. 15th). Then, if sales within one day (14th-16th) in an annual, semi-annual or quarterly cycle account for half of the number of sales, and more than 50 sales are reported for the CUSIP, I identify sales fitting the pattern as passive sales.

I calculate yield to maturity and DV01 numerically as before, using the reported transaction price (or consideration received) scaled by par value. I treat transactions reported exactly at par separately (and assume only the par value is reported correctly), as this is likely incorrect data. For these, I match to the DV01 per unit of par value from the quarterly view for the previous quarter, matching NAIC Company Code and CUSIP. If the bond does not match in the previous quarter, I match to the current quarter (as the bond may have been purchased for the first time that quarter).

I use transaction data to calculate weighted yield to maturity of all bonds purchased, by insurer-quarter, to measure reaching for yield. To do so, I take the weighted average (weighting by fair value) of all purchases in the quarter, by NAIC Group. I exclude bonds reported exactly at par from this calculation. Therefore, I use only prices reported on the day of the transaction, in the relevant quarter.

Data is also available to construct a view of daily trading in derivatives. All derivatives
positions reported open at the end of each reporting period provide initiation dates, as discussed above. All transactions terminated within a year are reported separately, which allow terminations as well as transactions only held within a quarter to be identified. Prior to 2010, this data was reported on Schedule DB – Part C Section 3 (all collars, swaps and forwards terminated during current year). After 2010, this data was reported on Schedule DB – Part A Section 2 (all options, caps, floors, collars, swaps and forwards terminated during current year). I use quarterly data for initiations when possible. I proceed to find changes in DV01 resulting from transactions as above.

B.1.4 Shadow reinsurance

To identify shadow reinsurance (Koijen & Yogo forthcoming), I obtain data for all reinsurance relationships, as reported by cedents, from SNL (this data is reported on Schedule S – Part 3 Section 1). I collect this data (available on an annual basis) for 2005-2014. Life reserve credits taken and modified coinsurance reserves are reported. I also collect information on whether the reinsurer is an affiliate and on whether the reinsurer is authorized. I collect the AM Best financial strength rating for the reinsurer. Following Koijen & Yogo (forthcoming), I define shadow reinsurance as reinsurance where the reinsurer is either an affiliate or unauthorized, and the reinsurer does not have an AM Best rating. I then take the sum of life reserve credits taken and modified coinsurance reserve. As I focus on bonds held in the general account, I also collect information on whether reinsurance relationships pertain to the general account or not (I define general account relationships as those where the term separate account is not reported, but general account is reported).
Appendix C

Appendix to Chapter 3

C.1 Effective institutional risk aversion

Why should banks or firms care about risk management? In this Appendix, I follow Froot et al. (1993) and relate institutional risk aversion to financial frictions. Suppose a bank has risky internal funds $w$. In the following period it has concave productive opportunities $f(I)$. As internal funds may not be sufficient, the bank would sometimes like to borrow in order to invest more. However, investment and output are not observable to external financiers and cannot be used to collateralize borrowing. Instead, all borrowing must be collateralized by risky cash flows $y$, distributed $g(y)$, generated by existing assets. This cash flow is observable to external financiers at a cost of $c$. Financiers are risk neutral and the competitive rate of return they require is normalized to 0.

The bank wants to maximize the value of output and the portion of $y$ it retains, subject to the lender’s IR constraint:

$$P(w) = f(I) + \int_D^\infty (y - D)g(y)dy + \lambda \left( \int_{-\infty}^D (y - c)g(y)dy + \int_D^\infty Dg(y)dy - (I - w) \right)$$  \hspace{1cm} (C.1)
The first order conditions are
\[
\frac{\partial P}{\partial D} = (\lambda - 1)(1 - G(D)) - \lambda c g(D) = 0 \tag{C.2}
\]
\[
\frac{\partial P}{\partial I} = f_I - \lambda = 0 \tag{C.3}
\]
Bankruptcy costs generate underinvestment
\[
f_I = \frac{1 - G(D)}{1 - G(D) - c g(D)} > 1 \tag{C.4}
\]
assuming an interior solution (i.e. \(1 - G(D) - c g(D) > 0\)) and positive monitoring costs.

Note that Equation C.3 implies that \(\lambda = f_I\), while the first order condition with respect to \(w\) implies that \(P_w = \lambda\). Therefore the concavity of the profit function is determined by
\[
P_{ww} = f_{II} \frac{dI^*}{dw} \tag{C.5}
\]
This is the same expression as Equation 3.1. In order for the profit function to be concave, then, investment must respond positively to the level of internal funds so that \(P_{ww} < 0\). This can be guaranteed when \(g\) has an increasing hazard rate.

Begin by combining Equations C.2 and C.3 and totally differentiating with respect to \(w\):
\[
(f_I(I^*(w)) - 1)(1 - G(D(w))) = f_I(I^*(w))c g(D(w)) \Rightarrow f_{II} \frac{dI^*}{dw} (1 - G(D)) - G(D)D'(w)(f_I - 1) = f_{II} \frac{dI^*}{dw} c g(D) + f_I c g'(D)D'(w) \tag{C.6}
\]
Next, I solve for \(D'(w)\), by totally differentiating the lender’s IR constraint, which determines how \(D\) responds to changes in \(w\):
\[
\int_{-\infty}^{\int_{D(w)} (y - c)g(y)dy + \int_{D(w)} D(w)g(y)dy = I^*(w) - w \Rightarrow D'(w) = \frac{\frac{dI^*}{dw} - 1}{1 - G(D) - c g(D)} \tag{C.7}
\]
Substituting Equations C.7 and C.4 into Equation C.6, provides an expression for \(\frac{dI^*}{dw}\)
terms of $f''$, $c$, and $g$:

$$\frac{dI^*}{dw} = \frac{1}{1 - f_{II}\Gamma}$$

where

$$\Gamma = \frac{1}{c} \frac{(1 - G(D) - cg(D))^3}{g(D)G'(D) + g'(D)(1 - G(D))}$$

As $f$ is concave and I have already assumed $1 - G(D) - cg(D) > 0$, $\frac{dI^*}{dw}$ has the same sign as $g(D)G'(D) + g'(D)(1 - G(D)) \propto \frac{d}{dD} \frac{g(D)}{1 - G(D)}$

For concavity of the profit function it is therefore sufficient for the hazard rate of $g$ to be strictly increasing. It can also be shown that the same condition generates a convex cost function (where the cost is the additional deadweight cost arising from external finance). This condition is satisfied for the Normal and Uniform distributions. In the case of the uniform distribution it is possible to explicitly calculate the face value of debt and deadweight cost of external finance. If $y$ is distributed uniform on $[0, U]$:

$$D(e) = U - c - \sqrt{(U - c)^2 - 2 \times 30 \times e}$$

$$C(e) = \frac{c}{U} D(e)$$

The requirement that the hazard rate of $g$ be increasing is not always satisfied - for instance, for the exponential distribution the hazard rate is 1. Indeed, it can be shown that in this case the deadweight cost of external finance is linear and not convex, which does not generate the concavity of the profit function.
C.2 Proofs

C.2.1 Proof of Proposition 3

Let $X_D = A_F \sigma_p^2$ and $X_S = A_B \sigma_S^2$ be the utility costs of risk on the demand and supply sides of the market when a fixed rate is used. Then the equilibrium price is determined as

\[
\frac{\mu_p - \mu^*}{X_D} = \frac{\mu^* - \mu_S}{X_S} \quad \text{(C.8)}
\]

\[
\implies \mu^* = \frac{\mu_S X_D + \mu_p X_S}{X_D + X_S} \quad \text{(C.9)}
\]

Denote welfare when a fixed rate is used by $\Omega$. Welfare depends on the surplus from lending, $\mu_p - \mu_S$:

\[
\Omega = \frac{1}{2} \frac{(\mu_p - \mu_S)^2}{X_D + X_S} \quad \text{(C.10)}
\]

The introduction of a floating rate changes the utility costs of risk to

\[
Y_D = A_F (\sigma_p^2 + \sigma_R^2 - 2\pi)
\]

\[
Y_S = A_B (\sigma_S^2 + \sigma_R^2 - 2\rho)
\]

The expressions for $\nu^*$ and $\Omega(R_1)$ (welfare when a floating rate is used) are similar to Equations C.9 and C.10. Rearrangements show that the change in interest rates is

\[
\mu^* - \nu^* = \frac{(\mu_p - \mu_S) (Y_D X_S - X_D Y_S)}{(X_D + X_S) (Y_D + Y_S)} \quad \text{(C.11)}
\]

This can be written as

\[
\text{Sgn}(\mu^* - \nu^*) = \text{Sgn} \left( \frac{X_S - Y_S}{X_S} - \frac{X_D - Y_D}{X_D} \right) \quad \text{(C.12)}
\]

Similarly the sign of the welfare difference is

\[
\text{Sgn} (\Omega(R_1) - \Omega) = \text{Sgn} (X_D - Y_D) + (X_S - Y_S) \quad \text{(C.13)}
\]

This proves Proposition 3.
C.2.2 Proof of Proposition 4

Equations 3.11 and 3.12 follow from the same argument used to prove Proposition 3. This leaves Equation 3.13. Denote welfare when swaps are used and their exogenous cost is $\lambda$ by $\Omega(R_1, \lambda a^*)$. I have already established that $\Omega(R_1, 0) > \Omega(R_1)$. Let $Z_D$ and $Z_S$ be the utility costs of risk when swaps are used. The threshold cost of optimal hedging can be found by equating these levels of welfare

$$
\Omega(R_1, \bar{C}) = \Omega(R_1)
$$

$$
\frac{1}{2} (\mu_P - \mu_S)^2 = \frac{1}{2} \frac{(\mu_P - \mu_S - \bar{C})^2}{Z_D + Z_S}
$$

From this quadratic equation I select the smaller root

$$
\bar{C} = (\mu_P - \mu_S) \left(1 - \sqrt{\frac{Z_D + Z_S}{Y_D + Y_S}}\right)
$$

as the maximal cost must be smaller than the surplus $\mu_P - \mu_S$. The total utility costs of risk are $\Phi(R_1) = Z_D + Z_S$ and $\Phi(R_1) = Y_D + Y_S$.

This proves Proposition 4.

C.2.3 Proof of Proposition 5

The discussion prior to Proposition 5 explains why when hedging is a zero NPV transaction, fixed rates with the bank hedging with swaps and floating rates with both the firm and the bank hedging with swaps are equivalent. For this part I assume that $\pi = 0$. The same reasoning used in the proof of Proposition 3 explains the interest rate and welfare differences relative to fixed rates.

Similarly, the discussion before Proposition 5 establishes that the cost of hedging is lower with floating rates when firms also hedge, as risk tolerance is higher. Welfare, as a function of risk tolerance in the market for swaps, is

$$
\Omega(T) = \frac{1}{2} \frac{(\mu_P - \mu_S - \lambda(T)a^*)^2}{\Phi(p)}
$$

(C.14)
where $\Phi(\rho)$ takes into account that the bank behaves as if it has reduced its risk by $\rho \alpha^*$ (continue to assume $\pi = 0$ for now). Substituting for the cost of hedging from Equation 3.16, I find

$$
\lambda(T) \alpha^* = \frac{\mu_p - \mu_s}{T \Phi(\rho)} \rho \alpha^*
$$

$$
\implies \Omega(T) = \frac{1}{2} \left( \frac{\mu_p - \mu_s}{\Phi(\rho)} \right)^2 \left( 1 - \frac{1}{\Phi(\rho)} \frac{\rho^2}{\sigma_R^2} \right)^2
$$

(C.15)

When $\pi \neq 0$, this expression becomes\(^1\)

$$
\Omega(T) = \frac{1}{2} \left( \frac{\mu_p - \mu_s}{\Phi(\rho, \pi)} \right)^2 \left( 1 - \frac{1}{\Phi(\rho, \pi)} \frac{\rho - \pi}{\sigma_R^2} \right)^2
$$

(C.16)

For $\pi \in (0, \rho)$, the cost of hedging is decreasing in $\pi$ and welfare is increasing in $\pi$.

This proves Proposition 5.

C.2.4 Proof of Proposition 6

Welfare as a function of the level of manipulation $K$ is

$$
\Omega(K) = \frac{1}{2} \left( \frac{\mu_p - \mu_s}{\Phi(K)} \right)^2 \left( 1 - \frac{1}{\Phi(K)} \frac{\rho - \pi}{K \sigma_R^2} \right)^2
$$

(C.17)

The effect of increasing $K$ is

$$
\frac{\partial \Omega(K)}{\partial K} = \left( 1 - \frac{1}{\Phi(K)} \frac{\rho - \pi}{K \sigma_R^2} \right) \left\{ \frac{1}{T} \frac{\mu_p - \mu_s}{2 \Phi^2(K) K \sigma_R^2} \left( 2 \Phi'(K) \right) + \frac{3 \Phi'(K)}{\Phi(K)} \right\} - \left( \frac{\mu_p - \mu_s}{2 \Phi^2(K)} \Phi'(K) \right)_{>0} \quad (C.18)
$$

The two marked terms are positive because $\Phi'(K) > 0$: both lenders and borrowers bear more risk as $K$ increases. For example, the optimal level of risk reduction for the bank is $\frac{\rho^2}{K \sigma_R^2}$. The effect of added risk when hedging is zero NPV is a clear negative effect when $T$ is sufficiently large

$$
\lim_{T \to \infty} \frac{\partial \Omega(K)}{\partial K} = - \frac{(\mu_p - \mu_s)^2 \Phi'(K)}{2 \Phi^2(K)} < 0
$$

(C.19)

\(^1\)Note that the corresponding version of Equation 3.16 then provides an expression for $\lambda(\alpha^* + \beta^*)$. 196
This proves Proposition 6.

C.3 Details

C.3.1 Optimal hedging with costly derivatives

Begin by simplifying the notation: let $H = \kappa - \mu_S$, $\sigma_R^2 = 1$ and $\sigma_S^2 = \sigma^2$. I want to show

$$\frac{\kappa - \mu_S - \lambda \alpha^*(\kappa, \lambda)}{A_B \text{Var}(-S_1 + \alpha^*(\kappa, \lambda)R_1)} = \frac{\kappa - \mu_S - \lambda \alpha^*}{A_B \text{Var}(-S_1 + \alpha^*R_1)}$$

$$\iff \frac{H - \lambda \left(\rho - \frac{1}{\lambda \theta}\right)}{A(\sigma^2 + \left(\rho - \frac{1}{\lambda \theta}\right)^2 - 2 \left(\rho - \frac{1}{\lambda \theta}\right) \rho)} = \frac{H - \lambda \rho}{A(\sigma^2 - \rho^2)}$$

The equality can be verified from

$$\frac{H - \lambda \left(\rho - \frac{1}{\lambda \theta}\right)}{A(\sigma^2 + \left(\rho - \frac{1}{\lambda \theta}\right)^2 - 2 \left(\rho - \frac{1}{\lambda \theta}\right) \rho)} = \frac{A \theta (H - \lambda \rho) - \lambda^2}{A^2 \theta (\sigma^2 - \rho^2) + \frac{\lambda^2}{\theta}}$$

$$= \frac{A \theta (H - \lambda \rho)}{A^2 \theta (\sigma^2 - \rho^2)} \left(\frac{\lambda^2}{A^2 \theta (\sigma^2 - \rho^2) + \frac{\lambda^2}{\theta}}\right) + \frac{\lambda^2}{A^2 \theta (\sigma^2 - \rho^2) + \frac{\lambda^2}{\theta}} = \theta$$

where the final equality follows from $\theta(Y - X) = \lambda^2$.

C.3.2 Optimal contracting

In general the optimal contract need not be linear. Consider a simplified problem: suppose $P, S$ are functions of a random variable $R$. In the more general problem I analyze in this paper, $P, S_1$ and $R_1$ are jointly distributed, but this simple version provides useful intuition.\(^2\)

Consider a standard optimal risk sharing problem. What is the optimal function for the payment from the firm to the bank $f(R)$ subject to a participation constraint for the bank? Suppose $R$ has pdf $g(R)$. The Lagrangian for this problem is

$$\mathcal{L} = \max_{f(R)} \int U^F[P(R) - f(R)]g(R)dR + \lambda \left(\bar{U} - \int U^B[f(R) - S(R)]g(R)dR\right)$$

(C.20)

\(^2\)A similar exercise is performed by Froot et al. (1993).
Pointwise maximization provides the Borsch risk sharing rule, where I write the marginal utilities as functions of the resulting wealth.

\[- \frac{U^F_W(P(R) - f(R))}{U^B_W(f(R) - S(R))} = \lambda \]  

(C.21)

Implicit differentiation and rearrangement provides

\[
\left[ - \frac{U^F_W}{U^F_W} \left( \frac{df^*(R)}{dR} - \frac{dP}{dR} \right) \right] + \left[ - \frac{U^B_W}{U^B_W} \left( \frac{df^*(R)}{dR} - \frac{dS}{dR} \right) \right] = 0
\]

(C.22)

and therefore

\[
\frac{df^*(R)}{dR} = \frac{A_F \frac{dP}{dR} + A_B \frac{dS}{dR}}{A_F + A_B}
\]

(C.23)

Thus \( f \) should be linear only if \( P \) and \( S \) are linear functions of \( R \).

### C.3.3 Competition in derivatives markets

Equation 3.18 can be rearranged to find an inverse demand function from the perspective of dealers, as a function of \( Q \), the total demand for swaps that all \( N \) dealers choose.

\[
\lambda(Q) = (L''(\omega)\alpha^* - Q)T_{B,F}\sigma_R^2
\]

(C.24)

\( T_{B,F} \) is the combined risk tolerance of banks and firms. An individual dealer’s problem is then to maximize production, \( q_i \), holding \( r = \sum_{j\neq i} q_j \) fixed. This objective can be written as

\[
\max_{q_i} q_i \lambda(q_i + r) - \frac{1}{2} A_i q_i^2 \sigma_R^2
\]

(C.25)

The dealer takes into account how its demand decision will affect its return for accepting risk as well as the utility cost of bearing this risk. Recall that I have assumed \( A_i = \frac{N}{T_D} \). The first order condition provides

\[
q_i = \frac{T_{B,F}(L''(\omega)\alpha^* - r)}{2T_{B,F} + A_i}
\]

(C.26)
In a symmetric equilibrium it must be the case that \( r = (N - 1)q \). Substituting this in, each dealer demands

\[
q^* = \frac{T_{B,F}L''(\omega)\alpha^*}{(N + 1)T_{B,F} + A_i}
\]

(C.27)

The equilibrium cost of hedging, as in Equation 3.21, is

\[
\lambda(Nq^*)\alpha^* = \frac{1 + \frac{T_D}{NT_{B,F}}L''(\omega)\beta^2}{T_{D,B,F} + \frac{T_D}{N}}
\]

(C.28)

As \( N \) goes to infinity, this approaches the competitive cost of hedging, \( \lambda^*\alpha^* \), shown in Equation 3.20. To see that it is always greater, note that

\[
\frac{1 + \frac{T_D}{NT_{B,F}}}{T_{D,B,F} + \frac{T_D}{N}} = \frac{1}{T_{D,B,F}} \left( 1 + \frac{T_D^2}{T_{B,F}(T_D + NT_{D,B,F})} \right)
\]

(C.29)