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Banks' exposure to interest rate risk and the transmission of monetary policy

by
Matthieu Gomez
Augustin Landier
David Sraer
David Thesmar

ESRB
European Systemic Risk Board
European System of Financial Supervision

Abstract

We show that the cash-flow exposure of banks to interest rate risk, or *income gap*, affects the transmission of monetary policy shocks to bank lending and real activity. We first use a large panel of U.S. banks to show that the sensitivity of bank profits to interest rates increases significantly with measured income gap, even when banks use interest rate derivatives. We then document that, in the cross-section of banks, income gap predicts the sensitivity of bank lending to interest rates. The effect of income gap is larger or similar in magnitudes to that of previously identified factors, such as leverage, bank size or even asset liquidity. To alleviate the concern that this result is driven by the endogenous matching of banks and firms, we use loan-level data and compare the supply of credit to the same firm by banks with *different* income gap. This analysis allows us to trace the impact of banks' income gap on firm borrowing capacity, investment and employment, which we find to be significant.

Keywords: Interest rate risk, monetary policy, bank lending
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1 Introduction

Bank profits are exposed to interest rates movements. Some banks issue interest bearing deposits so that their profits shrink when rates go up as they have to increase the compensation of depositors. Other banks tend to lend at variable interest rate so that their profits go up when the short rate increases. The gap between the interest rate sensitivities of assets and liabilities is called the "income gap": it measures the extent to which banking profits respond to monetary policy tightening (Flannery, 1983). If the Modigliani-Miller proposition for banks does not hold and banking profits affect lending activity (Kashyap and Stein, 1995), the income gap of banks may affect the extent to which monetary policy is transmitted to the real economy. This paper documents empirically that banks with a larger income gap respond to a monetary policy tightening by lending relatively more, which in turn affect the ability of their borrowers to invest and hire.

We start by documenting the exposure of banks' cash flows to interest rate risk. Using bank holding company (BHC) data on U.S. banks – available quarterly from 1986 to 2013 – we measure a bank's income gap as the difference between the dollar amount of the bank's assets that re-price or mature within a year and the dollar amount of liabilities that re-price or mature within a year, normalized by total assets. We show substantial variations in the measured income gap, both in the cross-section and in the time-series. We also document that banks do not fully hedge their interest rate exposure. In our data, a bank's income gap strongly predicts the sensitivity of the bank's future profits to interest rates. This result echoes earlier work by Flannery and James (1984), who show that income gap explains how S&Ls' stock returns react to changes in interest rates. It is also consistent with recent findings by Begeneau et al. (2012), who show that for the four largest US banks, net derivative positions tend to amplify, not offset, balance sheet exposure to interest rate risk. This incomplete hedging is also consistent with English et al. (2012), who document that unexpected increases in interest rates cause bank share prices to drop, especially for banks with a low maturity mismatch.

We then provide evidence that income gap strongly predicts how bank-level lending reacts to interest rate movements. Since interest rate risk exposure affects bank cash-flows, it may affect their ability to lend if external funding is costly. Quantitatively, we find that a 100 basis point increase in the Fed funds rate leads a bank at the 75^{th} percentile of the income gap distribution to increase its lending by about .4 ppt more than a bank at the 25^{th} percentile. This magnitude is to be compared to quarterly loan growth in our data, which equals 1.8%. The estimated effect is thus large in spite of potential measurement errors in our income gap measure. It also resists a battery of robustness checks. In particular, our estimation is unchanged after controlling for factors previously identified in the literature as determining the sensitivity of lending to interest rates like leverage, bank size and asset liquidity. In particular, income gap is a much stronger determinant of the sensitivity of lending to interest rates than leverage. We find the estimated effect to be larger for smaller banks and for banks that report no hedging of interest-rate risk, which is consistent with the idea that smaller banks are more financially constrained and that income gap is better measured for banks that do not hedge. We also report evidence that the effect propagates through internal capital markets from the income gap of the bank holding company to banking subsidiaries.

The rest of our analysis exploits loan-level data from Dealscan. A potential concern with the previous results is that they are driven by the endogenous matching of banks and firms. As is standard in the banking literature, we alleviate this concern by using loan-level data, which allows us to control for credit demand shocks through the inclusion of borrower-time fixed effects (Khwaja and Mian, 2008; Gan, 2007). We find that the effect of income gap on the sensitivity of bank lending to interest rates remains essentially similar, both in terms of magnitude and statistical significance, after including these additional fixed-effects. This result, consistent with random matching between banks and firms, is reminiscent of earlier findings in the literature (Khwaja and Mian, 2008; Jiménez et al., 2012; Iyer et al., 2014).

We further exploit this loan level dataset, by linking lenders' income gap to the real behavior of their borrowers, both in terms of investment and hiring. This analysis relies on the identifying assumption that banks and firms are randomly matched, an assumption warranted by our loan-level findings as well as additional analyses discussed in the paper. We find that firms borrowing from higher gap banks tend to borrow relatively more when interest rates go up, suggesting –in line with the relationship banking literature– very little substitution between sources of outside borrowing. We then document that the income gap of a firm's main lender affects the firm's sensitivity of investment and hiring to interest rates. For instance, assuming the average bank has a gap of 30% (this corresponds to the 2013 asset weighted average), a 100bp increase in Fed funds rate would lead the average firm to increase employment by .6% more than average. We find a similar effect for capital expenditures.

The mechanism we document at the micro-level has potentially important effect for the transmission of monetary policy. In the data, banks' average income gap is positive. Part of this surprising finding is due to the fact that we treat transaction deposits or savings deposits as liabilities that do not reprice immediately with the short-term rate, though having a zero contractual maturity. In doing so, we follow the literature that finds that interest rates on these core deposits adjust only sluggishly to changes in short-term market rates (English et al. (2012), Hannan and Berger (1991), Neumark and Sharpe (1992),Drechsler et al. (2014)). Given an aggregate positive income gap, our cross-sectional estimate suggests that the exposure of the banking sector to interest rate movement may potentially dampen the effect of monetary policy shocks, both in terms of lending activity and real effects.

Our paper is mainly related to the literature on the bank lending channel of transmission of monetary policy. This literature seeks to find evidence that monetary policy affects the economy via credit supply. The bank lending channel is based on a failure of the Modigliani-Miller proposition for banks. Consistent with this argument, monetary tightening has been shown to reduce lending by banks that are smaller (Kashyap and Stein (1995)), unrelated to a large banking group (Campello (2002)), hold less liquid assets (Kashyap and Stein (2000)) or have higher leverage (Kishan and Opiela (2000), Gambacorta and Mistrulli (2004)). We find that the "income gap" effect we document is essentially orthogonal to these effects, robust across specifications. In line with the more recent banking literature, we are also able to document that these effects are not driven by endogenous matching of banks to borrowers (Khwaja and Mian, 2008; Jiménez et al., 2012; Iyer et al., 2014). This allows us to trace the impact of interest rate shocks onto firm growth. Via its focus on interest risk exposure, our paper also relates to the emerging literature on interest rate risk in banking and corporate finance (Flannery and James (1984), Chava and Purnanandam (2007), Purnanandam (2007), and Begeneau et al. (2012), Vickery (2008)). These papers are mostly concerned with the analysis of banks' risk-management and its implication for stock returns. We complement this literature by focusing on bank lending and borrower behavior.

The rest of the paper is organized as follows. Section 2 presents the datasets used in the paper. Section 3 examines the link between income gap, profits and lending policy, using bank level data only. Section 4 shifts the focus to loan-level data: We control for non-random matching of banks to firms and investigate the effect of income gap on real corporate behavior. Section 5 further discusses interpretations of our results. Section 6 concludes.

2 Data and Descriptive statistics

2.1 Data construction

2.1.1 Bank-level data

We use quarterly Consolidated Financial Statements for Bank Holding Companies (BHC) available from WRDS (form FR Y-9C). These reports have to be filed with the Federal Reserve by all US bank holding companies with total consolidated assets of $500 million or more. Our data covers the period going from 1986:1 to 2013:4. We restrict our analysis to all BHCs with more than $1bn of assets in 2010 dollars. The advantage of BHC-level consolidated statements is that they report measures of the bank's income gap every year from 1986 to 2011 (see Section 2.2.1). Commercial bank-level data that have been used in the literature (Kashyap and Stein (2000); Campello (2002)) do not have a consistent measure of income gap over such a long period.

For each of these BHCs, we use the data to construct a set of dependent and control variables.

We report summary statistics for these variables in Table 1 and provide details on the construction of these variables in Appendix A.[1] We use two sets of dependent variables in our analysis. First are income-related variables that we expect to be affected by movements in interest rates: net interest income and net profits. We also use non-interest income as a "placebo" variable, since non-interest income should not be directly affected by variations in interest rates and income gap. We normalize all these variables by total assets.[2] Second, we look at two variables measuring credit growth at the bank level: (1) the quarterly change in log commercial & and industrial loans and (2) the quarterly change in log total loans.

As shown in Table 1, the quarterly change in interest income is small compared to total assets as interest rates do not change much from quarter to quarter. On average, quarterly net interest income accounts for about 0.9% of total assets, while the bottomline (earnings) is less than 0.2%. Non-interest income is as large as interest income on average (1% of assets compared to 0.9%), but much more variable (s.d. of 0.023 vs 0.003).

Our analysis uses as control variables the determinants of the sensitivity of bank lending to interest rates that have been discussed in the previous literature. In line with Kashyap and Stein (2000), we control for equity normalized by total assets, size (log of total assets) and the share of liquid securities. The share of liquid securities variable differs somewhat from Kashyap and Stein (2000)'s definition (Fed funds sold + AFS securities) due to differences between BHC consolidated data and call reports. In our data, available-for-sale securities are only available after 1993 and Fed funds sold are only available after 2001. To construct our measure of liquid securities, we thus deviate from Kashyap and Stein (2000)'s definition and take all AFS securities normalized by total assets. Consequently, liquidity measure is available for the 1994-2013 sub-period only.

These control variables, obtained from accounts consolidated at the BHC-level, have orders of magnitudes that are similar to existing studies on commercial bank-level data: Average equity-to-asset ratio is 8.7% in our data, compared to 9.5% in Campello (2002)'s sample (which covers

[1] We describe the "income gap" measure in Section 2.2.1 in detail.

[2] All ratios are trimmed by removing observations that are more than five interquartile ranges away from the median. Our results are qualitatively similar when trimming at the 5th or the 1st percentile of the distribution.

the 1981-1997 period). The share of liquid assets is 27% in our sample, compared to 32% in his sample.

2.1.2 Loan-level Data

We also use more granular loan-level data. These data allow us to connect banks to individual borrowers. Our source here is the Dealscan database which contains publicly available information on over 100,000 corporate loans booked since 1987. It contains detailed transaction-level information on the size, maturity and the terms (fees, rates) of individual loan deals, as well as the identity of the borrowers and the lenders. For the majority of originations, DealScan reports the syndicate structure but not the actual loan shares. Such information loss is, however, negligible: For the sample of syndicates with non missing loan shares, the syndicate structure explains most of the variations in lender shares, with an explanatory power of 94.15%. For observations for which loan shares are missing, we thus impute loan shares from the average lender shares of syndicates with a similar structure (i.e. same number of lead lenders and participants).

We then construct the panel using the following procedure. DealScan contains the origination date, amount, and termination date of individual loan deals. We combine this information with loan shares to construct a yearly panel of outstanding loans for each borrower-lender pair that is active –i.e. for which there is at least one outstanding loan. Thus, we work on the loan-level data at the annual frequency instead of quarterly because loan-level data are too granular to be useful at such high frequency (i.e. there would be too many observations corresponding to zero lending). Since the coverage of banks by Dealscan tends to be volatile, we drop lenders for which aggregate lending growth is higher than 200% or lower than -50%. [3] Finally, we drop lenders with a different top-holder BHC in year t or $t+1$. Our key dependent variable is then the symmetric loan growth measure $\Delta L_{i \to j,t}$ which is the change in loan outstanding from bank i for firm j normalized by the across period average (see Appendix A). This growth rate measure has the advantage of being

[3] Aggregate lending growth is obtained by summing loans across all of the bank borrowers. A very high or very low growth may reflect merger activities or alternatively abrupt increase of the bank coverage in DealScan.

bounded by -2 and +2. It also accommodates initiation and terminations of lending relationships: It is equal to +2 when the bank starts lending and -2 when it stops lending to a given firm.

We then complement these data with information about the lender, most importantly the income gap of its current top-holder BHC. To do so, we manually match the biggest lenders in DealScan to US commercial banks, based on the names and cities reported in DealScan on the one hand and in the Reports of Condition and Income (Call Reports) on the other hand. US commercial banks report their current top-holder BHC in the Call Reports (`rssd9348`) : this allows us to construct a match table between Dealscan lenders and top-holder BHCs. In total, we match 300 lenders to 139 BHCs. The matched lenders represent 3.86% of the total number of US lenders in DealScan but they account for 44.91% of the total number of loans. The remaining lenders are either institutions that are not part of a BHC or smaller commercial banks that could not be matched. The BHCs identified through our procedure in Dealscan are bigger than the average BHC in the bank level data (we report the results of this comparison in Appendix Table D.1). This is not a surprise given that we manually matched only the biggest banks in Dealscan (another reason is that DealScan only covers the biggest deals). These banks also tend to have a bigger average gap. We find, however, that the standard deviation of income gap among the matched BHCs (.16) is simlar to the s.d. in the overall BHC sample (.19).

DealScan contains coarse information on the borrower: debt, zip code, industry SIC code, and total sales at origination. In order to investigate real effects of bank lending, we add accounting information about publicly listed borrowers from COMPUSTAT. To implement this, we use a updated version of the crosswalk provided by Chava and Roberts (2008). This crosswalk allows to match 9,767 borrowers out of the 25,481 borrowers in our sample. For these firms, we retrieve from COMPUSTAT information on employment (compustat item EMP), total assets (AT) and total financial debt (DLC+DLTT). These three variables are winsorized, based on the median plus or minus 5 times the interquartile range.

2.1.3 Interest Rates

We use three time-series of interest rates. In most of our regressions, we use the Fed funds rate as our measure of short-term interest rate, available monthly from the Federal Reserve's website. We define quarterly interest rates as the interest rate prevailing in the last month of the quarter. In the penultimate Section, we also use the spread on the 10-year treasury bond, available from the Fed's website. Finally, we construct a measure of expected short interest rates using the Fama and Bliss (1987) series of zero coupon bond prices. For each quarter t, we use as our measure of expected future short rate the 1-year forward rate as of $t-8$.[4]

2.2 Exposure to Interest Rate Risk

2.2.1 Income Gap: Definition and Measurement

We use the definition of the income gap of a financial institution in Mishkin and Eakins (2009):

$$\text{Income Gap} = \text{RSA} - \text{RSL} \tag{1}$$

where RSA is a measure of the amount of assets that either reprice, or mature, within one year, and RSL the amount of the liabilities that mature or reprice within a year. RSA (RSL) is the number of dollars of assets (liability) that will pay (cost) variable interest rate. Hence, the income gap measures the extent to which a bank's net interest income are sensitive to interest rates changes. Because the income gap is a measure of exposure to interest rate risk, Mishkin and Eakins (2009) propose to assess the impact of a potential change in short rates Δr on bank income by calculating: Income Gap $\times \Delta r$.

However, this relation has no reason to hold exactly. The income gap measures a bank's exposure to interest rate risk imperfectly. First, the cost of debt rollover may differ from the short rate. New short-term lending/borrowing will also be connected to the improving/worsening

[4]This forward is calculated using the zero coupon bond prices according to the formula $p_{2,t-8}/p_{3,t-8} - 1$, where $p_{j,s}$ is the price of the discount bond of maturity j at date s.

position of the bank on financial markets (for liabilities) and on the lending market (for assets). This introduces some noise in the relationship between banks income and Income Gap $\times \Delta r$. Second, depending on their repricing frequency, assets or liabilities that reprice may do so at times where short rates are not moving. This will weaken the correlation between change in interest income and Income Gap $\times \Delta r$. To see this, imagine that a bank holds a \$100 loan, financed with fixed rate debt, that reprices every year on June 1. This bank has an income gap of \$100 (RSA=100, RSL=0). Now, assume that the short rate increases by 100bp on February 20. Then, in the first quarter of the year, bank interest income is not changing at all, while the bank has a \$100 income gap and interest rates have risen by 100bp. During the second quarter, the short rate is flat, but bank interest income is now increasing by $\$1 = 1\% \times \$100$. For these two consecutive quarters, the correlation between gap-weighted rate changes and interest income is in fact negative. This represents another source of noise in the relation between banks' income and Income Gap $\times \Delta r$. Finally, banks might be hedging some of their interest rate exposure, which would also weaken the link between income and Income Gap $\times \Delta r$. Despite these sources of measurement error, we believe that this measure of income gap is particularly attractive for our purposes, given its simplicity and direct availability from BHC data.

In the data, we construct the income gap using variables from schedule HC-H of form FR Y-9C, which is specifically dedicated to the interest sensitivity of the balance sheet. RSA is directly provided (item bhck3197). RSL is decomposed into four elements: Long-term debt that reprices within one year (item bhck3298); long-term debt that matures within one year (bhck3409); variable-rate preferred stock (bhck3408); interest-bearing deposit liabilities that reprice or mature within one year (bhck3296), such as certificates of deposits. Empirically, the latter is by far the most important determinant of the liability-side sensitivity to interest rates. All these items are available every year from 1986 to 2011. We scale these variables by total assets, and report summary statistics in Table 2.

The average income gap is 12.6% of total assets. This means that, for the average bank, an increase in the short rate by 100bp will raise bank revenues by 0.126 percentage points of assets.

There is significant cross-sectional dispersion in income gap across banks, which is crucial for our empirical analysis. About 78% of observations correspond to banks with a *positive* income gap. For these banks, an increase in interest rates yields an *increase* in cash flows. A second salient feature of Table 2 is that RSL (interest rate-sensitive liabilities) mostly consists of variable rate deposits, that either mature or reprice within a year. Long term debt typically carries a fixed rate.

That the gap is positive can seem surprising because one expects banks to be maturity transformers, thus borrowing short and lending long. The explanation for this seemingly counterintuitive result comes partially from our treatment of deposits. In the BHC data, the item corresponding to short-term deposit liabilities (bck3296) does not include transaction deposits or savings deposits.[5] As mentioned in English et al. (2012), interest rates on these "core" deposits, while having a zero contractual maturity, are known to adjust quite sluggishly to changes in short-term market rates (Hannan and Berger (1991), Neumark and Sharpe (1992)). Therefore, despite their short maturity, it is natural to exclude them from our measure of income gap, as they will not induce direct cash-flow changes when interest rates change. However, if these "core" deposits adjust slightly to changes in Fed funds rates, our income gap measure will over-estimate the real income gap.

This treatment of deposits, however, can only partially explain the non-negative average income gap measured in our data. If we were to make the assumption that all non-interest bearing deposits had short maturity as in English et al. (2012), we would still find that the average income gap is zero, not negative. A reason for this is that we measure the *income* gap and not the *duration* gap. The income gap is a cash-flow concept. It measures the extent to which a bank's interest income is sensitive to the short rate. The duration gap, by contrast, is a value concept. It measures the extent to which equity *value* is sensitive to the short rate. For a given bank, the duration gap can be negative while the income gap is positive, implying opposite elasticities of cash-flows and equity values to interest rates. This happens for instance when the maturity of long-term assets is substantially longer than that of long-term deposits (which account for most of the liabilities). In

[5] See http://www.federalreserve.gov/apps/mdrm/data-dictionary.

fact, the positive average elasticity of banks' earnings to interest rates has already been observed in the literature. In its seminal contribution, Flannery (1981) shows that the average income gap for large banks is either close to zero or positive. Flannery (1983) extends the result to small banks. More recently, English et al. (2012) shows that a 100 basis point increase in interest rates increases the median bank's net interest income relative to assets by almost 9 basis points and decreases its market value of equity by 7%. These numbers are very much in line with our average income gap of 12.6%. Although understanding the average income gap in the economy is important, we should emphasize that the sign of the average income gap is irrelevant for our empirical analysis, since the identification strategy exploits cross-sectional differences in income gap.

2.2.2 Direct evidence on Interest Rate Risk Hedging

In this section, we ask whether banks use derivatives to neutralize their "natural" exposure to interest rate risk. We can check this directly in the data. The schedule HC-L of the form FR Y-9C reports, starting in 1995, the notional amounts in interest derivatives contracted by banks. Five kinds of derivative contracts are separately reported: Futures (bhck8693), Forwards (bhck8697), Written options that are exchange traded (bhck8701), Purchased options that are exchange traded (bhck8705), Written options traded over the counter (bhck8709), Purchased options traded over the counter (bhck8713), and Swaps (bhck3450).

We scale all these variables by assets, and report summary statistics in Table 3. Swaps turn out to be the most prevalent form of hedge used by banks. For the average bank, they account for about 18% of total assets. This number, however, conceals the presence of large outliers: a handful of banks –between 10 and 20 depending on the year– have total notional amount of swaps greater than their assets. These banks are presumably dealers. Taking out these outliers, the average notional amount is only 4% of total assets, a smaller number than the average income gap. 40% of the observations are banks with no derivative exposure.

Unfortunately, the data only provide us directly with notional exposures. Notional amounts may conceal offsetting positions (see Begeneau et al. (2012) for an inference of net exposure using public data). To deal with this issue, we directly look at the sensitivity of each bank's revenue to interest rate movement and show that it is related to the income gap (see Section 3.3).

3 Bank-level Evidence

In this section, we provide evidence based on bank-level data. We first validate the income gap measure: We find that the income gap is strongly correlated with the sensitivity of interest income and profits to interest rates. Second, we move to the focus of the paper, i.e. that the income gap explains the sensitivity of bank lending to interest rates.

3.1 Methodology

In this Section, we follow the specification typically used in the literature (Kashyap and Stein (1995), Kashyap and Stein (2000) or Campello (2002)), and estimate the following linear model for bank i in quarter t:

$$\begin{aligned}\Delta Y_{it} = &\sum_{k=0}^{k=4} \alpha_k (\text{gap}_{it-1} \times \Delta \text{fed funds}_{t-k}) + \sum_{x \in Control} \sum_{k=0}^{k=4} \gamma_{x,k} (x_{it-1} \times \Delta \text{fed funds}_{t-k}) \\ &+ \sum_{k=0}^{k=4} \eta_k \Delta Y_{it-1-k} + \phi.\text{gap}_{it-1} + \sum_{x \in Control} \mu_x . x_{it-1} + \delta_t + \epsilon_{it}\end{aligned} \tag{2}$$

where the control variables are $Control = \{\text{Size, Equity, Liquidity}\}$, and standard errors are clustered at the BHC level. All variables are scaled by total assets. Y_{it} stands for the different outcome variables we explore in this Section: Profits and its component, and lending activity. These variables are formally defined in Appendix A. $\sum_{k=0}^{k=4} \alpha_k$ is the cumulative effect of interest rate changes on change in the outcome variable Y, given the income gap of bank i and is the coefficient of interest in Equation (2). If the income gap variable contains information on banks' interest rate exposure and if banks do not fully hedge this risk, we expect $\sum_{k=0}^{k=4} \alpha_k > 0$. Consistent with the literature, we control for known determinants of the sensitivity of bank lending to interest rates: bank size, bank equity and bank liquidity (as described in Section 2). All the controls are included directly, as well as interacted with current and four lags of interest rate changes. These controls have been shown to explain how bank lending reacts to changes in interest rates. Their economic justification in a profit equation is less clear, but since our ultimate goal is to explain the cross-section of bank lending, we include these controls in the profit equations for consistency.

3.2 Interest Rate Shocks and Interest Income

Our first test is a sanity check: We use net interest income (interest income minus interest expenses) normalized by lagged assets as our first explanatory variable. We report the estimation results in Table 4, column (1) to (5). The bottom panel reports the coefficient of interest, $\sum_{k=0}^{k=4} \alpha_k$, i.e. the cumulative effect of a change in interest rate on the change in net interest income, as well as the p-value of the F-test for $\sum_{k=0}^{k=4} \alpha_k = 0$. Column (1) provides estimation results over the whole sample. $\sum_{k=0}^{k=4} \alpha_k = 0$ is significantly different from 0 at the 1% confidence level (p value < .01). Quantitatively, a \$1 increase in $Gap_{it-1} \times \Delta FedFunds_t$, after 5 consecutive quarters, raises interest income by about 0.06 dollars. The income gap captures a BHC's interest rate exposure in a statistically meaningful way.

As expected, the effect uncovered in Column (1) of Table 4 is observed across bank sizes and is unaffected by the use of hedging by BHCs. This is because the link between the gap and interest income is a near accounting identity. It may fail to hold exactly for the reasons mentioned in Section 2.2.1 but should not be affected by bank size of hedging policy. Columns (2)-(3) split the sample into large and small banks. "Large banks" are defined as the 50 largest BHCs each quarter in terms of total assets. The effect of the income gap on BHCs' sensitivity of net interest income to interest rates is similar across large and small banks. For both groups, $\sum_{k=0}^{k=4} \alpha_k$ is estimated at .06 and is statistically different from 0 at the 1% confidence level. A test of equality of $\sum_{k=0}^{k=4} \alpha_k$ across the two groups yields a p-value of 0.83, so that we cannot reject the null hypothesis that these coefficients are in fact equal, as they should be. Columns (4)-(5) split the sample into banks that report some notional exposure to interest rate derivatives and banks that report no interest rate derivative exposure. This sample split reduces the period of estimation to 1995-2013, as notional amounts of interest rate derivatives are not available in the data before 1995. The sample size drops accordingly from 37,888 BHCs-quarter to 26,322 BHCs-quarter. For both groups of banks, we find that the net interest income of banks with a larger income gap increases significantly more following an increase in interest rates, with a cumulated effect of .05 (resp. .07) for banks with (resp. without) derivative exposure. As expected, across the two groups yields a p-value of 0.19.[6]

If our measure perfectly captured a BHC's income exposure to interest rates, we would expect $\sum_{k=0}^{k=4} \alpha_k$ to be estimated at .25, since our interest rates are annualized but income is measured quarterly. Instead, Table 4 reports a coefficient estimate of 0.06. As mentioned in Flannery (1981) and explained in Section 2.2.1, beyond measurement error, there are several reasons to expect a coefficient estimate below .25. Explicit or implicit commitments to renew existing loans without a full pass-through of rate changes to the customer might add noise to the relationship between net interest income and changes in interest rates. Reset dates of variable rate loans do not exactly occur at the beginning of each quarter. ARMs, which make up a big fraction of variable rate exposure of banks, have lifetime and periodic caps and floors that reduce the sensitivity of their cash flows to interest rates. All these effects can dampen the elasticity of net interest income to interest rates and probably explain why our estimate of $\sum_{k=0}^{k=4} \alpha_k$ is significantly lower than .25.

To further assess the validity of our income gap measure, we run a "placebo" test in Columns (6)-(10) of Table 4. We use non-interest income as a dependent variable in Equation (2). Non-interest income includes servicing fees, securitization fees, management fees and trading revenue. While non-interest income may be sensitive to interest rate fluctuations, there is no reason why this sensitivity should depend on a BHC's income gap. Columns (6)-(10) of Table 4 reproduce the analysis of Columns (1)-(5) using non-interest income as a dependent variable. In all these specifications, the estimated $\sum_{k=0}^{k=4} \alpha_k$ is lower than .01 and statistically indistinguishable from 0.

[6] In non-reported regressions, we further restrict the sample to BHCs whose notional interest rate derivative exposure exceeds 10% of total assets (some 4,000 observations): even on this smaller sample, the income gap effect remains strongly significant and has the same order of magnitude.

3.3 Interest Rate Shocks, Earnings and Value

We show in this section that banks with larger income gap experience a larger relative increase in total earnings and market value following an increase in interest rates. We first estimate Equation (2) using total earnings scaled by total assets as a dependent variable. The coefficient estimates are presented on Columns (1) to (5) of Table 5. The estimated $\sum_{k=0}^{k=4}\alpha_k$ is positive and significantly different from 0 at the 1% confidence level across these specifications. The coefficient estimates in Column (1) imply that a \$1 increase in $Gap_{it-1} \times \Delta FedFunds_t$ after 5 consecutive quarters raises earnings by about \$0.07. This order of magnitude is similar to the effect on net interest income estimated in Columns (1)-(5) of Table 4. This is not surprising since we know from Columns (6)-(10) of Table 4 that the income gap has no effect on non-interest income. We obtain a similar estimate for $\sum_{k=0}^{k=4}\alpha_k$, when restricting the sample to large banks (Column (2)), small banks (Column (3)), banks with no notional exposure to interest rate derivatives (Column (4)) and banks with some notional exposure to interest rate derivatives (Column (5)).

We then estimate Equation (2) using BHCs market value scaled by total assets as a dependent variable. The coefficient estimates are presented on Columns (6) to (10) of Table 5. The estimated $\sum_{k=0}^{k=4}\alpha_k$ is positive and significantly different from 0 at the 1% confidence level for all specifications except when the sample is restricted to large banks, in which case $\sum_{k=0}^{k=4}\alpha_k$ is not significantly different from 0. Quantitatively, a \$1 increase in $Gap_{it-1} \times \Delta FedFunds_t$ raises the market value of banks equity by about \$1.8. Since the same shock to $Gap_{it-1} \times \Delta FedFunds_t$ raises total earnings by \$0.07, this implies an earnings multiple of approximately 25, which is large but plausible. The estimated $\sum_{k=0}^{k=4}\alpha_k$ is significantly smaller when estimated over the sample of large banks (Column (8)), but is otherwise comparable to its full sample estimate when estimated over the sample of small banks (Column (7)), banks with no derivatives exposure (Column (9)) and banks with derivative exposure (Column (10)).

These results indicate that for most banks in our sample, interest rate hedging does not significantly reduce banks' balance sheet exposure to interest rate risk. This conclusion seems to hold even for the largest banks, which is consistent with Vickery (2008) and Begeneau et al. (2012).

3.4 Interest Risk and Lending

The response of banks' earnings to monetary policy shocks depend on their income gap. In the presence of financing frictions, the response of banks' lending to monetary policy should also depend on their income gap (Kashyap and Stein, 1995). To test this hypothesis, we follow Kashyap and Stein (2000) and estimate equation (2) using the quarterly change in log-lending as the dependent variable.

We control for bank size and bank equity.[7] In all regressions, we include these controls directly as well as interacted with current and four lags of interest rate changes. These interaction terms help to measure the sensitivity of lending to interest rates. For instance, we expect high equity banks and large banks to be less sensitive to interest rate fluctuations (Kashyap and Stein (1995)). This is because changes in the cost of funding affect cash flows, which reduces lending by financially constrained banks. We also expect banks with liquid assets to lend relatively more when rates increase (Kashyap and Stein (2000)).

We report the results in Table 6. Columns (1) to (5) use C&I loan growth as a dependent variable. Columns (6) to (10) use total lending growth as a dependent variable. Columns (1) and (6) use the whole sample. Columns (2) and (7) restrict the sample to small banks, Columns (3) and (8) to large banks, Columns (4) and (7) to banks that report no notional exposure to interest rate derivatives, Columns (5) and (8) to banks reporting no interest rate derivatives exposure. We focuse first on the results using total lending growth as a dependent variable. $\sum_{k=0}^{k=4} \alpha_k$ is estimated over the whole sample at 1.1 and is statistically significant at the 1% level. This effect is economically significant. If we compare a bank at the 25^{th} percentile of the income gap distribution (0.01) and a bank at the 75^{th} percentile (0.24), and if the economy experiences a 100 basis point increase in the Fed funds rate, total loans in the latter bank will grow by about .25

[7] Asset liquidity is available only since 1993. Thus, our main specifications do not include this control, but we include it in robustness Table 7 and find our estimates to be unchanged.

percentage points more. This has to be compared with a sample average quarterly loan growth of about 1.7%.

The estimate of $\sum_{k=0}^{k=4} \alpha_k$ increases when estimated on the sample of banks with no notional exposure to interest rate derivatives: it is then 1.7 and is significantly different from 0 at the 1% confidence level (Column (9)). When estimated on the sample of banks reporting some notional exposure, $\sum_{k=0}^{k=4} \alpha_k$ is only .89 and is marginally significant (p-value of .11) (Column (10)). The difference between the point estimates across these two samples is, however, not significantly different from 0 (p-value = 0.29).

The estimate of $\sum_{k=0}^{k=4} \alpha_k$ is smaller when estimated on the sample of large banks (Column (8)) than when estimated on the sample of small banks (.8 vs. 1.2). While the small-bank estimate is statistically significant at the 1% confidence level, the large-bank estimate is insignificant. However, the two estimates are not statistically different (p-value = 0.72). The results obtained when using C&I lending as a dependent variable are essentially similar, except that the estimate of $\sum_{k=0}^{k=4} \alpha_k$ on the sample of banks reporting some hedging is insignificant (Column (5)) and that the large-bank estimate is negative and insignificant (Column (3)).

In contrast to the income gap, the equity ratio control we include in the regressions has no impact on the sensitivity of lending to rates, but the size control goes in the right direction. In row 4 of the bottom panel of Table 6, we report the sum of the coefficients on interaction terms with size, measured as banks total assets. We do indeed find that larger banks are significantly less likely to reduce lending when interest rates increase. This effect is significant for both types of lending measures. In rows 6, we report the same estimates for the coefficients on interaction terms with equity. In most specifications, our results show that equity rich banks are not less likely to cut lending when rates increase. All in all, this analysis suggests that the income gap is a more relevant predictor of bank lending sensitivity to rates than the equity ratio.

One last useful exercise consists in comparing our cross-sectional estimate with numbers obtained on aggregate time series about the transmission of monetary policy shocks. The exercise cannot be exact as it amounts to comparing numbers obtained with different methodologies, but it is still helpful in order to assess the meaningfulness of the income gap channel that we highlight in this paper. We use Bernanke and Blinder (1992) as a benchmark. Using a VAR methodology, they find that, in response a 1 s.d. shock to Fed Funds rates, aggregate bank loans decrease by some 0.5% after 12 months. Our effect goes opposite to the aggregate transmission effect of monetary policy, as the average gap is positive. In our data, a one s.d. of change in Fed Funds rates equals 1.2%. The average income gap is 13% of total assets. The cumulative impact on total loans is 1.1 (Table 6, column 6). Thus, our long-term (12 months) response to a 1 s.d. shock to Fed Funds rates is equal to $1.1 \times .13 \times 1.2 = .2$ which is, in absolute value, nearly half of the aggregate response estimated by Bernanke and Blinder (1992). This exercise should be taken with a grain of salt, as our point estimate (1.1) fluctuates somewhat across specifications (it is actually much bigger when estimated on loan-level data). Taking our micro estimates to the macro also involves ignoring general equilibrium effects (expanding banks crowding out shrinking ones) which we should be taking into account. It however suggests that the income gap channel has the potential to be sizable and significantly dampening to the aggregate response of the economy to monetary policy shocks. Such dampening occurs because, in the data, the income gap is positive as discussed in Section 2.2.1.

3.5 Robustness

First, our definition of the income gap treats all core deposits as fixed-rate liabilities (see discussion in Section 2.2.1). This choice is justified from the abundant evidence from the banking literature documenting that deposits are sluggish, and respond little to interest rates. In unreported regressions, we re-estimate Equation (2)) using alternative definitions of the income gap that subtract 0, 25, 50, 75 and 100% of all non-interest bearing deposits. The coefficient estimates obtained with these alternative definitions are similar to our main estimates. This result is not surprising since non-interest bearing deposits are a relatively small fraction of total liabilities (about 12.6% of liabilities on average).

Second, we have re-estimated our regressions controlling for bank asset liquidity interacted with interest rates movements, in the spirit of Kashyap and Stein (2000). We do not have this control in our main specification because it restricts the sample to 1993-2013. Table 7 contains the regression results with the new controls. Despite the smaller sample size, the estimate of $\sum_{k=0}^{k=4} \alpha_k$ are similar to those obtained in our main analysis of Table 6. In our sample, asset liquidity does not significantly predict how BHCs' lending react to changes in interest rates. If anything, the estimated effects have the "wrong" economic sign: banks with more liquid assets tend to reduce their lending more when interest rates increase. The discrepancy with Kashyap and Stein (2000) originates from our use of BHC-level data instead of commercial bank data. As previously discussed, we focus on BHC data because they contain the income gap over a much longer period (1986-2013).

Third, in Appendix B, we use an alternative technique, also used in the literature, to estimate Equation (2). This estimation proceeds in two steps. First, each quarter t, we estimate the sensitivity of ΔY_{it} to the gap_{it-1} in the cross-section of banks. Then, we ask whether the time series of this slope coefficient is correlated with changes in interest rates. We show in Table B.1 that the estimates using this alternative method are very similar to the ones we discuss below.

Last, we exploit internal capital markets to somewhat alleviate the concern that borrowers are not randomly assigned to banks. We fully deal with this concern in the next Section, where we exploit loan-level data that allow us to control for demand shocks. But internal capital markets also allow us to test the robustness of our results. The intuition is the following: Commercial banks belonging to larger bank holding companies have two income gaps: their own as well as the one of the BHC. The income gap of the BHC is arguably more exogenous to the commercial bank. In Appendix C, we describe how we re-estimate a version of equation (2) at the commercial bank level, introducing both the income gap of the bank itself and the gap of its top holding BHC. The sample size is reduced because income gaps of commercial banks are only available from 1997 to 2013. We find, however, that while the CB level gap is insignificant in our regressions, the BHC level gap remains statistically significant. We also show that our effect is present in banking groups with at least 3 or even 5 subsidiaries.

4 Loan-Level Evidence

In this Section, we confirm and extend the results above on loan level data. This approach has two main advantages. First, it helps to control for the fact that banks may be non-randomly matched to borrowers. This would be a concern if, for instance, banks were choosing their income gap in response to the expected sensitivity of their borrowers to interest rates. Loan level data alleviate this reverse causality concern because we can control for firm level credit demand shocks, as in Khwaja and Mian (2008). The second advantage of using loan level data is that it allows us to investigate the real effects of credit supply shocks on firm investment and employment.

4.1 Testing for Sorting

In this Section, we first provide several pieces of evidence that banks' income gaps are orthogonal to borrower characteristics. Loan-level data allow us to do this because we can observe borrowers directly. The main concern here is that banks may choose their income gap to match the sensitivity of loan demand to interest rate, i.e. that high gap may be an endogenous response to the fact that customers borrow more when rates are high (Froot et al. (1993),Vickery (2006)).

We start with borrowers' *observable* characteristics. We use information on borrowers available from Dealscan –hence for the entire sample and not just the matched sample with Compustat. To directly test Vickery (2006)'s hypothesis, we use information from Dealscan on the entire sample of loans to compute the sensitivity (β) of total debt growth to interest rate changes in each zip code and SIC code (both at the 3 digits level)[8]. We also construct average characteristics at the bank level by directly averaging the characteristics of all its borrowers (weighted by loan shares): Sales, debt, age (i.e. number of years since the borrower enters Dealscan), public status and loan maturity. These determinants may be argued to be correlated with loan demand sensitivity to interest rates in a manner not fully captured by our β's. Table 8 displays the average of these bank-level covariates after splitting banks into four quantiles of income gap. We also report the

[8] We remove zip codes and industries with less than 10 borrowers

sample s.d. for comparison, as well as the p-value of the regression coefficient of each average borrower characteristic on the bank's gap. We find that no borrower characteristic is significantly related to the income gap.

Another test of this sorting hypothesis comes from comparing banks lending to the same firm. If high income gap banks were to lend to specific firms, one would find that that two banks lending to the same firm should have correlated gaps. We implement this intuition using two approaches. First, for firms with multiple lenders in the same year, we regress the income gap of the firm's largest lender on the income gap of the firm's *second* largest lender, as in Greenstone et al. (2015). Second, for firms issuing multiple loans sequentially, we regress the income gap of their *future* main lenders on the income gap of their current main lenders. None of these test allows us to reject the hypothesis that banks lending to the same firms have uncorrelated gap policies (see Table D.2).

4.2 Interest rate shocks and lending supply shocks

We now examine whether banks with high income gap increase more their lending when interest rates go up. The advantage of loan-level data is that we can include a borrower-year fixed effect in such a regression, thus controlling for borrower specific demand shocks as in Khwaja and Mian (2008). More precisely, we estimate the following linear model for bank i and firm j in year t:

$$\begin{aligned}\Delta L_{i\to j,t} =& \alpha(\text{gap}_{it-1} \times \Delta\text{fed funds}_t) + \sum_{x\in Control} \gamma_x(x_{it-1} \times \Delta\text{fed funds}_t) \\ &+\eta_k \Delta L_{i\to j,t-1} + \phi.\text{gap}_{it-1} + \sum_{x\in Control} \mu_x.x_{it-1} + \delta_{jt} + \epsilon_{it}\end{aligned} \tag{3}$$

where $L_{i\to j,t}$ denotes the outstanding loans from bank i to firm j. Compared to the baseline model (2), the unit of observation is a lender-borrower relationship. When a borrower-year fixed effect δ_{jt} is included, identification of α effectively comes from the differential lending response to interest rates of banks that lend to the same borrower. $\Delta L_{i\to j,t}$ is the symmetric bank-firm specific growth rate of loans described in Section 2.1.2, designed to account for relationship terminations and initiations and bounded by -2 and +2.

We report regression results in Table 9; We find slightly bigger estimates that in bank level data but the order of magnitude is similar. In Column (1), we first run this specification without borrower x year fixed effect. We find a coefficient of 5.3, very comparable to the aggregate lending effect shown in Table 6 of 1.7. Such similarity is reassuring given that we are using very different datasets for lending activity (BHC data in the previous section and Dealscan here). In Column (2), we restrict the sample to firms matched with multiple banks; These firms are the ones on which the specification with borrower-year fixed effect will be identified. We find no material change in the point estimate (4.9) and it remains significant at 5%. In Column (3), we add borrower $\times$ year fixed effects. The effect of income gap on lending growth does not lose significance, and keeps the same value (4.7) even though the inclusion of borrower fixed effects doubles the R^2 to more than 60%. The investigation of Table 9 suggests that controlling for credit demand shocks does not change our estimates, or put differently, that bank-firm matching is not endogenous to the problem at hand. This result is standard in the banking literature (Khwaja and Mian (2008); Jiménez et al. (2012); Iyer et al. (2014)) but it is comforting that it also applies in our set-up. It also allows us to move to the investigation of real effects.

4.3 Real Effects

We test here whether firms matched to banks with, say, high income gap, tend to be able to invest and grow more when interest rates are high. The idea behind this test is that bank-firm relationships are sticky, and that it is difficult for a firm which faces a reduction in lending to quickly find alternative sources of finance. This would lead the firm to potentially scale down total borrowing, and therefore investment and employment.

To examine this question, we estimate the following linear model for firm j in year t:

$$\begin{aligned}\Delta \log Y_{jt} =& \sum_{k=0}^{k=1} \alpha(\text{gap}_{it-1} \times \Delta\text{fed funds}_{t-k}) \\ &+ \sum_{k=0}^{k=1} \sum_{x \in BankControl} \gamma_{kx}(x_{it-1} \times \Delta\text{fed funds}_{t-k}) + \sum_{x \in BankControl} \mu_x . x_{it-1} \\ &+ \sum_{x \in FirmControl} \mu_{xt} x_{jt-1} + \phi.\text{gap}_{jt-1} + \sum_{k=0}^{k=1} \eta \Delta Y_{jt-k-1} + \delta_t + \epsilon_{it}\end{aligned} \tag{4}$$

The dependent variables are alternatively the firm debt growth, employment growth and total asset growth described in Section 2.1.2. In these regressions, gap_{it-1} is the income gap of the firm's lead arranger. The idea is that the banking relationship is mostly built on information exchange between the borrower and the lead arranger. We also need to restrict ourselves to firms for which accounting information is available in Compustat. We only keep firm-year observations with a fiscal year ending in December, so that their balance sheet data match the reporting period of banks. We show in Table D.3 that our main loan-level results do not change when we focus on the subsample of Compustat-matched firms.

In terms of identification, our analysis of real effects requires that we work at the firm level, which prevents us from incorporating firm-year dummies as in the previous loan level analysis. The identification strategy here thus relies on the assumption that banks with higher income gap do not sort into firms with different sensitivity to interest rates. This hypothesis is supported by the loan-level evidence of Section 4.1, where we established that controlling for borrower-year fixed effect did not affect lending response to income gap. Still, we include several borrower controls available in Compustat that may determine firm decisions : four size bin dummies (based on quartiles of assets in previous years), four-digit SIC code dummies and state dummies, all interacted with year dummies. Finally, errors are two-way clustered by firm and bank.

Results are presented in Table 10 for total debt, total assets and employment. For each variable we experiment specifications with firm- and bank-level controls interacted with the full set of year dummies. Columns 1-3 use total financial debt as the Y variable. We obtain an annual effect 2.9, very similar in magnitude to the measured effect on individual loans from Table 9 –which was 4.7. Such evidence is indicative that very little substitution, if any, is going on between potential lenders. This is in line with the existing banking literature (e.g. Khwaja and Mian (2008) or Iyer et al. (2014)). We then move to "real variables": Columns 4-9 indicate that total assets or employment have an elasticity of about 1/2 to the change in debt induced by the interest rate exposure of lenders. The effects on employment and total assets are of similar sizes, indicative of a roughly constant capital to labor ratio. Results also suggest that the progressive inclusion of lender and borrower controls does not affect the point estimate too much. Comparing firms in the top (.3) and bottom quartile (.15) of effective income gap, and assuming an annual increase in short rates by 100bp, we would expect a differential response in asset growth by some .2 percentage points, and a differential employment growth by some .3 percentage points. In Appendix Table D.4, we replicate this analysis on quarterly data, using debt and assets from Compustat quarterly (unfortunately employment is not available in quarterly accounts). We find similar estimates.

To conclude this Section, we discuss whether our micro estimates have the power to matter at the aggregate level. To implement this exercise, we ignore general equilibrium effects and directly extrapolate our micro number to the entire economy (GE effects would spontaneously dampen the aggregate impact of our micro estimate). We then make the assumption that the average firm faces a bank income gap of 18%, which corresponds to the average in our sample. Last, we take the most saturated estimates of columns 3,6, and 9. Let us now assume a one standard deviation increase in interest rates (in these annual data, over 1986-2013, the volatility of the Fed Funds rate is 1.6%). Compared to the average bank, our loan-level estimates of the income gap effect suggest that aggregate firm borrowing would decrease by $2.9 \times .18 \times 1.6\% = .8\%$. This number may be compared with the volatility of aggregate bank credit growth, which is equal to 4.6% during the 1986-2013 period (Source: Federal Reserve). Similarly, we estimate the response of total assets and employment to a 1 s.d. shock to short rates to be equal to respectively .4% and .6%. Again we can compare this to the s.d. of aggregate capital growth rate and employment growths which are both around 2% (computations made using BLS and BEA data). Overall, the real effects induced by the income gap channel of monetary policy are sizable and have the power to significantly contribute to the transmission of monetary policy. Given that the average gap is positive, they go in the direction of dampening the macro effect of changes in interest rates.

5 Discussion

5.1 Credit Multiplier

This Section uses interest rate shocks to identify the credit multiplier of banks in our sample. We estimate equation (2) using as a dependent variable the quarterly *increase* in the \$ amount of loans normalized by lagged assets, instead of the change on log loans. This scaling by assets allows us to directly interpret the sum of the interacted coefficients $\sum_{k=0}^{k=4} \alpha_k$ as the \$ impact on lending of a \$1 increase in the interest-sensitive income, i.e. gap $\times\ \Delta r$. $\sum_{k=0}^{k=4} \alpha_k$ is estimated at .81 and is significantly different from 0 at the 1% confidence level. Thus, a \$1 increase in gap $\times\ \Delta r$ leads to an increase of lending by \$.81. At the same time, Table 4 shows that the same \$1 increase in gap $\times\ \Delta r$ generates an increase in total earnings of about \$0.07. Assuming that the sensitivity of lending to interest rates comes only through this income shock, these estimates imply a credit multiplier of 0.81/0.07=11.5: a \$1 increase in income leads to an increase in lending by \$11.5.

This credit multiplier is slightly lower than what bank leverage suggests: In our sample, the average asset-to-equity ratio is 13.1. Given that net income also represents additional reserves, the credit multiplier we obtain is consistent with existing reserve requirements in the US, which are around 10 for large banks. These estimates do, however, need to be taken with caution since lending may be affected by gap $\times\ \Delta r$ through channels other than net income, as we discuss in the next section.

5.2 Short vs Long Rates: Cash flow vs Collateral Channel

An alternative interpretation of our results is that the income gap is a noisy measure of the duration gap. The duration gap measures the difference of interest rate sensitivity between the *value* of assets and the *value* of liabilities (Mishkin and Eakins (2009)). Changes in interest rates may therefore affect the value of a bank's equity. Changes in the value of equity may in turn have an impact on how much future income a bank can pledge to its investors. For a bank with a positive duration gap, an increase in interest rates raises the value of equity and therefore its debt capacity: it can lend more. This alternative channel also relies on a failure of the Modigliani-Miller theorem for banks, but it goes through bank value instead of banks net income. This is akin to a balance sheet channel, à la Bernanke and Gertler (1989), but for banks.

Directly measuring the duration gap is difficult as it essentially relies on strong assumptions about the duration of assets and liabilities. Instead, to distinguish income effects and balance sheet effects, we exploit the fact that the effect of interest rates on bank value partly comes from long-term rates. To see this, notice that the present value at t of a safe cash-flow C at time $t+T$ is $\frac{C}{(1+r_{t,T})^T}$, where $r_{t,T}$ is the risk-free yield between t and $t+T$. Thus, as long as there are shocks to long-term yields that are not proportional to shocks to short-term yields, we can identify a balance sheet channel separately from an income channel. Consider for instance an increase in long-term rates, keeping short-term rates constant. If our income gap measure affects lending through shocks to asset values, we should observe empirically that firms with lower income gap lend relatively less following this long-term interest rates increase. By contrast, if our income gap measure affects lending only through contemporaneous or short-term changes in income, such long-term rate shock should not impact differently the lending of high vs. low income gap banks.

We implement this test in Table 11. We add to our benchmark equation (2) interaction terms between the income gap – as a proxy for the duration gap – and five lags of changes in long term interest rates, measured as the yield on 10 years treasuries. The coefficients on these interaction terms are reported in the lower part of the top panel of Table 11. In the bottom panel, we report the sum of these coefficients (the cumulative impact of interest rates) as well as their p-value. We use as dependent variables interest income (Column (1)), market value of equity (Column (2)), C&I lending growth (Column (3)) and total lending growth (Column (4)).

We find no evidence that long term interest rates affect BHCs' cash flows, value or lending. If anything, the cumulative effect goes in the opposite direction to what would be expected if the income gap was a proxy for the duration gap. Additionally, estimates of the income gap effect on BHCs lending sensitivity to interest rates are unaffected by the inclusion of the long rate interaction terms. This test suggests that monetary policy affects bank lending via income gap induced income shocks much more than through shocks to the relative value of banks' assets and liabilities. However, it is important to emphasize that the power of test is limited by the fact that we do not directly measure the duration gap.

6 Conclusion

This paper shows that banks retain significant exposure to interest rate risk. Our sample consists of quarterly data on US bank holding companies from 1986 to 2013. We measure a bank's income exposure to interest rates through its income gap, defined as the difference between assets and liabilities that mature in less than one year. The average income gap in our sample is 12.6% of total assets (28% in asset-weighted terms), but it exhibits significant cross-sectional variation. The income gap strongly predicts how banks' profits respond to changes in interest rates.

We also find that banks exposure to interest rate risk has implications for the transmission of monetary policy. An increase in the short rate directly affects banks' incomes through their income gap and, in the presence of credit frictions, their lending policy. We are able to confirm these results on loan level data, and are even able to trace the impact of these shocks on actual firm growth: Firms that are linked with high gap banks tend to grow faster (in terms of assets and employment) when interest rates go up. Given that the average gap is positive, the income gap effect tends to dampen the recesionnary effect of monetary policy on bank lending and the real economy. The income gap has a significant explanatory power on the sensitivity of lending to changes in interest rates, larger or similar in magnitudes than previously identified factors, such as leverage, bank size or even asset liquidity. Finally, we report evidence consistent with the hypothesis that our main channel is an income effect, as opposed to a collateral channel. Interest rates affect lending because they affect banks' net income, not because they affect the market value of equity.

Our results suggest that the allocation of interest rate exposure across agents (banks, households, firms, government) is an important variable to understand how an economy responds to monetary policy. In particular, the distribution of interest rate risk across agents is crucial to analyze the redistributive effects of monetary policy and thus to trace the roots of the transmission of monetary policy.

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Tables

Table 1: Summary Statistics: Dependent and Control Variables

	mean	sd	p25	p75	count
Net interest income / assets	0.009	0.004	0.008	0.010	47394
Non interest income / assets	0.004	0.011	0.002	0.004	47419
Earnings / assets	0.002	0.005	0.002	0.003	47419
Market value of equity / assets	0.152	0.193	0.092	0.183	23243
Δ Interest	0.000	0.001	-0.000	0.000	44161
Δ Non-interest	0.000	0.001	-0.000	0.000	42858
Δ Earnings	0.000	0.001	-0.000	0.000	42805
Δ Market Value	0.005	0.023	-0.007	0.015	22104
Δ log(C&I loans)	0.015	0.090	-0.028	0.055	44631
Δ log(total loans)	0.017	0.046	-0.006	0.037	45185
Log of assets	15.033	1.403	14.009	15.665	47427
Equity to assets ratio	0.090	0.045	0.070	0.100	47427
Fraction Liquid assets	0.225	0.124	0.141	0.287	35205
Mean local % ARM	0.220	0.086	0.164	0.234	47427
Local $\beta_{\text{Debt / Int. rate}}$	6.434	1.021	6.015	6.691	47427

Note: Summary statistics are based on the quarterly Consolidated Financial Statements (Files FR Y-9C) between 1986 and 2013 restricted to US bank holding companies with total consolidated assets of $1Bil or more in 2010 dollars. All variables are quarterly.

Table 2: Income Gap and Its Components

	mean	sd	p25	p75	count
Income Gap =	0.126	0.187	0.012	0.243	47043
Assets maturing/resetting < 1 year	0.426	0.152	0.325	0.525	47424
- Liabilities maturing/resetting < 1 year =	0.299	0.157	0.191	0.384	47043
Short Term Liabilities	0.288	0.157	0.180	0.374	47420
+ Variable Rate Long Term Debt	0.010	0.027	0.000	0.008	47253
+ Short Maturity Long Term Debt	0.001	0.005	0.000	0.000	47207
+ Prefered Stock	0.000	0.002	0.000	0.000	47063

Note: Summary statistics are based on the quarterly Consolidated Financial Statements (Files FR Y-9C) between 1986 and 2013 restricted to US bank holding companies with total consolidated assets of $1Bil or more in 2010 dollars. The variables are all scaled by total consolidated assets (bhck2170) and are defined as follows: Interest Sensitive Liabilities =(bhck3296+bhck3298+bhck3409+bhck3408)/bhck2170; Interest Sensitive Assets=(bhck3197)/bhck2170; Short Term Liabilities=bhck3296/bhck2170; Variable Rate Long Term Debt=bhck3298/bhck2170; Short Maturity Long Term Debt=bhck3409/bhck2170; Prefered Stock=bhck3408/bhck2170

Table 3: Summary Statistics: Derivatives Hedges of Interest Rate Risk

	mean	sd	p25	p75	count
Futures	0.023	0.156	0.000	0.000	33127
Forward Contracts	0.040	0.296	0.000	0.002	33146
Written Options (Exchange Traded)	0.008	0.069	0.000	0.000	33112
Purchased Options (Exchange Traded)	0.010	0.086	0.000	0.000	33110
Written Options (OTC)	0.029	0.193	0.000	0.003	33139
Purchased Options (OTC)	0.028	0.185	0.000	0.000	33161
Swaps	0.177	1.499	0.000	0.034	46689
At least some I.R. hedging	0.586	0.493	0.000	1.000	33107

Note: Summary statistics are based on Schedule HC-L of the quarterly Consolidated Financial Statements (Files FR Y-9C) between 1995 and 2013 restricted to US bank holding companies with total consolidated assets of $1Bil or more in 2010 dollars. Schedule HC-L is not available prior to 1995. The variables report notional amounts in each kind of derivatives at the bank holding-quarter level and are all scaled by total consolidated assets (bhck2170). Variables are defined as follows: Futures contracts = bhck8693/bhck2170; Forward contracts = bhck8697/bhck2170; Written options (exchange traded) = bhck8701/bhck2170; Purchased options (exchange traded) = bhck8705/bhck2170; written options (OTC) = bhck8709/bhck2170; Purchased options (OTC) = bhck8713/bhck2170; Swaps=bhck3450/bhck2170. HEDGED is a dummy equal to one if a bank has a positive notional amount in any of the seven types of interest hedging derivatives in a given quarter.

Table 4: Income Gap, Interest rates, and Interest Income

	ΔInterest$_{it}$					ΔNon Interest Income$_{it}$				
	All	Small	Large	No Hedge	Some Hedge	All	Small	Large	No Hedge	Some Hedge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Gap_{it-1} \times \Delta FedFunds_t$	.019***	.019***	.018	.033***	.02**	-.0017	-.0019	.00072	-.0096	.0067
	(3.4)	(3.1)	(1.5)	(3.5)	(2.2)	(-.38)	(-.38)	(.074)	(-1.4)	(.66)
$Gap_{it-1} \times \Delta FedFunds_{t-1}$	.038***	.038***	.041***	.035***	.044***	-.0044	-.0047	.0018	-.0025	.0044
	(6.7)	(6.2)	(3.1)	(3.9)	(4.5)	(-.98)	(-.96)	(.17)	(-.33)	(.49)
$Gap_{it-1} \times \Delta FedFunds_{t-2}$	.0035	.0057	-.012	.0074	.00079	-.0026	-.0017	-.011	.0013	-.0059
	(.8)	(1.3)	(-.87)	(1)	(.12)	(-.61)	(-.37)	(-.85)	(.18)	(-.7)
$Gap_{it-1} \times \Delta FedFunds_{t-3}$	.0072	.0051	.024*	-.0038	.014**	.011**	.012**	.005	.0032	.012
	(1.6)	(1.1)	(1.8)	(-.48)	(2.2)	(2.4)	(2.5)	(.5)	(.42)	(1.4)
$Gap_{it-1} \times \Delta FedFunds_{t-4}$	-.006	-.0059	-.00072	-.00088	-.021***	-.0013	-.0043	.016	.0093	-.0044
	(-1.4)	(-1.3)	(-.05)	(-.13)	(-3.1)	(-.37)	(-1.1)	(1.5)	(1.4)	(-.55)
Observations	37888	34041	3847	11622	16549	35253	31582	3671	11165	14349
R^2	.11	.11	.16	.14	.099	.16	.16	.21	.18	.16
Sum of gap coefficients	.06	.06	.06	.07	.05	0	0	.01	0	.01
p-value of gap coefficients	0	0	0	0	0	.88	.86	.2	.75	.19
p-value of equality test	.	.58		.32		.	.21		.32	
Sum of size coefficients	0	0	-.16	0	0	0	0	0	0	0
p-value of size coefficients	0	0	.01	.35	0	0	0	.87	0	0
Sum of equity coefficients	.03	.03	.05	.02	.07	-.04	-.06	.14	-.02	-.01
p-value of equity coefficients	.24	.28	.72	.61	.02	.2	.05	.22	.56	.75

Note: This table estimates:

$$\Delta Y_{it} = \sum_{k=0}^{k=4} \alpha_k (\text{gap}_{it-1} \times \Delta \text{fed funds}_{t-k}) + \sum_{x \in Control} \sum_{k=0}^{k=4} \gamma_{x,k} (x_{it-1} \times \Delta \text{fed funds}_{t-k}) + \sum_{k=0}^{k=4} \eta_k \Delta Y_{it-1-k} + \phi . \text{gap}_{it-1} + \sum_{x \in Control} \mu_x . x_{it-1} + \delta_t + \epsilon_{it}$$

ΔY is the quarterly change in interest income divided by lagged total assets (Interest$_{it}$-Interest$_{it-1}$)/(Assets$_{it-1}$) in Columns (1)-(5) and change in *non* interest income normalized by lagged assets in Columns (6)-(10). Columns (1) and (6) report estimates for the entire sample. Columns (2)-(3) and (6)-(7) break down the sample into small and large banks. Columns (4)-(5) and (9)-(10) break down the sample into banks reporting some positive notional exposure to interest rate derivatives and banks with no such exposure. The controls are $log(assets_{it-1})$, book equity$_{it-1}$/assets$_{it-1}$, Local $\beta_{\text{Debt / Int. rate,}}$ Local % ARM_{1988}. s quarter fixed effects. Standard errors are clustered at the BHC level. "Sum of gap coefficients" report the coefficient estimate for $\sum_{k=0}^{k=4} \alpha_k$. We also report the p-value of a test of significance for $\sum_{k=0}^{k=4} \alpha_k$, as well as a test of equality of these sums across subsamples (large vs small banks, hedged vs unhedged banks). These equality tests use the SURE procedure to nest the two equations in a single model.

Table 5: Income Gap and Interest rates: Earnings and Market Value

	$\Delta Earnings_{it}$					$\Delta MarketValue_{it}$				
	All	Small	Big	No Hedge	Some Hedge	All	Small	Big	No Hedge	Some Hedge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Gap_{it-1} \times \Delta FedFunds_t$	.029***	.031***	.022	.03**	.038**	.5*	.47*	.71	.81**	.78*
	(3.7)	(3.6)	(1.1)	(2.2)	(2.4)	(1.9)	(1.7)	(.97)	(2.2)	(1.8)
$Gap_{it-1} \times \Delta FedFunds_{t-1}$	.03***	.033***	.0025	.059***	.029*	.65**	.72***	-.26	1.1**	.71
	(3.4)	(3.4)	(.12)	(3.5)	(1.9)	(2.5)	(2.7)	(-.28)	(2.5)	(1.6)
$Gap_{it-1} \times \Delta FedFunds_{t-2}$	.0057	.0019	.035	-.01	.021	.15	.16	.78	.42	.022
	(.69)	(.22)	(1.5)	(-.66)	(1.5)	(.56)	(.57)	(.86)	(.97)	(.048)
$Gap_{it-1} \times \Delta FedFunds_{t-3}$	.0051	.003	.0087	.015	-.0014	.2	.28	-1.1	-.63	.72**
	(.7)	(.38)	(.49)	(.97)	(-.1)	(.86)	(1.2)	(-1.4)	(-1.6)	(2.1)
$Gap_{it-1} \times \Delta FedFunds_{t-4}$	.0055	.0054	.019	.0061	-.011	.11	.074	.79	.6	-.51
	(.76)	(.7)	(1.2)	(.45)	(-.78)	(.51)	(.32)	(1.2)	(1.2)	(-1.5)
Observations	35625	31997	3628	11094	15228	19498	18186	1312	6160	9804
R^2	.22	.22	.27	.24	.22	.32	.33	.29	.32	.35
Sum of gap coefficients	.07	.07	.08	.09	.07	1.6	1.7	.9	2.3	1.7
p-value of gap coefficients	0	0	0	0	0	0	0	.22	0	0
p-value of equality test	.	.55		.27		.	.28		.39	
Sum of size coefficients	0	0	-.06	0	0	.04	.03	-3.4	.02	.08
p-value of size coefficients	0	0	.46	.82	.04	.05	.12	.19	.8	.01
Sum of equity coefficients	.13	.14	-.11	-.07	.24	3.1	2.7	6.6	5.5	1.9
p-value of equity coefficients	.2	.16	.61	.46	.22	.23	.32	.3	.29	.51

Note: This table estimates:

$$\Delta Y_{it} = \sum_{k=0}^{k=4} \alpha_k (\text{gap}_{it-1} \times \Delta \text{fed funds}_{t-k}) + \sum_{x \in Control} \sum_{k=0}^{k=4} \gamma_{x,k} (x_{it-1} \times \Delta \text{fed funds}_{t-k}) + \sum_{k=0}^{k=4} \eta_k \Delta Y_{it-1-k} + \phi . \text{gap}_{it-1} + \sum_{x \in Control} \mu_x . x_{it-1} + \delta_t + \epsilon_{it}$$

ΔY is the quarterly change in Earnings divided by lagged total assets (Earnings_{it}-Earnings_{it-1})/(Assets_{it-1}) in Columns (1)-(5) and change in market value of equity normalized by lagged assets in Columns (6)-(10). Columns (1) and (6) report estimates for the entire sample. Columns (2)-(3) and (6)-(7) break down the sample into small and large banks. Columns (4)-(5) and (9)-(10) break down the sample into banks reporting some positive notional exposure to interest rate derivatives and banks with no such exposure. The controls are $log(assets_{it-1})$, book $\text{equity}_{it-1}/\text{assets}_{it-1}$, Local $\beta_{\text{Debt / Int. rate,}}$ Local % ARM_{1988}. The regression also includes quarter fixed effects. Standard errors are clustered at the BHC level. "Sum of gap coefficients" report the coefficient estimate for $\sum_{k=0}^{k=4} \alpha_k$. We also report the p-value of a test of significance for $\sum_{k=0}^{k=4} \alpha_k$, as well as a test of equality of these sums across subsamples (large vs small banks, hedged vs unhedged banks). These equality tests use the SURE procedure to nest the two equations in a single model.

Table 6: Income Gap, Interest Rates and Lending

	Δlog(C&I)					Δlog(Total Loans)				
	All	Small	Big	No Hedge	Some Hedge	All	Small	Big	No Hedge	Some Hedge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Gap_{it-1} \times \Delta FedFunds_t$	-.27	-.023	-1.5	-.21	-.68	-.35	-.5	.76	-.23	-.15
	(-.44)	(-.035)	(-.81)	(-.2)	(-.68)	(-1)	(-1.4)	(.74)	(-.45)	(-.28)
$Gap_{it-1} \times \Delta FedFunds_{t-1}$	.65	.77	-.73	.53	1.6	.22	.51	-2.2**	1**	.019
	(.97)	(1.1)	(-.32)	(.47)	(1.4)	(.68)	(1.5)	(-2.1)	(2)	(.036)
$Gap_{it-1} \times \Delta FedFunds_{t-2}$	.9	1.5**	-3.2	-.19	.69	.75**	.77**	.93	.43	.47
	(1.3)	(2.1)	(-1.3)	(-.14)	(.71)	(2.4)	(2.3)	(1.1)	(.94)	(.82)
$Gap_{it-1} \times \Delta FedFunds_{t-3}$	1.7***	1.6**	2.9	3.5**	1.7*	.58*	.57*	.65	.91*	.49
	(2.6)	(2.3)	(1.2)	(2.4)	(1.9)	(1.8)	(1.7)	(.7)	(2)	(.94)
$Gap_{it-1} \times \Delta FedFunds_{t-4}$	-1.3**	-1.5**	1.4	-1.2	-2.6***	-.044	-.12	.66	-.4	.065
	(-2.1)	(-2.4)	(.61)	(-1)	(-2.8)	(-.14)	(-.38)	(.77)	(-.93)	(.14)
Observations	39158	35240	3918	11922	16848	38848	34927	3921	11805	16506
R^2	.095	.099	.1	.081	.12	.22	.22	.27	.25	.22
Sum of gap coefficients	1.7	2.2	-1.2	2.4	.69	1.1	1.2	.8	1.7	.89
p-value of gap coefficients	.01	0	.59	.04	.5	0	0	.49	0	.11
p-value of equality test	.	.14		.28		.	.72		.29	
Sum of size coefficients	.21	.22	-11	.13	.25	.01	-.01	-8	-.07	.07
p-value of size coefficients	0	0	.26	.75	.03	.71	.78	.11	.68	.27
Sum of equity coefficients	-9.8	-9.8	1.4	4.9	-20	-3.7	-4	-.61	-1.9	-8.1
p-value of equity coefficients	.12	.14	.94	.56	0	.35	.32	.95	.42	.06

Note: This table estimates:

$$\Delta Y_{it} = \sum_{k=0}^{k=4} \alpha_k(\text{gap}_{it-1} \times \Delta\text{fed funds}_{t-k}) + \sum_{x \in Control} \sum_{k=0}^{k=4} \gamma_{x,k}(x_{it-1} \times \Delta\text{fed funds}_{t-k}) + \sum_{k=0}^{k=4} \eta_k \Delta Y_{it-1-k} + \phi.\text{gap}_{it-1} + \sum_{x \in Control} \mu_x.x_{it-1} + \delta_t + \epsilon_{it}$$

ΔY is the quarterly change in log C&I lending divided by lagged total assets in Columns (1)-(5) and quarterly change in log total lending normalized by lagged assets in Columns (6)-(10). Columns (1) and (6) report estimates for the entire sample. Columns (2)-(3) and (6)-(7) break down the sample into small and large banks. Columns (4)-(5) and (9)-(10) break down the sample into banks reporting some positive notional exposure to interest rate derivatives and banks with no such exposure. The controls are $log(assets_{it-1})$, book $\text{equity}_{it-1}/\text{assets}_{it-1}$, Local $\beta_{\text{Debt / Int. rate}}$, Local % ARM_{1988}. The regression also includes quarter fixed effects. Standard errors are clustered at the BHC level. "Sum of gap coefficients" report the coefficient estimate for $\sum_{k=0}^{k=4} \alpha_k$. We also report the p-value of a test of significance for $\sum_{k=0}^{k=4} \alpha_k$, as well as a test of equality of these sums across subsamples (large vs small banks, hedged vs unhedged banks). These equality tests use the SURE procedure to nest the two equations in a single model.

Table 7: Robustness: Controlling for Liquidity

	Δlog(C&I)					Δlog(Total Loans)				
	All	Small	Big	No Hedge	Some Hedge	All	Small	Big	No Hedge	Some Hedge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Gap_{it-1} \times \Delta FedFunds_t$	.039	.23	-.52	.43	-.74	.014	-.17	1.3	.16	.015
	(.055)	(.3)	(-.27)	(.4)	(-.73)	(.038)	(-.43)	(1.2)	(.31)	(.027)
$Gap_{it-1} \times \Delta FedFunds_{t-1}$	.55	.78	-1.6	-.2	1.6	.13	.46	-2.5**	.65	.056
	(.71)	(.95)	(-.71)	(-.18)	(1.4)	(.35)	(1.2)	(-2.5)	(1.3)	(.11)
$Gap_{it-1} \times \Delta FedFunds_{t-2}$	.64	1.2	-3.3	.26	.41	.69*	.67	1.5*	.43	.34
	(.81)	(1.5)	(-1.3)	(.2)	(.41)	(1.9)	(1.6)	(1.7)	(.94)	(.6)
$Gap_{it-1} \times \Delta FedFunds_{t-3}$	2.6***	2.5***	3.1	3**	1.7**	.45	.54	-.26	.61	.32
	(3.3)	(3)	(1.2)	(2.1)	(2)	(1.3)	(1.4)	(-.27)	(1.3)	(.61)
$Gap_{it-1} \times \Delta FedFunds_{t-4}$	-2***	-2.5***	1.8	-1.2	-2.6***	-.066	-.21	.89	-.14	.15
	(-2.7)	(-3.2)	(.89)	(-.92)	(-2.7)	(-.21)	(-.62)	(.95)	(-.3)	(.33)
Observations	30466	27377	3089	11921	16845	30006	26968	3038	11804	16503
R^2	.092	.098	.11	.082	.12	.22	.22	.31	.25	.22
Sum of gap coefficients	1.8	2.3	-.58	2.3	.42	1.2	1.3	.81	1.7	.88
p-value of gap coefficients	.01	0	.81	.05	.68	0	0	.54	0	.12
p-value of equality test	.	.27		.24		.	.72		.3	
Sum of size coefficients	.37	.38	-6.6	.12	.22	.05	.03	-5.8	-.06	.05
p-value of size coefficients	0	0	.57	.76	.05	.25	.46	.32	.68	.35
Sum of equity coefficients	-9	-9.4	14	5.3	-20	-1.5	-1.9	2.2	-1.8	-8.1
p-value of equity coefficients	.22	.21	.42	.53	0	.69	.62	.82	.47	.05
Sum of liquidity coefficients	-1.3	-2.1	1.3	-.24	-3	-.69	-.69	-2.2	-.43	-.89
p-value of liquidity coefficients	.31	.11	.76	.89	.14	.3	.33	.19	.67	.35

Note: This table estimates:

$$\Delta Y_{it} = \sum_{k=0}^{k=4} \alpha_k(\text{gap}_{it-1} \times \Delta\text{fed funds}_{t-k}) + \sum_{x \in Control} \sum_{k=0}^{k=4} \gamma_{x,k}(x_{it-1} \times \Delta\text{fed funds}_{t-k}) + \sum_{k=0}^{k=4} \eta_k \Delta Y_{it-1-k} + \phi.\text{gap}_{it-1} + \sum_{x \in Control} \mu_x.x_{it-1} + \delta_t + \epsilon_{it}$$

ΔY is the quarterly change in log C&I lending divided by lagged total assets in Columns (1)-(5) and quarterly change in log total lending normalized by lagged assets in Columns (6)-(10). Columns (1) and (6) report estimates for the entire sample. Columns (2)-(3) and (6)-(7) break down the sample into small and large banks. Columns (4)-(5) and (9)-(10) break down the sample into banks reporting some positive notional exposure to interest rate derivatives and banks with no such exposure. The controls are $log(assets_{it-1})$, book $\text{equity}_{it-1}/\text{assets}_{it-1}$, Local $\beta_{\text{Debt / Int. rate}}$, Local % ARM_{1988} and liquid assets $_{it-1}/\text{assets}_{it-1}$. The regression also includes quarter fixed effects. Standard errors are clustered at the BHC level. "Sum of gap coefficients" report the coefficient estimate for $\sum_{k=0}^{k=4} \alpha_k$. We also report the p-value of a test of significance for $\sum_{k=0}^{k=4} \alpha_k$, as well as a test of equality of these sums across subsamples (large vs small banks, hedged vs unhedged banks). These equality tests use the SURE procedure to nest the two equations in a single model.

Table 8: Testing for Sorting along Observable Characteristics

	Income Gap Quartile				Overall	
	1	2	3	4	std. dev.	p-value
Income Gap	-.0221	.0844	.186	.339	.146	
SIC code $\beta_{\text{Debt / Int. rate}}$	5.39	5.38	5.41	5.51	1.69	.247
Zipcode $\beta_{\text{Debt / Int. rate}}$	5.07	4.84	4.89	4.49	2.69	.318
Share public	.54	.559	.6	.592	.187	.168
Sales at close (millions)	6,800	8,771	8,693	9,025	10,120	.692
Total Debt (millions)	1,376	1,819	1,933	1,909	1,483	.594
Loan maturity (months)	45.9	47.6	46.4	45.1	12.7	.105
Age	6.48	6.82	7.16	7.37	2.2	.0868

Note: We construct average characteristics at the bank level by averaging the characteristicis of all its borrowers (weighted by loan shares) for each bank-year observation of our loan level data. The table displays the average of these bank-level covariates after splitting banks into four quantiles of income gap. All variables are demeaned with respect to year. The fifth column reports the standard deviation of the variable summarized in each row. The sixth column reports the p-value for the regression of the row variable on the income gap. Standard errors are clustered at the bank level.

Table 9: The Impact of Income Gap on Lending Within Borrowers

	$\Delta L_{i\to j,t}$		
	All Firms	Firms with Multiple Banks	
	(1)	(2)	(3)
$Gap_{it-1} \times \Delta FedFunds_t$	5.3**	4.9**	4.7**
	(2.4)	(2.2)	(2.3)
Observations	290167	273502	273502
Borrowers	11174	8378	8378
Lenders	287	287	287
BHC top-holders	130	130	130
FE	Year	Year	Firm $\times$ Year
R^2	.27	.28	.61

Note: This table estimates:

$$\begin{aligned}\Delta L_{i\to j,t} =& \alpha(\text{gap}_{it} \times \Delta\text{fed funds}_t) + \sum_{x\in Control} \gamma_x(x_{it-1} \times \Delta\text{fed funds}_t) \\ &+ \eta \Delta L_{i\to j,t-1} + \phi.\text{gap}_{it} + \sum_{x\in Control} \mu_x.x_{it-1} + \delta_{jt} + \epsilon_{it}\end{aligned}$$

$\Delta L_{i\to j,t}$ is the change in loans outstanding from bank i to firm j normalized by the across period average. The controls are $log(assets_{it-1})$, book equity$_{it-1}$/assets$_{it-1}$, included directly, but also interacted with the full set of year dummies. The first colum includes all firms. The second colums only includes firms matched with multiple banks. The third columns adds borrower-year fixed effects. Standard errors are clustered at the bank level.

Table 10: The Effect of Income Gap on Borrowers Decisions

	Δ Debt			Δ Employment			Δ Assets		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Gap_{it-1} \times \Delta FedFunds_t$	4.7**	5.1***	2.9**	2.4***	2.2***	2.2***	2.9***	2.7***	1.2**
	(2.4)	(2.8)	(2.4)	(3.9)	(3.8)	(5.6)	(3)	(3.1)	(2)
Lender controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Borrower Controls	No	No	Yes	No	No	Yes	No	No	Yes
Observations	37511	37511	37511	37511	37511	37511	37511	37511	37511
Borrowers	3417	3417	3417	3417	3417	3417	3417	3417	3417
Lenders	104	104	104	104	104	104	104	104	104
$E[\Delta$ dep. variable]	.063	.063	.063	.018	.018	.018	.064	.064	.064
R^2	.031	.031	.4	.078	.078	.44	.094	.094	.46

Note: This table estimates for a firm i in year t with lead arranger b:

$$\begin{aligned}\Delta Y_{it} =& \alpha(\text{gap}_{bt-1} \times \Delta\text{fed funds}_t) + \phi.\text{gap}_{bt-1} \\ &+ \sum_{x \in BankControl} \gamma_x(x_{bt-1} \times \Delta\text{fed funds}_t) + \sum_{x \in BankControl} \mu_x.x_{bt-1} \\ &+ \sum_{x \in FirmControl} \mu_{xt} x_{it-1} + \eta \Delta Y_{it-1} + \delta_t + \epsilon_{it}\end{aligned} \tag{5}$$

ΔY is alternatively the annual change in total debt (Column (1) (2) (3)), annual change in employment (Column (4) (5) (6)) and annual change in investment (Column (7) (8) (9)). The lender controls are $log(assets_{it-1})$ and book equity$_{it-1}$/assets$_{it-1}$, included directly but also interacted with the full set of year dummies. The borrower controls are four size bin dummies, state dummies and four-digit SIC code dummies, all interacted with year dummies. Standard errors are two-way clustered at the firm and bank level.

Table 11: Short vs. Long-Term Rates

	ΔInterest Income	ΔMarket Value	Δlog(C&I)	Δlog(Total Loans)
	(1)	(2)	(3)	(4)
$Gap_{it-1} \times \Delta FedFunds_t$	.022***	.38	.057	.37
	(3.4)	(1.3)	(.077)	(.98)
$Gap_{it-1} \times \Delta FedFunds_{t-1}$	.039***	.77***	.029	.12
	(6.5)	(2.7)	(.039)	(.36)
$Gap_{it-1} \times \Delta FedFunds_{t-2}$	-.00075	.38	.59	.56
	(-.16)	(1.3)	(.75)	(1.5)
$Gap_{it-1} \times \Delta FedFunds_{t-3}$	.0048	.3	2.2***	.48
	(.97)	(1.1)	(3)	(1.4)
$Gap_{it-1} \times \Delta FedFunds_{t-4}$	-.0034	-.043	-1.2*	.042
	(-.77)	(-.17)	(-1.7)	(.13)
$Gap_{it-1} \times \Delta 10years_t$	-.00072	.18	-.74	-1.1***
	(-.17)	(.88)	(-1.3)	(-3.7)
$Gap_{it-1} \times \Delta 10years_{t-1}$	-.0063	.029	.31	-.75**
	(-1.5)	(.13)	(.49)	(-2.2)
$Gap_{it-1} \times \Delta 10years_{t-2}$	.0029	-.22	.65	-.23
	(.72)	(-.95)	(1.1)	(-.74)
$Gap_{it-1} \times \Delta 10years_{t-3}$	.0033	-.36	.097	-.16
	(.82)	(-1.6)	(.17)	(-.53)
$Gap_{it-1} \times \Delta 10years_{t-4}$	.0014	-.21	-.39	.29
	(.36)	(-1)	(-.68)	(1)
Observations	34293	17676	35561	35277
R^2	.12	.33	.097	.22
Sum of gap coefficients (Fed Funds)	.06	1.8	1.7	1.6
p-value	0	0	.04	0
Sum of gap coefficients (10$years$)	0	-.57	-.07	-2
p-value	.96	.36	.96	.03

Note: This table estimates:

$$\Delta Y_{it} = \sum_{k=0}^{k=4} \alpha_k (\text{gap}_{it-1} \times \Delta \text{fed funds}_{t-k}) + \sum_{x \in Control} \sum_{k=0}^{k=4} \gamma_{x,k} (x_{it-1} \times \Delta \text{fed funds}_{t-k}) + \sum_{k=0}^{k=4} \sigma_k (\text{gap}_{it-1} \times \Delta 10years_{t-k})$$
$$+ \sum_{x \in Control} \sum_{k=0}^{k=4} \theta_{x,k} (x_{it-1} \times \Delta 10years_{t-k}) + \sum_{k=0}^{k=4} \eta_k \Delta Y_{it-1-k} + \phi.\text{gap}_{it-1} + \sum_{x \in Control} \mu_x . x_{it-1} + \delta_t + \epsilon_{it}$$

ΔY is the quarterly change in net interest income (Column (1)), quarterly change in market value (Column (2)), quarterly change in log C&I lending (Column (3)), quarterly change in log total lending (Column (4)), divided by lagged total assets. The controls are $log(assets_{it-1})$, book $\text{equity}_{it-1}/\text{assets}_{it-1}$, Local $\beta_{\text{Debt / Int. rate}}$, Local % ARM_{1988}. The regression also includes quarter fixed effects. Standard errors are clustered at the BHC level. "Sum of gap coefficients (Fed Funds)" reports the coefficient estimate for $\sum_{k=0}^{k=4} \alpha_k$. "Sum of gap coefficients (10$years$)" reports the coefficient estimate for $\sum_{k=0}^{k=4} \sigma_k$. p-value corresponds to the p-value of a test of significance for the estimated coefficients.

APPENDIX

A Variable Definitions

This Section describes the construction of all variables in detail. i is an index for the bank, t for the quarter.

A.1 Bank-level Variables

This Section gathers the variables constructed using the Consolidated Financial Statements of Bank Holding Companies (form FR Y-9C). Note that flow variables (interest and non-interest income, earnings) are defined each quarter "year to date". Hence, each time we refer to a flow variable, we mean the *quarterly*, not year-to-date, flow. To transform a year-to-date variable into a quarterly one, we take the variable as it is for the first quarter of each year. For each quarter $q = 2, 3, 4$, we take the difference in the year-to-date variable between q and $q - 1$.

- **ΔInterest**$_{it}$: Change in interest income = [interest income (bhck4107) at t + interest expense (bhck4073) at $t-1$ - interest income (bhck4107) at $t-1$ - interest expense (bhck4073) at t] / (total assets (bhck2170) taken in $t - 1$]. Note that bhck4073 and bhck4107 have to be converted from year-to-date to quarterly as explained above.

- **ΔNon Interest**$_{it}$: Change in non interest income = [non interest income (bhck4079) at t - non interest income (bhck4079) at $t - 1$] / (total assets (bhck2170) taken in $t - 1$]. Note that bhck4079 has to be converted from year-to-date to quarterly as explained above.

- **ΔEarnings**$_{it}$: Change in earnings = [earnings (bhck4340) at t - earnings (bhck4340) at $t - 1$] / (total assets (bhck2170) taken in $t - 1$]. Note that bhck4340 has to be converted from year-to-date to quarterly as explained above.

- **ΔValue**$_{it}$: Change in interest income = [Equity market value at t - Equity market value at $t - 1$] / (total assets (bhck2170) taken in $t - 1$]. Equity market value is obtained for publicly listed banks after matching with stock prices from CRSP. It is equal to the number of shares outstanding (shrout) $\times$ the end-of-quarter closing price (absolute value of prc).

- **Δlog(C&I loans$_{it}$)**: commercial and industrial loan growth = log[C&I loans to US adressees (bhck1763) at t + C&I loans to foreign adressees (bhck1764) at t] - log[C&I loans to US adressees (bhck1763) at $t-1$ + C&I loans to foreign adressees (bhck1764) at $t-1$].

- **Δlog(Total loans$_{it}$)**: Total loan growth = log [Total loans (bhck2122) at t] - log[Total loans (bhck2122) at $t-1$].

- **ΔEarnings$_{it}$**: Change in earnings = [earnings (bhck4340) at t - earnings (bhck4340) at $t-1$] / (total assets (bhck2170) taken in $t-1$]. Note that bhck4340 has to be converted from year-to-date to quarterly as explained above.

- **Gap$_{it-1}$**: Income gap = [assets that reprice or mature within one year (bhck31970) - interest bearing deposits that reprice or mature whithin one year (bhck3296) - long term debt that reprices within one year (bhck3298) - long term debt that matures within one year (bhck3409) - variable rate preferred stock (bhck3408)] / total assets (bhck2170)

- **Equity$_{it-1}$**: Equity ratio = 1 - [total liabilities (bhck2948) / total assets (bhck2170)]

- **Size$_{it-1}$**: log (total assets (bhck2170))

- **Liquidity$_{it-1}$**: Liquidity ratio = [Available for sale securities (bhck1773)+ Held to Maturity Securities (bhck1754)] / total assets (bhck2170)

A.2 Times series Variables

This Section gathers different measures of interest rates used in the paper.

- **ΔFed Funds$_t$**: First difference between "effective federal funds" rate at t and $t-1$. Fed funds rates are available monthly from the Federal Reserve's website: each quarter, we take the observation corresponding to the last month.

- **Δ10yrs$_t$**: First difference between yields of 10 year treasury securities at t and $t-1$, available from the Federal Reserve's website.

- **ΔExpected FF$_t$**: Change in past "expected" 1 year interest rate between $t-1$ and t. Expected 1 year rate at t is obtained from the forward rate taken at $t-8$ (two years ago), for a loan between t and $t+3$ (for the coming year). This forward rate is computed using the Fama-Bliss discount bond prices. At date $t-8$, we take the ratio of the price of the 2-year to the 3-year zero-coupon bond, minus 1.

A.3 Loan level Variables

This Section explains how variables used in loan level regression are constructed.

- $\Delta L_{i\to j,t}$ is the growth of total outstanding loans made by bank i to firm j between t and $t+1$:

$$\Delta L_{i\to j,t} \equiv 2\frac{L_{i\to j,t+1} - L_{i\to j,t}}{L_{i\to j,t+1} + L_{i\to j,t}}$$

  This measure is always bounded by -2 and 2. It also accomodates initiation and terminations of lending relationships. We have also experimented specifications with changes in logs, and obtained similar results.

- BHC level variables are obtained from the BHC data for the top holder of bank i at date t, most importantly the income gap, but also BHC size etc.

B Time-Series Regressions

We provide here estimates using an alternative specification also used in the literature (Kashyap and Stein (2000), Campello (2002)).

B.1 Methodology

We proceed in two steps. First, we run, *separately for each quarter*, the following regression:

$$X_{it} = \gamma_t gap_{it-1} + controls_{it} + \epsilon_{it} \tag{6}$$

where X_{it} is a cash flow or lending LHS variable.$controls_{it}$ include: $X_{it-1}, ..., X_{it-4}$, $log(assets_{it-1})$, $\frac{equity_{it-1}}{assets_{it-1}}$. From this first step, we obtain a time-series of X to gap sensitivity γ_t.

In our second step, we regress γ_t on change in fed funds rate and four lags of it, as well as four quarter dummies:

$$\gamma_t = \sum_{k=0}^{k=4} \alpha_k.\Delta fedfunds_{t-k} + quarterdummies_t + \epsilon_{it} \tag{7}$$

Again, we expect that $\sum_{k=0}^{k=4} \alpha_k > 0$: in periods where interest rates increase, high income gap firms tend to make more profits, or lend more.

We report the results using this methodology in Tables B.1 and B.2. Results are a little bit weaker using this approach, but have the same order of magnitude. Results on profits and cash flows are still all significant at the 1% confidence level, and have the same order of magnitude. Results on lending, controlling for size and leverage, but not for liquidity, remain significant at the 1 or 5% level for total lending growth. They become a bit weaker, albeit still significant at the 5% level for the whole sample, for C&I loans. Controlling for liquidity restricts the sample to 1994-2011 (BHC data do not report liquidity holdings before 1994) and reduces the sample size by a third. Significance weakens, but income gap effects on total lending remains statistically significant at the 5% level for the whole sample and small firms, as well as firms with some interest rate derivative exposure. This alternative estimation procedure provides estimates with very similar orders of magnitude.

Table B.1: Time Series Approach: Profits

	$\Delta Interest_{it}$					$\Delta Earnings_{it}$				
	All	Small	Big	No Hedge	Some Hedge	All	Small	Big	No Hedge	Some Hedge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta FedFunds_t$	.015**	.017***	-.0096	.013	.028**	.034***	.037***	.016	.058***	.026*
	(2.6)	(2.9)	(-.5)	(1.4)	(2.5)	(4)	(4.2)	(.65)	(4)	(1.8)
$\Delta fedfunds_{t-1}$	.028***	.028***	.029	.032***	.02*	.027***	.03***	-.0056	.017	.054***
	(4.3)	(4.2)	(1.3)	(3.4)	(1.7)	(2.8)	(3.1)	(-.2)	(1.1)	(3.5)
$\Delta fedfunds_{t-2}$	.0048	.0071	-.02	.0019	.012	-.01	-.014	.044	-.0011	-.022
	(.77)	(1.1)	(-.95)	(.2)	(1.1)	(-1.1)	(-1.5)	(1.6)	(-.076)	(-1.4)
$\Delta fedfunds_{t-3}$	.0081	.0045	.033*	.012	-.0045	.0094	.008	-.023	.0013	.02
	(1.4)	(.74)	(1.7)	(1.3)	(-.4)	(1.1)	(.89)	(-.92)	(.086)	(1.3)
$\Delta fedfunds_{t-4}$	-.0026	-.0027	-.0076	-.017*	-.0028	.016**	.013	.062***	.014	.0047
	(-.49)	(-.5)	(-.44)	(-1.9)	(-.27)	(2)	(1.7)	(2.7)	(1)	(.33)
N	93	93	93	63	63	93	93	93	63	63
ar2										
Sum of coefficients	.05	.05	.02	.04	.05	.07	.07	.09	.08	.08
p-value	0	0	.21	0	0	0	0	0	0	0

We run *each quarter* the following regression:

$$X_{it} = \gamma_t gap_{it-1} + controls_{it} + \epsilon_{it}$$

where X_{it} is net interest income (Columns (1)-(5)) and total earnings (Columns (6)-(10)). $controls_{it}$ include: $X_{it-1}, ..., X_{it-4}$, $log(assets_{it-1})$, $\frac{equity_{it-1}}{assets_{it-1}}$. We then estimate:

$$\gamma_t = \sum_{k=0}^{k=4} \alpha_k . \Delta fedfunds_{t-k} + quarterdummies_t + \epsilon_{it}$$

"Sum of coefficients" reports the coefficient estimate for $\sum_{k=0}^{k=4} \alpha_k$. p-value is the p-value from a significance test of the estimate of $\sum_{k=0}^{k=4} \alpha_k$.

Table B.2: Time Series Approach: Lending

	Δlog(C&I loans)					Δlog(Total loans)				
	All	Small	Big	No Hedge	Some Hedge	All	Small	Big	No Hedge	Some Hedge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta FedFunds_t$	.27	.48	-1.1	-.046	.89	-.04	-.096	.42	-.039	.32
	(.31)	(.55)	(-.45)	(-.041)	(.56)	(-.1)	(-.21)	(.39)	(-.062)	(.46)
$\Delta fedfunds_{t-1}$	.41	.54	-.9	.21	-.19	-.28	-.0059	-1.9	-.09	.63
	(.42)	(.55)	(-.32)	(.18)	(-.11)	(-.63)	(-.012)	(-1.6)	(-.14)	(.85)
$\Delta fedfunds_{t-2}$	.43	.9	-4	.68	-.94	.75*	.78	-.25	.16	.68
	(.46)	(.94)	(-1.5)	(.59)	(-.56)	(1.7)	(1.6)	(-.22)	(.25)	(.93)
$\Delta fedfunds_{t-3}$	1.5*	1.3	4.4*	2.3*	3.3*	.78*	.62	2.7**	.43	.35
	(1.8)	(1.4)	(1.7)	(2)	(2)	(1.9)	(1.4)	(2.5)	(.67)	(.48)
$\Delta fedfunds_{t-4}$	-1.1	-1.2	1.1	-2.6**	-.6	.0066	.019	-1.2	.48	.1
	(-1.4)	(-1.5)	(.48)	(-2.4)	(-.39)	(.018)	(.047)	(-1.3)	(.79)	(.15)
N	93	93	93	63	63	93	93	93	63	63
ar2										
Sum of coefficients	1.6	2	-.52	.55	2.4	1.2	1.3	-.29	.94	2.1
p-value	.08	.03	.84	.63	.14	0	0	.79	.15	0

We run *each quarter* the following regression:

$$X_{it} = \gamma_t gap_{it-1} + controls_{it} + \epsilon_{it}$$

where X_{it} is log C&I lending (Columns (1)-(5)) and total lending (Columns (6)-(10)). $controls_{it}$ include: $X_{it-1}, ..., X_{it-4}$, $log(assets_{it-1})$, $\frac{equity_{it-1}}{assets_{it-1}}$.
We then estimate:

$$\gamma_t = \sum_{k=0}^{k=4} \alpha_k.\Delta fedfunds_{t-k} + quarterdummies_t + \epsilon_{it}$$

"Sum of coefficients" reports the coefficient estimate for $\sum_{k=0}^{k=4} \alpha_k$. p-value is the p-value from a significance test of the estimate of $\sum_{k=0}^{k=4} \alpha_k$.

C Internal Capital Markets

This Appendix exploits the existence of internal capital markets within BHC. As we showed in Section 3.2, a BHC with a higher income gap receive a larger net income shock following an increase in monetary policy. Through internal capital markets, this liquidity shock will propagate to the BHC divisions (Rosengren and Peek (2000), Gilje et al. (2013), Cetorelli and Goldberg (2012)). Using commercial bank level data, we can then investigate whether, *controlling for the commercial bank own income gap*, this liquidity shock leads to increased lending. This strategy is valid under the identifying assumption that, conditional on a commercial bank own income gap, the BHC choice of income gap is unrelated to the sensitivity of the commercial bank lending opportunities to interest rates. This identification strategy is analogous in spirit to that used in the seminal contribution by Lamont (1997), who uses shocks to oil-divisions in conglomerates as an exogenous source of variation in internal financing available to non-oil divisions, and in the context of bank conglomerates by Campello (2002).

We estimate the following equation for a commercial bank i, belonging to a BHC j in quarter t:

$$\begin{aligned}\Delta Y_{i,j,t} = &\sum_{k=0}^{k=4}\alpha_k(\text{BHC gap}_{jt-1}\times\Delta\text{fed funds}_{t-k}) + \sum_{k=0}^{k=4}\zeta_k(\text{CB gap}_{i,j,t-1}\times\Delta\text{fed funds}_{t-k})\\ &+\phi.\text{BHC gap}_{jt-1}+\psi.\text{CB gap}_{i,j,t-1}+\sum_{x\in Control}\sum_{k=0}^{k=4}(\mu_x.x_{i,j,t-1}+\gamma_{x,k}(x_{i,j,t-1}\times\Delta\text{fed funds}_{t-k}))\\ &+\sum_{k=0}^{k=4}\eta_k\Delta Y_{i,j,t-1-k}+\delta_t+\epsilon_{i,j,t},\end{aligned} \tag{8}$$

where $Control$ = {Size, Equity, Liquidity, Local $\beta_{\text{Debt / Int. rate}}$, Local % ARM_{1988}}, and standard errors are clustered at the BHC level. All variables are scaled by total assets. Y_{it} is total lending growth or C&I lending growth. $\sum_{k=0}^{k=4}\alpha_k$ is our coefficient of interest. A positive and significant $\sum_{k=0}^{k=4}\alpha_k$ implies that commercial banks belonging to BHCs with a large income gap cut lending less following a monetary tightening than commercial banks belonging to BHCs with a small income gap, even if the commercial banks all have the same own income gap.

One issue with estimating equation (8) is that we need to compute the income gap at the commercial bank level, which restricts the sample period to 1997-2013. Table C.1 presents the estimation of equation (8) on the sample of commercial banks with more than \$500m in total assets. Panel A uses total lending growth as a dependent variable; Panel B uses C&I lending growth as a dependent variable. The explanatory variables in Column (1) are the commercial bank-level income gap, equity and size interacted with change in interest rates. Column (2) includes the same variables, but measured at the BHC level. Columns (3)-(5) have both set of controls. Column (3) restricts the sample to BHCs with more than 1 commercial bank, Column (4) to BHCs with more than 2 commercial banks and Column (5) to BHCs with more than 3 commercial banks.

Throughout the specifications, we see that the commercial bank-level income gap has little explanatory power on the sensitivity of the commercial bank lending to interest rates. This can be interpreted as a validation that capital budgeting decisions are taken at the BHC level, which validates our main approach of using BHC-level data. The commercial bank-level income gap may however still be an important control in that it may reflects the loan demand faced by the commercial bank. Panel A shows that when interest rates increases, a commercial bank belonging to a BHC with a large income gap will cut its total lending significantly less than a commercial bank with a comparable income gap, but belonging to a BHC with a smaller income gap. Quantitatively, consider two commercial banks with a similar income gap, a similar capitalization ratio and of a similar size; one of these commercial banks belongs to a BHC with an income gap at the 75$^{\text{th}}$ percentile of the income gap distribution, while the other belongs to a BHC with an income gap at the 25$^{\text{th}}$ percentile. Assume that the two BHCs that own these two commercial banks have more than three commercial banks. Following a 100 basis point increase in interest rates, the first commercial bank will increase lending by 1.2 percentage points more (Panel A, Column (5) of Table C.1). All the estimates of $\sum_{k=0}^{k=4} \alpha_k$ in Table C.1 are significant at the 1% confidence level.

The estimates obtained when using C&I lending as a dependent variable are similar once we restrict the sample to BHCs with more than two commercial banks. Column (5) of Panel B reports an estimated $\sum_{k=0}^{k=4} \alpha_k$ of 4.4, significantly different from 0 at the 5% confidence level. The corresponding estimate when looking at total lending is 5.5, so that the economic magnitudes are very close.

Table C.1: Internal Capital Markets

	(1)	(2)	(3)	(4)	(5)
Panel A: Total Loans					
Sum of CB gap coefficients	.07	.	-.96	-1.7	-3.1
p-value	.91	.	.43	.24	.04
Sum of BHC gap coefficients	.	1.2	2.7	3.7	5.5
p-value	.	.01	0	0	0
Observations	26782	26782	9423	6838	5012
Panel B: C& I Loans					
Sum of CB gap coefficients	1.3	.	.26	-.68	-2.5
p-value	.22	.	.88	.73	.27
Sum of BHC gap coefficients	.	1.1	1.9	5.4	4.4
p-value	.	.22	.32	.03	.06
Observations	27217	27217	9610	6920	5123

Note: This table estimates

$$\Delta Y_{i,j,t} = \sum_{k=0}^{k=4} \alpha_k(\text{BHC gap}_{jt-1} \times \Delta\text{fed funds}_{t-k}) + \sum_{k=0}^{k=4} \zeta_k(\text{CB gap}_{i,j,t-1} \times \Delta\text{fed funds}_{t-k}) + \phi.\text{BHC gap}_{jt-1}$$
$$+ \psi.\text{CB gap}_{i,j,t-1} + \sum_{x \in Control} \sum_{k=0}^{k=4} (\mu_x.x_{i,j,t-1} + \gamma_{x,k}(x_{i,j,t-1} \times \Delta\text{fed funds}_{t-k})) + \sum_{k=0}^{k=4} \eta_k \Delta Y_{i,j,t-1-k} + +\delta_t + \epsilon_{i,j,t},$$

where i is a commercial bank, j is the BHC it belongs to and t is a quarter. ΔY is the quarterly change in log total lending normalized by lagged assets (Panel A) and quarterly change in log C&I lending divided by lagged total assets (Panel B). The controls are $log(assets_{it-1})$, book equity$_{it-1}$/assets$_{it-1}$, Local $\beta_{\text{Debt / Int. rate,}}$ Local % ARM$_{1988}$. Column (1) includes only the commercial-bank level controls. Column (2) include only the BHC-level controls. Columns (3)-(5) include both. Columns (1)-(5) are estimation run on the entire sample of commercial banks with total assets above \$500m. In Column (3), the sample is further restricted to BHCs with more than 1 commercial bank; in Column (4) more than 2 commercial banks; in Column (5) more than 3 commercial banks.

D Supplementary Tables

Table D.1: Comparison of the subsample of BHC matched with Dealscan

	BHC Sample		Difference
	All	DealScan match	t-stat
Log of assets	15.033	16.854	15.784
Income Gap	0.126	0.218	9.853
Δ Non-interest	0.000	0.000	6.618
Δ Earnings	0.000	0.000	5.487
Earnings / assets	0.002	0.002	3.658
Net interest income / assets	0.009	0.009	-3.136
Non interest income / assets	0.004	0.005	2.706
Δ Market Value	0.005	0.005	2.186
Fraction Liquid assets	0.225	0.210	-1.876
Δ log(C&I loans)	0.015	0.017	1.415
Market value of equity / assets	0.152	0.145	-0.948
Equity to assets ratio	0.090	0.088	-0.824
Local β Debt / Int. rate	6.434	6.499	0.728
Mean local % ARM	0.220	0.224	0.536
Δ Interest	0.000	0.000	-0.109
Δ log(total loans)	0.017	0.017	-0.029

Note : The table splits the BHC sample in the subsample matched with Dealscan and the subsample not matched with Dealscan. Each variable in the first column is regressed on a dummy indicated whether the BHC is matched in DealScan in a given year and the t-statistics is reported. Standard errors are clustered at the BHC level

Table D.2: Testing for Sorting along Unobservable Characteristics

	Income Gap (Second Lender)	Income Gap (Future Lender)
	(1)	(2)
Income Gap (Main Lender)	-.0064	-.022
	(-.069)	(-.48)
Observations	29303	4210
Borrowers	8772	2683
Lenders	249	217
BHC top-holders	110	102
FE	Year	Year
R^2	.17	.19

Note: This table estimates for a firm j in year t:

$$g\tilde{a}p_{jt} = \delta_t + \alpha \text{gap}_{jt} + \epsilon_{jt}$$

The regressor is the income gap of the bank with the largest outsanding loan to the firm. In Column (1), the dependent variable is the income gap of the bank with the *second* largest loan. In Column (2), the dependent variable is the income gap of the bank with the *future* largest loan. The sample is composed of firms for which the two banks are matched with different BHCs. Standard errors are two-way clustered with respect to the two BHCs.

Table D.3: The Impact of Income Gap on Lending Within Borrowers (Compustat Firms)

	Δ Loan		
	All Firms	Firms with Multiple Banks	
	(1)	(2)	(3)
$Gap_{it-1} \times \Delta FedFunds_t$	5.7**	5.3**	5.3**
	(2.6)	(2.4)	(2.5)
Observations	213668	204967	204967
Borrowers	6276	4928	4928
Lenders	286	285	285
BHC top-holders	129	129	129
FE	Year	Year	Firm × Year
R^2	.28	.28	.59

Note: This table estimates:

$$\begin{aligned}\Delta L_{i\to j,t} =& \alpha(\text{gap}_{it} \times \Delta\text{fed funds}_t) + \sum_{x\in Control} \gamma_x(x_{it-1} \times \Delta\text{fed funds}_t) \\ &+ \eta\Delta L_{i\to j,t-1} + \phi.\text{gap}_{it} + \sum_{x\in Control} \mu_x.x_{it-1} + \delta_{jt} + \epsilon_{it}\end{aligned}$$

The controls are $log(assets_{it-1})$, book equity$_{it-1}$/assets$_{it-1}$. The sample is compsed of firms matched with Compustat. The first colum includes all firms. The second colums only includes firms matched with multiple banks. The third columns adds borrower-year fixed effects. Standard errors are clustered at the bank level.

Table D.4: The Effect of Income Gap on Borrowers Decisions: Quarterly Regressions

	Δ Debt			Δ Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
$Gap_{it-1} \times \Delta FedFunds_t$	2.6***	.36	-.074	2.7***	.45	.41
	(3.6)	(.3)	(-.068)	(6.4)	(.66)	(.54)
$Gap_{it-1} \times \Delta FedFunds_{t-1}$	-.86	1.4	1.5	-.26	1.5	1.4
	(-.96)	(.59)	(.67)	(-.54)	(.95)	(.86)
$Gap_{it-1} \times \Delta FedFunds_{t-2}$	-.6	-.29	.3	-.72*	-.26	-.28
	(-.69)	(-.19)	(.21)	(-1.7)	(-.35)	(-.36)
$Gap_{it-1} \times \Delta FedFunds_{t-3}$	3.4***	1.9	2.5**	.85*	-1.2	-1
	(3.8)	(1.5)	(2)	(1.8)	(-1)	(-.92)
$Gap_{it-1} \times \Delta FedFunds_{t-4}$	.75	-.0081	.25	1.3***	1.6***	1.3*
	(1.1)	(-.005)	(.15)	(3.7)	(2.8)	(1.9)
Sum of gap coefficients	5.3	3.3	4.5	3.9	2.1	1.8
p-value of gap coefficients	0	.11	.02	0	0	.01
Lender controls	No	Yes	Yes	No	Yes	Yes
Borrower Controls	No	No	Yes	No	No	Yes
Observations	100416	100416	100326	107347	107347	107298
Borrowers	3884	3884	3876	4080	4080	4075
Lenders	97	97	97	99	99	99
$E[\Delta$ dep. variable$]$	.0051	.0051	.0051	.014	.014	.014
R^2	.04	.04	.16	.092	.093	.21

Note: This table estimates for a firm i in year t with lead arranger b:

$$\begin{aligned}\Delta Y_{it} = & \sum_{0\leq k\leq 4} \alpha_k(\text{gap}_{bt-1} \times \Delta\text{fed funds}_{t-k}) + \phi.\text{gap}_{bt-1} \\ & + \sum_{x\in BankControl}\sum_{0\leq k\leq 4} \gamma_{kx}(x_{bt-1} \times \Delta\text{fed funds}_t) + \sum_{x\in BankControl}\sum_{0\leq k\leq 1} \mu_{xk}x_{bt-1} \\ & + \sum_{x\in FirmControl}\sum_{0\leq k\leq 4} \nu_{xkt}x_{it-1} + \sum_{0\leq k\leq 4} \eta_k \Delta Y_{it-1-k} + \delta_t + \epsilon_{it}\end{aligned} \tag{9}$$

ΔY is alternatively the quarterly change in total debt (Column (1) (2) (3)) and quarterly change in investment (Column (4) (5) (6)). The dependent variable is constructed using Compustat Quarterly Data, which contains quarterly information on debt and asset (while information on employment is only available in the Annual Data). The lender controls are $log(assets_{it-1})$ and book equity$_{it-1}$/assets$_{it-1}$. The borrower controls are four size bin dummies, state dummies and four-digit SIC code dummies, all interacted with year dummies. Standard errors are two-way clustered at the firm and bank level.

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Matthieu Gomez
Princeton University; email: **matthieu.gomez@gmail.com**

Augustin Landier
Toulouse School of Economics; email: **augustin.landier@tse-fr.eu**

David Sraer
UC Berkeley, NBER and CEPR; email: **sraer@berkeley.edu**

David Thesmar
HEC Paris and CEPR; email: **thesmar@hec.fr**

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Website	**www.esrb.europa.eu**

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