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Bank vs Dealer Capital as a Priced Risk

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Abstract. Recent papers have found that intermediary capital can explain prices across a number of asset classes (e.g. He, Kelly, and Manela, 2017; Adrian, Etula, and Muir, 2014). I test intermediaries' explanatory power during the period of Glass-Steagall restrictions, in which commercial banks were ineligible to trade many categories of assets. Surprisingly, I do not find that the capital or assets of dealers eligible to trade asset classes explain those prices better than the ineligible banks. Instead, the ineligible commercial banks appear to explain prices better in the time series and at least as well in the cross-section. These findings provide some support for the idea that the apparent explanatory power of intermediaries arises passively, for example from correlation with time-varying risk preferences, rather than from their interaction with markets.

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A recent literature has found that banking sector leverage and capital have explanatory power over asset returns, for example: He et al. (2017); Adrian et al. (2014); Baron and Muir (2019); Adrian et al. (2013); Haddad and Sraer (2020); Haddad and Muir (2020).

The findings have primarily been motivated by intermediary asset pricing models (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014). These models typically start with some sort of a friction or segmentation that separates intermediaries from households or end investors. Because intermediaries act as the arbitrageurs and marginal investors in all risky assets, their wealth is a priced risk factor.

One challenge with this interpretation of the empirical findings is the number of different roles that banks play. Large dealers act as arbitrageurs, but also as lenders, borrowers, operational service providers, and more. Each of these roles must contribute to some portion of the variation in dealer valuation and balance sheets. So how do we know that it is the dealer's role as an arbitrageur that is related to the cross-section of returns, rather than its role as a lender and borrower? For recent data, it is not easy to separate out these functions. Bank consolidation starting in the 1990s means that many of the largest lenders are also some of the largest dealers.

However, before the mid 1990s it is possible to separate lending and deposit-taking institutions from trading institutions in the USA. The 1933 Banking Act created a legal separation (the "Glass-Steagall" provisions) between commercial banks and investment banks. Commercial banks, from 1956 often incorporated as "Bank Holding Companies" (BHCs), could take deposits but could not purchase or sell non-government-issued (or "bank-ineligible") securities. Investment banks could trade bank-ineligible securities but faced restrictions on lending and deposit taking.

In light of these restrictions, I test the explanatory power of commercial bank vs other bank capital on returns on bank-ineligible assets in both the time series and the cross-section. Surprisingly, I find that commercial bank balance sheets appear to explain bank-ineligible returns somewhat better than other banks.

For the cross-section tests, I recreate the primary dealer capital ratio factor of He et al. (2017), but with the set of primary dealers separated into BHCs and other banks. I find that the BHC capital ratio explains security returns as well as or marginally better than that of other banks. A Bayesian model selection approach also finds BHC capital ratios more likely to explain prices. Borrowing costs of financial firms (as proxied by the LIBOR spread) do not seem to have explanatory power outside of CDS, suggesting that the effects do not arise from commercial banks lending to intermediaries who act as investors. However, the relatively short sample period prevents the tests from drawing very strong conclusions.

For a longer sample, I also conduct time series tests using the underlying data sources and approach from Baron and Muir (2019). I find that from 1939-89 commercial bank asset growth predicts the time series of equity and stock returns whereas broker-dealer asset growth does not.

"Passive" models — in which sentiment or risk preference varies over time and simply correlates with intermediary wealth or leverage — provide a possible explanation for these findings.[2] Intermediaries could have apparent explanatory power over returns not because of any interaction with markets, but rather because they provide a window into the representative agent's marginal rate of substitution. For example Santos and Veronesi (2018) describe a general equilibrium model with a lending and deposit taking bank in which bank leverage emerges as a factor even with no financial frictions. Since commercial banks are more involved with lending and deposit taking from individuals and corporates, they could provide a better factor than securities dealers.

"Indirect" intermediary asset pricing channels are also possible. If shocks to commercial bank wealth drive up risk premia on bank-eligible assets (i.e. loans and government bonds), this could increase the risk premium on correlated bank-ineligible assets. But the findings do cast some doubt on the idea that bank capital appears as a factor because dealers are acting as marginal investors in publicly traded assets.

The rest of this paper is organised as:

1. An overview of the Glass-Steagall restrictions
2. The cross-sectional tests, including methodology, data and findings
3. The time series tests, including methodology, data and findings
4. Discussion of the implications for active, passive, and indirect channels for intermediary asset pricing
5. A brief conclusion

1. Glass-Steagall

The Glass-Steagall restriction period allows us to view an unusually clean separation between commercial banking and securities dealing. Glass-Steagall refers to a set of provisions contained in the Banking Act of 1933. These provisions prohibited dealing and underwriting in "bank ineligible" asset classes by commercial banks, often incorporated as bank holding companies (BHCs).[3]

Bank-ineligible assets included corporate debt, corporate equities, commodities, and derivatives of of these assets. Bank-eligible assets included government securities, certain interest rate derivatives, and foreign exchange.

These provisions were gradually weakened from the late 1980s until their final repeal in 1999 in the 'Graham-Leach-Bliley' act. Restrictions were weakened in two ways. Most importantly, the Federal Reserve Board began granting Bank Holding Companies exemptions to buy or build affiliates with increasingly large amounts of bank-ineligible activity

[2] The terminology of "passive," "direct," and "indirect" channels is borrowed from Baron and Muir (2019)
[3] Commercial banks here also includes national banks, state banks, and their affiliates, but BHCs are the largest category by assets or revenue after the 1950s.

(Cohen, 1997). Second, the OCC and other regulators allowed BHCs to conduct certain types of trade with limited risk in some bank-ineligible asset classes (Omarova, 2009).

A description of the nature of restrictions and timeline of their easing is provided in appendix 1. The most important points for this paper are:

- Up to 1989, the Glass-Steagall restrictions were strict, with very little bank-ineligible activity allowed in BHCs
- For corporate debt and equities, some activity was allowed in subsidiaries of BHCs from Q2 1989 onward, but tightly controlled and limited to 5% market share and 10% of revenue. In practice few dealers were acquired by banks
- For equity options, no significant activity was permitted in BHCs until 1995 Q1
- For commodity derivatives, somewhat more permissive rules allowed slightly more trading activity by BHCs in the early 1990s, although with limitations on instrument type and risk
- From 1997 onwards BHCs were allowed to own substantially larger securities dealer subsidiaries

For time series tests, data is available back to 1946. I therefore limit the tests to a restrictive definition of the Glass-Steagall period and only study the period 1946-1989 Q1.

For cross-sectional tests, data is only available back to 1970 at earliest. For some asset classes, data is not available until the 1980s. I therefore use a slightly looser definition of the Glass Steagall period of 1970-1994 Q4. This brings equities options and commodities returns into the regression and is still subject to tight restrictions.

To test the force of these restrictions at the end of 1994, I also estimate the trading activity by all BHC and non-BHC primary dealer banks in 1995 based on contemporary annual reports (see table 14). I find that non-BHC primary dealers held approximately 20x more assets and generated approximately 20x more revenue in the relevant asset classes than the BHCs. These estimates put an approximate upper bound on the extent of BHC activity in the ineligible classes. They are in fact likely to substantially overstate BHC activity, because it is not possible to fully separate out the bank-eligible from bank-ineligible activity based on annual reports. As an additional robustness check, I also repeat the cross-sectional regressions for 1970-1989 Q1.

2. Cross-sectional test

2.1 Motivation

He et al. (2017) find evidence that the capital ratio of primary dealers explains the cross-section of returns across multiple asset classes from 1970-2012. Due to their large size and important role in the markets, primary dealers are argued to be plausible candidates for the marginal investor across multiple asset classes.

However, up until the 2000s it was common for commercial banks that are not securities dealers to be primary dealers. Primary dealer status allows a bank to buy debt directly from the government at primary auctions. Even purely lending banks need to buy government debt for risk and liquidity management and for their treasury portfolios. For example, at the start of the dataset in 1970, there were 12 primary dealers, 7 of which were BHCs.

I therefore focus on the Glass-Steagall period and separate the primary dealers into BHCs which could not trade certain classes of securities and non-BHCs which could, to determine which prices assets better.

To account for the potential that commercial banks are lending to the marginal investors even if they are unable to invest in securities, I also include a regression of financial sector borrowing cost on returns. If financial sector lending is the source of the risk factor, then we should find that their borrowing cost is explains returns well. If instead economy-wide risk preferences are the source of the risk price, broader corporate or retail borrowing costs would be more likely to have explanatory power.

2.2 Data

2.2.1 Capital ratios

As per He et al. (2017), capital ratio is calculated as the market value of equity over the book value of debt plus the market value of equity. This proxies for the true market capital ratio, and is a common approach in the corporate finance literature. The assumption in this formula is that deviations of the market value of bank debt from the book value are small relative to deviations of the market value of assets from the book value.

The novel contribution from this paper is the construction of a primary dealer capital ratio dataset specifically for BHCs vs other banks. Creating this dataset required mapping each of the 50 banks that were primary dealers before 1999 to a status as a BHC or non-BHC based on contemporary legal and press documentation, as well as combining market capitalisation and balance sheet data from CRSP, Compustat, and S&P Capital IQ. The details of the construction of the dataset are described in appendix 2.

The overall data series (combining BHCs and others) matches He et al. (2017)'s figures closely, with an 88% correlation in the resulting risk factors. The time series of the overall primary dealer capital ratio constructed by this paper and from the He et al. (2017) paper is shown in figure 1. Remaining differences are likely due to data construction choices on treatment of mergers and acquisitions as well as potential slight differences in data availability in underlying sources.

The capital ratios for BHCs and non-BHCs is shown in figure 2. Bank Holding companies show significantly greater volatility in capital ratios earlier on in the time series, due to the differing nature of their business models and the lower asset base of the non-BHCs early in the sample. Correlation between the two risk factors is only 45% from 1970-1998. Both risk factors as well as the original He et al. (2017) factor are shown in figure 4.

Both BHCs and non-BHCs have significant size and number of members throughout the observation period. Neither drops below four banks at any point. Non-BHCs start with about 1/6th of the market assets of BHCs, but grow rapidly and overtake BHCs in 1991 when Nomura joins the sample.[4]

2.2.2 Other returns

To avoid potential arbitrariness or data mining concerns in our choice of test portfolios, I use exactly the same dataset as in He et al. (2017).[5] Equities portfolios consist of the Fama and French (1993) 25 size and value sorted portfolios. Government bond returns consist of 10 maturity-sorted portfolios from CRSP. Corporate portfolios are ten portfolios sorted on yield spreads from Nozawa (2017) starting in 1973. Sovereign bonds use six portfolios from Borri and Verdelhan (2017) sorted on credit ratings and covariance with US equity markets, starting in 1995. Options use 27 SP 500 call and put portfolios from Constantinides, Czerwonko, Carsten Jackwerth, and Perrakis (2011) sorted on moneyness and maturity, starting in 1986. Foreign exchange portfolios use six interest-rate-sorted currency portfolios from Lettau, Maggiori, and Weber (2014) and six momentum-sorted portfolios from Lukas Menkhoff (2012), starting in 1976. Commodities portfolios are returns to futures for 23 different commodities. CDS portfolios consist of 20 portfolios of returns on 5 year CDS, sorted on spread.

The return on risky corporate debt is also constructed from the existing He et al. (2017) dataset. In particular, I use the average return of the riskier half of the 10 corporate credit portfolios from Nozawa minus the risk free rate. Alternate specifications (e.g. using the difference vs the returns on longer term government debt or using the difference between returns on the the top 5 vs bottom 5 portfolios by credit spread) do not significantly change the results.

The spread of 3 month LIBOR (sourced from FRED) over the risk free rate to proxy for return on financial sector debt. LIBOR measures the unsecured borrowing cost between large banks, and therefore functions as a natural proxy for intermediary borrowing costs. Ang, Gorovyy, and van Inwegen (2011) also investigate hedge fund leverage and find that most borrowing is priced on LIBOR with an additional small spread, and therefore also use LIBOR as a proxy for hedge fund borrowing cost.

This spread should serve as a close proxy for excess returns on short term lending to financial institutions, since true returns are not available. Only one US primary dealer or LIBOR panel bank has defaulted since the LIBOR time series starts in 1986. Therefore, except for a single observation the 3 month LIBOR should measure the 3 month return

[4] Nomura became a primary dealer in 1986, but balance sheet data is not available from S&P Capital IQ until 1991.

[5] Kindly made available by Asaf Manela.

on unsecured lending to primary dealers. LIBOR data is only available since 1986 Q1, when the benchmark was launched, and hence the regressions using LIBOR only cover the period 1986-2012.

2.3 Methodology

For consistency with the existing literature and to avoid the potential for p-hacking, I first employ the same methodology and presentation for cross-sectional regressions as in He et al. (2017).[6]

However, the short size of the relevant subsample (100 quarterly observations) could lead to concerns about the applicability of GMM asymptotic inference. I therefore also employ the Bayesian factor posterior selection approach from Bryzgalova, Huang, and Julliard (2019). Besides having a finite sample distribution theory, this approach has the added benefits of giving an intuitive posterior probability interpretation for model selection, and robustness to model misspecification.

2.3.1 Fama Macbeth regression specification

As per the original He et al. (2017) specification, I employ a Fama Macbeth regression with the two stages:

$$\text{Time series: } R_t^i - R_t^f = \alpha^i + \beta_W^i (R_t^W - R_t^f) + \beta_\eta^i \Delta\eta_t + \epsilon_t^i$$
$$\text{Cross-section: } R_t^i - R_t^f = \lambda_0 + \lambda_W \beta_W^i + \lambda_\eta \beta_\eta^i + v^i$$

Where W is a value weighted stock index and η is the primary dealer capital ratio. This matches the continuous time expected return equation (2).

A balanced regression is performed for each asset class, discarding any periods with missing observations. A final unbalanced regression is performed across all asset classes, using all data points.[7] Standard errors are then calculated using a GMM approach around the Fama Macbeth regression, to account for non-normality and heteroskedasticity in the data.

There are only two points of difference from the He et al. (2017) regressions. First, I remove asset classes that BHCs were able to trade from the dataset (so called 'bank eligible' assets). This includes government debt securities, which BHCs were allowed to trade, and FX assets, which are not securities or derivatives.[8]

Second, I use a narrower time period, limiting my scope to the period Glass-Steagall restrictions. As described in section 3, here I define this period as 1970 Q1-1994 Q4. I

[6] To test robustness, an alternative purely GMM-based specification has also been calculated with similar results (although somewhat wider confidence intervals), and is available on request

[7] Moment variance estimates are calculated discarding any periods with missing observations. An alternative approach using the methodology from Stambaugh (1997) for estimating variance matrices with incomplete data was also tested with minimal differences

[8] The portfolios are based on currency holdings rather than returns on currency forwards or options.

argue in section 3 and appendix 1 based on legal sources and bank annual reports that the restrictions still retained significant force in both periods. As an additional robustness check, I also conduct the cross-sectional regressions for 1970-1989Q1 in tables 5, 6, and 7.

When attempting to test the significance of financial sector borrowing cost, data is only available from 1986 onward. This factor is therefore only compared to the He et al. (2017) factor post-Glass-Steagall.

2.3.2 Bayesian methodology

I use the methodology form Bryzgalova et al. (2019) to conduct calculate the relative posterior probability of models with BHC vs non-BHC capital used as a factor. This methodology uses an uninformative "spike and slab" prior to shrink away useless factors, and then estimates posterior likelihoods by drawing from a Gibbs sampler assuming a normal distribution of asset returns. The details of the methodology and its advantages are described in Bryzgalova et al. (2019).

For the purposes of this analysis, the approach has three key advantages. First, it allows finite sample inference without aymptotics. Second, posterior probabilities allow an intuitive comparison of the relative likelihood of each type of bank capital, instead of testing each model separately against a null of 0. Third, The analysis is robust to inclusion of weak and spurious factors, unlike the traditional GMM or Fama Macbeth approach.[9]

Using this methodology, I compute the posterior probabilities of each possible combinations of BHC capital, non-BHC capital, and market return factors. I compare the posterior likelihoods of:

1. Models with BHC capital as a factor, but not non-BHC capital
2. Models with non-BHC capital as a factor, but not BHC capital
3. Models with both capital ratios as factors
4. Models with neither capital ratios as factors

Each of these posterior probabilities combines the probabilities both of models with a market return factor and of models without a market return factor.

2.4 Findings

2.4.1 Glass-Steagall tests

Summary findings from the all-asset-class Fama Macbeth regressions are shown in table 1, while the relevant posterior model probabilities are shown in tabke 2. The full detailed tables for each of the Fama MacBeth regressions in each asset class is also presented in tables 8 and 9.

[9] See Bryzgalova et al. (2019) for more details

Table 1: Summary all-asset-class unbalanced Fama Macbeth regression results for 2-factor models using BHC capital ratios vs non-BHC capital ratios as a factor. Both models use excess market equity returns as the second factor. 1970-1994 Q4. GMM t-statists in parentheses.

	(1) BHC	(2) Non-BHC
BHC capital ratio	8.756**	
T-stat	(2.229)	
Non-BHC capital ratio		-3.874
T-stat		(-0.839)
Market return	1.02	1.201
T-stat	(0.555)	(0.755)
Constant	0.627	0.753
T-stat	(1.021)	(1.412)
R2	0.366	0.121
MAPE	1.193	1.18
Assets	76	76
Periods	100	100
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2: Summary Bayesian model posterior likelihood results for 2-factor models using BHC capital ratios vs non-BHC capital ratios as factors, using the 'slab and spike' prior described in Bryzgalova et al. (2019). Each posterior probabilities figure includes the probability of a specifications with and without including market returns as a factor. The 'shrinkage parameter' ψ is set to 30 and number of iterations of the Gibbs sampler is 10K. Results do not differ substantially with tuning parameters between 1 and 100. 1970-1994Q4

	FF25	US_bonds	Options	Commod	All
BHC capital factor	32.9%	29.8%	20.0%	26.4%	24.6%
Non-BHC capital factor	4.9%	18.1%	21.4%	23.5%	16.4%
Both factors	59.4%	36.9%	50.5%	26.7%	51.7%
Neither factor	2.6%	15.3%	7.9%	23.3%	7.3%
Periods	100	84	35	33	100

The results are not overwhelming, but do suggest that the BHC capital ratio is more likely to price the cross-section of returns than non-BHC capital, contrary to the implications of the banks-as-marginal-investors theory.

The Bayesian analysis tells us that the posterior likelihood of BHC-capital-only models is higher than that of non-BHC-capital-only models for equities (6.7x higher), bonds (1.6x higher), and the all-asset class sample (1.5x higher). However, probabilities are roughly the same for options and commodities, possibly because the small samples prevent the posteriors from straying far from the even priors. In general, models with both factors also appear more likely than either factor alone.

Turning to the frequentist evidence, in the all-asset-class regressions the capital ratio parameter estimate is significant at a 5% level. For the more restrictive 1970-89Q1 period, results are still significant at a 10% level. In contrast, the non-BHC capital ratio parameter is not significant. The R squared level is also higher for BHC capital.

However, looking at specific asset classes Fama Macbeth regressions, the evidence is murkier. The non-BHC capital ratio has somewhat more significant coefficients for corporate bonds, while the BHC capital ratio has somewhat more significant coefficients for equity, although neither breach 5%. Options are significant for both, although with the wrong sign for non-BHC capital. Neither capital ratio is significant for commodities, although this is asset class had somewhat weaker Glass-Steagall restrictions during the 1990s — described in section 3 and appendix 1.

In summary, it appears that the capital ratios of banks that could not hold non-government securities is no less likely, and indeed somewhat more likely to explain the cross-section of non-government security returns than those of banks that could trade them. This provides suggestive evidence that the relationship between bank capital ratios and returns is driven by shifting risk preferences and macro factors rather than interaction with securities markets.

It is also possible that these effects are driven by indirect effects of the BHCs through covariance of bank-eligible assets with bank-ineligible assets, as described in section 4.1.2 — i.e. shocks to commercial banks change risk premia on loans and government bonds which in turn change risk premia on bank-ineligible assets through rebalancing of portfolios by agents that can invest in both classes. However, it could be considered be somewhat surprising that:

- The indirect effects of BHC capital shocks are more apparent than the direct effects from non-BHC capital shocks
- The indirect effects are more visible in equities than corporate bonds, despite the intuition that corporate bonds would be closer correlates with loans and government bonds

2.4.2 Controlling for borrowing costs

Financial sector borrowing costs do not appear to explain returns. Table 10 shows the results of a cross-sectional regression using LIBOR spreads and market returns as a factor outside of CDS. Only CDS has a significant coefficient for the LIBOR spreads, and the rest of the R squared values are low relative to other regressions. It is unclear why CDS alone have a significant factor, especially given that their underlying risks should also exist in the corporate bonds asset class. One possible explanation that CDS are a uniquely dealer-intermediated market, and thus intermediary wealth matters more as a factor. Another possible explanation is that some CDS contracts include meaningful counterparty risk that increase their expected returns — these would naturally covary with the capital of the dealers that issue them.

In contrast, excess return on risky corporate debt does appear to explain a large portion of the results. Replacing the intermediary capital factor with excess return on risky bonds, shown in table 12, shows roughly the same explanatory power as the original regression from He et al. (2017), shown in table 11.[10] T-statistics for both factors are similar, as are R squared values. The R squared for the regression using risky bonds is slightly higher for all-asset-class regression and within .1 for other asset classes except equities. For equities, the intermediary capital risk factor shows significantly greater explanatory power, although asset class is generally the hardest for either formulation to adequately explain relative to existing factor benchmarks.

In summary, from 1986 onward financial sector lending cost does not appear to have significant explanatory power outside of the CDS market, suggesting that commercial banks' explanatory power over returns is not mostly a result of their effects on financial sector borrowing cost. In contrast, simple excess returns on corporate credit does seem to provide an approximately equally accurate pricing of the cross-section of returns, suggesting that broad risk preference or macroeconomic factors are responsible.

3. Time series prediction test

3.1 Motivation

The cross-sectional tests are not fully conclusive due to the relative short time period — a meaningful sample of publicly listed banks is only available from the 1970s, and and Glass Steagall ends in the 1990s. To test the hypotheses on a longer time series, we can utilise the time-series prediction tests from Baron and Muir (2019). This paper documents commercial bank and securities dealer asset growth going back to 1870 in the UK, US, and Japan and finds that both types of bank growth predict asset returns on a one and two year horizon.

Using a similar approach and data, I look at time series prediction using the subset of the Baron and Muir (2019) data in the United States from 1946–1989 when the Glass-Steagall restrictons held, to see if commercial banks predict excess returns on stocks and on corporate debt when they were unable to trade those assets. Because few banks were publicly listed before 1960, market wealth or capital ratios cannot be constructed. Instead I follow Baron and Muir (2019) in using the growth of book assets. Under an intermediary asset pricing theory, asset growth should proxy for intermediary wealth and risk appetite, with high risk-appetite or wealth being associatted with high asset growth. Under a theory of time-varying risk preferences, we also expect asset growth to be procyclical and predictive of returns, as both debt growth and market values are.

[10] To make the figures more comparable, both regressions include only the periods where commercial bond data is available. The He et al. (2017) specification therefore does not match exactly the figures from the original paper.

3.2 Data

Data sources follow Baron and Muir (2019) closely. For 1946–1970, commercial bank assets are sourced from archival records from the Board of Governors of the Federal Reserve system Board of Governors of the Federal Reserve System (1976). This data source notes that data was obtained from 'the reports of bank holding companies, commercial banks, and nondeposit trust companies', which are all categories subject to Glass-Steagall restrictions. More detail on the restrictions is described in appendix 1. Commercial banks after 1970, and securities dealer banks both use data from the Federal Reserve Board's flow-of-funds online database.[11]

Historical returns on corporate debt is sourced from Welch and Goyal (2007), and risk free rates and stock market returns use CRSP data from Ken French's data library.

3.3 Methodology

Methodology also closely resembles Baron and Muir (2019), with only slight differences to account for my shorter time period and slightly different selection of assets (i.e. only bank-ineligible assets).

Four different regressions are run on the data. Each uses the same two regressors — annual growth in assets of commercial banks and securities dealers. The regressands are 1 and 2 year excess returns on both stocks and corporate bonds.

Corporate excess returns are calculated as the return on corporate bonds, minus the return on long term government debt. This can be interpreted as the returns from a portfolios that is long corporate bonds and short safe debt with an approximately equivalent maturity. By using spreads over long term debt I avoid capturing excess returns on government debt, which could be traded by commercial banks. Stock market excess returns use a simple spread over the risk free rate.

Following Baron and Muir (2019), I use annual instead of quarterly growth in assets and returns. Measurement error is likely to be very high in quarterly growth given the slow accrual of changes in asset values into accounting statements. This is particularly true for lending portfolios, which are not valued on a mark-to-market basis. For example, quarterly bank asset growth only explains 11% of the variation in capital ratios 1970-2012, whereas annual changes explain 48%.[12]

To increase the statistical power of the test given our relatively short timeframe, I differ from the original approach of Baron and Muir (2019) by using overlapping quarterly observations. This overlap in measurement periods creates autocorrelation in the error

[11] The two data series are 'Total Assets, All Commercial Banks' and 'Aggregate balance sheets of U.S. Security Brokers and Dealers'.

[12] R squared from regressions of changes in intermediary capital ratio levels from He et al. (2017) on commercial bank and securities dealer quarterly and annual changes. All parameters are significant at 1$ level. F-statistic of quarterly regression is 9.6, with p value of 0.01%, while F-statistic of annual regression is 17.0 with p value of $5 * 10^{-6}$.

terms. The regression therefore uses autocorrelation consistent standard errors with a bandwidth five Bartlett Kernel, following Newey and West (1987).[13]

In this exercise, I do not control for other macroeconomic factors. The fuller treatment of the general findings in Baron and Muir (2019) finds that they do not disappear after including various macroeconomic factors.

3.4 Findings

Results are shown in 3. The regression finds that commercial bank asset growth has significant explanatory power over changes in the one and two year excess returns on both stocks and corporate bonds. P values are under 5% for 1 year returns and under 1% for two year returns. All signs are negative as predicted by both theories, and economically meaningful — e.g. a 1% increase in commercial bank assets is associated with a 1.4% decrease in next year's returns on stocks.

Table 3: Regressions of 1 and 2 year ahead excess returns on stocks and bonds and of changes in risk free rates on commercial bank and securities dealer annual asset growth, 1946 Q4 – 1989 Q1, HAC standard errors in parentheses.

	Dependent variable:			
	1y stock ret	2y stock ret	1y corp ret	2y corp ret
	(1)	(2)	(3)	(4)
Com. bank assets	-1.360^{**}	-1.701^{***}	-0.163^{**}	-0.277^{***}
Std err	(0.653)	(0.589)	(0.082)	(0.086)
Sec. dealer assets	0.082	-0.106	0.022	0.025
Std err	(0.127)	(0.120)	(0.016)	(0.017)
Constant	0.176^{***}	0.314^{***}	0.013^{**}	0.026^{***}
Std err	(0.048)	(0.043)	(0.006)	(0.006)
Observations	128	128	128	128
Note:				*p<0.1; **p<0.05; ***p<0.01

In contrast, none of the securities dealers coefficients are significant in the joint regression. This finding is mostly robust to a univariate regression approach too — using a single regressor of securities dealer asset growth, only the 2 year equity returns are significant at a 5% level, while all coefficients in a single regressor commercial bank asset growth model remain significant.

[13] Recent literature has highlighted problems with finite sample inference using overlapping observations (e.g. Boudoukh, Israel, and Richardson, 2019). Although these problems are typically greater for very long observation windows, I include a non-overlapping annual version as a robustness check in table 4. Securities return results are qualitatively the same, but coefficients on commercial returns are no longer distinguishable from 0.

These results suggest that the predictive power over returns does not come from banks' investments in or interactions with securities markets. Instead it could arise through their role as leverage provider to the economy, and the resulting correlation with time varying risk preferences.

As with the cross-sectional results, the results are also compatible with indirect intermediary asset pricing effects from commercial banks. Although again it would be somewhat surprising that the indirect effect sizes are larger and more significant than the indirect effects.

Interestingly, these findings appear to run somewhat contrary to the broader finding from Baron and Muir (2019) that the power of financial sector balance sheets to forecast asset returns is greater when intermediaries participate more in a given asset class. They create a dummy variable for decades where banks or securities dealers owned high or low shares of the total equities market and government bond market (corporate bonds are not tested). The interaction term between the dummy variable and returns proves significant and often larger than the returns coefficient itself.

The likely explanation for this difference is that the US does not play a large role in their interaction regression for equities markets. US banks and securities dealers both appear to have a 0 dummy variable for equities for the entire time period, due to their low share of asset holdings. So the variations between securities dealers and commercial banks are not used in the equities regression, and instead the effects are driven by time series differences in Japan and the UK and between-country differences.

It is possible that the banks as the marginal investor theory performs uniquely poorly in the US. The great liquidity of the US equities market may allow securities dealers to make markets with uniquely low inventories, thus requiring less compensation for risk. Bank capital as a factor could be more related to macro factors or time-varying risk preferences in the US, but more related to direct intermediary asset pricing effects in other countries.

4. Implications of asset restrictions for bank capital as a factor

Under several of the most well-known intermediary asset pricing models, the wealth of the unrestricted intermediary class should fully explain prices in the restricted assets. The wealth of restricted intermediaries should therefore not add any additional information. The paper's findings that commercial bank wealth appears to explain the prices of bank-ineligible assets better than dealer wealth contradicts these models.

However, some additional "indirect" pricing ability of shocks to the restricted intermediary wealth is still possible under slightly different intermediary asset pricing models, if the unrestricted intermediary wealth does not fully explain asset prices. In this case, risk premia on restricted assets that covary highly with unrestricted assets may also be affected by some shocks to the restricted intermediaries. Some significant effect of commercial bank wealth on bank-ineligible asset prices is therefore compatible with these models. It is still surprising that commercial bank wealth would work better than dealer wealth, though.

Under alternative "passive" explanations for the intermediary capital factor, the intermediary providing leverage to the households — i.e. commercial banks — should be most likely to appear as a factor. This type of passive explanation presents the most natural explanation why commercial bank wealth would price bank-ineligible assets better than dealer wealth.

This section gives a brief example of each category of model and shows the implications for the relationship of restricted and unrestricted intermediary wealth or capital with asset prices.

4.1 Intermediary asset pricing

4.1.1 CRRA intermediaries as the marginal investor

Many leading intermediary asset pricing models feature an intermediary with constant relative risk aversion (CRRA) utility that acts as the marginal investor due to some restriction on trading. The intermediary's Euler equation specifies asset pricing and so risk premia are a function of intermediary wealth. In such a model, if we add a separate class of restricted intermediaries (i.e. commercial banks), the wealth of the unrestricted intermediaries (i.e. investment banks) will price the assets with trading restrictions, and the wealth of restricted intermediaries should not add additional information.

To illustrate, we can consider the simple model proposed for the empirical tests in He et al. (2017). In this model, a representative agent (the intermediary) owns all risky assets in the economy. Its wealth can be represented as $\eta_t W_t$, where W_t is the value of all risky assets, and η_t is the intermediary's wealth divided by its assets. In other words, $\eta = \frac{equity_t}{assets_t}$, and represents an intermediary capital ratio.

The intermediary has CRRA utility with risk aversion γ, which leads to consumption and marginal utility that is proportional to its wealth. Since the intermediary is the sole investor, its marginal utility, $e^{-\rho t}(W_t \eta_t)^{-\gamma}$, is the economy's state price density. The usual equation for expected returns on any asset therefore gives us:

$$E_t(dR_t^i) - r_t^f dt = \gamma Cov_t\left(dR_t^i, \frac{dW_t}{W_t}\right) + \gamma Cov_t\left(dR_t^i, \frac{d\eta_t}{\eta_t}\right) \tag{1}$$

We can re-write this in with the typical β, λ price of risk notation:

$$E_t(dR_t^i) - r_t^f dt = \lambda_W \beta_{W,t}^i + \lambda_\eta \beta_{\eta,t}^i \tag{2}$$

In other words, intermediaries are the marginal investors in all asset classes and therefore their wealth is the sole priced risk. This wealth factor can be decomposed into the value of all assets, and the bank's capital ratio. The model clearly implies that changes in bank capital ratios and market wealth will jointly price the cross-section of asset returns.

If there are any assets in which banks cannot invest, then the bank capital ratio should only appear as a risk factor if it covaries with that of the true investors, and it should be less significant and explain less variance than that of the true investors.

To see this we can consider a minor extension of the model with two types of assets and two intermediaries — one of which can invest in one asset, the other in both.

Suppose the investment bank (I) has a share of assets θ_t^I, and a capital ratio η_t^I and can own government securities, or stocks with return $R^{s,i}$, or the risk free rate.[14] A commercial bank (C) owns the rest of the assets and can only invest in government securities or the risk free rate.

Now the wealth of investment banks is $W_t^I \eta_t^I \theta_t^I$. By the same logic as before, the expected return of stocks (i.e. the restricted asset) will be fully explained by investment bank wealth;

$$E_t\left(dR_t^{s,i}\right) - r_t^f dt = \lambda_W \beta_{W,t}^{s,i} + \lambda_{\eta^I} \beta_{\eta^I,t}^{s,i} + \lambda_{\theta^I} \beta_{\theta^I,t}^{s,i}$$

If we misspecify our cross-sectional regression by using commercial banks instead of investment banks, then we will be estimating the price of risk associated with $\beta_{\eta^C}^i$ rather than $\beta_{\eta^I}^i$. We are still likely to find a significant coefficient so long as there is a covariance across assets between $\beta_{\eta^I}^i$ and $\beta_{\eta^C}^i$ that is not explained by $\beta_{W,t}^{s,i}$. In this simple model, this will be the case. Both types of intermediary own some amount of government securities, and thus stocks that have a higher covariance with government bonds will have a $\beta_{\eta^I}^i$ and $\beta_{\eta^C}^i$.

However, as long as changes in η^I and η^C have less than perfect correlation, then a regression using η^I should explain a greater portion of the variance than one using η^C, and should have more significant estimates of the price of risk. In practice, capital ratios for commercial and investment banks are reasonably far from one. In the sample I construct for empirical tests (see section 5) the shocks to η^I and η^C have a 45% correlation.

A similar logic holds for other models. For example, in He and Krishnamurthy (2013) an asset's risk premium is determined by the intermediary's consumption growth (which is equal to its changes in wealth under certain parameters) and in Kondor and Vayanos (2019) the risk premium is a function of an arbitrageur intermediary's wealth.

4.1.2 "Indirect" channels

It is possible to write intermediary asset pricing models models in which shocks to intermediaries restricted from trading (e.g. commercial banks) matter for asset pricing even after accounting for shocks to the unrestricted intermediaries. In particular, if the shocks being measured are not shocks to the marginal utility of the investor, then the shocks to the un-

[14] The θ parameter of share of assets is not included in any regressions. In He et al. (2017) this is assumed to be a constant of 1 for simplicity. Clearly this cannot be entirely true since there are risky assets not owned by primary dealers. However the specific form of this model is not too important — it is meant to introduce a framework for using capital ratios rather than pure equity values in line with a range of other work in intermediary asset pricing.

restricted intermediary do not fully explain prices. Shocks to the restricted intermediaries can therefore thave indirect effects on the restricted assets.

For example, Haddad and Muir (2020) consider a simple one period model where household and intermediaries both have constant absolute risk aversion utility, which leads to risk premium expressions similar to the classic Markowitz results, but with a distortion that depends on the intermediary's risk aversion parameter.

If we consider the intermediary capital shocks to be to be risk aversion shocks instead of wealth shocks then they explain expected return. High risk aversion is associated with a high risk premium. Since we are not measuring changes to marginal utility directly, there is room for other variables to also explain risk premia. Changes to risk aversion of intermediaries that invest in assets with a high degree of covariance will also indirectly affect returns. A more detailed derivation of this result is contained in appendix 3.

While indirect effects of shocks to restricted intermediaries are possible, one might expect to see more evidence of direct effects of socks to the unrestricted intermediary if both types are subject to similar shocks. Shocks to the unrestricted intermediaries must matter for all assets in which they invest in such a model, whereas indirect effects are weaker for assets with less covariance with the restricted assets.

4.2 Passive models

One alternative explanation for the apparent explanatory power of bank capitalisation is that they "passively" correlate with macroeconomic variables that explain asset prices. If risk preferences vary over time (e.g. due to habit formation), periods with high risk should be linked to higher bank values and leverage and also higher expected returns. Similarly, bank values and leverage could covary with investor sentiment as in Baron and Xiong (2016).

Santos and Veronesi (2018) consider a frictionless economy with external habit formation, a lending and deposit-taking intermediary, and an exogenous stochastic income process with a single state variable (I) representing economic uncertainty. They derive closed form solutions for certain parameters in which:

- The intermediary's debt is a decreasing function of I (i.e. procyclical)
- The intermediary's ratio of market value over debt, is also a decreasing function of I. This implies capital ratio as defined in the prior section is procyclical.
- The state price density in the economy is:

$$M_t = e^{-\rho t} Y_t^{-1} I_t \tag{3}$$

Where Y is aggregate income.

Since I is not observable, other monotonic functions of I will explain the cross-section and predict the time-series of returns. Clearly, this includes intermediary leverage and capital ratios.

In theory, many other variables should be linked to I. Macroeconomic indicators should measure it, as should asset prices whose returns depend on expected volatility (e.g. options, risky debt). But leverage provider balance sheets may have less measurement error than macroeconomic aggregates.

Securities dealers are not included in this model, so their functioning as a pricing factor is ambiguous. If they are not providing leverage to households, then their balance sheet may not be as clear a window into the marginal rate of substitution. However, one would still expect some ability to price assets if their price is a function of the volatility of income.

This model is of course only one among many proposed options. The exact forms of risk preferences and economic uncertainty are chosen to give closed form solutions. But the idea that household risk tolerance, leverage, and economic uncertainty move together is more important than the specific form of the preferences. This comovement shows how bank leverage could be related to asset prices without any role as investors in those assets. If the leverage provision functions of banks are found to explain prices better than the investing and market making functions, then the model presents a plausible alternative to intermediary asset pricing explanations.

5. Conclusion

The Glass-Steagall restriction period allows us to view an unusually clean separation between commercial banking and securities dealing.

I use these restrictions to test if some of the recent findings of intermediaries' ability to explain asset prices are due their role as bankers or dealers. Surprisingly, I find that the banker balance sheets appear to predict securities returns better than the dealer balance sheets. I also find that the banker capitalisation does no worse, and perhaps somewhat better, at explaining the cross-section of returns.

These findings cast some amount of doubt on the typical intermediary asset pricing interpretation that intermediaries' ability to explain returns is due to their role as an investor. The results do not prove any specific alternative explanation. And some versions of intermediary asset pricing are compatible with banker capital having an explanatory power through "indirect" effects on assets covarying with the banks' portfolio. However, a natural alternative that fits with these findings is that risk preferences vary through time — due to habit formation or any other reason — and banks just provide a window into these shifting marginal rates of substitution.

Appendix

A.1. Details of Glass-Steagall restrictions

This appendix describes the Glass-Steagall restrictions on commercial bank, argues that it meaningfully restricted commercial bank trading activity through the mid 1990s, and presents evidence on the size of trading activity in BHCs in 1995.

The legal description is based on Federal Reserve bulletins, contemporary bank annual reports, and accounts from legal practitioners, particularly Cohen (1997).

History and legal force

Glass-Steagall was a set of provisions contained in the Banking act of 1933. These provisions severely limited dealing and underwriting by national banks and their affiliates, state member banks, and all depository institutions. Dealing was flatly prohibited except for 'bank eligible' securities — primarily US Government securities (see sections 5, 16, 20, & 21 of the Banking Act of 1933). Derivatives on bank ineligible securities were also prohibited, as were commodities and their derivatives. The Bank Holding Company act of 1956 further strengthened these restrictions and extended them to any entity affiliated with a bank in a holding company structure (Omarova, 2009).

In principal the text allowed regulators to permit a BHC to acquire a securities firm if its securities activity was sufficiently small. However from 1933 to 1984 there are no known attempts by banks to establish or buy securities dealers or underwriters that would meet this definition of 'engaged principally' (Cohen, 1997).

In 1984 Citicorp became the first bank to apply for a securities dealer affiliate, but was rejected and withdrew its application (Federal Reserve Board of Governors, 1985).

In 1987, the Federal reserve granted the first exemptions for affiliates, but this was limited to commercial paper, municipal revenue bonds, and mortgage backed-securities (Federal Reserve Board of Governors, 1987). These assets are not included in the bank-ineligible asset classes tested in this paper.

The first approvals for affiliates trading in corporate debt and equity securities did not arrive until 1989 (Federal Reserve Board of Governors, 1989). Subsidiaries could not obtain more of 10% of their revenue from dealing, and could not have over 5% market share for any type of security, and were subject to strict controls and firewalls.

In 1994, effective 1995, the OCC for the first time permitted national banks to engage in equity derivatives transactions. Commodities derivatives saw somewhat more permissive regulation in the 1990s, with exemptions were granted for certain categories of commodity linked-deposits and matched term commodities swaps in which the bank did not assume substantial commodity risk starting in the early 1990s (Omarova, 2009).

More substantial liberalisation for corporate debt and equity securities was approved in 1996 and effective March 1997. Revenue limits for affiliates were raised to 25% and firewalls weakened. Contemporary accounts note that this was a major change — it allowed BHCs to 'substantially expand dealing capabilities' (Chase Manhattan Corp, 1997), and opened up acquisitions of securities firms, which had previously only occurred on a very small scale. Affiliate approvals for commodities trading remained impossible for BHCs even after 1997 (Cohen, 1997).

After revenue limits were raised, the Glass-Steagall provisions had lost much of their bite. They were finally eliminated in the Financial Modernization Act of 1999 (the 'Graham-Leach-Bliley' act).

The timeline of legal events therefore implies:

- Up to 1989, the Glass-Steagall restrictions were strict, with very little bank-ineligible activity allowed in BHCs
- For corporate debt and equities, some activity was allowed in subsidiaries of BHCs from Q2 1989 onward, but tightly controlled and limited to 5% market share and 10% of revenue. In practice few dealers were acquired by banks
- For equity options, no significant activity was permitted in BHCs until 1995 Q1
- For commodity derivatives, somewhat more permissive rules allowed slightly more trading activity by BHCs in the early 1990s, although with limitations on instrument type and risk
- From 1997 onwards BHCs were allowed to own substantially larger securities dealer subsidiaries

I run the cross-sectional regressions from 1970-1989 Q1 for the more restrictive case or 1970-1994 Q4 for the more permissive case to capture more asset classes and ensure reasonable restrictiveness of the regulation. The legal evidence suggests that this more permissive case still entailed strong restrictions on at least corporate debt, equities, and equity options.

Bank balance sheets as of 1995

To test whether the legal restrictions really held, I also estimate trading activity by all primary dealer banks as of 1995, based on contemporary 10-K reports. Since the restrictions were easing over the period, these figures should put an approximate upper bound on the level of trading and investment activity taking place in BHCs in our extended sample to 1994.

Revenue and asset estimates are shown in table 14. In summary, 95% of both revenues and assets from the relevant asset classes among primary dealers appears to come from non-BHCs. In other words the non-BHCs held approximately 20x as much assets and conducted approximately 20x as much revenue-generating sales and trading. In contrast, across all activities BHCs compose 40% of the assets and 35% of the revenues of the primary dealer sample.

These figures are far from exact — 10-K reports do not segment revenues or assets in a comparable way between companies. But the errors are likely to substantially overstate the amount of BHC activity in bank-ineligible classes. For most of the banks some large categories of bank-eligible activity (particularly government securities and interest rate swaps) could not be split from ineligible activity and so is left in the figures. BHCs' market share in these assets is likely to to have been greater than their share in ineligible assets due to the lack of legal restrictions.

A.2. Construction of BHC intermediary capital dataset

The steps taken to construct the data include:

1. All primary dealers since 1960 are listed with start and end dates, based on lists from the New York Federal Reserve.
2. Banks that were never owned by a publicly listed entity are removed
3. Each of the 50 remaining banks that acted as a primary dealer at some point before 1999 is identified as either a BHC or not. Assessments are based on contemporary sources including annual reports, government records, and media. The list of primary dealer public parent companies, their dates, their status as a BHC, an the source for the determination of BHC status is shown in table 15. Foreign banks were assumed not to be BHCs, because they were not subject to Glass Steagall regulation on their non-US activities and thus were able to trade bank-ineligible securities regardless of the status of their US subsidiary.
4. Market capitalisation and book liabilities data is sourced for each parent company. For US firms data comes from CRSP and Compustat. For non-US firms, the same data is sourced from S&P Capital IQ.[15]
5. When a primary dealer was acquired by another primary dealer, only the data for the acquiring bank is used for as long as it was a primary dealer. The CRSP/ Compustat data on balance sheet and market values is adjusted for acquisitions, this avoids double-counting. But when a primary dealer was later acquired by a entity that was not a primary dealer, the acquired banks equity is used up until the date of acquisition to deliver the most accurate picture of contemporary values.
6. For a small number of data points where liabilities are not available but market value is, the next or previous period available liabilities are used instead.
7. Value-weighted capital ratios are calculated as the sum of all bank market values divided by the sum of market values and liabilities $\eta_t = \frac{MktValue_t}{MktValue_t + Liabilities_t}$.

[15] Note that this differs slightly from He et al. (2017), who use Datastream for foreign bank assets and values. Physical access to an Eikon terminal for datastream data was not feasible during the Covid-19 closures.

8. The risk factor is then constructed as innovations in the AR1 regression of $\eta_t = \rho_0 + \rho_1 \eta_{t-1} + u_t$, divided by the lagged capital ratio: ${}^{\Delta}\eta_t = u_t / n_{t-1}$. This matches the formula from He et al. (2017).

A.3. Indirect effects in the Haddad and Muir model

This appendix considers a very minor extension of the model from Haddad and Muir (2020) in which one class of intermediaries is able to invest in some assets but not others. The original model consists of:

- n 1 period assets with fixed supply vector S, price vector p, and payoff vector μ with covariance matrix Σ
- One intermediary that can freely choose invest in all assets
- A household that owns the intermediary, but cannot control its investments
- The household can choose to invest in all assets but face quadratic cost per unit of risk invested, parameterized by the diagonal nxn matrix C. I.e. cost is $\frac{1}{2}D'\Sigma_{diag}CD$, where D is the investment size and Σ_{diag} is the diagonal elements of Σ
- All agents have constant absolute risk aversion utility with risk aversion coefficient γ_H for households γ_I for the intermediary

In the original model the vector of risk premia is:

$$\mu - p = \gamma_H \Sigma(\Sigma + \frac{1}{\gamma_I}\Sigma_{diag}C)^{-1}(\Sigma + \frac{1}{\gamma_H}\Sigma_{diag}C)S$$

The only addition to this model is to include a restricted intermediary with absolute risk aversion coefficient γ_C also owned by the household, which can only invest in the first k assets. Following the same derivation steps as in Haddad and Muir (2020), the risk premium vector then becomes:

$$\mu - p = \gamma_H \Sigma(\Sigma + \frac{1}{\gamma_I}\Sigma_{diag}C + \frac{1}{\gamma_C}\Sigma_{k,diag}C)^{-1}(\Sigma + \frac{1}{\gamma_H}\Sigma_{diag}C)S$$

Where $\Sigma_{k,diag}$ is an nxn matrix consisting of the first k diagonals of Σ followed by 0s in all other elements.

From this formula we can observe:

- Changes in H or I's risk aversion will affect all risk premia
- If all restricted assets have 0 covariance with all unrestricted assets, the restricted assets will have the same risk premia as in the original model — i.e. they will be unaffected by γ_C. This is because Σ will be block diagonal with respect to the first k and last n-k blocks.
- Allowing for covariance between the first k and last n-k assets, changes to C's risk aversion will affect all risk premia. However the size and direction of that effect will depend on the covariances between asset payoffs.

A.4. Tables and Figures

Table 4: Non-overlapping annual period regressions of 1 and 2 year ahead excess returns on stocks and bonds and of changes in risk free rates on commercial bank and securities dealer annual asset growth, 1946 Q4 – 1989 Q1, standard errors in parentheses.

	Dependent variable:			
	1y stock ret	2y stock ret	1y corp ret	2y corp ret
	(1)	(2)	(3)	(4)
Com. bank assets	-1.454^{**}	-2.467^{**}	-0.081	-0.183
Std err	(0.654)	(0.920)	(0.119)	(0.138)
Sec. dealer assets	0.136	0.013	0.003	0.007
Std err	(0.155)	(0.218)	(0.028)	(0.033)
Constant	0.166^{***}	0.334^{***}	0.010	0.021^{**}
Std err	(0.048)	(0.068)	(0.009)	(0.010)
Observations	43	43	43	43
R^2	0.110	0.178	0.013	0.045
Adjusted R^2	0.066	0.137	-0.037	-0.002
Residual Std. Error (df = 40)	0.163	0.230	0.030	0.035
F Statistic (df = 2; 40)	2.475^{*}	4.325^{**}	0.254	0.953

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Summary all-asset-class unbalanced Fama Macbeth regression results for 2-factor models using BHC capital ratios vs non-BHC capital ratios as a factor. Both models use excess market equity returns as the second factor. Regressions for 1970-1989 and 1970-1994 are included separately. GMM t-statistics are included in parentheses.

	1970Q1–1989Q1		1970Q1–1994Q4	
	(1) BHC	(2) Non-BHC	(3) BHC	(4) Non-BHC
BHC capital ratio	7.283*		8.756**	
T-stat	(1.691)		(2.229)	
Non-BHC capital ratio		3.044		-3.874
T-stat		(0.858)		(-0.839)
Market return	1.889	0.123	1.02	1.201
T-stat	(0.549)	(0.033)	(0.555)	(0.755)
Constant	0.218	1.612	0.627	0.753
T-stat	(0.240)	(1.135)	(1.021)	(1.412)
R2	0.507	0.351	0.366	0.121
MAPE	2.083	2.144	1.193	1.18
Assets	76	76	76	76
Periods	77	77	100	100

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Cross-sectional test of changes in primary dealer Bank Holding Company capital ratios and equity market excess returns as factors with quarterly data 1970 Q1 - 1989 Q1. GMM T-statistics in parentheses.

	FF25	US_bonds	All
BHC cap ratio	14.052	7.831	7.283*
T-stat	(1.614)	(0.757)	(1.691)
Market return	4.294	9.091	1.889
T-stat	(1.197)	(1.791)	(0.549)
Constant	-2.26	-1.814	0.218
T-stat	(-0.692)	(-0.956)	(0.24)
R2	0.244	0.827	0.507
MAPE	0.639	0.102	2.083
Assets	25	10	76
Periods	77	61	77

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Cross-sectional test of changes in capital ratios of primary dealers that are not Bank Holding Companies and equity market excess returns as factors with quarterly data 1970 Q1 - 1989 Q1. GMM T-statistics in parentheses.

	FF25	US_bonds	All
Non-BHC cap ratio	6.442	21.936*	3.044
T-stat	(1.063)	(1.901)	(0.858)
Market return	-3.792	7.887	0.123
T-stat	(-1.638)	(1.036)	(0.033)
Constant	5.521***	-1.625	1.612
T-stat	(2.737)	(-0.597)	(1.135)
R2	0.22	0.86	0.351
MAPE	0.651	0.089	2.144
Assets	25	10	76
Periods	77	61	77
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: Cross-sectional test of changes in primary dealer Bank Holding Company capital ratios and equity market excess returns as factors with quarterly data 1970 Q1 - 1994 Q4. GMM T-statistics in parentheses.

	FF25	US_bonds	Options	Commod	All
BHC cap ratio	10.137*	13.219	21.184**	-0.003	8.756**
T-stat	(1.722)	(1.424)	(2.245)	(-0.001)	(2.229)
Market return	1.551	7.233	-4.063	-1.643	1.02
T-stat	(0.649)	(1.377)	(-1.04)	(-0.794)	(0.555)
Constant	0.026	-1.577	4.773*	0.324	0.627
T-stat	(0.012)	(-0.965)	(1.733)	(0.406)	(1.021)
R2	0.599	0.94	0.955	0.127	0.366
MAPE	0.349	0.061	0.288	1.913	1.193
Assets	25	10	18	23	76
Periods	100	84	35	33	100
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 9: Cross-sectional test of changes in capital ratios of primary dealers that are not Bank Holding Companies and equity market excess returns as factors with quarterly data 1970 Q1 - 1994 Q4. GMM T-statistics in parentheses.

	FF25	US_bonds	Options	Commod	All
Non-BHC cap ratio	0.544	24.806	-36.859^{**}	-8.976	-3.874
T-stat	(0.118)	(1.624)	(-2.832)	(-1.397)	(-0.839)
Market return	-1.333	7.871	-3.99	-0.847	1.201
T-stat	(-0.935)	(1.051)	(-1.023)	(-0.344)	(0.755)
Constant	3.404^{***}	-1.605	4.843	-0.131	0.753
T-stat	(2.965)	(-0.653)	(1.634)	(-0.135)	(1.413)
R2	0.073	0.952	0.809	0.328	0.121
MAPE	0.61	0.052	0.709	1.705	1.18
Assets	25	10	18	23	76
Periods	100	84	35	33	100
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 10: Cross-sectional test of the LIBOR spread and excess returns on the markets factors with quarterly data 1986 Q1 - 2012 Q4. GMM T-statistics in parentheses.

	FF25	US_bonds	Sov_bonds	Options	CDS	Commod	FX	All
Libor - Rf	-0.045	0.1	-0.023	-0.519	0.121^{***}	-0.077	0.003	
T-stat	(-0.677)	(0.91)	(-0.273)	(-1.756)	(3.518)	(-1.334)	(0.062)	(NA)
Market return	-0.739	5.014^{**}	3.981	7.783	6.311^{***}	1.322	8.205	
T-stat	(-0.411)	(2.371)	(1.249)	(1.022)	(2.936)	(0.852)	(2.676)	(NA)
Constant	2.986^{**}	0.582^{***}	0.628	-3.392	-0.116	-0.39	-0.385	
T-stat	(2.022)	(3.991)	(0.992)	(-0.485)	(-1.234)	(-0.452)	(-0.672)	(NA)
R2	0.259	0.647	0.686	0.985	0.956	0.229	0.443	
MAPE	0.408	0.191	0.524	0.143	0.079	1.201	0.47	
Assets	25	20	6	18	20	23	12	124
Periods	108	104	65	103	47	105	96	108

Table 11: Cross-sectional test of changes in capital ratios of all primary dealers (from He et al., 2017) and market returns as factors with quarterly data 1970 Q1 - 2012 Q4, only periods where bond data is available. GMM T-statistics in parentheses.

	FF25	US_bonds	Sov_bonds	Options	CDS	Commod	FX	All
HKM cap ratio	7.238**	7.556***	7.047*	22.42**	10.34***	5.79	19.381***	8.885**
T-stat	(2.34)	(2.586)	(1.663)	(2.016)	(3.278)	(1.623)	(3.124)	(2.399)
Market return	1.814	1.426	1.238	2.815	0.444	-0.775	10.134**	1.756
T-stat	(1.096)	(0.822)	(0.318)	(0.669)	(0.155)	(-0.369)	(2.172)	(0.938)
Constant	0.003	0.409	0.339	-1.111	-0.397***	1.114	-0.942	-0.089
T-stat	(0.002)	(1.436)	(0.333)	(-0.311)	(-2.707)	(0.886)	(-0.829)	(-0.098)
R2	0.528	0.836	0.808	0.987	0.647	0.176	0.534	0.748
MAPE	0.388	0.128	0.317	0.144	0.188	1.199	0.441	0.65
Assets	25	20	6	18	20	23	12	124
Periods	152	148	65	103	43	101	135	152

Table 12: Cross-sectional test of the excess return of risky corporate bonds and market returns as factors with quarterly data 1970 Q1 - 2012 Q4. GMM T-statistics in parentheses.

	FF25	US_bonds	Sov_bonds	Options	CDS	Commod	FX	All
Bonds - Rf	2.368**	0.841***	1.331**	1.486	2.095***	1.159	6.413	2.364***
T-stat	(2.407)	(2.579)	(2.297)	(1.116)	(3.639)	(1.423)	(1.267)	(3.277)
Market return	1.429	3.06**	0.851	8.245***	-1.961	-0.326	15.694***	3.143
T-stat	(0.926)	(2.026)	(0.321)	(3.00)	(-0.585)	(-0.162)	(2.582)	(1.84)
Constant	0.755	0.314	0.614***	-5.66	-0.269***	0.083	-3.087	-1.152
T-stat	(0.601)	(4.363)	(1.009)	(-2.728)	(-3.535)	(0.097)	(-1.454)	(-1.995)
R2	0.244	0.821	0.912	0.915	0.663	0.167	0.515	0.82
MAPE	0.538	0.133	0.28	0.373	0.169	1.295	0.444	0.778
Assets	25	20	6	18	20	23	12	124
Periods	152	148	65	103	43	101	135	152

Table 13: Cross-sectional test of the excess return of risky corporate bonds over LIBOR, LIBOR over the risk free rate, and market returns as factors with quarterly data 1970 Q1 - 2012 Q4. GMM T-statistics in parentheses.

	FF25	US_bonds	Sov_bonds	Options	CDS	Commod	FX	All
Bonds - LIBOR	0.228	0.999***	1.579***	3.658	1.203*	1.778*	5.825	
T-stat	(0.423)	(4.1)	(2.934)	(0.638)	(2.093)	(1.483)	(1.924)	(NA)
LIBOR - Rf	-0.022	-0.092	0.098	-0.541	0.127***	-0.09	0.086	
T-stat	(-0.365)	(-1.213)	(1.255)	(-1.585)	(3.553)	(-1.169)	(0.998)	(NA)
Market return	-1.018	-1.355	3.729	5.403	4.653	2.054	9.654	
T-stat	(-0.547)	(-0.909)	(0.965)	(0.811)	(2.135)	(1.049)	(1.613)***	(NA)
Constant	3.159	0.326	-0.436	-1.171	-0.1	-0.882	-3.213	
T-stat	2.043	2.413	-0.522	-0.161	-1.133	-0.955	-1.538	
R2	0.269	0.924	0.963	0.988	0.957	0.4	0.649	
MAPE	0.414	0.098	0.171	0.116	0.074	1.1	0.445	
Assets	25	20	6	18	20	23	12	124
Periods	104	104	65	103	43	101	96	104

Fig. 1: Comparison of the intermediary capital ratio from He et al. (2017) in dark blue and constructed for this paper in light blue, 1970 Q1 – 2012 Q4.

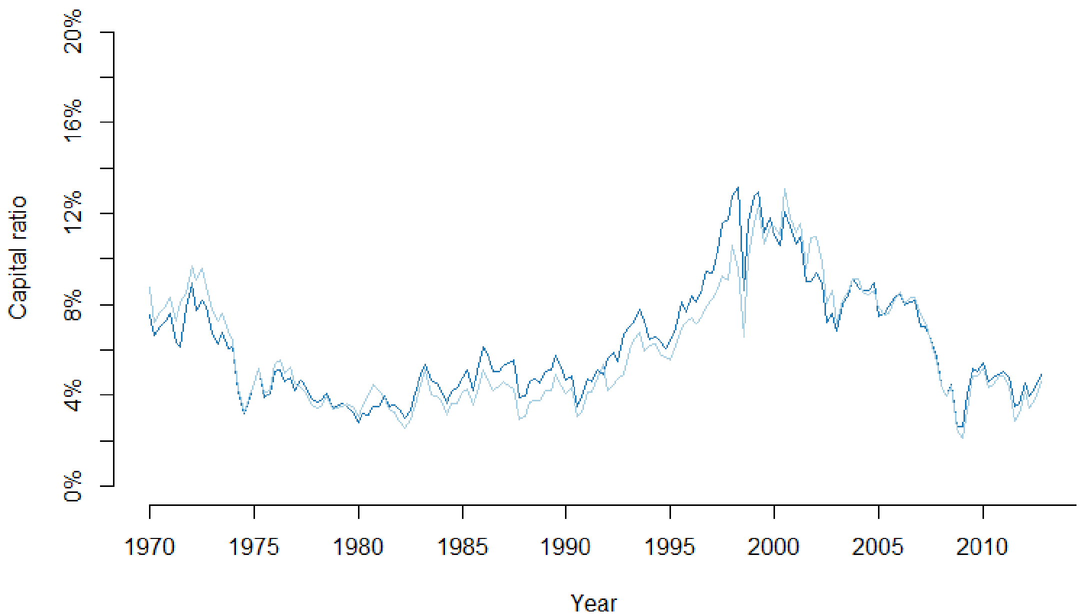

Fig. 2: Comparison of Bank Holding Company (blue) and non-Bank Holding Company (light blue) intermediary capital ratios, 1970 Q1 – 2012 Q4. Note that data after 1996 is not used and not meaningful for either of these categories.

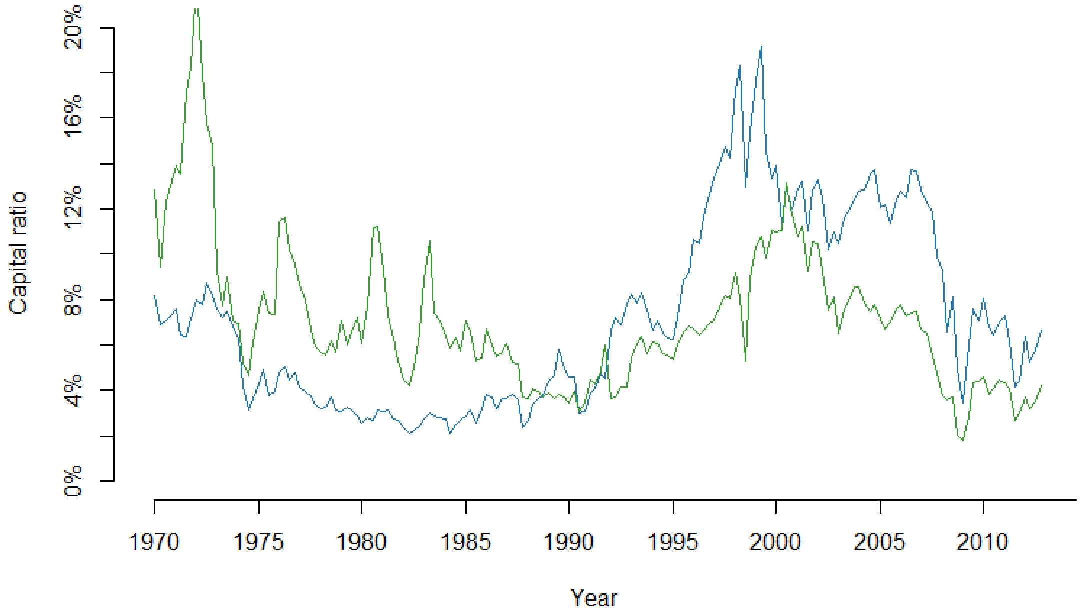

Fig. 3: Total primary dealer assets in Bank Holding Companies (blue) vs non-Bank Holding Companies (green), 1970 Q1 – 1999 Q2, log scale.

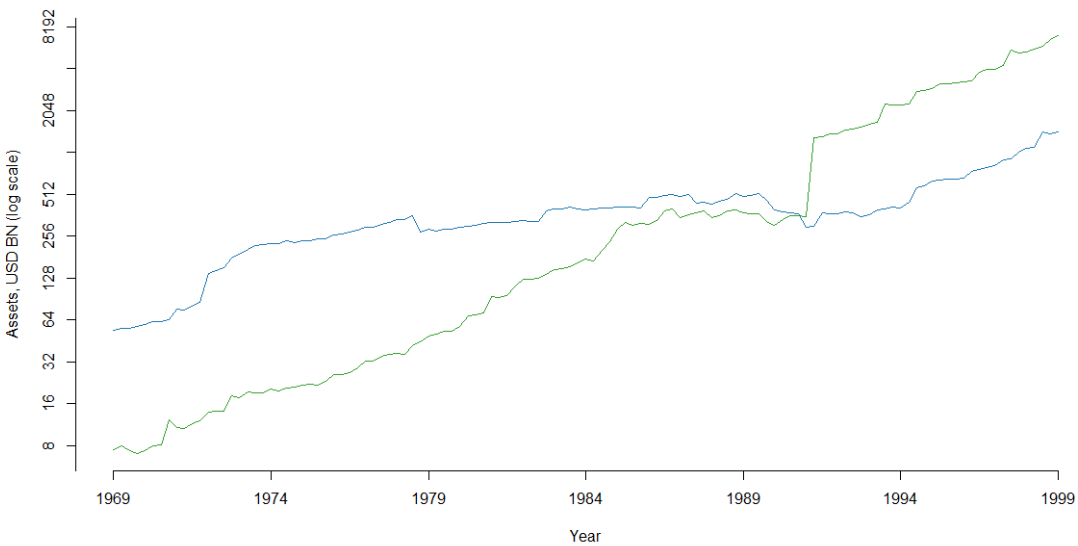

Fig. 4: Comparison of intermediary capital risk factors, 1969 Q4 – 2012 Q4. Blue is Bank Holding Company capital, green is non-Bank-Holding-Company capital, and orange is the He et al. (2017) factor. Note that BHC and non-BHC data after 1996 is not used and not meaningful.

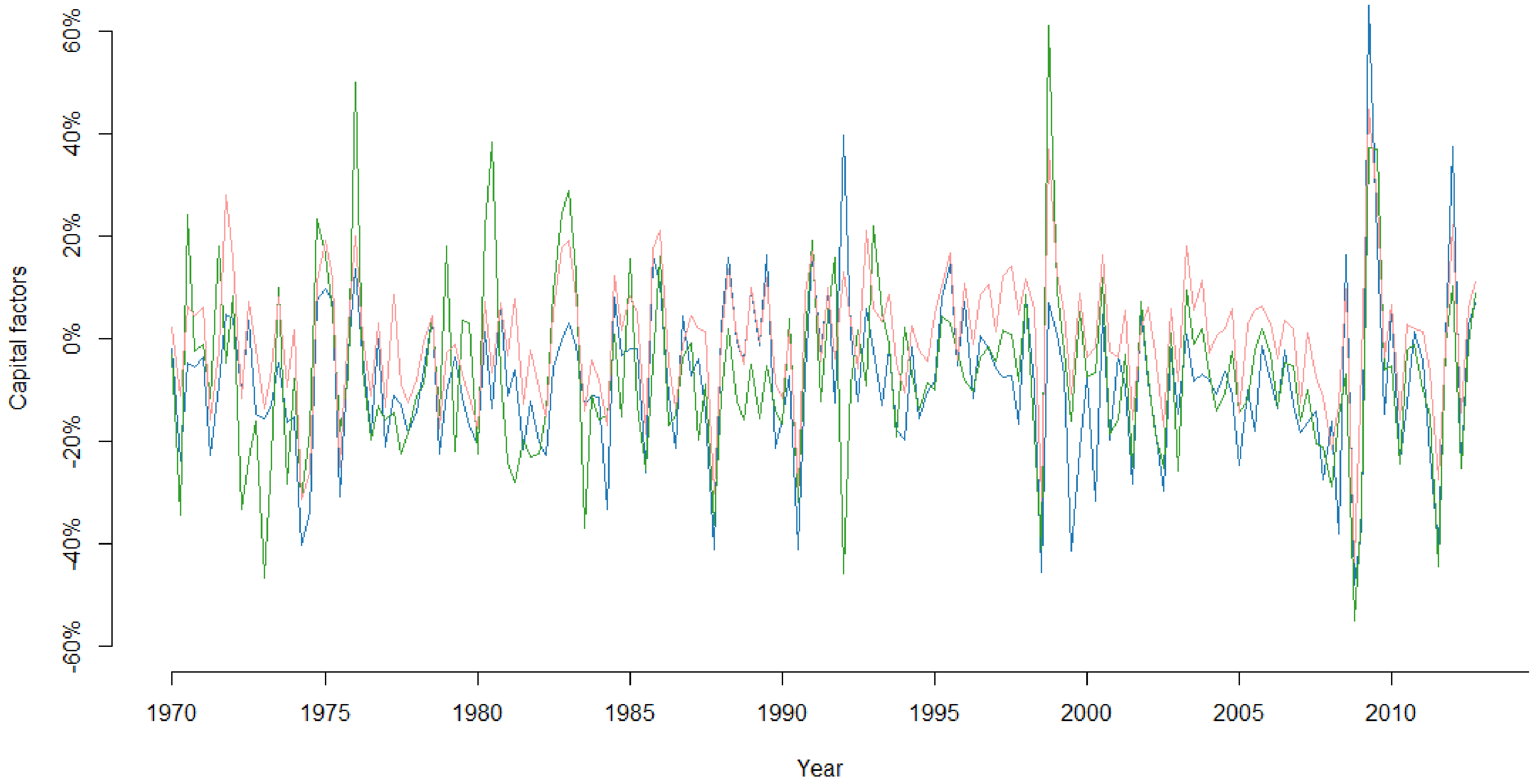

Table 14: Estimated revenue and assets from BHC-ineligible activity for each public Primary Dealer in 1995. Estimates are approximations from annual reports. BHC-ineligible activity is likely overstated due to inclusion of government debt trading.

	Revenue (USD MM)				**Assets (USD BN)**			
	BHC-ineligible	Total	Share	Notes	BHC-ineligible	Total	Share	Notes
BHCs								
Chase Manhattan	429	15,718	*2.7%*	Includes rates and govt securities	3.9	304	*1.3%*	Corp securities, loans, stocks, and commodities
First Chicago	203	4,413	*4.6%*	Includes rates and govt securities	1.7	122	*1.4%*	Estimated from avg ratio of assets/revenue
Nationsbank	103	8,154	*1.3%*	All securities trading	0.8	187	*0.5%*	Estimated from avg ratio of assets/revenue
Zions Bank	18	311	*5.7%*	Estimated from avg ratio of assets/revenue	0.1	6	*2.6%*	Securities held on trading account
Total	753	28,596	*2.6%*		6.6	619	*1.1%*	
BHC's share of total	*5.1%*	*35.9%*			*5.4%*	*40.4%*		
Non-BHCs								
Morgan Stanley DW	3,041	9,820	*31.0%*	Includes rates and govt securities but not FX	41.1	182	*22.6%*	All non-govt debt instruments, equities, &
Merrill lynch	2,616	10,265	*25.5%*	Equities and taxable fixed income only	21.5	177	*12.2%*	Estimated from avg ratio of assets/revenue
Salomon Inc	2,431	3,151	*77.2%*	Includes rates and govt securities	16.4	188	*8.7%*	Does not include govt debt
Paine webber	1,811	3,350	*54.1%*	Corp debt & equity plus commissions	2.9	46	*6.4%*	Corp debt securities and equities only
Lehman	1,450	2,078	*69.8%*	Includes rates and govt securities	11.0	83	*13.3%*	Does not include govt debt
Bear stearns	1,327	1,220	*108.8%*	Share >100% due to negative NIM	9.3	32	*28.7%*	FY ending June '95. Corp deb & equity only.
Travelers	1,016	16,583	*6.1%*	Includes all trading revenue	3.2	114	*2.8%*	Corp debt securities and equities only
Banker's trust	333	4,678	*7.1%*	Includes rates and govt securities. Uses '93 data	9.4	92	*10.2%*	Corporate debt & equities only. Uses '93 data
Total	14,025	51,145	*27.4%*		115	914	*12.6%*	
Non-BHC's share of t	*94.9%*	*64.1%*			*94.6%*	*59.6%*		

Sources: Chase Manhattan Corp (1997), First Chicago NBD Corp (1998), Nationsbank Corp (1996), Zions Bancorporation (1996), Morgan Stanley Dean Witter Discover & Co (1998), Merrill Lynch & Co Inc (1996), Salomon Inc (1996), Paine Webber Group Inc (1996), Lehman Brothers Inc (1996), Bear Stearns Companies Inc (1996), Bankers Trust New York (1994), Travelers Group Inc (1996)

Table 15: Full list of all Primary Dealers used before 1999 for calculation of intermediary capital ratios, their starting and ending dates as dealers, their status as a BHC, and the source from which the BHC status was derived.

Dealer name	BHC status	Start date as dealer	End date as dealer	Source for BHC status
Discount Corp.	No	'60-05-19	'93-08-10	Bloomberg Company Profiles (2020a)
First Boston	No	'60-05-19	'93-10-11	Quint (1975)
Irving	No	'60-05-19	'89-07-31	Quint (1988)
Merrill Lynch	No	'60-05-19	'09-02-11	Merrill Lynch & Co Inc (1996)
Salomon Smith Barney	No	'60-05-19	'03-04-06	Celarier (1998)
Bankers Trust	BHC	'60-05-19	'90-12-13	Hansell (1997). Note that series ends when Deutsche Bank enters
Continental	BHC	'60-05-19	'91-08-30	Federal Deposit Insurance Corporation. Division of Research and Statistics (1997)
First Chicago (NBD)	BHC	'60-05-19	'99-03-31	First Chicago NBD Corp (1998)
JP Morgan C C	BHC	'60-05-19	Current	Chase Manhattan Corp (1997)
Citicorp (before acquisition by Smith Barney)	BHC	'61-06-15	'79-08-22	Travelers Group Inc (1996). Data series ends when Smith Barney data series starts
First Interstate	BHC	'64-07-31	'88-06-17	Adelson (1988)
Harris	BHC	'65-07-15	'95-05-31	BMO Harris (2020)
Bank of America (before acquisition by Nationsbank)	BHC	'71-11-17	'93-07-06	Nationsbank Corp (1996). Series ends when Nationsbank data enters
Paine Webber	No	1: '72-06-22 2: '76-11-25	1: '73-06-27 2: '00-12-04	Paine Webber Group Inc (1996)
Lehman	No	1: '73-02-22 2: '76-11-25	1: '74-01-29 2: '08-09-22	Lehman Brothers Inc (1996)
Northern Trust	BHC	'73-08-08	'86-05-29	Northern Trust Corp (1994)
DLJ	No	1: '74-03-06 2: '95-10-25	1: '85-01-16 2: '00-12-31	ABC News (2006)
First Pennco	BHC	'74-03-07	'80-08-27	AP (1989)
Goldman Sachs	No	'74-12-04	Current	Not public until '99
Weeden	No	'76-06-17	'78-05-15	Piper Sandler (2019)
Dean Witter Reynolds	No	'77-11-02	'98-04-30	Morgan Stanley Dean Witter Discover & Co (1998)
Hutton	No	'77-11-02	'87-12-31	Sterngold (1988)
Morgan Stanley	No	'78-02-01	Current	Morgan Stanley Dean Witter Discover & Co (1998)
CitigroupBarney	No	'79-08-22	Current	Travelers Group Inc (1996)
Bear Stearns	No	'81-06-10	'08-10-01	Bear Stearns Companies Inc (1996)
Manufac. Hanover	BHC	'83-08-31	'91-12-31	Chase Manhattan Corp (1997)

Table 15: Full list of all Primary Dealers used before 1999 for calculation of intermediary capital ratios, their starting and ending dates as dealers, their status as a BHC, and the source from which the BHC status was derived.

Dealer name	BHC status	Start date as dealer	End date as dealer	Source for BHC status
Greenwich	No	’84-07-31	’09-04-01	Bloomberg Company Profiles (2020b)
Daiwa	No	’86-12-11	Current	Foreign bank
Nomura	No	1: ’86-12-11 2: ’09-07-27	1: ’07-11-30 2: Current	Foreign bank
Thomson McKinnon	No	’86-12-11	’89-07-07	Asset Manager
Security Pacific	BHC	’86-12-11	’91-01-17	Office of the Federal Register (1991)
Westpac Pollock	No	’87-02-04	’90-06-27	Foreign bank
Lloyds	No	’87-12-22	’89-04-28	Foreign bank
Nikko	No	’87-12-22	’99-01-03	Foreign bank
Sanwa	No	’88-06-20	’98-07-20	Foreign bank
Wertheim Schroder	No	’88-06-24	’90-11-08	Foreign bank
BNY	BHC	’89-08-01	’90-08-09	Bank of New York Mellon Corp (2008)
Barclays (incl BdZW)	No	1: ’89-12-07 2: ’98-04-01	1: ’96-06-30 2: Current	Foreign bank
UBS	No	’89-12-07	Current	Foreign bank
Fuji	No	’89-12-28	’02-03-31	Foreign bank
Deutsche Bank	No	’90-12-13	Current	Foreign bank
Nationsbank and Bank of America post acquisition	BHC	’93-07-06	Current	Nationsbank Corp (1996)
Zions	BHC	’93-08-11	’02-03-31	Zions Bancorporation (1996)
Credit Suisse	No	’93-10-12	Current	Foreign bank
HSBC	No	’94-05-09	Current	Foreign bank
CIBC	No	’96-03-27	’07-02-08	Foreign bank
BNP Paribas (incl Paribas)	No	1: ’97-05-01 2: ’00-09-15	1: ’00-09-14 2: Current	Foreign bank
ABN Amro	No	’98-09-29	’06-09-15	Foreign bank
Banc One	BHC	’99-04-01	’04-08-01	Senate Committee on Banking, Housing, and Urban Affairs (1994)
SG Americas	No	1: ’99-07-01 2: ’11-02-02	1: ’01-10-31 2: Current	Foreign bank

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