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Have Large Scale Asset Purchases Increased Bank Profits?

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Abstract

This paper empirically examines the effects of the Federal Reserve's Large Scale Asset Purchases (LSAP) on bank profits. We use a new dataset on individual LSAP transactions and bank holding company data from the Fed's FRY-9C regulatory reports to construct a large panel of banks for 2008Q1 to 2009Q4. Our results suggest that banks that sold Mortgage-backed Securities to the Fed ("treatment banks") experienced economically and statistically significant increases in profitability after controlling for common determinants of bank performance. Banks heavily "exposed" to MBS purchases should also experience increases in profitability through asset appreciation. Our results also provide evidence for this type of spillover effect and suggest that large banks may have been more affected. Although our results suggest that MBS purchases increased bank profits, we find only mixed evidence that these were associated with increased lending. Our findings are thus consistent with the hypothesis that the Federal Reserve undertook these policies, at least in part, to increase the profitability of their main constituency: the large banks.

JEL Codes: G21, G28, G32

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1 Introduction

The onset of the 2007-8 financial crisis led the Federal Reserve to lower short-term interest rates to nearly zero in an effort to prop up the financial sector and prevent the U.S. economy from sliding into a depression. With nominal rates up against the zero lower bound and thus having exhausted the traditional tools of monetary policy, the Fed resorted to more unconventional measures. In particular, it began purchasing large amounts of securities in what is known as the Large Scale Asset Purchase program (LSAP), or alternatively as "Quantitative Easing" (QE).[1] The public rationale for these asset purchases was to further boost the economy by specifically lowering yields on longer-term assets. But another plausible explanation is that the Federal Reserve was attempting to help its natural constituency, the large banks, as they were confronting the fall out from the financial crisis (Ferguson and Johnson, 2009a,b). In this view, jumpstarting the US economy directly was only a secondary concern.

This latter hypothesis relates to conjectures concerning the "capture" of the Federal Reserve by banking interests, a view with a long history and, in terms of the economics literature, one that goes back at least as far as to the work of Chicago economists such as George Stigler (see Epstein, 1982, for a discussion). A more general version of this argument sees the Federal Reserve as a "contested terrain" on which various sectors of capital, including finance, and, on the other hand, labor, fight for control over monetary and regulatory policy (see Epstein, 1994; Epstein and Ferguson, 1984; Ferguson, 1995). In this context the question is: which groups have the key influence over the making of monetary policy in a particular period?

Although there has been a large empirical literature concerning the broader macroeconomic impacts of QE, apart from one recent study (Lambert and Ueda, 2014) there have been no studies of the impacts on QE on the profitability of the banks themselves, which would be helpful in assessing this key question in the political economy of central bank policy: what was the impact of QE on the profitability of the banks?

By contrast, a large literature on the effectiveness of quantitative easing in affecting interest rates, asset prices and other macroeconomic variables, has emerged since the first round of asset purchases in early 2009. A number of studies, often using high-frequency data and Fed policy announcements, have found that QE has effectively lowered long-term yields (Vissing-Jorgensen and Krishnamurthy, 2011; Gagnon et al., 2011; Swanson et al., 2011; D'Amico et al., 2012; Wright, 2012). Others have looked at the effect of QE on macroeconomic variables such as output and inflation. Chen et al. (2012) present a DSGE model with segmented asset markets and show through simulations that QE has positive – though likely modest – effects on GDP growth and inflation. Watzka and Schenkelberg (2011) use a SVAR with sign-restrictions motivated by theory and present evidence from Japan's experience during the 1990s that QE successfully stimulated growth. Using an identification through heteroskedasticity approach, Gilchrist and Zakrajv̌sek (2013) find that QE significantly lowered the private sector's credit risk. Curiously, however, they find no evidence that QE led to decreases in the credit risk of financial intermediaries.

The channels through which QE might affect financial markets and the macroeconomy have also received

[1] In what follows we will use these two broad terms interchangeably.

increased attention. Quantitative easing may affect asset prices and the macroeconomy more generally through what has often been dubbed the "portfolio balance" channel. If securities of different maturities are imperfect substitutes, Fed purchases of long-term securities should decrease their availability in the market and ceteris paribus increase their price – this is the so-called "scarcity effect".[2] This channel has been tested empirically for Treasury purchases by D'Amico et al. (2012) and specifically for purchases of mortgage-backed securities (MBS) by Hancock and Passmore (2014). Hancock and Passmore show that the Fed share of the MBS market robustly predicts lower MBS yields, although the effects are only significant if the Fed holds a sufficiently large share of the market.

We know of only one study of the impacts of QE on individual banks (Lambert and Ueda, 2014). Lambert and Ueda use bank level data and study the impact of QE measured as a "monetary surprise" or as a divergence from a "Taylor Rule" measure of monetary policy, on bank profits. Using these bank level and broad measures of monetary policy, they find that QE has either a negative or an ambiguous impact on U.S. bank profits.

By contrast, our paper uses a more granular approach to studying QE: we have utilized transactions level data on assets purchased by the Federal Reserve during the first phase of QE and on the counterparty banks with whom they transacted. This approach allows us to look at actual transactions and to utilize a framework that helps identify the causality of the effects of purchases on bank profits.

More specifically, we examine the effects of the Fed's MBS purchases on bank profits using a large and novel panel data set. We combine transactions-level data on LSAP purchases with income and balance sheet data from bank holding company regulatory filings. This allows us to construct bank-specific QE "treatment" variables and identify the treatment effect of Fed MBS purchases. In other words, whereas previous studies have employed changes in variables that only vary across time t, our main explanatory variables vary across both banks i and time t, allowing us to fully exploit the properties of panel data. We consider two complementary QE "treatment" variables. First, we construct a treatment dummy for banks that were counterparties to MBS transactions carried out under LSAP programs. This allows us to capture direct effects on bank profitability from asset purchases. These can include the profits on individual sales of MBS, which may have been bought at a premium, as well as fees and commissions if the counterparty bank was acting as a broker for a third party. Second, we also construct a pseudo-treatment variable for banks that were "exposed" to the market-wide or spillover effects of MBS purchases. Consistent with the portfolio balance channel, banks with greater holdings of MBS prior to QE should be more affected by changes in MBS prices following Fed purchases.

Our results show that purchases of MBS led to economically and statistically significant increases in bank profitability, defined as the return on assets in percentage terms. The profitability of banks that were LSAP counterparties improved by around 0.35 of a percentage point relative to non-counterparty banks and non-LSAP periods. As a reference, this is roughly proportional to the median return on assets in the sample, suggesting that the effects were quite large. The effect on banks that were indirectly exposed to

[2]This theory dates back at least to Tobin (1961). A recent contribution is Vayanos and Vila (2009).

MBS purchases is also large and statistically significant, though smaller than for counterparty banks. These results imply that banks positioned to sell MBS to the Fed reaped an additional boost in profits relative to the rest of the financial sector through their direct participation in LSAP transactions.

We also provide evidence of significant heterogeneity in the magnitude of the exposure effect. The effect of MBS purchases on exposed banks is greater for larger banks. In fact, the effect is not significantly different from zero for small banks with total assets less than the sample median. Large banks with total assets greater than the median, on the other hand, have much larger and statistically significant effects. To verify that these effects indeed operate through changes in asset prices, we run separate regressions with realized gains on assets as the dependent variable. The results are consistent with this channel.

The rest of the paper proceeds as follows. Section 2 first provides information on the timing of the rounds of Quantitative Easing and then describes the specific time frame and data set used in our analysis. It then discusses the rationale behind the main explanatory variables. Section 3 presents our benchmark results. Section 4 discusses extensions of the benchmark results, as well as robustness checks. Finally, Section 5 concludes.

2 Timeframe, Data, and Main Variables

The first round of asset purchases – or "quantitative easing" (QE1) – was formally announced on November 25, 2008 and initially covered Agency mortgage-backed securities (MBS), long-term Treasuries, and government-sponsored enterprises (GSE) debt. A second round of purchases (QE2) was subsequently announced on November 3, 2010, followed by a third and final round (QE3) beginning in August 2012. We focus our attention on QE1 and study the impact of MBS purchases in particular. This is done for two reasons. First, the collapse of the MBS market placed considerable strain on financial institutions. It is therefore natural to study the impact of explicit efforts to prop up this important financial market. Second, the Fed's MBS purchase program was by far the largest relative to the purchases of long-term Treasuries and GSE debt. The initial MBS purchase limit was $500 billion but was subsequently expanded to $1.25 trillion. The limits for GSE debt and Treasuries purchases were comparatively modest: $200 billion and $300 billion, respectively.

The data set consists of a panel of 862 bank holding companies (henceforth referred to simply as "banks") at a quarterly frequency over the period 2008Q1 to 2009Q4.[3] We use data on LSAP transactions released by the Board of Governors of the Federal Reserve and the New York Fed. Under the Dodd-Frank Act the Fed is required to publish data on each transaction carried out in the conduct of monetary policy within at most two years. Each transaction records the name of the counterparty, the type of security traded, the amount purchased or sold, and the price paid. The LSAP transactions data is combined with quarterly bank holding

[3]This specific timeframe was chosen to isolate the first round of quantitative easing and thus minimize the likelihood of other confounding factors, such as the purchases of other asset classes during subsequent QE rounds. The empirical results are robust to considering a longer sample window.

Table 1: Counterparties to LSAP transactions. Purchase denotes the total (in $ billions) amount of MBS purchased by the Fed from the listed counterparty. Sale denotes MBS the counterparty bought from the Fed. A (✓) indicates a good match between the subsidiary broker/dealer and a U.S.-based holding company. A (–) indicates a potential, though uncertain match.

Counterparty	Purchase	Sale	Match?
BNP Paribas Securities Corp.	75.513	23.637	–
Barclays Capital Inc.	142.243	31.526	✓
Cantor Fitzgerald & Co.	8.925	0.250	No data
Citigroup Global Markets Inc.	189.134	52.488	✓
Credit Suisse Securities (USA) LLC	319.013	97.540	No data
Deutsche Bank Securities Inc.	311.476	118.978	–
Goldman, Sachs & Co.	167.466	48.754	✓
J.P. Morgan Securities LLC	168.835	42.993	✓
Jefferies & Company, Inc.	1.737	0.203	No data
Merrill Lynch, Pierce, Fenner & Smith Inc.	199.570	73.482	No data
Mizuho Securities USA Inc.	1.412	0.150	No data
Morgan Stanley & Co. LLC	222.275	75.630	✓
Nomura Securities International, Inc.	40.838	9.311	No data
RBC Capital Markets, LLC	10.377	1.417	–
RBS Securities Inc.	66.986	26.200	✓
UBS Securities LLC	102.762	11.543	No data

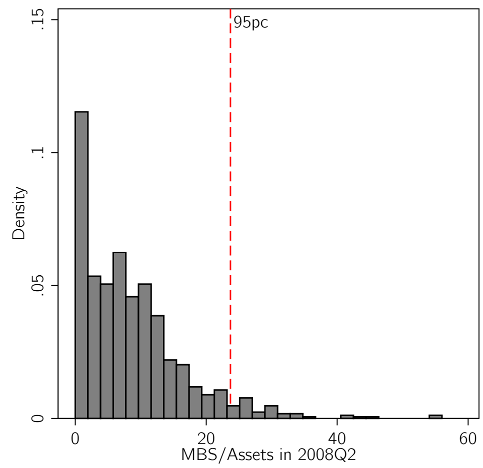
Source: Authors' calculations based on data from the Board of Governors of the Federal Reserve and the New York Fed.

company panel data from the Fed's FRY-9C reports.

To construct the bank LSAP treatment variables, it was necessary to match each counterparty, when possible, to their parent holding company. We used ownership structure records from the Federal Financial Institutions Examination Council. This was straightforward for broker/dealers owned by large domestically-owned banks since each had a clear parent holding company. Subsidiaries of foreign banks were more difficult and in some cases were omitted from the analysis in order to avoid potential problems stemming from the messy matching. This is because large foreign banks may not have a single domestically chartered holding company or none at all. In other cases, the foreign owned holding company may be sold off or restructured multiple times, creating breaks in the series and changes in levels. In other cases, data was simply not available because the transaction counterparty is not a financial holding company and and is not legally required to file regulatory reports. From the original 16 counterparties, we were able to establish six matches between the Fed LSAP transactions data and the FRY-9C reports. This is summarized in Table 1 (see the Data Appendix for further details). Rows with "no data" refer to broker/dealers without a larger financial holding company parent. Rows with "–" refer to counterparties owned by large foreign parent companies with complex domestic operations.

The LSAP treatment group (G_{it}) is defined as any bank that sold or bought MBS from the Fed while treatment quarters (T_{it}) are those during which QE purchases were taking place. The interaction between the group and treatment quarters, thus, is the bank treatment dummy variable ($P_{it} = T_{it} \cdot G_{it}$) and is equal

Figure 1: Distribution of Mortgage-backed securities as a share of total assets in 2008Q2. Banks to the right of the red 95 percentile cutoff line are classified as exposure banks.



to one if the given bank was a LSAP counterparty and if LSAP transactions took place in the given quarter, and equal to zero otherwise. The LSAP purchases treatment dummy (P_{it}) captures any direct effects on profitability from selling MBS to the Fed, as well as any indirect effects. Potential direct effects may operate through the premiums that the Fed paid for MBS as well as trading or commission fees if the bank was acting as a broker for a third party. Further indirect effects could operate through signaling channels. For instance, market observers could interpret the Fed transactions as evidence of an implicit guarantee, which could lower a treatment bank's cost of funding.

We define exposure banks as those with significant holdings of MBS as a share of their total assets prior to the first round of QE. Specifically, a bank belongs to the exposure group if its MBS share is greater than the 95th percentile (see Figure 1). This can be used to construct a pseudo treatment variable by interacting the exposure group with LSAP quarters.[4] As with the treatment dummy above, the exposure dummy (E_{it}) takes a value of one if the bank is exposed and if the Fed purchased MBS during that particular quarter. As already noted, there is evidence that QE has increased MBS prices through the portfolio balance channel (Hancock and Passmore, 2014). Our exposure variable is thus intended to capture the effect of these higher asset prices on bank profitability. Exposure can thus be interpreted as a measure of the broader spillover effects from QE.

The dependent variables include an accounting measure of profits and realized gains on assets. We use a standard measure of bank profitability: the return on assets (ROA_{it}). This is defined as net income divided by total assets (in percentage terms). Realized gains are a component of net income and are measured relative to a bank's total assets. We later examine the effect of MBS purchases on bank lending and use

[4] This specification is relaxed below by allowing the level of exposure to vary continuously. The results are also robust to alternative cutoff lines.

two alternative measures of bank lending. The first is total bank loans as a share of total assets. We find evidence that the loans share contains a unit root and thus include it in first differences in the regressions below. The second measure of bank lending is the log percentage change in total loans.

Identification requires conditioning on all relevant covariates. To this end, we draw on the extensive literature on the determinants of bank profitability to identify variables that have consistently appeared in and deemed important by previous studies (see Dietrich and Wanzenried, 2011; García-Herrero et al., 2009; Athanasoglou et al., 2008, for recent contributions.). This literature has stressed the importance of taking into account both bank-specific determinants of profitability (e.g. bank size, capital adequacy, the structure of income) as well as macroeconomic and industry-wide factors (e.g. GDP growth, inflation, industry concentration). The full set of variables used in our analysis, as well as summary statistics, are shown in Table 2. Details on the construction and sources of each variable are contained in the Data Appendix.

Table 2: Summary statistics and expected signs.

Variable	Obs	Mean	Std. Dev.	Expected Sign $ROA_{it}/GAIN_{it}$	Expected Sign Lending
Dependent variables					
Return on assets (ROA_{it})	6891	.022	1.433		
Capital gains / assets ($GAIN_{it}$)	6903	-.009	.161		
Change in loans / assets ($\Delta LOAN\_S$)	6026	-.395	2.774		
Log loan growth ($\Delta \ln(LOAN_{it})$)	6026	.567	5.355		
Treatment variables					
LSAP purchase counterpary (P_{it})	6903	.004	.066	+	
Exposure Dummy (E_{it})	6891	.025	.157	+	
Treatment quarter dummy (T_t)	6903	.5	.5		
Continuous exposure ($MBS_{2008} \cdot T_t$)	6880	4.302	7.012	+	
Bank-specific covariates					
Tier 1 capital ratio	6891	8.826	2.709	+	+
Interest income share	6891	83.445	14.355	-	
Cost to revenue ratio	6891	.825	1.546	-	
Lagged nonperforming assets	6028	2.842	2.842	-	-
Number of subsidiary banks	6901	1.711	2.707	+/-	
Interest sensitive assets / total assets	6891	37.621	14.013	-	
Market funding share	4905	90.879	5.902		+/-
Macroeconomic/Industry-level covariates					
Output gap	6903	-.009	.019	+	+
Herfindahl-Hirshman industry concentration	6903	.068	.003	+	
Commercial prime / 10-year bond spread	6903	2.452	1.226		+
Case-Shiller 20-City Home Price Index	6903	154.882	12.944	+	+
VIX Stock market volatility index	6944	32.155	12.301		-
Chicago Fed financial stress index	6944	0.933	0.849		-

The rationales for each bank-specific variables are the following. The Tier 1 capital ratio, measured as capital divided by risk-adjusted total assets, is a standard measure of capital adequacy. A higher capital ratio should be associated with greater profitability since better capitalized banks tend to have a lower chance of default and hence lower funding costs. The total costs to revenue ratio is included as a (inverse) measure of operational efficiency. Less efficient banks – that is, those with greater expenses per unit of revenues – should have lower profits. Interest income as a share of total income is included to capture the diversification of income streams. A higher interest income share implies a bank's income stream is poorly diversified and hence potentially more vulnerable to adverse shocks. Nonperforming assets are included as a proxy for asset quality. We expect a higher share of nonperforming assets (i.e. lower asset quality) to be associated with lower profits. Because nonperforming assets are likely endogenous, this variable is included in the regressions with a one quarter lag.

Due to the high degree of collinearity between many relevant macroeconomic variables, for the benchmark specification we only consider the output gap and the Herfindhal-Hirshman Index (HHI) of financial industry concentration. The output gap is included to control for cyclical factors affecting bank profits and was constructed by detrending real GDP with the Hodrick-Prescott filter. A positive output gap indicates GDP is above trend and is expected to be associated with higher bank profits. The HHI has long been included in bank performance regressions, dating back to the seminal work in this literature by Short (1979). A higher HHI means that the banking industry is more concentrated and less competitive, implying that some banks have market power and can earn monopoly rents. This should be associated with greater profits. The lending regressions include additional time-varying macroeconomic covariates. These are also listed along with summary statistics and expected signs in Table 2. The spread between the commercial bank prime rate and the yield on the 10-year Treasury and the Case-Shiller 20-city home prices index are expected to lead to higher lending. Our two measures of financial instability, the VIX index of stock volatility and the Chicago Fed financial stress index, are expected to be associated with lower lending.

3 Empirical Strategy and Results

3.1 Benchmark Bank Profits Regressions

Our benchmark specification consists of panel regressions with bank fixed-effects and serially and cross-sectionally correlated disturbances. In order to avoid omitted variable bias from macroeconomic factors that may not be perfectly captured by our chosen covariates, model (1) includes a full set of time dummies. The inclusion of time dummies also makes it possible to interpret the coefficient on the treatment dummy as the average treatment effect of the treated (ATET). However, including the time dummies makes it necessary to drop the macroeconomic explanatory variables (that only vary along t).

$$ROA_{it} = \alpha_i + \eta_t + \tau P_{it} + \gamma E_{it} + \boldsymbol{\beta}\mathbf{X}_{it} + u_{it} \tag{1}$$

Here, α_i and η_t are vectors of bank and time fixed-effects, respectively. The treatment effect of MBS purchases on counterparty banks is captured by τ, while the effect from exposure to QE is captured by γ. $\mathbf{X}_{it}$ is a vector of bank-specific covariates (described in detail above). Alternatively, model (2) drops the time dummies and instead explicitly accounts for macroeconomic covariates ($\mathbf{M}_{it}$).

$$ROA_{it} = \alpha_i + \tau P_{it} + \gamma E_{it} + \boldsymbol{\beta}\mathbf{X}_{it} + \boldsymbol{\lambda}\mathbf{M}_{it} + u_{it} \tag{2}$$

Because of the highly interconnected nature of the financial system, it is reasonable to expect that shocks to one bank should spillover and affect other banks. In other words, the disturbance term most likely exhibits cross-sectional dependence. If not dealt with, this could pose severe problems for inference since the standard error estimates would be invalid. To test for cross-sectional dependence we use the test devised by Pesaran (2007) and implemented in Stata by De Hoyos and Sarafidis (2006). The Pesaran test is preferable in settings with a modest time dimension and a large number of cross-sections (i.e. small T and large N). The test results easily reject the null hypothesis of cross-sectional independence, suggesting that unadjusted standard errors are unreliable.

The inclusion of time dummies should account for separable common factors but not for more general forms of cross-sectional dependence such as error dependence. To address this issue we use robust standard errors corrected using the method of Driscoll and Kraay (1998).[5] Driscoll-Kraay errors are a flexible and powerful way to account for very general forms of cross-sectional dependence. They also have the additional advantage of correcting for serial correlation and heteroskedasticity. Because of these desirable properties, Driscoll-Kraay errors are reported in all the estimates below.[6]

We also consider specifications with a lagged dependent variable. Conditioning on past outcomes renders the treatment and control groups more comparable and therefore strengthens the causal interpretation of our results. However, as is well known, the within-transformation of panel fixed effects regressions can lead to potentially serious biases in the estimated coefficients (Nickel bias). Thus, as a robustness check, we also present estimates from the system-GMM estimator of Arellano and Bover. Nevertheless, it is worth emphasizing that system-GMM assumes that the disturbances are potentially heteroskedastic and correlated within but not between panels. It is therefore inappropriate for settings with error cross-sectional dependence, as this can lead to biased coefficient estimates. Moreover, as Sarafidis and Wansbeek (2012) notes, error cross-sectional dependence can inflate test statistics for the over identifying restrictions tests and lead to erroneous rejections of the null. Therefore, although system-GMM is not entirely reliable in this setting, it should be viewed as an additional check on the benchmark specification.

The benchmark results with and without a lagged dependent variable are reported in columns (1) through (4) of Table 3. The coefficient estimates for the LSAP treatment and exposure dummies are positive and statistically significant in every specification. These can be interpreted as the treatment and pseudo-treatment effects of Fed MBS purchases. The sign and size of the coefficient estimates imply that QE increased bank profits, both directly for banks that sold securities to the Fed, and indirectly through broader spillover effects for exposed banks. The point estimates for the bank treatment dummy (P_{it}) range from 0.54 to 0.62.

[5] A program for estimating panel fixed-effects models with Driscoll-Kraay errors was implemented by Hoechle (2007). Hoechle also extends Driscoll and Kraay (1998) to allow unbalanced panels.

[6] It is worth keeping in mind, however, that Driscoll-Kraay errors rely on $T \to \infty$ for consistency and therefore may be weak for panels with a small time dimension.

Table 3: Return on assets regressions. Columns (1) - (4) report the benchmark specifications with Driscoll-Kraay standard errors for the determinants of bank profits. Columns (5) - (6) report the results of System-GMM estimation treating nonperforming assets as potentially endogenous.

Dependent variable: Return on Assets (ROA_{it})	Benchmark (Driscoll-Kraay Errors)				System-GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
P_{it}	0.622**	0.604**	0.560**	0.540*	0.619**	0.628**
	(0.179)	(0.188)	(0.225)	(0.236)	(0.272)	(0.287)
E_{it}	0.157***	0.142***	0.096***	0.078***	0.236**	0.230*
	(0.039)	(0.034)	(0.013)	(0.018)	(0.104)	(0.137)
Capital Ratio	0.254**	0.257**	0.211**	0.214**	0.175***	0.182***
	(0.078)	(0.080)	(0.063)	(0.065)	(0.029)	(0.027)
Cost to Revenue Ratio	-0.132**	-0.130**	-0.122**	-0.119**	-0.177	-0.148
	(0.050)	(0.051)	(0.039)	(0.039)	(0.160)	(0.151)
Interest Share of Income	-0.002	-0.001	-0.000	-0.000	0.000	0.000
	(0.007)	(0.007)	(0.006)	(0.006)	(0.004)	(0.004)
Lagged Nonperforming Assets	-0.200***	-0.213***	-0.122***	-0.131***	-0.124***	-0.117***
	(0.046)	(0.048)	(0.015)	(0.018)	(0.017)	(0.016)
Interest Sensitive Assets	-0.004***	-0.002**	-0.003**	-0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Number of Bank Subsidiaries	0.096***	0.105***	0.059***	0.067***	-0.006	-0.007
	(0.025)	(0.024)	(0.014)	(0.014)	(0.012)	(0.010)
Output Gap		6.138***		6.456***		5.335***
		(1.415)		(1.204)		(0.620)
Industry Concentration (HHI)		15.337***		-1.575		-12.581***
		(4.051)		(6.797)		(2.697)
ROA_{it-1}			0.457*	0.462*	0.736***	0.736***
			(0.201)	(0.199)	(0.036)	(0.036)
Constant	-1.261**	-2.494***	-1.205**	-1.292*	-0.876*	-0.233
	(0.397)	(0.560)	(0.372)	(0.656)	(0.480)	(0.470)
Observations	5,984	5,984	5,984	5,984	5,984	5,984
Number of Banks	856	856	856	856	856	856
R-squared within	0.289	0.278	0.400	0.391		
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
Hansen J-stat					387.8	549.6
Number of ins.					134	137

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These estimates imply that the treatment effect of MBS purchases on counterparty banks is quite large. As a reference point, the median return on assets for the whole sample is 0.32, suggesting that treatment increased counterparty profits by more than the sample median. For instance, a hypothetical large bank with $1 trillion in total assets would experience an increase in profitability of up to $6.2 billion. The indirect spillover effect on banks exposed to MBS purchases ranges from 0.08 to 0.16 across the benchmark specifications. This effect is also quite large, although evidently smaller than for counterparty banks. To illustrate, the sample average total assets of exposure banks is roughly $8 billion. this corresponds to an increase in profits of roughly $12.8 million.

All of the bank-specific covariates, with the exception of the interest share of income, are statistically significant and have the expected signs. Consistent with the existing literature, better capitalized banks tend to be more profitable, while less operationally efficient banks, as captured by the cost to revenue ratio, on average have lower profits. Asset quality also appears to significantly impact bank profitability, as indicated by the negative coefficient on lagged nonperforming assets. The coefficient on the share of assets sensitive to changes in interest rates is also negative and significant. This indicates, as anticipated, that the fall in interest rates during the crisis disproportionally impacted the profits of banks with more vulnerable balance sheets. Finally, the number of bank subsidiaries owned by a given parent holding company is positively associated with profitability.

The system-GMM estimates are presented in the last columns of Table 3 (columns (5) and (6)). The estimates for the autoregressive parameter confirm the presence of significant Nickell bias. The coefficient on the lagged dependent variable (ROA_{it-1}) is larger in the GMM model (0.736) compared to the OLS estimates (0.457). The coefficient estimates for the LSAP treatment dummy in the GMM model are very similar to the benchmark estimates in columns (1) through (4). The exposure effect (E_{it}) is somewhat larger in the GMM model: 0.236. However, as already noted, system-GMM assumes disturbances are cross-sectionally independent and as such is unreliable in settings with error cross-sectional dependence. Moreover, the Hansen J-statistic for over identifying restrictions is quite large and rejects the null hypothesis. This casts casts doubts on the validity of the model and is likely to occur when error cross-sectional dependence is present. In this context, the GMM estimates should be considered as an upper-bound estimate on the magnitude of the effects and not as a substitute for the benchmark specifications.

3.2 Realized Gains Regressions

As previously discussed, quantitative easing is expected to operate through the so-called portfolio balance channel, which should increase the price of mortgage-backed securities. Therefore, ceteris paribus, banks with more MBS on their balance sheet prior to QE should experience capital gains on these assets and hence have larger profits. In this section we present suggestive evidence that is consistent with this particular channel. Specifically, we regress realized gains scaled by total bank assets on the MBS purchases exposure dummy as well as bank-specific and macroeconomic covariates. Testing this channel is important because failing to find a significant and economically meaningful effect would amount to a falsification of our hypothesis and call into question the theoretical foundation of the benchmark estimates.

The regression results are shown in Table 4, where all four specifications report Driscoll-Kraay errors. Consistent with the hypothesized channel, the exposure dummy has a positive sign and is statistically significant. What is most important, however, is that the size of the estimated effect on capital gains is roughly proportional to the overall exposure effect on bank profits. In other words, the increase in capital gains as a result of LSAP exposure explains nearly all of the estimated effect on profits. This confirms that quantitative easing increases bank profits through the portfolio balance channel and its impact on asset prices.

It is worth noting that asset quality appears to have the opposite effect on capital gains as it does on bank profits. This is puzzling because capital gains are a component of net income and as such asset quality should be expected to have the same sign across both regressions. One possible explanation for this puzzle is that the share of nonperforming assets captures a bank's appetite for riskier but potentially more lucrative investments.

Table 4: Capital Gains Regressions

Dependent Variable: Capital gains per assets ($GAIN_{it}$)	(1)	(2)	(3)	(4)
E_{it}	0.077***	0.107***	0.113***	0.102***
	(0.009)	(0.011)	(0.011)	(0.012)
Capital Ratio	0.007***	0.008**	0.010***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Lagged Nonperforming Assets	0.003**	0.008***	0.009***	0.006**
	(0.001)	(0.002)	(0.002)	(0.002)
Output Gap		-0.358		
		(0.457)		
VIX Stock Volatility Index			-0.002***	
			(0.000)	
Chicago Fed Financial Stress Index				-0.027***
				(0.004)
Constant	-0.066**	-0.113***	-0.073*	-0.088**
	(0.019)	(0.029)	(0.036)	(0.027)
Observations	6,012	6,012	6,012	6,012
Number of groups	862	862	862	862
R-squared within	0.094	0.028	0.054	0.062
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.3 The Response of Loan Supply

In this section we briefly examine the connection between MBS purchases carried out during quantitative easing and changes in bank lending. We use two different measures of bank lending: the change in loans as a share of total assets and the real logarithmic growth rate of loans. Panel unit root tests suggest that the loan share of assets and log real loans both contain unit roots and as such it was appropriate to first difference both variables.

We estimate models (1) and (2) including the following bank-specific covariates: risk adjusted capital adequacy, lagged nonperforming assets as a share of total assets, and the share of assets financed through market funding. The latter variable captures the vulnerability of banks to funding shocks and hence how easily their loan supply could dry up in the advent of a financial crash. The importance of this variable has been emphasized by, among others, Brei et al. (2012). Market funding is defined as the non-deposit share of liabilities – that is, the difference between liabilities and deposits divided by total liabilities.

As before, we also estimate models including macroeconomic or industry-specific variables. These are: the output gap, the spread between bank prime lending rate and the ten-year treasury yield, as well as the Case-Schiller 20-city home price index. The output gap is included to control for cyclical factors and is expected to have a positive sign – that is, bank loan growth is expected to be higher when output is above potential. The lending spread captures the relative return to lending to businesses as opposed to the government and is expected to have a positive sign. Finally, the Case-Schiller index is intended to capture overall conditions in the housing market and is expected to be positively associated with lending growth.

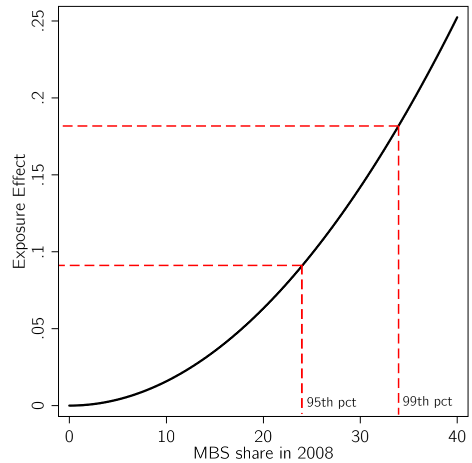
Results for this exercise are reported in Table 8. Columns (1) - (4) report the specifications with the change in the loan share as the dependent variable while the specifications in columns (5) - (8) use real log loan growth as an alternative measure. These regressions provide some evidence that exposure to MBS purchases may have led to increased lending growth but the results are inconclusive and not robust. Problematically, two seemingly complementary measures of lending growth lead to very different estimates. The exposure dummy is positive and significant in three of the four models with the change in the loan share as the dependent variable. However, it is not significantly different from zero when the log growth of real loans is used instead and even has a negative sign in specification (7). The counterparty treatment dummy is not significantly different from zero in any of the specifications. Therefore, we can conclude that although there is partial evidence that MBS purchases increased lending through the portfolio balance spillover channel, counterparty banks that directly sold MBS to the Fed were not induced to lend more as a result.

4 Robustness Exercises

4.1 Continuous Exposure Regressions

We now examine the robustness of the results to an alternative measure of bank exposure. Specifically, the assumption of discrete membership in the exposure group is relaxed and instead is allowed to vary continuously. This is achieved by interacting the share of MBS in 2008Q2 with a dummy for QE quarters. This specification allows the average exposure effect to increase in the MBS share. It also allows us to examine if the results are very sensitive to the definition of exposure (that is, if the 95th percentile cutoff is

Figure 2: Continuous exposure effect.



crucial for the results). In addition, we examine whether exposure has a nonlinear effect by introducing a quadratic term in the regressions.

The results from this robust exercise are reported in Table 5. The simple case with a linear the continuous exposure term is reported with and without macroeconomic covariates in columns (1) and (2), respectively. The coefficient of interest, $MBS_{2008} \cdot T_t$, is positive and significant. This coefficient can be interpreted as the exposure effect during QE quarters conditional on the size of MBS holdings in 2008. For instance, banks with the median MBS share in 2008 – roughly 7 percent of total assets – experience a mere 0.04 percentage point increase in the return on assets. In contrast, banks with an MBS share in the 95th percentile – roughly 24 percent of total assets – experience an increase in the return on assets as large as 0.14 percentage points. As an additional robustness exercise, we consider a specification where the 2008 MBS share enters quadratically (columns (3) and (4)). This specification appears to fit moderately better than the linear case and is depicted graphically in Figure 2.

The main takeaway from the continuous exposure specifications is that the results do not crucially depend on the 95th percentile cutoff used to define the exposure group in the benchmark model. Indeed, the results appear quite robust to a continuos setup. Moreover, there also appears to be a certain degree of nonlinearity in the exposure effect. This implies that in order to experience economically significant increases in profitability from QE banks must hold a substantial amount of MBS relative to the size of their balance sheets.

4.2 Size Heterogeneity

Next, we test if any heterogeneity exists in the size of the LSAP exposure effect and in particular if the effect on profits is greater for larger banks. The exposure dummy $E_{it} = T_t \cdot G_i^E$, where G_i^E is the exposure group dummy for banks with an MBS share greater than the 95th percentile, is interacted with each bank's log

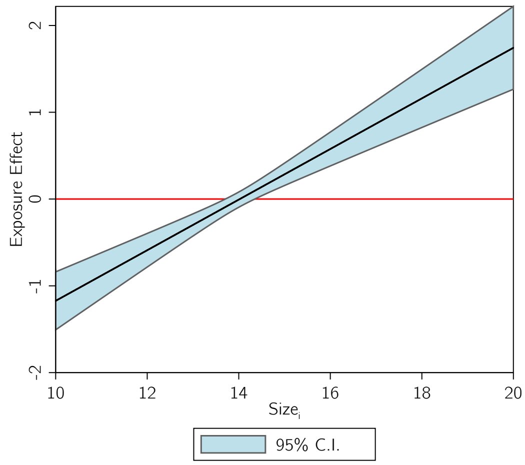
Table 5: Continuous exposure regressions. Columns (3)-(4) report the results from a nonlinear specification of the exposure variable $(MBS_{2008})^2 \cdot T_t$.

Dependent variable: Return on Assets (ROA_{it})	(1)	(2)	(3)	(4)
$MBS_{2008} \cdot T_t$	0.0058***	0.0045**		
	(0.0006)	(0.0017)		
$(MBS_{2008})^2 \cdot T_t$			0.0002***	0.0002***
			(0.0000)	(0.0000)
Capital Ratio	0.3050***	0.3096***	0.3051***	0.3098***
	(0.0801)	(0.0824)	(0.0801)	(0.0823)
Cost to Revenue Ratio	-0.0003	-0.0006	-0.0002	-0.0006
	(0.0142)	(0.0142)	(0.0142)	(0.0142)
Interest Share of Income	-0.0042	-0.0038	-0.0042	-0.0039
	(0.0068)	(0.0066)	(0.0068)	(0.0066)
Lagged Nonperforming Assets	-0.2031***	-0.2163***	-0.2027***	-0.2158***
	(0.0425)	(0.0425)	(0.0422)	(0.0421)
Number of Subsidiaries	0.0622*	0.0782**	0.0616*	0.0775**
	(0.0270)	(0.0267)	(0.0269)	(0.0264)
Interest Sensitive Assets	-0.0013	0.0008	-0.0014	0.0007
	(0.0017)	(0.0013)	(0.0017)	(0.0012)
Output Gap		6.8358**		6.6987***
		(1.8631)		(1.5911)
Industry Concentration (HHI)		12.2342*		11.6982*
		(5.0028)		(5.9553)
Constant	-1.6333***	-2.7321***	-1.6318***	-2.6910***
	(0.3723)	(0.6180)	(0.3721)	(0.6830)
Observations	6,003	6,003	6,003	6,003
Number of groups	859	859	859	859
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No
R-squared within	0.354	0.342	0.355	0.342

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 3: Exposure ATET as a function of bank size.



total assets in 2008Q2. Specifically, we estimate (3), where the average treatment effect (ATE) is estimated as $E[ROA_{it}|T_t = 1, G_i^E = 1, \mathbf{X}] = \gamma_1 + \gamma_2 size_i + \gamma_3$. Similarly, the average treatment effect of the treated (ATET) is given by $\gamma_1 + \gamma_2 size_i$. In other words, the effect of exposure to MBS purchases is a function of bank size.

$$ROA_{it} = \eta_t + (\gamma_1 + \gamma_2 size_i)T_t \cdot G_i^E + \gamma_3 G_i^E + \boldsymbol{\beta}\mathbf{X}_{it} + u_{it} \tag{3}$$

The vector $\mathbf{X}_{it}$ includes all the bank-specific covariates from the benchmark specification. The point estimates for the coefficients of interest (γ_1, γ_2, and γ_3) are reported in the top half of Table 6 both with and without covariates. To interpret the coefficients, however, it is necessary to calculate the marginal effects evaluated at a specific bank size. Thus, the bottom half of Table 6 reports the ATET evaluated at the mean bank size, as well as the 95th and 99th percentiles. The ATET is also depicted graphically in Figure 3.

The results suggest that there is substantial heterogeneity in the magnitude of the exposure effect by bank size. Banks with an average level of log assets have a treatment effect that is roughly comparable to the benchmark results, as one should expect. However, the exposure effect increases dramatically as banks grow in size. For instance, the ATET for banks with log assets corresponding to the sample 95th percentile is roughly 0.8 percentage points or roughly \$100 million. These results suggest an important distributional consequence of quantitative easing, namely that big banks appear to have benefitted substantially more than smaller banks.

4.3 Small Treatment Group Adjustment

One potential problem with estimating the direct effect of LSAP purchases on counterparty banks is the small number of treatment banks. As already noted, due to data limitations we were only able to include six of the LSAP counteraparty banks in the analysis. This is potentially problematic since inference in these

Table 6: Exposure size heterogeneity

Dependent variable: Return on Assets (ROA_{it})				With Covariates		
		95% C.I.			95% C.I.	
	coef	lower	upper	coef	lower	upper
$T_t \cdot G_i^E$	-2.815*	-5.045	-0.587	-4.089*	-6.54	-1.638
$T_t \cdot G_i^E \cdot size_i$	0.216*	0.051	0.381	0.291*	0.117	0.467
G_i^E	0.215*	0.019	0.412	0.147*	0.090	0.203
ATET						
$size_i$ = mean	0.248*	0.080	0.415	0.052	-0.037	0.140
$size_i$ = 95th pct	0.776*	0.320	1.232	0.766*	0.384	1.148
$size_i$ = 99th pct	1.352*	0.540	2.164	1.545*	0.793	2.300
Observations		6878			6017	
Number of Banks		861			861	
R-Squared		0.066			0.412	
Bank FE		No			No	
Time FE		Yes			Yes	

types of estimators is typically based on the assumption that both the treatment and control groups are very large. Indeed, Conley and Taber (2011) show that if the number of treatment groups is fixed, the fixed effects estimator is unbiased but inconsistent as the control group increases in size. As an additional robustness exercise we implement an adjustment for small treatment group size proposed by Conley and Taber.

Formally, let N_1 and N_0 denote the number of treatment and control groups, respectively. In Conley and Taber's notation, let α denote the treatment parameter of interest and η_i the disturbance term. Conley and Taber show that as $N_0 \to \infty$ the fixed effects estimator will converge to the true parameter plus a noise term: $\hat{\alpha}_{FE} \xrightarrow{p} \alpha + W$, where $\xrightarrow{p}$ denotes convergence in probability and the noise term W is given by

$$W = \frac{\sum_{j=1}^{N_1} \sum_{t=1}^{T} (d_{it} - \bar{d}_i)(\eta_{it} - \bar{\eta}_i)}{\sum_{j=1}^{N_1} \sum_{t=1}^{T} (d_{it} - \bar{d}_i)^2}. \tag{4}$$

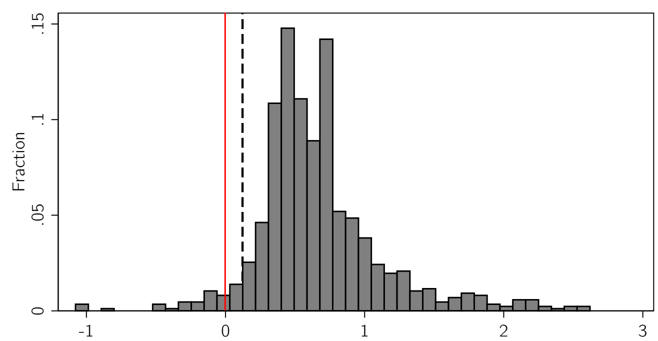
Here the term d_{it} denotes the treatment dummy and a "hat" over a variable denotes its group mean. Conley and Taber's key insight is that as long as the residuals for the treatment and control groups are drawn from the same distribution, the noise term W can be estimated using the empirical distribution of the residuals from the control groups. This can in turn can be used to construct adjusted confidence intervals for $\hat{\alpha}_{FE}$.

We reestimate our benchmark model for the determinants of bank profits and use the residuals to calculate the Conley-Taber adjusted confidence intervals. This is shown in Table 7, which as a reference also reports the confidence intervals with Driscoll-Kraay errors and normally distributed, heteroskedastic errors. The columns labeled P_{it} report the coefficient estimates for the LSAP counterparty treatment dummy. The key point from this exercise is that the estimated coefficients are still significantly different from zero after carrying out the Conely-Taber adjustment. This is also illustrated in Figure 4, which depicts the empirical distribution of $\alpha + W$. The dashed line shows the 5th percentile and is well to the right of zero, indicating that the estimated coefficient is statistically significant at the 90 percent level.

Table 7: Conley-Taber Adjustment.

Dependent Variable: Return on Assets (ROA_{it})				With Covariates		
		90% CI			90% CI	
	P_{it}	lower	upper	P_{it}	lower	upper
Normal	0.728	0.201	1.255	0.634	0.113	1.155
Driscoll-Kraay Errors	0.728	0.511	0.945	0.634	0.399	0.870
Conley-Taber Adjustment	0.728	0.102	1.584	0.634	0.120	1.227
Observations		6927			6055	
Number of Banks		872			872	
Bank FE		Yes			Yes	
Time FE		Yes			Yes	

Figure 4: Empirical distribution of $\alpha + W$. The dashed line shows the 5th percentile.



5 Conclusion

This paper empirically examined the impact of MBS purchases under QE I on bank profits. Using a treatment effect framework, it provided evidence that QE did in fact increase bank profits relative to non-treatment banks and non-QE quarters. Banks that were counterparties to Fed MBS purchases – "treatment" banks – experienced large and statistically significant increases in profits after controlling for standard determinants of bank performance. We also provided evidence of indirect spillover effects on bank profits, which likely operate through changes in MBS prices and are consistent with the portfolio balance transmission channel for the effectiveness of QE. Banks with large holdings of MBS relative to total assets prior to QE – "exposure" banks – experienced significant increases in profitability relative to non-exposure banks, though this effect is smaller than the direct treatment effect for counterparty banks. This suggests that banks positioned to sell MBS to the Fed during QE reaped economic benefits in addition to the broader benefits experienced by the financial sector as a whole.

We also presented evidence of heterogeneity and nonlinearities in the magnitude of the indirect spillover effects. Spillover effects appear to be considerably greater for larger banks (with total assets in the top two quartiles of the sample). The results also suggest that in order to reap meaningful benefits, banks must have held a substantial amount of MBS relative to total assets in quarters prior to QE.

These findings shed light on the distributional consequences of the Fed's unconventional monetary policy since the onset of the 2007-8 financial crisis. Although QE has likely boosted output and prevented a deeper recession, employment growth has remained sluggish during the recovery period. This paper identifies one clear winner from QE: large banks and specifically those that sold MBS to the Fed.

Extensions of this work could shed light on important related questions: what have been the impacts of QE on the profits of corporations operating in other sectors of the economy? Have the impacts changed over the various rounds of QE? Why did the Federal Reserve end its QE program in October, 2014? We plan to pursue these questions in future research.

References

Panayiotis P. Athanasoglou, Sophocles N. Brissimis, and Matthaios D. Delis. Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money*, 18(2):121–136, April 2008. ISSN 10424431. doi: 10.1016/j.intfin.2006.07.001. URL `http://linkinghub.elsevier.com/retrieve/pii/S1042443106000473`.

Michael Brei, Leonardo Gambacorta, and Goetz von Peter. Rescue packages and bank lending. *Journal of Banking & Finance*, 2012. URL `http://www.sciencedirect.com/science/article/pii/S0378426612002865`.

Han Chen, Vasco Curdia, and Andrea Ferrero. The macroeconomic effects of large-scale asset purchase programmes*. *The economic journal*, 122(564):F289–F315, 2012. URL `http://onlinelibrary.wiley.com/doi/10.1111/j.1468-0297.2012.02549.x/full`.

Timothy G. Conley and Christopher R. Taber. Inference with "difference in differences" with a small number of policy changes. *The Review of Economics and Statistics*, 93(1):113–125, 2011. URL `http://www.mitpressjournals.org/doi/abs/10.1162/REST_a_00049`.

Stefania D'Amico, William English, David López-Salido, and Edward Nelson. The federal reserve's large-scale asset purchase programmes: Rationale and effects*: LSAP RATIONALE AND EFFECTS. *The Economic Journal*, 122(564):F415–F446, November 2012. ISSN 00130133. doi: 10.1111/j.1468-0297.2012.02550.x. URL `http://doi.wiley.com/10.1111/j.1468-0297.2012.02550.x`.

Rafael E. De Hoyos and Vasilis Sarafidis. Testing for cross-sectional dependence in panel-data models. *The Stata Journal*, 6(4):482–496, 2006.

Andreas Dietrich and Gabrielle Wanzenried. Determinants of bank profitability before and during the crisis: Evidence from switzerland. *Journal of International Financial Markets, Institutions and Money*, 21(3):307–327, July 2011. ISSN 10424431. doi: 10.1016/j.intfin.2010.11.002. URL `http://linkinghub.elsevier.com/retrieve/pii/S1042443110000831`.

John C. Driscoll and Aart C. Kraay. Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80(4):549–560, November 1998.

Gerald Epstein. Federal reserve policy and monetary instability. In Alan Stone and Edward J. Harpham, editors, *The Political Economy of Public Policy*. Sage Publications, Beverly Hills, 1982.

Gerald Epstein. A political economy model of comparative central banking. In Gary Dymski and Robert Pollin, editors, *New Perspectives in Monetary Macroeconomics: Explorations in the Tradition of Hyman Minsky*. University of Michigan Press, Ann Arbor, 1994.

Gerald Epstein and Thomas Ferguson. Monetary policy, loan liquidation and industrial conflict: The federal reserve and the open market operations of 1932. *Journal of Economic History*, 44(4):957–983, December 1984.

Thomas Ferguson. *Golden Rule; The Investment Theory of Party Competition and the Logic of Money-Driven Political Systems*. Univeristy of Chicago Press, Chicago, 1995.

Thomas Ferguson and Robert Johnson. Too big to bail: The "paulson put," presidential politics, and the global financial meltdown part i: From shadow financial system to shadow bailout. *International Journal of Political Economy*, 38(1):3–34, Spring 2009a.

Thomas Ferguson and Robert Johnson. Too big to bail: The "paulson put," presidential politics, and the global financial meltdown part ii: Fatal reversal–single payer and back. *International Journal of Political Economy*, 38(2):5–45, Summer 2009b.

Joseph Gagnon, Matthew Raskin, Julie Remache, and Brian Sack. The financial market effects of the federal reserve's large-scale asset purchases. *International Journal of Central Banking*, 7(1):3–43, 2011. URL `http://www.ijcb.org/journal/ijcb11q1a1.pdf?origin=publication_detail`.

Alicia García-Herrero, Sergio Gavilá, and Daniel Santabárbara. What explains the low profitability of chinese banks? *Journal of Banking & Finance*, 33(11):2080–2092, November 2009. ISSN 03784266. doi: 10.1016/j.jbankfin.2009.05.005. URL `http://linkinghub.elsevier.com/retrieve/pii/S0378426609001022`.

Simon Gilchrist and Egon Zakrajv̌sek. The impact of the federal reserve's large-scale asset purchase programs on corporate credit risk. *Journal of Money, Credit and Banking*, 45(s2):29–57, 2013. URL `http://onlinelibrary.wiley.com/doi/10.1111/jmcb.12070/full`.

Diana Hancock and Wayne Passmore. How the federal reserve's large-scale asset purchases (LSAPs) influence mortgage-backed securities (MBS) yields and u.s. mortgage rates. Working paper, Federal Reserve Board, 2014.

Daniel Hoechle. Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*, 7(3):281, 2007. URL `http://83.143.248.39/faculty/nulku/ECO400%20Advanced%20Time%20Series%20Econometrics/Panel/xtscc_paper.pdf`.

Frederic Lambert and Kenichi Ueda. The effects of unconventional monetary policies on bank soundness, 2014.

M. Hashem Pesaran. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2):265–312, March 2007. ISSN 08837252, 10991255. doi: 10.1002/jae.951. URL `http://doi.wiley.com/10.1002/jae.951`.

Vasilis Sarafidis and Tom Wansbeek. Cross-sectional dependence in panel data analysis. *Econometric Reviews*, 31(5):483–531, 2012. URL http://www.tandfonline.com/doi/abs/10.1080/07474938.2011.611458.

Brock K. Short. The relation between commercial bank profit rates and banking concentration in canada, western europe, and japan. *The Journal of Finance and Banking*, 3(3):209–219, September 1979.

Eric T. Swanson, Lucrezia Reichlin, and Jonathan H. Wright. Let's twist again: A high-frequency event-study analysis of operation twist and its implications for QE2 [with comments and discussion]. *Brookings Papers on Economic Activity*, pages 151–207, 2011. URL http://www.jstor.org/stable/41228525.

James Tobin. Money, capital, and other stores of value. *American Economic Review*, 51(2):26–38, May 1961.

Dimitri Vayanos and Jean-Luc Vila. A preferred-habitat model of the term structure of interest rates. *NBER Working Paper*, 2009. URL http://www.nber.org/papers/w15487.

Annette Vissing-Jorgensen and Arvind Krishnamurthy. The effects of quantitative easing on interest rates: Channels and implications for policy. *Brookings Papers on Economic Activity*, 2011.

Sebastian Watzka and Heike Schenkelberg. Real effects of quantitative easing at the zero-lower bound: Structural VAR-based evidence from japan. Beiträge zur Jahrestagung des Vereins für Socialpolitik 2011: Die Ordnung der Weltwirtschaft: Lektionen aus der Krise - Session: Governments, Banks and Central Banks in the Financial Crisis. ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, 2011. URL http://www.econstor.eu/handle/10419/48687.

Jonathan H. Wright. What does monetary policy do to long-term interest rates at the zero lower bound?: Monetary policy at the zero lower bound. *The Economic Journal*, 122(564):F447–F466, November 2012. ISSN 00130133. doi: 10.1111/j.1468-0297.2012.02556.x. URL http://doi.wiley.com/10.1111/j.1468-0297.2012.02556.x.

Table 8: Lending Regressions

	Dependent Variable: Δ Loans Share				**Dependent Variable:** Log Loan Growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
P_{it}	-0.116	0.036	-0.026	0.009	-0.506	-0.815	-1.312	-0.767
	(0.428)	(0.365)	(0.346)	(0.392)	(2.139)	(2.057)	(1.973)	(2.084)
E_{it}	0.486	0.649**	0.590**	0.621*	0.403	0.082	-0.445	0.137
	(0.258)	(0.234)	(0.167)	(0.266)	(0.223)	(0.273)	(0.348)	(0.263)
Capital Ratio	-0.246**	-0.223***	-0.218***	-0.228***	0.681**	0.711***	0.696***	0.705***
	(0.067)	(0.059)	(0.058)	(0.058)	(0.185)	(0.180)	(0.177)	(0.180)
Lagged Nonperforming Assets	-0.248***	-0.246***	-0.249***	-0.248***	-0.193*	-0.289**	-0.388***	-0.267**
	(0.041)	(0.062)	(0.052)	(0.063)	(0.085)	(0.104)	(0.087)	(0.101)
Market-based Funding	-0.048***	-0.049***	-0.048***	-0.049***	0.126**	0.134**	0.138**	0.134**
	(0.010)	(0.011)	(0.011)	(0.011)	(0.046)	(0.047)	(0.049)	(0.046)
Output Gap		22.476**				51.607***		
		(8.345)				(3.615)		
Interest Spread			0.564***				0.903***	
			(0.098)				(0.125)	
Case-Shiller Housing Index				0.039*				0.098***
				(0.017)				(0.007)
Constant	7.865***	7.033***	5.398***	0.819	-14.517**	-16.457**	-18.999**	-32.006***
	(1.007)	(0.908)	(1.090)	(3.245)	(5.654)	(5.627)	(5.480)	(6.254)
Observations	4,434	4,434	4,434	4,434	4,434	4,434	4,434	4,434
Number of groups	862	862	862	862	862	862	862	862
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No	Yes	No	No	No
R-squared within	0.069	0.045	0.053	0.043	0.097	0.088	0.080	0.089

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

A Data Appendix

A.1 Holding company and subsidiary matches

In order to construct the LSAP counterparty treatment variables it was first necessary to match each transaction counterparty to its parent holding company. This section briefly describes each match, starting with the name of the subsidiary broker/dealer and its corresponding US-based holding company. Standardized RSSD ID codes are reported in parenthesis after company names.

- BNP Paribas Securities Corp. (2311326). Broker/Dealer owned by BNP Paribas. BNP Paribas' US-based holding company is Bancwest Corporation (1025608). Data is only available starting in 2009Q1.

- Barclays Capital Inc. (1909249). Broker/Dealer owned by Barclays PLC. Barclays has had two US-based holding companies: Barclays Delaware Holdings LLC (2938451) and Barclays Group US Inc. (2914521). Data for Barclays Group ends in 2010Q3 after it was reclassified as "domestic entity other." It appears as though part of its assets were absorbed by Barclays Delaware Holdings, though the series are not perfectly comparable.

- Citigroup Global Markets Inc. (2754521). Broker/Dealer owned by domestic holding company Citigroup Inc. (1951350).

- Deutsche Bank Securities Inc. (1900666). Deutsche Bank's US-based holding company is Deutsche Bank Trust Corporation (1032473). Data is only available after 2011.

- The Goldman Sachs Group, Inc. (2380443). Registered as bank holding company in 2008Q3. Data only available after 2008.

- J.P. Morgan Securities LLC (1155420). Subsidiary of JPMorgan Chase & Co. (1039502).

- Morgan Stanley & Co. LLC (1573239). Subsidiary of Morgan Stanley (2162966).

- RBC Capital Markets LLC (1599109). Owned by Royal Bank of Canada (1232497). RBC had two US-based holding companies before consolidating: RBC Bancorporation (USA) (1826056) and RBC USA Holdco Corporation (3226762). In 2010Q4 RBC Bancorporation was acquired by Holdco. RBC USA Holdco only has data after 2010Q4 while RBC Bancorporation only has data before the consolidation. Unfortunately, the two series are not comparable since Holdco also includes 8 other US subsidiaries.

- RBS Securities Inc. (1851106). Broker/Dealer owned by UK Financial Investments Limited (3833526), which owned the RBS Group. Only associated US-based holding company is Citizens Financial Group Inc. (1132449), which has been owned by the RBS Group since 1988.

A.2 Variable construction and FRY-9C series

This subsection provides the series codes from the FRY-9C reports for the main variables used above.

- Total assets (bhck2170)

- Total loans (bhck2122)
- Non-performing loans : assets past-due 30-89 days (bhck5524) + assets past-due 90 or more days (bhck5525) + nonaccrual assets (bhck5526)
- Tier 1 capital adequacy ratio (bhck7204)
- Realized gains on securities : gains on securities held-to-maturity (bhck3521) + gains on securities available-for-sale (bhck3196)
- Total revenue : interest income (bhck4107) + non-interest income (bhck4079) + realized gains (above)
- Interest income share: total interest income (bhck4107) / total revenue (above)
- Total expenditure : interest expenditure (bhck4073) + non-interest expenditure (bhck4093)
- Net income : total revenue (above) - total expenditure (above)
- Return on assets : net income (above) / total assets (bhck2170)
- Costs to revenue ratio : total expenditure (above) / total revenue (above)

(a) Total mortgage-backed securities

Due to numerous changes in reporting standards during the sample period it is necessary to combine several different series for the stock of mortgage-backed securities held as assets. The total includes MBS listed as held-to-maturity, available-for-sale, as well as MBS reported as trading assets. The total stock of MBS was obtained as:

total MBS = bhck1699 + bhck1702 + bhck1705 + bhck1707 + bhck1710 + bhck1713 + bhck1715 + bhck1717 + bhck1719 + bhck1732 + bhck1734 + bhck1736 + bhck3534 + bhck3535 + bhck3536 + bhckg301 + bhckg303 + bhckg305 + bhckg307 + bhckg325 + bhckg327 + bhckg379 + bhckg382 + bhckg313 + bhckg315 + bhckg317 + bhckg319 + bhckg329 + bhckg331 + bhckg380 + bhckg309 + bhckg311 + bhckg321 + bhckg323 + bhckg325 + bhckg327 + bhckg381 + bhckg379 + bhckk143 + bhckk145 + bhckk197 + bhckk151 + bhckk153 + bhckk147 + bhckk149 + bhckk155 + bhckk157 + bhckk198