The Deposits Channel Revisited

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Abstract

Drechsler, Savov, and Schnabl (2017) present a novel reformulation of the bank lending channel of monetary transmission based on market power in local deposits markets, which they term the deposits channel. In this paper we first perform a successful narrow replication of their key empirical results. We then revisit their results on lending in two ways. First, recent studies have pointed out the unique dynamics of credit card loans in Community Reinvestment Act loan origination data. When accounting for this heterogeneity, we find key results are sensitive to the inclusion of credit card banks that raise funds outside of local deposit markets. Second, we show that inconsistencies with related empirical studies can be explained by differences in market power measure, sample period, and the inclusion of alternative control variables. The results highlight that market power on opposing sides of bank balance sheets can impact monetary transmission through alternative channels. Overall, this paper suggests the mechanisms underlying the response of lending to monetary policy remains an important open question.

Keywords: Monetary policy, bank lending channel, market power.
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1 Introduction

Drechsler, Savov, and Schnabl (2017) (DSS henceforth) offer a new theoretical explanation for the response of loan supply to monetary policy, which the authors term the deposits channel. The traditional theory behind the bank lending channel of monetary transmission posits that due to binding reserve requirements, a monetary policy induced change in reserves will lead to a corresponding change in insured deposits, resulting in an expansion or contraction in loan supply. While there is substantial empirical evidence supporting the existence of a bank lending channel, the traditional theoretical explanation is implausible.[1] First, total reserves are too small to produce a quantitatively significant loan supply effect. Second, since 2008 there has been a large quantity of excess reserves rendering reserve requirements irrelevant. The deposits channel on the other hand explains an outflow of deposits following a monetary tightening as driven by bank market power in deposit markets, rather than by an outflow of reserves due to binding reserve requirements. Specifically, following an increase in the short-term policy rate, banks will increase deposit spreads more in markets where they have greater market power. This increase in deposit spreads will lead to an outflow of deposits, resulting in a contraction in lending.

DSS present two sections of empirical evidence in support of their model. The first section focuses on results on deposits, specifically how deposit spreads and deposit flows respond to an increase in the federal funds rate. Using a unique within-bank estimation method, they find that for branches of the same bank, there is a greater increase in deposit spreads and a larger outflow of deposits for branches located in more highly concentrated markets.[2] They further show in a weekly event study analysis that the increase in deposit spreads occurs contemporaneously with the increase in the federal funds rate. Overall, DSS provide robust evidence that market concentration influences the reaction of deposits to monetary policy as predicted by their model.

In order for the deposits channel to influence monetary transmission, the outflow of deposits following an increase in the policy rate must lead to a decline in bank loan supply. Accordingly, their second empirical section focuses on results on lending, providing evidence that banks which raise deposits in more concentrated markets reduce small business lending to a greater degree following a monetary tightening.

We revisit the DSS results on lending by connecting them to two strands of related literature. The outcome variable of interest in DSS is new small business loan originations from Community Reinvestment Act (CRA) data. Recent analysis of heterogeneity within the CRA data by the Board of Governors of the Federal Reserve System (2010) and Adams, Brevoort, and Driscoll (2020) document a significant increase in loans to small businesses by banks specializing in credit cards prior to the 2008 financial crisis. Accounting for these credit card banks is important in the deposits channel context because they tend to raise funds *outside* of local deposit markets. We, therefore, explore the sensitivity of the DSS results on lending to the inclusion of credit card banks in the sample. Second, there are

[1] For empirical evidence on the bank lending channel see Kashyap and Stein (2000), Kishan and Opiela (2000), and Gambacorta (2005) among many others.

[2] While DSS document incomplete interest rate pass-through in the short-run, previous empirical studies such as Neumark and Sharpe (1992), Driscoll and Judson (2013), and Yankov (2014) have also found evidence of incomplete interest rate pass-through in the long-run.

a number of studies investigating the relationship between bank competition and the lending channel which appear inconsistent with the DSS results. Specifically, Adams and Amel (2011), Brissimis, Delis, and Iosifidi (2014), and Segev and Schaffer (2020) provide evidence using U.S. data that lending is *less* responsive to monetary policy for banks with greater market power.[3]

In this paper we first perform a narrow replication of the DSS results based on publicly available data using R. We then attempt a wide replication aimed at reconciling DSS with the two strands of empirical literature discussed above.[4] We identify nine banks in the DSS sample that qualify as credit card specialists. The baseline bank-county results on lending are sensitive to the inclusion of these credit card banks, although county-level results are more robust to dropping them. The diverging conclusions reached by other empirical studies of the lending channel can be explained by differences in measure of bank market power, sample period, and choice of control variables. Overall, our results suggest the mechanisms underlying the transmission of monetary policy through bank lending remain an important area for further inquiry.

2 Empirical Analysis

2.1 Narrow Replication

We perform the narrow replication in two steps. First, we develop code in R and apply it to the publicly available DSS data set.[5] Our analysis focuses on Table VI and Table VII from DSS, as they contain the key cross-sectional results on lending. Table VI reports results from bank-county regressions over 1997-2013, where the dependent variable is the log of bank j's new small business lending in county c, and the independent variable of interest is an interaction between the annual change in the federal funds rate and one lag of bank j's Herfindal-Hirschman index.[6]

$$y_{jct} = \alpha_{jc} + \delta_{ct} + \beta Bank\text{-}HHI_{jt-1} + \gamma \Delta FF_t \times Bank\text{-}HHI_{jt-1} + \epsilon_{jct} \tag{2.1}$$

Table VII reports results from county-level regressions, where the dependent variables are new small business lending, employment, and wage bill. The independent variable of interest is an interaction between the change in the federal funds rate and county-level HHI.[7]

$$y_{ct} = \alpha_{c} + \delta_{t} + \beta County\text{-}HHI_{ct-1} + \gamma \Delta FF_t \times County\text{-}HHI_{ct-1} + \epsilon_{ct} \tag{2.2}$$

The key econometric challenge for empirical studies of the lending channel is to isolate the effect of monetary policy on loan supply. DSS do so by implementing county-time fixed effects in equation 2.1, which allows for a within-county estimation strategy. As DSS state "Testing this prediction is challenging because it again requires controlling for differences in lending opportunities...The key set of

[3] A number of cross-country studies including Olivero, Li, and Jeon (2011) Fungáčová, Solanko, and Weill (2014), and Leroy (2014) also conclude that greater bank market power weakens the response of lending to monetary policy.

[4] From a theoretical perspective, Repullo (2020) presents a critical review of the deposits channel model and Sá and Jorge (2019) question the relevance of the deposits channel in a low interest rate environment.

[5] The DSS data set and Stata code can be found here:
`https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/KHNXYJ`.

[6] Bank-HHI is calculated as a weighted average of branch-level county HHI, with branch deposit shares used as weights.

[7] County-HHI is a county average of bank-level HHI, with bank lending shares used as weights.

controls are the county-time fixed effects, which absorb changes in local lending opportunities (pages 1858-59)." The county-time fixed effects results corresponding to equation 2.1, which are presented in column 1 of DSS Table VI, should therefore be treated as the most rigorously identified estimates.[8]

Narrow replication results of Table VI are presented in Table 1 and are almost identical to the original. Our narrow replication of Table VII in Table 2 is, similarly, a close match. As shown in the online appendix, all other DSS results that do not rely on private data are replicated with a high degree of accuracy.[9] Appendix Table **??** contains definitions and sources for the variables used in our analysis.

As an additional exercise, we apply our code to an original data set constructed from primary sources. Narrow replication results for Table VI using our original data are presented in Appendix Table **??**. While not quite as accurate as those in Table 1, they remain very similar to the original. Appendix Table **??** contains a replication of Table VII with our original data, which also closely matches the results in DSS. Having performed a successful narrow replication of the key DSS cross-sectional results on lending at two levels, we next turn our attention to the wide replication. We use the publicly available DSS data set in the following sections in order to match the published results as closely as possible.

2.2 Heterogeneity in the CRA Data Next we consider the influence of small business credit card loans within the CRA data. As documented in Adams, Brevoort, and Driscoll (2020), a significant portion of loans under $100,000 in the CRA data are issued by banks specializing in small business credit cards. The Board of Governors of the Federal Reserve System (2010) report shows that small business loans originated by credit card banks increased more than tenfold from 1997 to 2008 before falling dramatically during the Great Recession. Due to these unique dynamics, and the potentially unrepresentative nature of credit card loans compared to traditional small business loans, it is important to account for this heterogeneity in the CRA data. It is particularly crucial in the context of the deposits channel, as these banks operate a small number of branches and primarily raise funds *outside* of local deposit markets.[10] For instance, the November 2008 CRA performance evaluation report for Chase Bank USA states "Chase USA is one of the largest credit card issuers in the United States," and "since Chase USA's one banking office is not open to the general public, a majority of the Bank's deposits come from JPMCB and other affiliates." Similar language can be found in the CRA performance evaluations for the other eight banks listed in Appendix Table **??**. Credit card banks also tend to be larger and have higher bank-level HHI relative to other banks in the DSS sample.[11] However, since they raise deposits and other funding nationally, local deposit market HHI has no meaning for these institutions.

To account for credit card loans in the CRA data one could, as in Adams and Amel (2011), simply drop all loans under $100,000. This would, however, reduce the DSS sample by almost a third. As an alternative, we follow Adams, Brevoort, and Driscoll (2020) by isolating a small number of banks that specialize in loans under $100,000. We identify nine credit card banks in the DSS sample with at least $1 billion in loans under $100,000 in a given year and with such loans making up at least 75% of

[8] Columns 2-4 in Table VI drop the county-time fixed effects, while time-varying fixed effects cannot be included in the county-level Table VII results corresponding to equation 2.2.

[9] These results include DSS Table I, Table III, Table V panel B, and Table VIII.

[10] The median number of branches across the nine banks for the DSS sample is 1.15.

[11] See Table **??** in the online appendix for descriptive statistics for each group of banks.

the bank's total originations. Further qualitative investigation confirms that all nine banks, listed in Appendix Table **??**, do in fact specialize in credit cards.[12]

To check the sensitivity of the DSS results on lending to the inclusion of small business credit card loans, we first re-estimate equation 2.1 dropping only these nine banks, with results presented in Table 3. When excluding the credit card banks the sign on the interaction coefficient flips and becomes positive (though insignificant) in all four columns. The nine credit card banks make up under 20% of the original DSS sample, but appear to have a significant influence on the bank-county evidence. We next consider the sensitivity of the county-level evidence. We re-estimate equation 2.2, dropping loans originated by the nine credit card banks, with results shown in Table 4. While the interaction coefficient for the impact on lending remains negative and statistically significant, the coefficient becomes insignificant and at times positive in the employment and wage regressions. The results, therefore, suggest that the DSS county-level evidence is also somewhat influenced by the inclusion of the credit card banks.

This raises the question: what explains the sensitivity of the DSS results to these nine credit card banks, particularly at the bank-county level, and what are the implications for the deposits channel? Notably, credit card loans in the CRA data peaked around the time the Great Recession was unfolding, accounting for 15% of new loan originations and 30% of bank-county observations in 2007-2008.[13] The result was that a large share of CRA loans made in 2008, as the federal funds rate sank to zero, were originated by a handful of banks which happened to also have relatively high Bank-HHI.

Under the deposits channel mechanism, the large quantity of loans originated in 2008 by credit card banks would be attributable to an influx of deposits as the banks narrowed their deposit spreads relatively more than competitors operating in more competitive local markets. However, this explanation does not apply to the credit card banks since, as noted, their relatively high Bank-HHI values do not reflect local deposit market power and do not have a meaningful economic interpretation. Moreover, the large quantity of loan originations by these banks seems to reflect a multi-year trend rather than a response to accomodative monetary policy. Thus, the outlier effect of credit card banks in 2008 on the DSS bank-county results ultimately appears attributable to statistical noise.

We further demonstrate the outlier effect of credit card banks by aggregating the nine credit card banks together, and all other retail banks together, and constructing a scatter plot of the outcome variable (log(new lending)) against the explanatory variable of interest (ΔFF x Bank-HHI) for each set of banks in Figure 1.[14] Panel A of the figure makes clear that there is a negative relationship between the two variables for credit card banks and a generally flat relationship for retail banks. There is much greater variation for the credit card banks, highlighting the volatile lending dynamics documented by Adams, Brevoort, and Driscoll (2020) and Board of Governors of the Federal Reserve System (2010). The far left credit card bank observation from 2008, marked in a square with a black x, particularly stands out as an extreme value. Panel B of Figure 1 drops the 2008 observations for both groups. The

[12]Wells Fargo Bank Northwest operated as a standard retail bank up until 2004, at which point its retail operations were consolidated and it began specializing in credit card services.

[13]See Figure **??** in the online appendix.

[14]Each point plots the log(new lending) and ΔFF x Bank-HHI pair in a given year, for the credit card banks in blue and for all other retail banks in red. Log(new lending) is constructed as the log of total new credit by group and ΔFF x Bank-HHI is constructed as a weighted mean using loan share as weights.

relationship between new lending and ΔFF x Bank-HHI becomes positive for credit card banks while remaining flat for retail banks, indicating the negative relationship observed for credit card banks in Panel A is driven by the crisis year. As a final test, we re-estimate equation 2.1 dropping all loans originated by the nine banks in 2008 *only*, with results presented in Appendix Table **??**. The magnitude of the ΔFF x Bank-HHI coefficient decreases by half and becomes statistically insignificant, confirming that the bank-county results in DSS Table VI are primarily driven by the credit card banks in 2008.

Overall, the implications for the deposits channel must be treated cautiously. The DSS results on deposits should not be influenced by credit card specialists, as those results come from a within-bank estimation strategy comparing deposit outflows at different branches of the *same* bank. However, the bank-county results in Table 3 suggest that an increase in deposit spreads and deposit outflows following a monetary tightening at branches in more concentrated markets may not ultimately result in a bank-level contraction in lending.[15] Overall, the results in this section suggest that evidence in favor of the deposits channel is less than conclusive, and that the mechanism underlying the response of loan supply to monetary policy remains an open question.

2.3 Related Empirical Studies A recent empirical literature has found that bank market power dampens the effect of monetary policy on loan supply (Adams and Amel 2011; Brissimis, Delis, and Iosifidi 2014; Fungáčová, Solanko, and Weill 2014; Leroy 2014; Segev and Schaffer 2020).[16] The results in DSS, both theoretical and empirical, appear to be inconsistent with these findings. In this section we investigate the factors driving the opposing results.

An obvious starting point is the measure of bank market power used in the analysis. DSS use a bank-level, deposit-weighted average of HHI in the counties that a bank has branches in, whereas the majority of the above studies use a Lerner index. The key for DSS is to specifically capture market power over deposits, rather than overall bank market power or market power over lending. Since the Lerner index is most directly interpreted as a proxy for loan pricing power, it is not necessarily inconsistent for DSS and the studies implementing Lerner indexes to reach opposite conclusions: market power over deposits may strengthen the response of lending to monetary policy while market power over loans may weaken it. To probe this point, we re-estimate equation 2.1 substituting the Lerner index for bank-HHI, with results reported in Table 5.[17] The coefficient on the interaction between the Lerner index and federal funds rate in columns one and two remains negative but is no longer statistically significant for the full sample. In columns three and four we end the sample before 2008, as many empirical monetary policy studies do to avoid the zero lower bound (ZLB) period, and report a positive and significant interaction

[15] The county-level lending results in Table 4 mitigate this concern to some degree, however, as noted in section 2.1, the most rigorously identified estimates are generated by the bank-county specification with county-time fixed effects.

[16] Reviewing the theoretical argument for the dampening impact of banks' market power on the monetary policy transmission is beyond the scope of this paper. See section 2.2 in Brissimis, Delis, and Iosifidi (2014) for an in-depth discussion of potential mechanisms. Additionally, see Corbae and Levine (2018) for a theoretical model where monetary policy has a larger effect on lending in more competitive banking systems.

[17] The Lerner index is calculated as (P-MC)/MC, where P is loan price and MC is the marginal cost of loan production. There is significant debate over marginal cost measurement in the literature. It is questionable for instance, whether the same measurement should be used for a heterogeneous sample of banks. Here, we use a standard calculation in the literature, as issues surrounding Lerner index calculation are beyond the scope of this replication paper. See the online appendix for full details regarding the calculation of the Lerner index used in our analysis.

coefficient, implying that greater market power over loan pricing dampens the response of lending to monetary policy. Appendix Table **??** shows that this result is robust to dropping the credit card banks discussed in section 2.2. In fact, the interaction coefficient becomes positive and statistically significant for the full sample when the credt card banks are removed. The differences between DSS and papers such as Brissimis, Delis, and Iosifidi (2014) and Segev and Schaffer (2020) can therefore be attributed to capturing different sources of bank market power and some sensitivity to the ZLB period.

Next, we turn our attention to reconciling DSS and Adams and Amel (2011) (A&A henceforth). Like DSS, A&A focus on small business loan origination from the CRA data as their outcome of interest, however, A&A report results indicating that lending is less responsive to monetary policy in more highly concentrated markets. There are three notable differences between the studies which could explain their opposing results. First, A&A analyze a much shorter sample period of 1997-2004 compared to the DSS sample period of 1997-2013. Second, DSS include time fixed effects and no county-level controls whereas A&A do the opposite. Third, while A&A and DSS both use a Herfindal-Hirschman Index to capture market power, they use different measures with significantly different interpretations.

DSS use three HHI measures in their analysis.[18] In the bank-county analysis, the key variable is "Bank-HHI." Bank-HHI is an annual, bank-level weighted average of the HHI in every county that a bank has a presence in. Thus, Bank-HHI does not capture concentration for a single market, and instead captures the average concentration across markets that a bank raises deposits in. In the DSS county-level analysis, Bank-HHI is aggregated up to "County-HHI," the weighted average of Bank-HHI across all banks lending in a county, which similarly captures average concentration across markets that a county's lending banks raise deposits in. A key control variable at both the bank-county and county-level in DSS is "Branch-HHI," which captures the time-invariant sample average HHI for an individual county in which a loan is originated. The HHI measure in A&A is similar to DSS Branch-HHI, but allows for annual variation. The A&A HHI therefore captures concentration for the individual market that a loan is originated in, and does not explicitly account for concentration in the markets which a county's lending banks raise funds in.

A&A conduct their analysis at the county-level only. Baseline results are presented in their Table 3a, which can be compared to the county-level Table VII results in DSS. To understand the factors driving the opposing results, we focus on the DSS weighted-average "County-HHI" measure rather than the time-varying "Branch-HHI" used in A&A, as sample period and the inclusion of county control variables end up being the critical factors. Indeed, we re-estimate equation 2.2 for rolling sample periods while including the county control variables used in A&A, with results presented in Table 6.[19] The appended equation 2.2 is estimated for ten sample periods, beginning with the 1997-2004 period corresponding to A&A, with each additional column in Table 6 adding an additional year so that the tenth corresponds to the full DSS sample.

The results show that, even when using the DSS measure of bank concentration, sample period and the inclusion of the control variables have a major influence on the estimated coefficients. Column one

[18] Defined in the first three rows of Appendix Table B.1.

[19] County controls include the log change in house prices, population and per capita income. See Appendix Table B.1.

shows results for the 1997-2004 sample that matches A&A. The coefficient on the interaction between the change in the federal funds rate and County-HHI is positive and statistically significant, consistent with the results in Table 3a of A&A. The coefficient turns primarily negative and at times statistically significant as additional years are added to the sample in columns two through ten.[20] Noticeably, the interaction coefficient becomes statistically insignificant for the full DSS sample when time-varying county controls are included, suggesting that the results in DSS Table VII may not be adequately isolating the response of loan supply from the response of loan demand.

The timing of the flip in the interaction coefficient's sign between columns one and two of Table 6 coincides with a change in the CRA reporting threshold. From 1997-2004 banks with at least $250 million in total assets were required to report, but that threshold increased to $1 billion in 2005. If the threshold change is responsible for the positive coefficient in column one of Table 6, we would expect the coefficient to turn negative when banks with less than $1 billion in assets are removed from the sample, however the interaction coefficient remains positive and marginally significant, suggesting that the change in reporting threshold is not driving the sample sensitivity.

To summarize, we find that apparent inconsistencies between DSS and the related empirical literature are driven by differences in measure of market power, sample period, and to a lesser degree, the inclusion of additional control variables. These results highlight the fact that further work is needed to better understand the relationship between banking sector competition and monetary transmission, especially when market power affects both sides of bank balance sheets. One possible approach is to use an adjusted Lerner index which captures market power only in deposit markets and compare it to the deposit based HHI. We leave this important extension for future work.

3 Conclusion

The mechanisms underlying the bank lending channel are key to understanding monetary policy transmission. DSS provide an intriguing new theoretical foundation based on market power in deposits markets. They present evidence that an increase in the federal funds rate leads to a larger increase in deposit spreads and a larger outflow of deposits for bank branches in more highly concentrated markets. They go on to show that this deposit outflow leads to a corresponding contraction in lending. They argue that their proposed deposits channel can explain the entire transmission of monetary policy through bank balance sheets.

In this paper we perform a successful narrow replication of DSS in R. We then relate their results on lending to two strands of related literature. In exploring the sensitivity of their findings to the presence of small business credit card loans in the CRA data, we find their bank-county results lose significance when nine banks specializing in credit card loans are removed from the sample. The outlier status of the credit card banks is driven by a single year, 2008, in which loan originations remained high while the federal funds rate fell to zero. These results suggest the evidence in favor of the deposits channel is inconclusive, and that the mechanism underpinning the lending channel remains an important area for

[20] The county house price index (HPI) is not available for all counties, resulting in a smaller sample in column ten of Table 6 than in DSS Table VII. Results are very similar when HPI is excluded and the full sample remains intact.

further inquiry. Moreover, the disproportionate representation of credit card loans in the CRA data, particularly in the mid-2000s, suggests that the CRA data constitutes a less than ideal laboratory for future investigations into the lending channel. We also explore inconsistencies with recent empirical studies of the relationship between bank competition and the lending channel. Divergences with these related studies can be explained by differences in measure of market power, sample period, and the inclusion of alternative control variables. Overall, our results highlight the need for further investigation into the mechanisms driving the response of bank lending to monetary policy. A particularly important area for future work will be to more precisely distinguish the effects of market power on the asset versus liabilities sides of bank balance sheets.

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Tables and Figures

Table 1: Narrow Replication of DSS Table VI (Bank-County Results)

	log(new lending)			
	(1)	(2)	(3)	(4)
ΔFF x Bank-HHI	-0.208^{**}	-0.198^{**}	-0.168^{**}	-0.166^{**}
	(0.085)	(0.088)	(0.076)	(0.075)
ΔFF x Branch-HHI		0.027^{*}	0.009	
		(0.016)	(0.023)	
Observations	621,667	621,667	621,667	621,667
R^2	0.831	0.816	0.247	0.247
Time f.e.	Y	Y	Y	Y
Bank f.e.	Y	Y	Y	Y
County f.e.	Y	Y	Y	Y
County-bank f.e.	Y	Y	N	N
County-time f.e.	Y	N	N	N

This table replicates Table VI from Drechsler, Savov, and Schnabl (2017). *p<0.10; **p<0.05; ***p<0.01.

Table 2: Narrow Replication of DSS Table VII (County-Level Results)

	log(new lending)		Δ Employment		Δ Wage Bill	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔFF x County-HHI	-0.093^{***}	-0.097^{***}	-0.014^{***}	-0.008^{***}	-0.011^{***}	-0.009^{**}
	(0.024)	(0.028)	(0.003)	(0.003)	(0.003)	(0.004)
ΔFF x Branch-HHI		0.003		-0.004^{***}		-0.001
		(0.009)		(0.001)		(0.001)
Time f.e.	Y	Y	Y	Y	Y	Y
County f.e.	Y	Y	Y	Y	Y	Y
Observations	54,097	54,097	54,097	54,097	54,097	54,097
R^2	0.948	0.948	0.201	0.202	0.272	0.272

This table replicates Table VII from Drechsler, Savov, and Schnabl (2017). *p<0.10; **p<0.05; ***p<0.01.

Table 3: DSS Table VI. Dropping Credit Card Banks.

	log(new lending)			
	(1)	(2)	(3)	(4)
ΔFF x Bank-HHI	0.011	0.008	-0.008	-0.009
	(0.034)	(0.030)	(0.033)	(0.032)
ΔFF x Branch-HHI		-0.003	-0.004	
		(0.009)	(0.015)	
Observations	513,253	513,253	513,253	513,253
R^2	0.833	0.815	0.195	0.195
Time f.e.	Y	Y	Y	Y
Bank f.e.	Y	Y	Y	Y
County f.e.	Y	Y	Y	Y
County-bank f.e.	Y	Y	N	N
County-time f.e.	Y	N	N	N

This table replicates Table VI from Drechsler, Savov, and Schnabl (2017) while dropping nine credit card banks. *p<0.10; **p<0.05; ***p<0.01.

Table 4: DSS Table VII. Dropping Credit Card Banks.

	log(new lending)		Δ Employment		Δ Wage Bill	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔFF X County-HHI	-0.114^{***}	-0.132^{***}	-0.003	0.002	0.001	0.003
	(0.028)	(0.031)	(0.003)	(0.003)	(0.003)	(0.004)
ΔFF X Branch-HHI		0.016		-0.005^{***}		-0.002
		(0.010)		(0.001)		(0.001)
Time f.e.	Y	Y	Y	Y	Y	Y
County f.e.	Y	Y	Y	Y	Y	Y
Observations	53,782	53,782	53,782	53,782	53,782	53,782
R^2	0.940	0.940	0.203	0.204	0.274	0.275

This table replicates the results of Table VII from Drechsler, Savov, and Schnabl (2017) while dropping nine credit card banks. *p<0.10; **p<0.05; ***p<0.01.

Table 5: DSS Table VI. With Lerner Index.

	Full Sample		Pre-ZLB	
	(1)	(2)	(3)	(4)
ΔFF x Lerner Index	-0.048	-0.033	0.122^{**}	0.126^{**}
	(0.053)	(0.049)	(0.049)	(0.049)
ΔFF x Branch-HHI		0.010		-0.056^{***}
		(0.015)		(0.018)
Observations	610,946	610,946	398,740	398,740
R^2	0.830	0.815	0.851	0.834
Time f.e.	Y	Y	Y	Y
Bank f.e.	Y	Y	Y	Y
County f.e.	Y	Y	Y	Y
County-bank f.e.	Y	Y	Y	Y
County-time f.e.	Y	N	Y	N

This table replicates Table VI from Drechsler, Savov, and Schnabl (2017), replacing Bank-HHI with the Lerner index. Columns (1) and (2) contain results for the original 1997-2013 sample period. Columns (3) and (4) contain results for the pre-ZLB 1997-2007 sample period. *p<0.10; **p<0.05; ***p<0.01.

Table 6: DSS Table VII. Sample Sensitivity with County Controls.

	log(new lending)				
	2004	2005	2006	2007	2008
ΔFF x County-HHI	0.065**	−0.036	−0.078***	−0.067**	0.017
	(0.027)	(0.028)	(0.029)	(0.027)	(0.023)
Observations	18,855	21,501	24,147	26,800	29,463
R^2	0.949	0.947	0.946	0.946	0.946
	2009	2010	2011	2012	2013
ΔFF x County-HHI	0.017	−0.003	−0.014	−0.025	−0.036
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Observations	32,128	34,802	37,475	40,145	42,813
R^2	0.951	0.952	0.953	0.954	0.954
Time f.e.	Y	Y	Y	Y	Y
County f.e.	Y	Y	Y	Y	Y

This table presents rolling results corresponding to the first column of Table VII from Drechsler, Savov, and Schnabl (2017) while controlling for additional county-level variables. *p<0.10; **p<0.05; ***p<0.01.

Figure 1: Credit Card Bank 2008 Outlier Effect