

ONLINE APPENDIX

The geographic flow of bank funding and access to credit: Branch networks, synergies, and local competition

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A Appendix

A.1 Datasets and level of observation

We rely on three main sources for the construction of our dataset. The first is the summary of deposits (SOD) collected by the Federal Deposit Insurance Corporation (FDIC), which provides county-level information on deposits outstanding (the “stock” measure) for each FDIC-insured bank.

The second is the Reports of Condition and Income (CALL) report collected by the FDIC. The CALL reports contain important bank-level characteristics, such as assets, total deposits (stock), total (mortgage) loans (stock), etc. It also provides loan turnover rate that we use to construct the “adjusted deposit flow” measures in deposits and loans described in detail in Section A.4.

Third, we make use of Home Mortgage Disclosure Act (HMDA) data collected by the Consumer Financial Protection Bureau, which provide county-level total mortgage loans issued by each reported institutions in a given year (a “flow” measure of loans).¹

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¹There are geographic restrictions on loan reporting. According to the Community Reinvestment Act, large banks must report on all loans regardless of location. Regardless of size, lenders located in an MSA must report on loans originated in an MSA but can choose not to report loans outside MSAs. Only small lenders outside of MSAs do not have to report, but according to the US census, about 83% of the population lived in an MSA during our sample period. Therefore, HMDA captures most residential mortgage lending activity.

Table A1 summarizes the above information. The SOD and HMDA data are available annually during our study periods (1998-2010). The CALL reports are reported quarterly. In practice, we found that the June (the second quarter) CALL reports deliver the highest matching rate with the SOD and HMDA datasets each year. We therefore use the second quarter CALL reports for all the FDIC insured banks.

Table A1: Main data sources

Dataset	Collector	Detailed Level	Variables
Summary of Deposits (SOD)	Federal Insurance Corporation (FDIC)	Deposit Institution-county level (Depository banks)	Amount of deposits (stock) Number of branches
Home Mortgage Disclosure Act Data (HMDA)	Consumer Financial Protection Bureau	Institution-county level (Depository banks & Shadow banks)	Amount of loans issued (flow) Securitization rate
Reports of Condition and Income (CALL report)	Federal Insurance Corporation (FDIC)	Institution level (Depository banks)	Amount of deposits (stock) Amount of loans (stock) Turn over rate of loans

A.2 Construction of the working sample

Table A2 describes how all of the datasets just described are matched. The last three columns report the number of institutions, the share of deposits, and the share of loans of each case at the national level in year 2000.

Note that in addition to the datasets just listed we also obtain credit union characteristics from the CALL reports (CALL-CU afterwards) collected by National Credit Union Administration (NCUA).² The NCUA CALL reports are generally organized in a similar fashion as the FDIC CALL reports. However, one important feature worth mentioning is that they contain not only the mortgage loan outstanding for each credit union, but also the amount of mortgage loans newly issued in the corresponding calendar year. Similar information on loan flow is not available among the depository institutions in the FDIC CALL reports.³

Institutions in both SOD and HMDA:

The depository institutions in our working sample are those banks (case 1) and saving associations (case 3) that can be matched between SOD and HMDA. In year 2000, there are 3971 case

²See [NCUA \(1998 - 2010\)](#).

³For credit unions, we must use the December CALL data because only this quarter can give us the mortgage loans issued in the whole calendar year (the loan “flow” measure).

Table A2: Classification of Banks & Matching Cases Between SOD, HMDA, and CALL

Case	Inst. Category & Matching Case	Availability in Datasets				Year 2000		
		HMDA	SOD	CALL	CU CALL	Nbr Banks	Share Deps	Share Loan
1	FDIC Core banks matched with HMDA	X	X	X		3971	68.2%	23.2%
2	FDIC Core banks unmatched with HMDA		X	X		5038	10.8%	3.8%
3	FDIC Savings Asso. matched with HMDA	X	X			697	10.8%	15.4%
4	FDIC Savings Asso. unmatched with HMDA		X			413	1.4%	0.2%
5	Foreign banks matched with HMDA	X		X		0	-	-
6	Foreign banks unmatched with HMDA			X		408	-	-
7	Shadow banks in HMDA	X				1243	0.0%	53.5%
8	Credit Unions in HMDA & CU CALL	X			X	1651	6.5%	3.2%
9	Credit Unions in HMDA but no CU CALL	X				26	-	-
10	Credit Unions in CU CALL but no HMDA				X	8788	2.2%	0.7%

1 banks, accounting for 68.2% of the national deposits and 23.2% of the national loans. Meanwhile, there are 697 case 3 saving associations, accounting for 10.8% of the national deposits and 15.4% of the national loans.

Notice that case 1 banks can also be matched with the CALL report, while case 3 cannot. Matching with CALL reports is important because they contain the institutional level of loan turnover rate, which is used in constructing our “adjusted flow” measure of deposits. For case 3, we impute their turnover rate by the average turnover rate of the case 1 banks in the same county.

Institutions in HMDA but not in SOD:

If an institution appears in HMDA but not in SOD, and if they cannot be further matched with the CALL reports or the Credit Union Call Reports, then they are labelled a shadow bank (case 7). These are mainly mortgage companies that finance their loans from sources other than deposits. In 2000, there are 1243 shadow banks, accounting for 53.5% of national loans.

Institutions that are not in SOD but are in the CALL reports are foreign banks (case 5). They are small in numbers, and also account for a tiny proportion of national deposits and loans. Therefore, they are excluded from our sample.

Credit unions (cases 8, 9, and 10) are large in number, but they are excluded from the sample for two reasons. First, their deposits and loans are only available at the institution level, not at the institution-county level. Second, they only account for a small proportion of national deposits and loans (8.7% and 3.9%, respectively, in 2000).

Institutions in SOD but not in HMDA:

Mortgage reporting for institutions smaller than a certain threshold is not compulsory. This is why most of the banks in SOD but not in HMDA (case 2 and 4 banks) tend to be small banks in assets. Although they are large in numbers (5451 institutions in year 2000), but they only account for 4.0% of total loans and 12.2% of total deposits.

Institutions not in SOD, not in HMDA:

Some foreign banks (case 6) and some credit unions (case 10) do not appear in either SOD or HMDA, but these groups are very small in terms of both deposits and loans.

Final sample: Our final working sample includes Case 1, 3, and 7 institutions. These are the institutions for which we know both their deposit distribution (Cases 1 and 3) and their loan distribution (Cases 1, 3, and 7) at the county level.

A.3 Multi-state banks

Table A3: Multi-state banks

year	All	Depository Banks				Shadow Banks	
	nbk	nbk	Multi-state in branches	Multi-state in loans	Multi-state in br or loans	nbk	Multi-state in loans
1998	6123	4740	188	1861	1861	1383	936
1999	6014	4667	235	1979	1979	1347	934
2000	5892	4649	263	2026	2026	1243	912
2001	5774	4592	306	2135	2135	1182	878
2002	5856	4622	334	2294	2294	1234	923
2003	6080	4624	358	2451	2451	1456	1124
2004	6619	4906	376	2632	2632	1713	1250
2005	6615	4830	422	2662	2662	1785	1310
2006	6659	4793	441	2723	2723	1866	1371
2007	6404	4767	466	2721	2721	1637	1202
2008	6166	4789	486	2810	2810	1377	1008
2009	5913	4723	492	2657	2657	1190	890
2010	5715	4576	495	2473	2473	1139	860

A.4 Alternative Measures of the Imbalance Index – Adjusted Deposit Flows and Loan Stocks

As mentioned in Section II.B in the main manuscript, the loan information in HMDA refers to the mortgage loans issued in a year, and should therefore be considered a *flow* measure. On the deposit side, the SOD provides information on the deposits available on a day of the year (June 30th), and it is a *stock* variable. One problem with using stocks is that some past deposit inflows, which make up today’s stock of deposits, have already been used to fund prior mortgages. To address this, deposit flows can be constructed from the SOD dataset as the net change in deposit stocks at the bank-county level by first-differencing by year. However, this represents a net change – newly attracted deposits minus withdrawn deposits.

There are two problems with using the net change. First, it can be negative, which makes it difficult to calculate the deposit share at the county level. Second, it is also the case that this

net change in deposits would underestimate the funds available to banks to create new loans, since a fraction of existing loans are repaid (come due) every year.

We therefore construct what we call an *adjusted flow* measure, that includes net deposit changes along with those deposits that are freed up today as a fraction of previously funded loans are paid off. The Call Reports provide information for each bank on the fraction of loans coming due each year and we use this to construct our measure.

In our main analysis, we continue to focus on stocks of deposits for the reasons mentioned in Section II.B in the main manuscript. However, we have performed all of our descriptive analyses using new loans and adjusted deposit flows. Our results are robust to this alternative measure of deposits – The Imbalance Index for adjusted deposit flows vs loan flows follows a similar pattern to stocks vs flows.

We also repeat the analysis with deposit stocks and replacing loan flows with loan stocks in the construction of the Imbalance Index. Again, our findings suggest that there is little change to the Imbalance Index from such a modification.

In what follows we provide a detailed explanation of the implementation of these two robustness checks, along with a discussion of the consequences for our analysis.

I. Adjusted deposit flows vs loan flows:

We start by introducing the following notation and variable definitions. For bank j in county m and year t , define:

- q_{jmt}^d : amount of deposits (stock) held by j in m as of t ,
- L_{jmt} : proportion of j 's deposits in m as of t used to fund mortgages throughout j 's network,
- R_{jmt} : loan turnover rate for j in m in t (i.e. the proportion of loans that will mature within a year),
- DF_{jmt} : amount of deposits newly available for j in m in t (i.e. the adjusted flow of deposits).

DF_{jmt} is constructed as follows:

$$DF_{jmt} = q_{jmt}^d - q_{jmt-1}^d + R_{jmt-1} \times L_{jmt-1}.$$

This adjusted flow measure is made up of two components:

- i. $q_{jmt}^d - q_{jmt-1}^d$: net change in the stock of deposits, reflecting the savings and withdrawal decisions of the local consumers.
- ii. $R_{jmt-1} \times L_{jmt-1}$: loans maturing and turning over within a year – funds that should be available for the purpose of credit.

There are two simplifying assumptions we must make when constructing the adjusted deposit flow measure:

- We do not have the loan turnover rate at the bank-market level. To deal with this, we use the bank level turnover rate to proxy for the bank-market level measure (i.e., we use R_{jt-1} in place of R_{jmt-1}).
- We do not observe the amount of deposits issued as loans at the bank-county level. Instead, we infer this using observables in the dataset: the total deposit stock (Q_{jt}^d), the total loan stock (L_{jt}), and the bank-county level deposit stock (q_{jmt}^d). The first two come from the CALL reports, while the last comes from the SOD dataset. Specifically, we assume that at the bank-market level the share of deposit stock used to fund loans throughout j 's network is the same as the bank-level share of deposit stock used to fund loans (i.e., $L_{jmt}/q_{jmt}^d = L_{jt}/Q_{jt}^d$). Therefore,

$$\begin{aligned} L_{jmt-1} &= L_{jt-1}/Q_{jt-1}^d \times q_{jmt-1}^d \\ &= \rho_{jt-1} \times q_{jmt-1}^d, \end{aligned}$$

where $\rho_{jt-1} = L_{jt-1}/Q_{jt-1}^d$ is the ratio between the loan (stock) and deposit (stock) at the bank level.

With the above adjustments, the adjusted deposit flow measure can be calculated as:

$$DF_{jmt} = q_{jmt}^d - q_{jmt-1}^d + R_{jt-1} \times \rho_{jt-1} \times q_{jmt-1}^d. \quad (1)$$

Data on deposits at the bank-county level come from the SOD dataset, while variables at the bank level (R and ρ) come from the CALL reports.

An additional complication arises in constructing our adjusted deposit flow measure because of mergers and the entry and exit of banks in our sample period. The construction of our adjusted flow measure requires bank-level and bank-county level information from two continuous years. Over time, there are banks that enter into or exit from the local market. Entry leads to missing values in year $t - 1$, while exit leads to missing values in year t . The more complicated cases are entry or exit due to mergers, where a bank's ID should be replaced by another one. Data on bank mergers, including timing information and information on the acquirer and acquiree are obtained from [FFIEC \(1998 - 2010\)](#).

Table [A4](#) lists all the possible scenarios when we compare observations at the bank-county level between year $t - 1$ and t . The scenarios listed in red are those in need of modification using the merger information, otherwise we will have missing values in the deposit flow for these cases.

- In 87% of the cases, a bank exists in both years, so that the standard formula of equation (1) can be used. This is scenario 0.
- Scenario 1 describes simple exit from a county. This is infrequent and represents just 1.2% of observations.
- Most banks exit from a market because of a merger (scenario 2). Their ID in year $t - 1$ needs to be replaced by the acquiring bank before applying the standard formula to the acquiring banks in year t . There are three subcases depending on whether surviving bank B's acquisition of bank A involves taking over A's branches in counties in which it wasn't active (2.1), and in which it was (2.2).

Table A4: Entry and Exit Scenarios

				Year $t - 1$	Year t	Flow calc w/o adjust.	Flow calc w/ merger adjust.	Nbr obs in 2000	% share
Scenario 0				A	A	Standard formula	Standard formula eq (1)	22,434	87.1
Scenario 1	Exit			A		Missing value in A	Missing value in A	322	1.3
		2.1	B takes over A's branches	A	B	Missing value in B	Replace A's ID w/ B's in $t - 1$, apply st form	1,541	6.0
Scenario 2	Exit through merger	2.2	Within market M&A	A,B	B	Part of B's $t - 1$ not counted	Replace A's ID w/ B's $t - 1$, apply st formula	315	1.2
Scenario 3	B denovo enter				B	Missing value in B	B's deposits in t	1,148	4.5

Note: A and B are banks, with B being the surviving bank. Year $t - 1$ and Year t columns indicate which of A and B have branches in the given county in the given year.

- Scenario 3 describes denovo entry (about 4.5%). We assign the deposit stock of this bank in year t as its adjusted deposit flow in year t .

Summary statistics and results:

- **Loan turnover rate, R_{jt} :** The CALL reports provide information at the bank level on “loans and leases with a remaining maturity of one year or less.” The ratio between this variable and the “total loans and leases” gives us the bank-level turnover rate for loans. The median (also the mean) turnover rate is around 30%.
- **Loan to Deposit ratio, ρ_{jt} :** The CALL reports provide information on both the loan stock and deposit stock variable. The ratio between these two can be calculated accordingly.

In the year 2000, the median value of the loan/deposit ratio is 0.90. We truncate the ratio at the 5% and 95% percentile, which means that the final value of the ratio will range between 0.49 and 1.28.⁴

- **The adjustment factor, $R_{jt} \times \rho_{jt}$:** Figure A1 shows the distribution of $R_{jt} \times \rho_{jt}$ over time. The median is around 0.3, which is comforting because the resulting adjusted deposit flows are unlikely to be negative.

Equation (1) does not guarantee our adjusted deposit flow measure will be positive. Fortunately, observations with negative values only account for a small proportion of the sample. The share of negative observations at the bank-county level is around 3.5%, and the share of negative observations at the bank level is around 1.3%.

Table A5 reports the summary statistics of the adjusted deposit flow, and compares it with the deposit stock and the loan flow (Total new loans). In Panel A, all variables are aggregated at the bank level. In Panel B, all variables are aggregated at the county level. The sample we use is the SOD-HMDA matched sample of depository institutions (cases 1 and 3).

From Panel A we can see that bank-level adjusted deposit flows are about a third of deposits, on average. However, despite their differences in magnitude, the deposit flow (DF) and deposit

⁴All values below 0.49 or above 1.28 will be replaced by 0.49 or 1.28, respectively.

Figure A1: Adjustment factor, $R_{jt} \times \rho_{jt}$

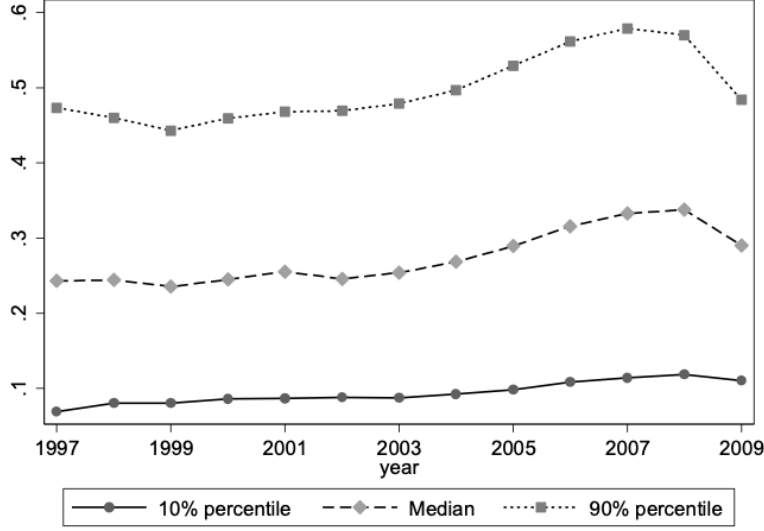


Table A5: Summary Statistics

Panel A: Bank Level Statistics: Depository Banks (61,250 bank-year obs.)					
Variable	Mean	S.D.	Pctile 5	Median	Pctile 95
Total deposits (stock)	998	11646	33	148	1734
Total deposits flow	328	4224	4	44	562
Total loan flow	188	3187	1	13	260

Panel B: County Level Statistics: Depository Banks (40,689 county-year obs.)					
Variable	Mean	S.D.	Pctile 5	Median	Pctile 95
HHI of deposits (stock)	4406	2928	1193	3456	10000
HHI of deposits flow	4597	2936	1250	3671	10000
HHI of loan flow	1799	1339	626	1398	4340

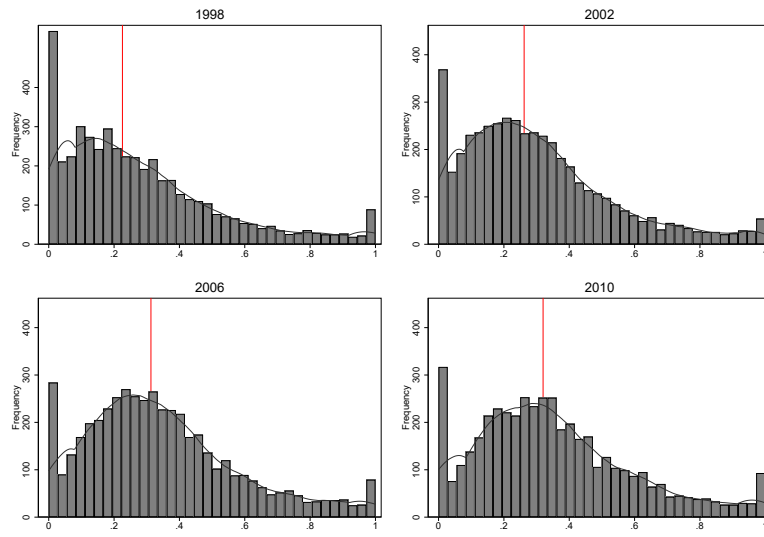
stock (DS) measures are highly correlated with each other. The correlation coefficient between the two is 0.906. Moreover, as can be seen from Panel B, the adjusted flow and stock measures imply very similar levels of concentration, on average.

Implications of the adjusted deposit flow for the Imbalance Index

Bank level: Using our sample of matched depository institutions, and dropping all observations with negative adjusted deposit flows, we can calculate the bank-level Imbalance Index between the distributions of adjusted deposit flows (DF) and loan flows (LF). Figure A2 of this response reports the distribution of the Imbalance Index changes over time. This figure can be directly compared to Figure 3 of the revised version of the paper. Doing so reveals that both in terms of magnitudes and evolution over time, findings are similar whether using adjusted deposit flows or deposit stocks.

Comparison of the bank-level Imbalance Index constructed using adjusted deposit flows (DF)

Figure A2: Bank-level Imbalance Index – Adjusted Deposit flow and Loan flow Distributions



with the Imbalance Index using deposit stocks (DS) reveals that they are, surprisingly, very similar. For example, in year 2000, the mean value of the bank-level Imbalance Index using adjusted deposit flows is 0.277, while the mean value of Imbalance Index using deposit stocks is 0.275. Figure A13 plots II_DF against II_DS , and most of the dots are tightly located around the 45 degree line. The correlation coefficient between II_DF and II_DS is 0.962.

Figure A3: Correlation: Imbalance Index using Adjusted Deposit Flow and Deposit Stock

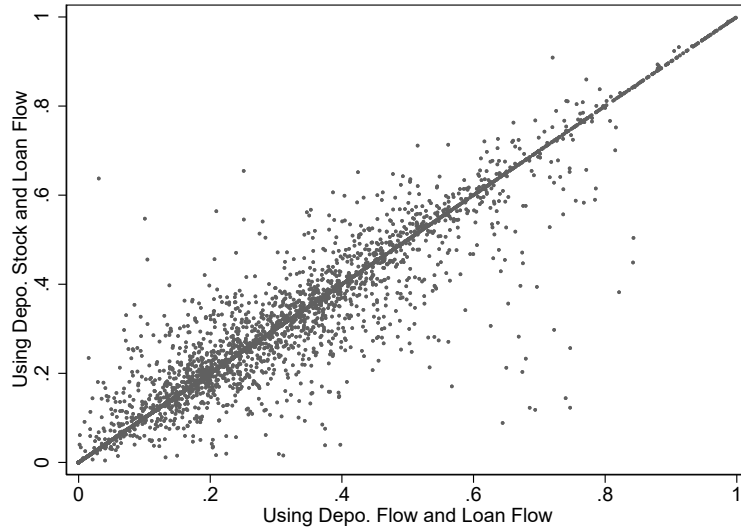


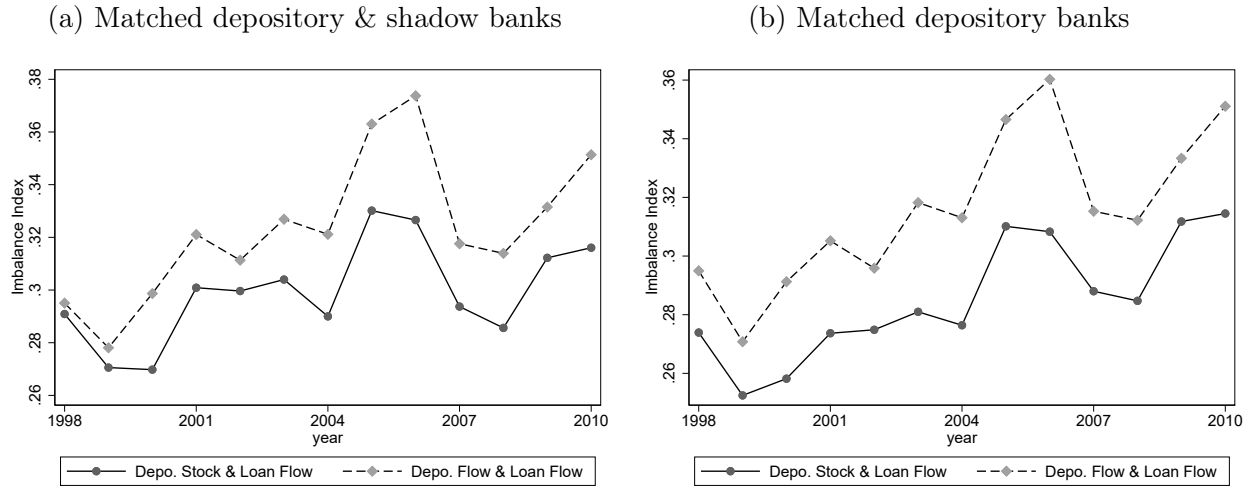
Table A6 reports the percentile of the Imbalance Index at the bank level using adjusted flows (panel A) and deposit stocks (panel B). Again, they all look very similar. Their trends are almost identical.

Table A6: Percentile of Imbalance Index at the Bank Level

Panel A: II using DF					Panel B: II using DS			
year	Mean	p10	p50	p90	Mean	p10	p50	p90
1998	0.247	0.000	0.203	0.538	0.245	0.000	0.206	0.531
1999	0.265	0.002	0.226	0.562	0.263	0.002	0.228	0.558
2000	0.277	0.004	0.238	0.577	0.275	0.004	0.238	0.572
2001	0.274	0.019	0.232	0.566	0.274	0.019	0.237	0.570
2002	0.284	0.030	0.248	0.574	0.284	0.030	0.250	0.573
2003	0.295	0.045	0.255	0.593	0.295	0.044	0.259	0.591
2004	0.313	0.051	0.281	0.616	0.310	0.051	0.279	0.606
2005	0.324	0.054	0.296	0.628	0.323	0.054	0.293	0.622
2006	0.330	0.062	0.302	0.635	0.329	0.062	0.300	0.636
2007	0.337	0.062	0.310	0.639	0.336	0.058	0.308	0.638
2008	0.342	0.068	0.318	0.642	0.339	0.070	0.312	0.638
2009	0.330	0.061	0.304	0.632	0.328	0.062	0.299	0.630
2010	0.329	0.042	0.302	0.638	0.328	0.042	0.303	0.634

National-level Imbalance Index: Figure A4 duplicates Figure 4 in the main manuscript, which plots the National-level Imbalance Index. Panel (a) shows results for matched depository & shadow banks (cases 1, 3, and 7). The loan variables are from HMDA (i.e., loan flow measure). The dashed curve uses the deposit stock, while the solid curve uses the adjusted deposit flow measure. The Imbalance Index constructed using adjusted flows rather than stocks is higher than for stocks in every year, but the two curves follow very similar patterns. Panel (b) shows the same information, but this time just for depository institutions. Again, the Imbalance Index based on adjusted flows is everywhere greater than for stocks, but the two curves are quite similar. Based on this, we think it is reasonable to stick with our stock measure for our analysis.

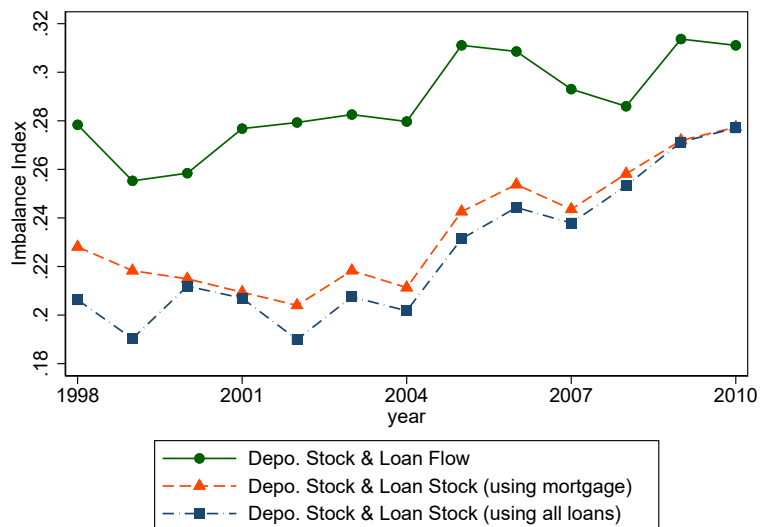
Figure A4: Imbalance Index: Deposit stocks vs Deposit Flows



II. Deposit stocks vs loan stocks:

We also construct the National-level Imbalance Index using loan stocks, so that we can compare results to those derived using our main measure of loan flow (constructed from HMDA data). Mortgage-loan stocks are constructed using the CALL reports, under the assumption that stocks have the same bank-county distribution as flows from HMDA. We also construct a version based on total loans (i.e., not just mortgages), again using the CALL reports.

Figure A5: Imbalance Index: Loan Flow vs Loan Stock



Note that this comparison focuses only on depository institutions, since we do not have CALL information for shadow banks.

Our findings suggest that the Imbalance Index that uses the loan flow measure is slightly higher than the Imbalance Index constructed with loan stocks. But the overall trends of the two curves are very similar.

A.5 Bank heterogeneity in Imbalance Index

NOTE: Ranking based on banks' assets in each year.

Table A7: Evolution of the Imbalance Index of the top 10 banks (by assets)

Rank	Bank Name	II	Rank	Bank Name	II
1998			2002		
1	CHASE MANHATTAN BANK	0.40	1	JPMORGAN CHASE BANK	0.49
2	CITIBANK, NA	0.34	2	BANK OF AMERICA, NA	0.34
3	BANK OF AMERICA NATIONAL TRUST AND SA	0.23	3	CITIBANK, NA	0.34
4	NATIONSBANK, NA	0.46	4	WACHOVIA BANK, NA	0.35
5	FIRST UNION NATIONAL BANK	0.41	5	WASHINGTON MUTUAL BANK	0.44
6	MORGAN GUARANTY TRUST COMPANY OF NY	0.97	6	BANK ONE, NA	0.47
7	BANKERS TRUST COMPANY	0.90	7	FLEET NATIONAL BANK	0.35
8	WELLS FARGO BANK, NA	0.36	8	U.S. BANK NA	0.44
9	FLEET NATIONAL BANK	0.50	9	WELLS FARGO BANK, NA	0.50
10	KEYBANK NA	0.36	10	SUNTRUST BANK	0.37
AVG		0.49	AVG		0.41
2006			2010		
1	BANK OF AMERICA NA	0.33	1	JPMORGAN CHASE BANK, NA	0.55
2	JPMORGAN CHASE BANK NA	0.66	2	BANK OF AMERICA, NA	0.46
3	CITIBANK NA	0.90	3	CITIBANK, NA	0.76
4	WACHOVIA BANK NA	0.39	4	WELLS FARGO BANK, NA	0.38
5	WELLS FARGO BANK NA	0.53	5	U.S. BANK NA	0.47
6	WASHINGTON MUTUAL BANK	0.44	6	PNC BANK, NA	0.50
7	U S BANK NA	0.49	7	HSBC BANK USA, NA	0.84
8	SUNTRUST BANK	0.40	8	SUNTRUST BANK	0.59
9	HSBC BANK USA NA	0.81	9	TD BANK, NA	0.37
10	WORLD SAVINGS BANK FSB	0.36	10	BRANCH BANKING AND TRUST COMPANY	0.31
AVG		0.53	AVG		0.52

Figure A6: Breakdown of imbalance index by bank size – size measured by counties

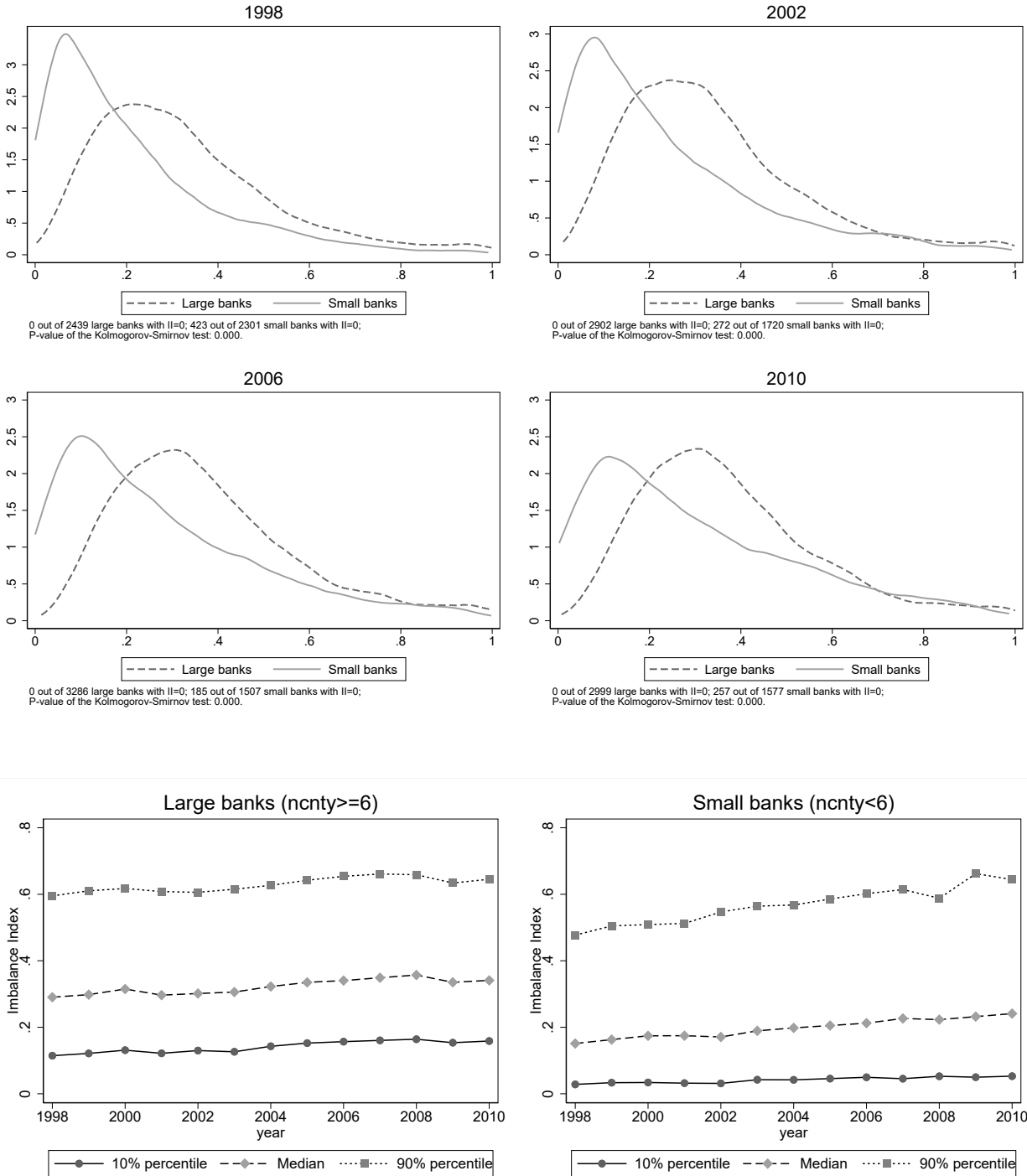


Figure A7: Breakdown of imbalance index by bank size – size measured by assets

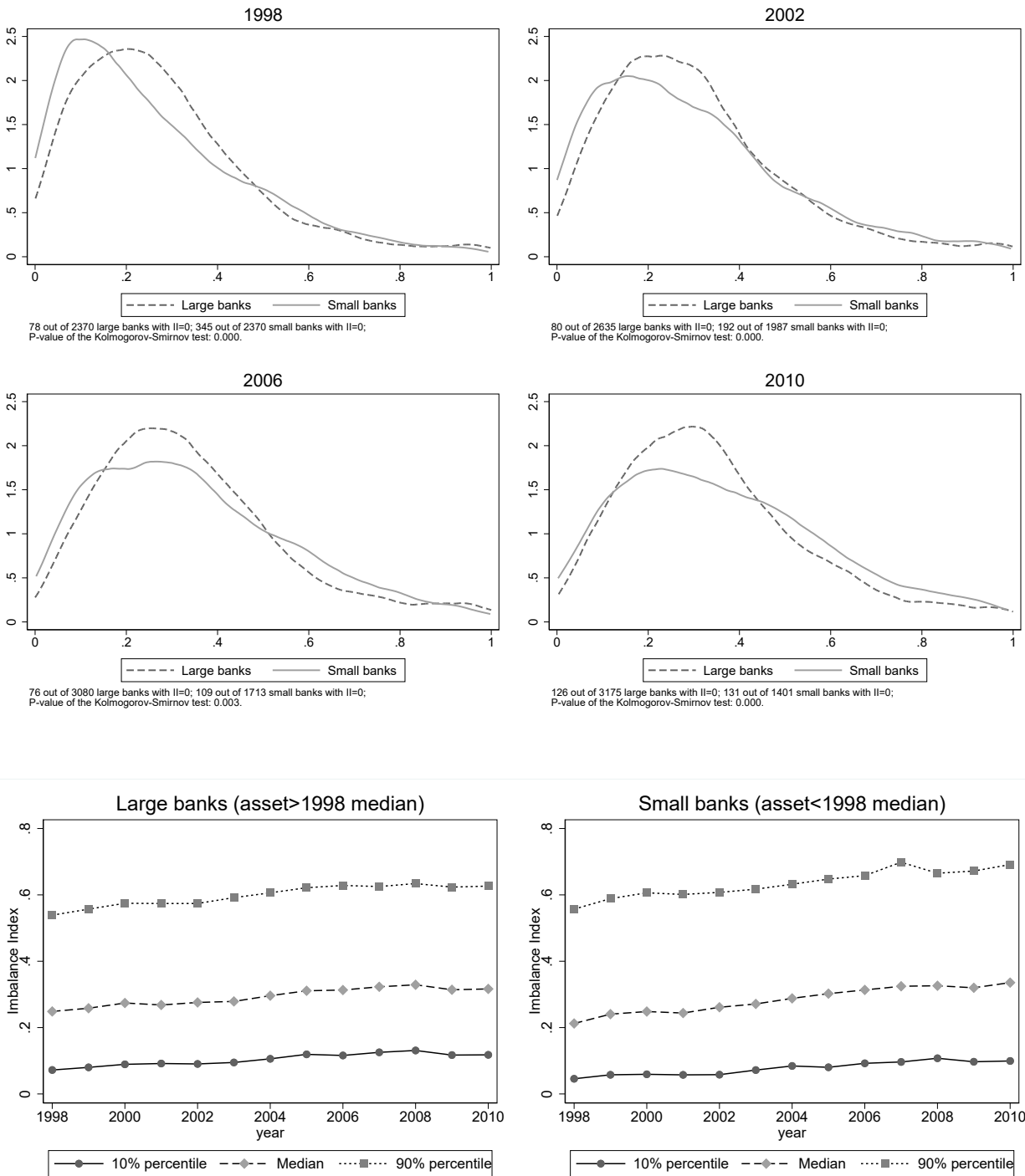


Figure A8: Breakdown of imbalance index by bank size – size measured by deposits

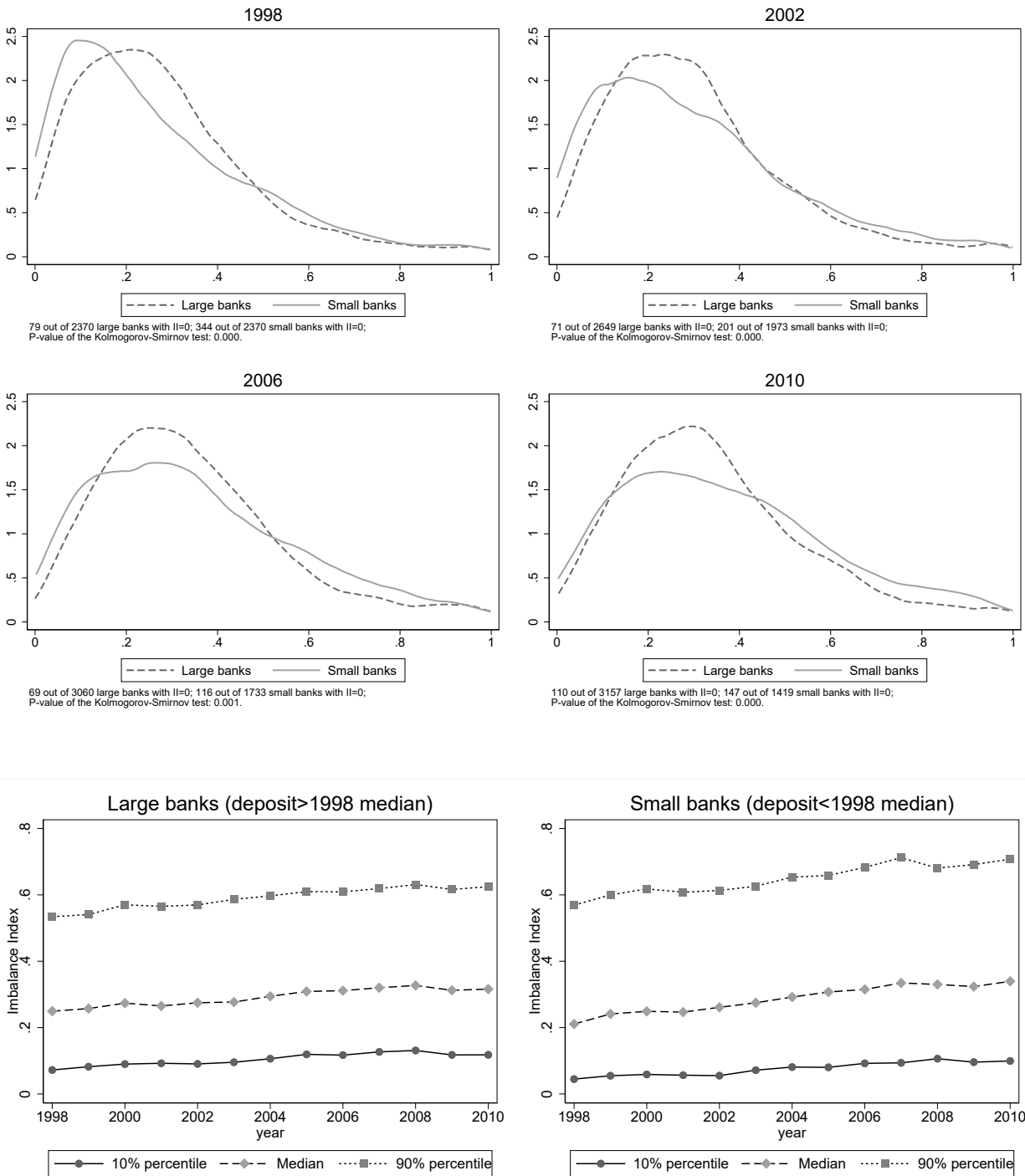
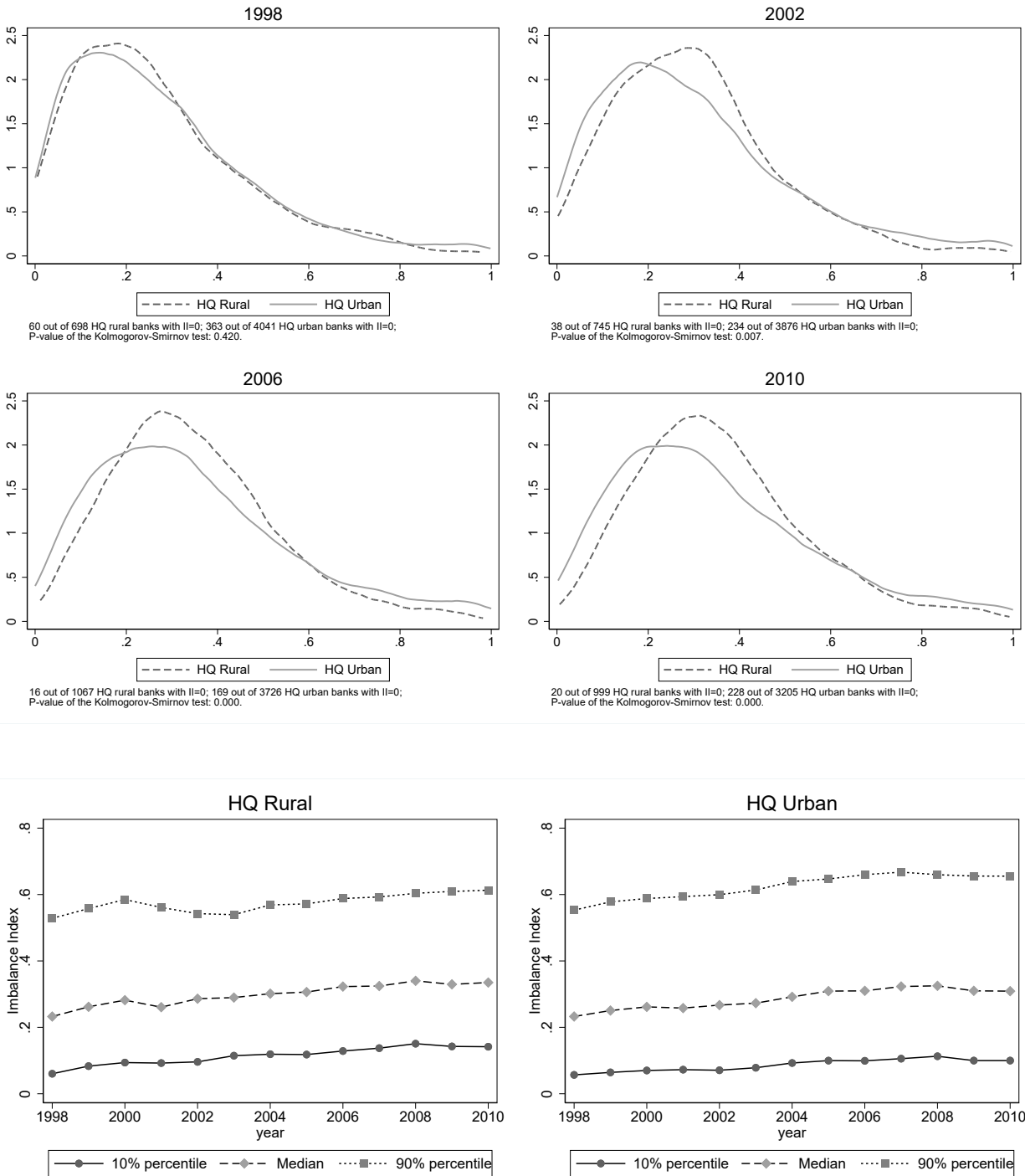


Figure A9: Breakdown of imbalance index by location – urban vs rural



A “rural county” is defined as rural population share is larger than 50%, based on population census in 2010. Reference: <https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html>

Figure A10: Breakdown of imbalance index by location – North, South, East, West

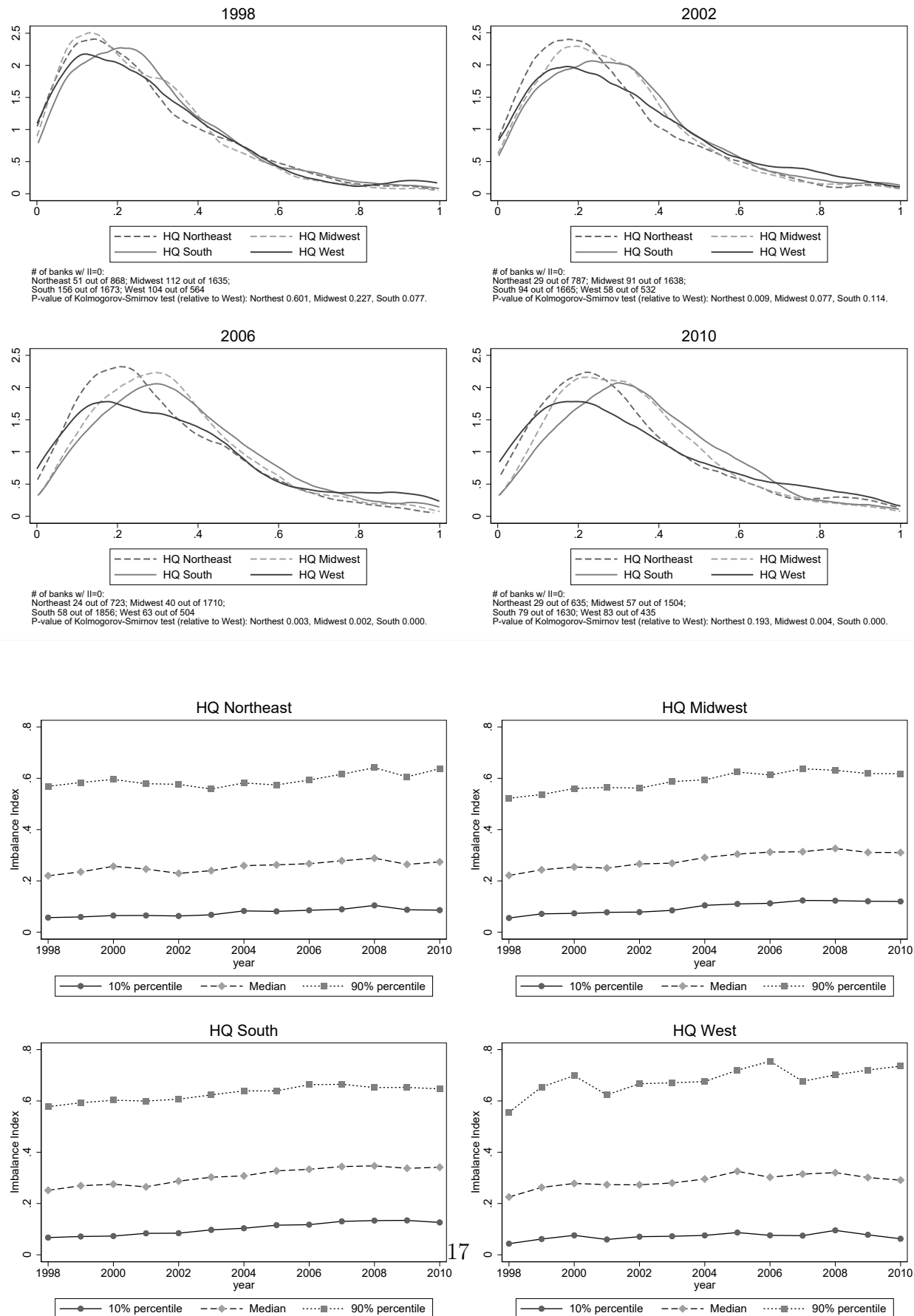


Figure A11: Breakdown of imbalance index by HQ-county income level (cutoff = 1998 median income)

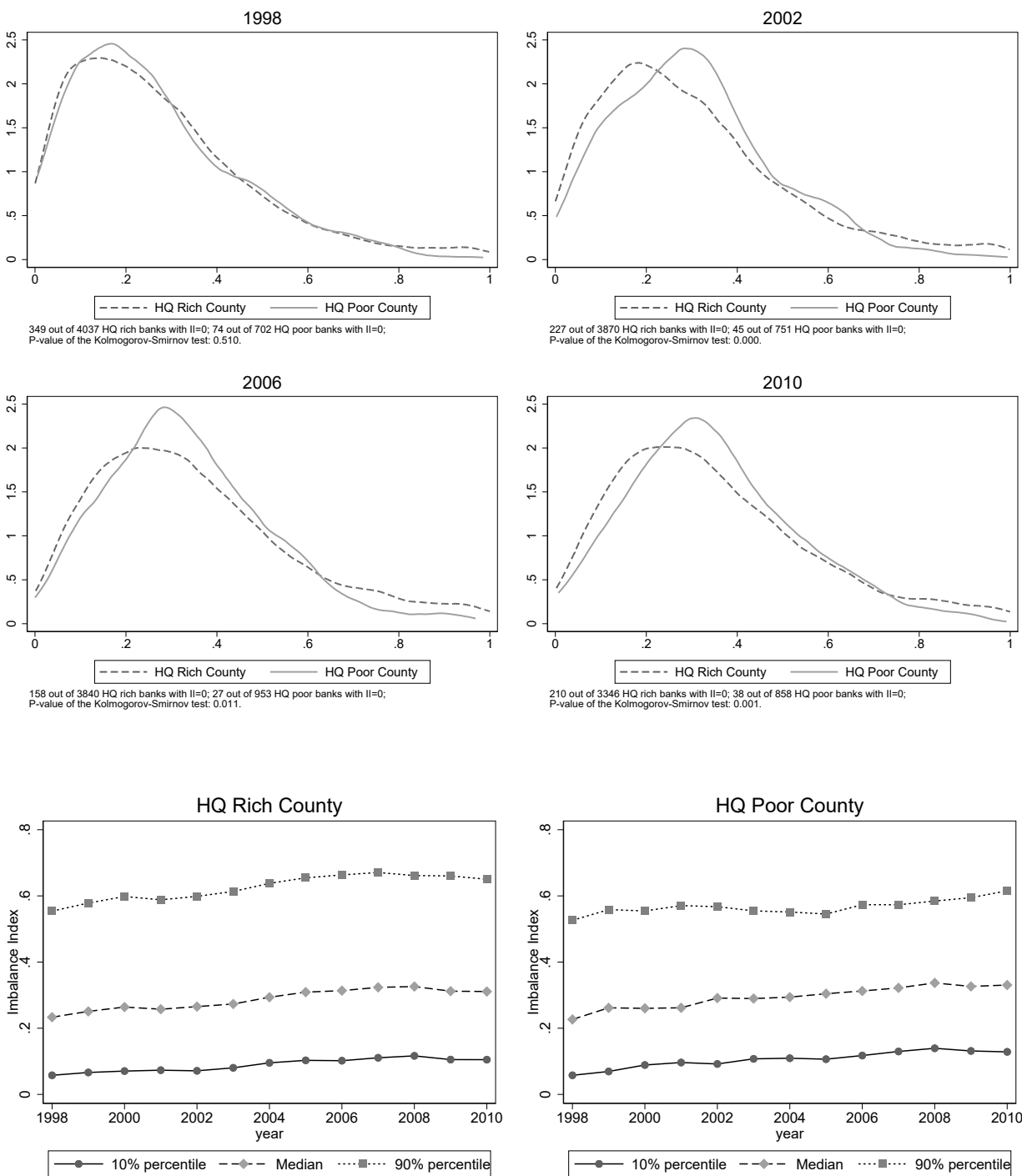
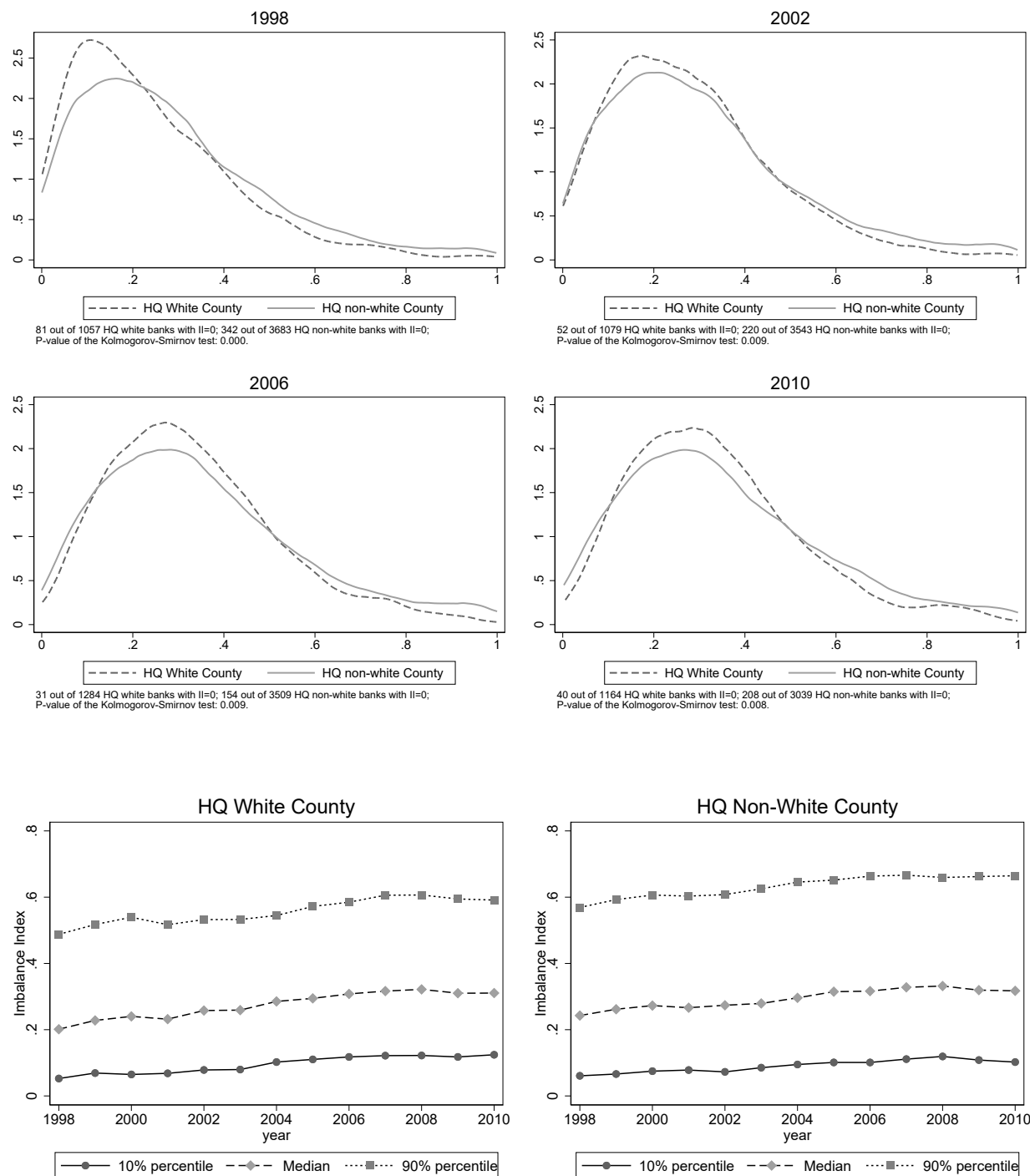


Figure A12: Breakdown of imbalance index by HQ-county white or non-white (cutoff = 1998 median white%)



A.6 Markup predictions and stylized facts about margins

The predictions of our model are consistent with the stylized facts about margins and spreads presented in recent work by [Drechsler, Savov and Schnabl](#) (DSS) in their 2017 QJE paper.

The main finding in DSS is that when the Fed funds rate rises, deposit spreads rise and the amount of deposit declines, and that these effects are stronger in more concentrated markets. Using our structural model we can measure market power in the local deposit market (i.e., the deposit spread (margin) at the bank-county-year level) by $1/(1 - s_{jmt})$. Then, using this measure we can investigate how it changes when the Fed funds rate rises, and how this varies depending on market concentration.

Our findings are presented below in Table A8 and confirm these results. Market power in local deposit markets is positively correlated with the Fed funds rate (as measured by T-bills), and this correlations is stronger if the HHI of deposits in the local market is higher.

Table A8: Market power in local deposit markets

DV: $1/(1 - s_j)$	(1)	(2)	(3)	(4)
T-bill (log)	0.002*** (0.001)	0.004*** (0.000)	0.016*** (0.001)	
HHI deposit (log)		0.307*** (0.001)	0.303*** (0.001)	0.180*** (0.004)
T-bill x HHI (log)			0.008*** (0.001)	0.013*** (0.001)
Constant	1.188*** (0.001)	1.696*** (0.002)	1.688*** (0.002)	1.505*** (0.006)
County FE				Y
Bank-year FE				Y
Observations	233,762	233,762	233,762	206,065
R-squared	0.000	0.250	0.250	0.526

Note: Robust standard errors of serial correlation and heteroscedasticity are reported in parentheses. * means p-value < 0.05; ** means p-value < 0.01; *** means p-value < 0.001.

A.7 Additional estimation results

Table A9: Alternative specifications of the loan equation

Variables		OLS Fixed Effects				GMM DiD & DiDiD			
<i>Number of branches</i>									
Second branch	0.1170***	(0.0118)	0.1254***	(0.0129)	0.1036***	(0.0231)	0.1586***	(0.0231)	
Third branch	0.0850***	(0.0113)	0.0810***	(0.0127)	0.0675***	(0.0158)	0.0946***	(0.0161)	
Fourth branch	0.0791***	(0.0119)	0.0666***	(0.0135)	0.0666***	(0.0144)	0.0793***	(0.0152)	
Fifth branch	0.0919***	(0.0132)	0.0998***	(0.0150)	0.0785***	(0.0168)	0.0999***	(0.0174)	
> Fifth	0.0084***	(0.0019)	0.0136***	(0.0025)	0.0043**	(0.0020)	0.0079***	(0.0023)	
<i>Securitization</i>									
% of loan resold	0.1585***	(0.0114)	0.3526***	(0.0127)	0.2207***	(0.0244)	0.3480***	(0.0281)	
<i>Econ of scope, Qd, and Ql</i>									
log own local deposit	0.2106***	(0.0076)	0.1005***	(0.0074)	0.3599***	(0.0319)	0.2094***	(0.0320)	
log own total deposit	-0.4342***	(0.0113)			-0.6726***	(0.0209)			
log own total loans	0.8706***	(0.0057)			0.7639***	(0.0159)			
log(total depo + total loan)			0.6377***	(0.0051)			0.2799***	(0.0092)	
<i>Market characteristics</i>									
log county income	-0.0231	(0.0523)	0.0409	(0.0585)					
log county population	-0.7766***	(0.0682)	-0.9523***	(0.0769)					
share pop. age ≤ 19	-4.4093***	(0.6998)	-3.5806***	(0.7894)					
share pop. age ≥ 50	-1.7499***	(0.4768)	-1.4570***	(0.5325)					
log house price index	0.3484***	(0.0310)	0.1789***	(0.0342)					
log nbr bankruptcy	-0.0212***	(0.0080)	-0.0219***	(0.0083)					
log nbr loan applications	0.4488***	(0.0129)	0.5000***	(0.0142)					
<i>Selection - Control function</i>									
Propensity score	0.1116	(0.3291)	1.6535**	(0.6935)	-1.0385***	(0.3011)	0.3256	(0.3591)	
Propensity score square	0.2786	(0.3420)	-2.1990***	(0.6850)	1.4218***	(0.2901)	0.5093	(0.3689)	
Propensity score cubic	-0.1959*	(0.1174)	0.5358**	(0.2124)	-0.4558***	(0.0903)	-0.3255***	(0.1209)	
<i>Fixed effects</i>									
Bank x County	YES		YES		YES		YES		
Time	YES		YES		NO		NO		
Country x Time	NO		NO		YES		YES		
Bank x Time	NO		NO		YES		YES		
Number of observations	194,267		194,267		196,090		196,090		
R-square	0.926		0.915						

Note: Robust standard errors of serial correlation and heteroscedasticity are reported in parentheses. * means p-value < 0.05; ** means p-value < 0.01; *** means p-value < 0.001.

Tables A10 and A11 present results demonstrating the robustness of our findings to different combinations of time series and spatial instruments. In addition, we have also considered specification in which we incorporate BLP-type instruments and lagged-by-3-period values into the set of instruments used in the main specifications. The main findings remain consistent.

Table A10: Alternative set of instruments for EOS: Deposit equation

Variables	Spec. 1		Spec. 2		Spec. 3		
<i>Number of branches</i>							
Second branch	0.6803***	(0.0089)	0.6792***	(0.0087)	0.6673***	(0.0090)	
Third branch	0.3801***	(0.0076)	0.3785***	(0.0074)	0.3722***	(0.0077)	
Fourth branch	0.2904***	(0.0079)	0.2889***	(0.0078)	0.2825***	(0.0081)	
Fifth branch	0.3645***	(0.0100)	0.3649***	(0.0097)	0.3525***	(0.0100)	
> Fifth	0.0335***	(0.0024)	0.0336***	(0.0023)	0.0310***	(0.0022)	
<i>Securitization</i>							
% of loan resold	-0.0354***	(0.0116)	-0.0448***	(0.0114)	-0.0573***	(0.0120)	
<i>Econ of scope and Qd</i>							
log own local loans	0.0692***	(0.0102)	0.0762***	(0.0099)	0.1146***	(0.0101)	
log own total deposit	0.0452***	(0.0049)	0.0497***	(0.0048)	0.0378***	(0.0050)	
Number of observations	241,909		241,909		241,909		

Note: All specifications include Bank x County, County x Time, and Bank x Time fixed effects. The instrumental variables used for the EOS in each specification are as follows. Spec.1, value of loans in the neighbouring counties, and value of loans in the neighbours of the neighbouring counties; Spec. 2, value of loans in the neighbouring counties, and value of loans in the neighbouring counties lagged by 2 periods; Spec. 3, value of loans in the neighbouring counties, and value of loans lagged by 2 periods.

Table A11: Alternative set of instruments for EOS: Loan equation

Variables	Spec. 1		Spec. 2		Spec. 3		
<i>Number of branches</i>							
Second branch	0.0957***	(0.0298)	0.0945***	(0.0296)	0.1433**	(0.0618)	
Third branch	0.0619***	(0.0191)	0.0611***	(0.0190)	0.0879**	(0.0355)	
Fourth branch	0.0692***	(0.0167)	0.0694***	(0.0167)	0.0866***	(0.0285)	
Fifth branch	0.0899***	(0.0201)	0.0889***	(0.0200)	0.1133***	(0.0348)	
> Fifth	0.0092***	(0.0022)	0.0094***	(0.0022)	0.0105***	(0.0036)	
<i>Securitization</i>							
% of loan resold	0.6623***	(0.0304)	0.6629***	(0.0304)	0.6634***	(0.0307)	
<i>Econ of scope and Qd</i>							
log own local deposit	0.3571***	(0.0437)	0.3614***	(0.0432)	0.2820***	(0.0907)	
log own total deposit	0.1672***	(0.0157)	0.1582***	(0.0119)	0.1737***	(0.0148)	
<i>Selection - Control function</i>							
Propensity score	-0.6647**	(0.3373)	-0.6403*	(0.3441)	-0.6357*	(0.3553)	
Propensity score square	0.9122***	(0.3288)	0.8727***	(0.3330)	1.0109***	(0.3568)	
Propensity score cubic	-0.3001***	(0.1004)	-0.2863***	(0.1003)	-0.3630***	(0.1255)	
Number of observations	196,090		196,090		196,090		

Note: All specifications include Bank x County, County x Time, and Bank x Time fixed effects. The instrumental variables used for the EOS in each specification are as follows. Spec.1, value of deposits lagged by 2 periods; Spec. 2, value of deposits lagged by 2 periods, and value of deposits in the neighbours of the neighbouring counties; Spec. 3, number of branches lagged by 2 periods, and value of deposits in the neighbouring counties lagged by 2 periods.

A.8 Description of an equilibrium and algorithm

Let $\mathbf{s}$ be the $2MJ \times 1$ vector of local market shares for deposits and loans for every bank and county. An equilibrium is a vector $\mathbf{s}$ that satisfies the following system of equations:

$$\left\{ \begin{array}{l} (A) \quad s_{jm}^d = 0, \forall (j, m), m \notin \mathcal{M}_j^d \\ (B) \quad s_{jm}^\ell = 0, \forall (j, m), m \notin \mathcal{M}_j^\ell \\ (C) \quad s_{jm}^d = \left(1 - \sum_{i=1}^J s_{im}^d\right) \exp \left\{ e_{jm}^d - \frac{1}{1 - s_{jm}^d} + \theta_\ell^d \ln(1 + H_m^\ell s_{jm}^\ell) + \theta_Q^d \ln Q_j^d \right\}, \forall (j, m), m \in \mathcal{M}_j^d \\ (D) \quad s_{jm}^\ell = \left(1 - \sum_{i=1}^J s_{im}^\ell\right) \exp \left\{ e_{jm}^\ell - \frac{1}{1 - s_{jm}^\ell} + \theta_\ell^\ell \ln(1 + H_m^d s_{jm}^d) + \theta_Q^\ell \ln Q_j^\ell \right\}, \forall (j, m), m \in \mathcal{M}_j^\ell \\ (E) \quad Q_j^d = \sum_{j=1}^J s_{jm}^d H_m, \forall j \end{array} \right.$$

where e_{jm}^d and e_{jm}^ℓ are exogenous terms that we define in the paper. For the description of the algorithms, it is convenient to represent this system of equations in the following compact form:

$$\left\{ \begin{array}{l} (A') \quad \mathbf{s}_m = \mathbf{f}_m(\mathbf{s}_m, \mathbf{Q}^d), \forall m = 1, 2, \dots, M \\ (B') \quad \mathbf{Q}^d = \mathbf{F}(\mathbf{s}) \end{array} \right.$$

The system of equations in (A') represents equations (A) to (D) for market m , and $\mathbf{f}_m$ is a vector-valued function with $2J$ elements. The system of equations in (B') is simply the system in (E) in vector form, and $\mathbf{F}$ is a vector-valued function with J elements.

The system of equations (A') possesses two properties that significantly ease the computation of an equilibrium. First, for a fixed value of the vector $\mathbf{Q}^d$, solving for the market shares in (A') is separable across counties. This means that the system of $2JM$ equations and unknowns can be divided into M separate systems, each with a dimension of $2J$. Second, for fixed $\mathbf{Q}^d$ and deposit shares s_{jm}^d , there exists a unique vector of loan shares that solves the system (A'). Likewise, for fixed $\mathbf{Q}^d$ and loan shares s_{jm}^ℓ , there is a unique vector of deposit shares that solves the system (A').

Taking these properties into account, our algorithm for computing an equilibrium follows these steps:

1. Initialization. We start by initializing the vector $\mathbf{Q}^d$. Typically, in most counterfactual experiments, this initial value is set to the banks' total deposits observed in the data. However, if the counterfactuals involve changes to branch networks, we adjust this initial value accordingly.
2. Iterative Process. During each iteration, we execute the following four steps sequentially:
 - Step 1. Compute the unique equilibrium for the vector of loan shares s_{jm}^ℓ in each county, given Q_j^d and local deposit shares s_{jm}^d for every j . This unique local equilibrium is computed using a Bisection algorithm.
 - Step 2. Compute the unique equilibrium of deposit shares s_{jm}^d , given Q_j^d and the local loan shares s_{jm}^ℓ computed in Step 1. We again use a Bisection algorithm for this computation.

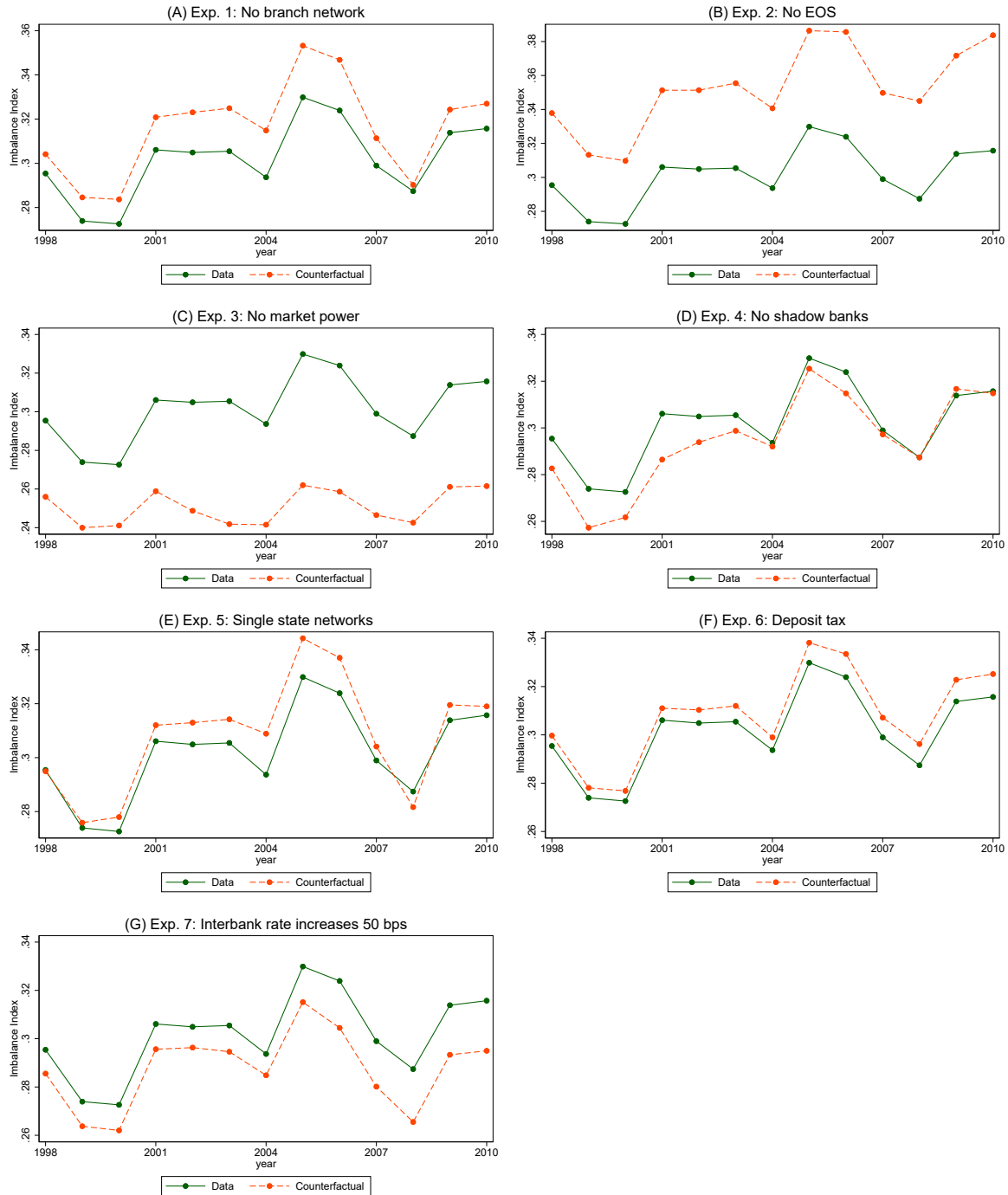
- Step 3. Using the market shares from Step 2, aggregate over counties to obtain Q_j^d for each j , thereby updating the vector $\mathbf{Q}^d$.
- Step 4. Check for convergence by calculating the distance between the values of the vector $\mathbf{Q}^d$ at the beginning and the end of the iteration.

This process can be repeated until the algorithm converges.

A.9 Additional Counterfactual results

A.9.1 Counterfactual National Imbalance Index

Figure A13: Evolution of the National Imbalance Index – Counterfactual scenarios



A.9.2 Validation of the Riegle-Neal Counterfactual

Here we test our Riegle-Neal counterfactual against the data. To do so we adopt the following strategy. We look for mergers involving two single-state banks.⁵ Specifically, we are interested in cases where in period t bank A operates only in state 1 and acquires bank B that operates only in state 2, such that in period $t + 1$, the survivor A' operates in states 1 and 2. There are 71 such cases throughout our sample period.

We then run our Counterfactual in which we effectively undo Riegle-Neal to see how outcomes change as we split A' into separate single-state banks A and B in $t + 1$.

The first rows of Panels A and B of Table A12 present the Imbalance Index for the counterfactual unmerged survivor and non-survivor banks respectively.

Next, following the referee's suggestion we compare these counterfactual separate entities from $t + 1$ to the data for A and B in t .⁶ The Imbalance Index scores for A and B in period t are presented in the second rows of Panels A and B of Table A12, respectively.

Finally, the third rows of Panels A and B present statistics on the differences between the counterfactual Imbalance Index in $t + 1$ and the Imbalance Index constructed using data from t , for survivor and non-survivor banks respectively.

Importantly, we would not expect the counterfactual outcomes for A and B from $t + 1$ to be identical to data outcomes for A and B from t , since naturally there could have been some other changes in the market. However, should outcomes be similar, then this would validate our approach.⁷

Results:

1. For both survivor and non-survivor banks, the mean Imbalance Index score of the year $t + 1$ counterfactual is very close to the mean Imbalance Index score of in the data in year t , as are their 25, 50, and 75 percentiles.
2. The difference between these two measures (the third row of each panel) is also very small at the mean, and the corresponding percentiles.

Overall, we believe that this test validates our Riegle-Neal counterfactual and allows us to learn about the importance of the ability to expand across states for the flow of credit.

A.10 Details on the increase in interbank rate counterfactual

In our model, the interbank rate r_0 affects both the marginal cost of loans and deposits through the bank's balance position in the interbank market, B_j . Specifically, r_0 increases the marginal cost of loans while decreasing the marginal cost of deposits. As a result, r_0 enters our equilibrium equations additively through the residual terms in the social surpluses for loans and deposits, where it reduces the social surplus of loans and increases the social surplus of deposits.

$$\eta_{jmt}^\ell = -\alpha^\ell r_0 + \dots$$

⁵That is, banks operating branches in only one state although they may make loans in multiple states.

⁶The referee had suggested using data from before 1998, but in fact any merger that takes place across state lines is the result of Riegle-Neal and so we do not need to go back to pre-1998. This is useful, since not many banks had actually taken advantage of the expansion opportunities afforded them by Riegle-Neal by this time (see Aguirregabiria, Clark and Wang 2016).

⁷The reason we look at expansion through mergers, instead of expansion through denovo entry is that, for the latter cases, there is no bank entity in state 2 in year t . By contrast, for expansion through mergers, for survivors, we can compare their CF II in $t+1$ in state 1 with their real II in t (Panel A of Table A12); and for non-survivor, we can compare the survivor's CF II in $t+1$ in state 2 with their real II in t (Panel B of Table A12).

Table A12: Test of Riegle-Neal Counterfactual: Mergers between Two Single-state Banks

	# obv	Mean	Std	p25	p50	p75
<i>Panel A: Survivor bank</i>						
CF II in t+1	71	0.299	0.157	0.181	0.292	0.403
Real II in t	71	0.313	0.158	0.174	0.309	0.427
$CF_{t+1} - Real_t$	71	-0.014	0.096	-0.043	0.001	0.034
$Diff/Real_t$	71	0.025	0.508	-0.182	0.004	0.137
<i>Panel B: Non-survivor bank</i>						
CF II in t+1	71	0.328	0.224	0.146	0.312	0.469
Real II in t	71	0.312	0.225	0.154	0.272	0.512
$CF_{t+1} - Real_t$	71	0.016	0.207	-0.071	-0.019	0.145
$Diff/Real_t$	66	0.764	3.626	-0.278	-0.080	0.404

$$\eta_{jmt}^d = \alpha^d r_0 + \dots$$

Importantly, the impact of r_0 on the equilibrium equations is determined by the magnitude of parameters α^ℓ and α^d .

Our main challenge in implementing a counterfactual experiment involving changes to the interbank interest rate (Experiment 7) is that it requires knowledge of parameters α^d and α^ℓ . Since we do not have access to the necessary bank-county level interest rate data to estimate these parameters directly, we have instead calibrated them so that our model aligns with the average demand-rate elasticities for loans and deposits reported in the literature.

Let $Elast_{jmt}^\ell$ and $Elast_{jmt}^d$ represent the absolute values of the demand-rate elasticities for loans and deposits, respectively, at the bank-county-year level. According to our model, the following relationships hold:

$$Elast_{jmt}^\ell = \alpha^\ell (1 - s_{jmt}^\ell) p_{jmt}^\ell$$

$$Elast_{jmt}^d = \alpha^d (1 - s_{jmt}^d) p_{jmt}^d$$

Let $\overline{Elast}^\ell$ and $\overline{Elast}^d$ represent the weighted averages of these elasticities over banks, counties, and time. Combining the above equations with the definition of these weighted averages, we obtain:

$$\overline{Elast}^\ell = \alpha^\ell \sum_{t=1}^T \sum_{j=1}^J \sum_{m=1}^M \frac{q_{jmt}^\ell}{Q^\ell} (1 - s_{jmt}^\ell) \bar{p}_{jt}^\ell$$

$$\overline{Elast}^d = \alpha^d \sum_{t=1}^T \sum_{j=1}^J \sum_{m=1}^M \frac{q_{jmt}^d}{Q^d} (1 - s_{jmt}^d) \bar{p}_{jt}^d$$

Here, Q^ℓ and Q^d represent the total sums of loans and deposits, respectively, across all counties, banks, and years in our sample. Our calibration of parameters α^ℓ and α^d consists of the values solving these two equations. For the bank-level average interest rates, $\bar{p}_{jt}^\ell$ and $\bar{p}_{jt}^d$, we use data from Call Reports. For the average elasticities, we use values of 3.75 for loans and 2.33 for deposits, based on estimates from [Dick \(2008\)](#) for deposits, and [Corbae and D'Erasmus \(2021\)](#) and [Buchak et al. \(2024\)](#) for loans.⁸

Using this approach, we calibrate α^d to be 1.21; and α^ℓ to be 0.64.

⁸[Corbae and D'Erasmus \(2021\)](#) estimate a loan elasticity of 1.01, while [Buchak et al. \(2024\)](#) estimate it at

6.5. Given that our model, sample period, and market definition differ from those in these papers, we use the midpoint of these estimates.

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