Measuring Inter-Industry Financial Transmission of Shocks

Daniel Paravisini[♣]
Columbia University GSB
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Abstract. This paper develops a methodology based on differential bank exposures to industry default risk to measure the financial transmission of shocks through the banking system. I apply the methodology to measure the effect of the defaults in the telecommunications industry in the U.S. in 2002 through the financial system on corporate finance and investment of firms in other industries. Financial transmission is identified by comparing the impact of the shock across otherwise identical firms (size, industry, region), but that differ in the degree of exposure of their lenders to the shock. The results indicate that exposure of a firm's lender to defaulting firms in the Telecoms industry has a significant impact on the amount of debt finance. If the main lender of the firm is in the top quartile of the distribution of loan portfolio exposure to the defaults, the firm experiences a 3 percentage point decline in leverage. The shock had a negative but insignificant effect on investment and stock returns.

Does the banking sector transmit and amplify real shocks across industries? Which banks are more likely to become a conduit for this financial transmission mechanism? How has the magnitude of this transmission channel changed over time? Answering these questions requires an empirical approach that produces consistent measures of financial transmission both in the cross section of banks and the time series. The empirical literature based on the 'natural experiment' approach has made a long way towards providing evidence that the financial transmission mechanism exists (see for example Chava and Purnanandam (2006),

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[♣] The author can be reached at dp2239@columbia.edu. I acknowledge the support of the FDIC-CFR and outstanding research assistance by Huidan Lin. This draft has benefited greatly from comments from Patrick Bolton, Steve Drucker, Atif Mian, Francisco Pérez-González, Veronica Rappoport, Tano Santos and Amir Sufi.

Gan (2006), Khwaja and Mian (2006), Paravisini (2006), Peek and Rosengren (1997)). But because this approach can provide only local estimates around the particular experiment under consideration, it has limited usefulness when attempting to address the questions posed above.

This paper proposes an empirical strategy to distinguish how much of the covariance between the leverage, investment and other outcomes of two firms is driven by financial transmission of a shock through the banking system. The intuition of the empirical strategy is better understood through a direct application. Suppose one wants to assess whether the defaults in the telecoms industry in 2002 affected, through the banking system, the supply of credit and investment of firms in other industries in the US. The fundamental empirical identification problem is how to disentangle the financial transmission channel, from changes in fundamentals affecting both the telecoms and other industries (e.g. changes in demand, changes in prices of inputs, changes in interest rates).

The financial transmission channel can be identified in this application by ranking firms according to the exposure of their *lenders* to the Telecoms default shock. One can exploit such ranking to compare how the leverage, investment and other outcomes of firms that are identical in every other respect (size, location, industry) vary with the shock according to the degree of exposure of their lenders. Suppose we observe two firms that are not in the telecoms industry, but that share product, geographical markets and other characteristics. For example, take two Texas based companies in the energy business which differ in that they obtain finance from different banks. The first firm borrows from JP Morgan Chase, who allocated around 12% of its loan portfolio to the communications industry during the first quarter of 2002. The second firm borrows from Bank One Corp., who allocated less than 3% of its portfolio to the Communications industry at that time. If there is a difference in outcomes between the two energy firms when the telecoms defaults occur, this difference can be causally attributed to financial transmission.

To produce such rankings in practice requires two pieces of information. First, it is necessary to obtain bank loan portfolio exposures to different industries. I construct proxies for these exposures using the loan level origination data in Dealscan. A proxy for bank loan portfolio exposures to different industries is obtained by aggregating at the lender level, the exposures created by each individual loan in the database. Because Dealscan reflects most large syndicated loans issued by the banking system, such an aggregation reflects more than 50% of the C&I loans of the banks that have some lending registered in the database. Regarding our specific example, portfolios constructed using such aggregation procedure indicate that there was substantial variation in the exposure to the four largest firms that defaulted in 2002 (WorldCom Inc., Adelphia Communication, Global Crossing Ltd, McLeod Inc). It ranged between close to zero, to 6.8% depending on the bank.

Matching firms to their lenders is the second data requirement to apply the methodology. Dealscan can also be used to produce this matching, since the database contains the identities of all the banks that participate in every loan syndicate. Once the firms have been matched to their borrowers, firm outcomes are obtained by matching again with Compustat. For the specific application in hand, I construct a sample of 1,590 firms that are both matched to their borrowers and Compustat. These firms are then ranked according to the exposure of their lenders to the four defaulting firms. I confirm that the ranking is not, a priori, correlated with firm characteristics: when the characteristics of the firms in the top and bottom half of the ranking are compared, there are no statistically significant differences in assets, leverage, investment to assets or adjusted returns.

The results indicate that firms that borrow from banks in the top quartile of the distribution of exposure to defaulted firms experience a 4 to 5 percentage point decline in leverage between the first quarter and the second quarter of 2002. This average effect becomes statistically insignificant when firm unobserved heterogeneity is taken into consideration.

I then illustrate how the methodology can be used to explore whether the transmission shock is heterogeneous across banks with different characteristics. In particular I explore three dimensions of variation: bank size, fraction of liquid assets and usage of credit derivatives. The results indicate there is a significant heterogeneity in the magnitude of the transmission across banks with different usage of credit derivatives. Firms that borrow from banks that are exposed to the defaults and do not use credit derivatives experience a decline of 3 percentage points in their leverage, even after accounting for unobserved firm heterogeneity. The effect is statistically insignificant when firms borrow from banks that use derivatives. I find no strong evidence of such heterogeneity across banks of different size and or liquid asset holdings alone.

The rest of the paper proceeds as follows. Section I describes the sources of data and variable definitions. Section II defines more precisely the empirical specification and applies it to measure the financial transmission of the Telecommunications Industry defaults. Section III shows how the methodology can be expanded to assess the relationship between bank characteristics and the magnitude of the transmission channel. The last section concludes.

I. Database Construction and Variable Definition

A. Constructing Loan Portfolios Using Dealscan

The Dealscan database is collected by Reuters/Loan Pricing Corporation from SEC and Federal Reserve filings, and directly from private debt markets. The initial sample contains information on 45,459 loans (96% syndicated) issued by 2,706 different lenders to U.S. firms from 1990 to 2005. In theory, construction of amounts of loans outstanding by bank and period of time using the database is simple, because the database contains information on the facility initiation date, the amount of each facility, the shares of each lender in the facility and the repayment schedule. In practice, however, the data on the lender shares of facilities is missing in 72% of the observations, and the entries for repayment schedules are missing for nine in every ten observations.

The following procedure is used to address the firs problem (missing lender shares).

1. Facilities with incomplete lead bank shares (3.15%) are assigned the median share of the other participant banks in the same facility. At the end of this step the information of the shares of lead banks is either all complete or all missing.
2. The second step is to deal with the facilities with all missing lead bank shares, but some participant bank shares (2%). I first assign median value of available participant bank shares to each missing participant bank shares. The unassigned share I distribute evenly across the lead banks.
3. I deal with the facilities with complete lead bank shares but all or some missing participant bank shares (8.5%) by assigning the remaining share equally amongst all participants without a share.
4. Deal with the facilities with all participant banks and the lender shares are all or partially missing (5.8%) by assigning 100/n to each participant without a share.
5. Facilities with all lead bank shares missing and all participant bank shares complete (1.66%): assign the remaining share equally among all leads.

After this procedure, the data contains facilities either with all lender shares assigned or all missing. Using the facilities with complete share information I estimate a logit model of the share of the loan on a set of predictors. The predictors are a full set of 2 digit SIC industry dummies, lender dummies, year of origination dummies, loan type dummies, a dummy for lead bank, deal amount, facility amount, maturity and a dummy if the loan is secured. Other likely predictors of shares are excluded because they are missing in a significant portion of the database (e.g. borrower sales and interest rate). I use the estimated model to impute the lender shares of all facilities used in the rest of the paper. With this procedure 75% of the facilities have complete lender share information.

To address the issue of the missing repayment schedule, the initiation and maturity dates are used to estimate the outstanding amount of loan for every facility in every quarter. A different procedure is followed to impute the outstanding amounts for term loans and credit lines. For term loans, I assume that the borrowing firm repays equally each quarter starting from the first quarter until the maturity quarter. For lines of credit, the amount available is assumed to be outstanding. Lines of credit with more than three years between initiation and maturity dates are assumed to be available for three years, after which the outstanding balance is set to zero. Lines of credit with less than three years between initiation and maturity are assumed to be outstanding until maturity.

Using the imputed lender shares and repayment schedules, I calculate the amount of debt that each facility implies for every bank in every quarter. The industry codes of the borrowers in Dealscan can then be used to aggregate the amounts outstanding at each bank-industry-quarter cell. To obtain a measure of how much of the actual loan portfolios of banks I aggregate the total outstanding by each bank-quarter and compare it with the C&I loans from the Call reports. The ratio of predicted stocks to C&I loans to U.S. firm during the 1995 to 2005 period is 52.3%. In other words, the predicted debt stocks amount to a substantial fraction of the outstanding loans reported in bank balance sheets during the period.

B. Bank Exposure to the Telecoms Industry Defaults

For the specific application of measuring the financial transmission of the defaults in the Telecoms industry I construct a measure of exposure based on the fraction of lending of each bank to four defaulted firms: WorldCom Inc., Adelphia Communication, Global Crossing Ltd, McLeod Inc. Table I shows the descriptive statistics of the shares of lending for the 36 banks that had some debt outstanding with these four firms during 2002, according to the imputation procedure described in the last subsection. During the first quarter of 2002 these banks allocated on average 1.7% of their total imputed stock of loans to these firms, and 4.6% of their stock of lending to the communications industry.

The share of lending to defaulted firms is used to classify banks by their exposure to the defaults. A bank is classified as exposed if its share of lending to the defaulted firms is in the top quartile of the share distribution during the first quarter of 2002 (before the defaults). Table II shows the descriptive statistics, by exposure to the shocks, of the sample of lenders in the Dealscan database that could be matched to the Commercial Bank, the Bank Holding Company and the Bank Merger databases from the Federal Reserve Board of Chicago. Exposed banks were on average larger, used less deposit finance and were more capitalized than the non exposed banks. The loan portfolio industry concentration of these banks according to the imputed shares was substantially lower than for the non-exposed ones. These statistics suggest that exposed banks also lent more to the defaulted firms in absolute terms than their unexposed counterparts.

C. Firm Classification by Lender Exposure

The next step is to classify borrowers according to the exposure of their lenders to the defaulted firms. I do this by first identifying the primary lender for each firm. The primary lender of a firm is defined as the lender that provides the largest fraction of a firm's credit according to the imputed stocks of debt. A firm is then classified as exposed if its primary lender is classified as exposed. A ranking based on the fraction of borrowing from exposed banks led to similar results than the ones presented here.

The descriptive statistics of the sample of firms in Dealscan that were matched to Compustat is shown in Table III. Panel 2 shows the firm statistics when the firm sample is divided according to primary lender exposure. The average level of assets, leverage and investment are statistically indistinguishable across groups. This observation is consistent with the hypothesis that the classification of firms by lender exposure is unlikely to be correlated with firm characteristics, a crucial identifying hypothesis of the empirical strategy of the paper.

II. Baseline Results

A. Empirical Specification

The financial transmission effect of a shock on firm outcomes can be estimated through the following general firm level specification:

$$Y_{it} = \alpha_i + \alpha_{Industry \times t} + \alpha_{State \times t} + \beta(DumExposed_i).Post_t + \gamma Post_t + \gamma X_{it} + \varepsilon_{it} \qquad \textbf{(1)}$$

Y_{it} is the outcome of interest of firm i at time t (for example leverage). The first three parameters in the right hand side are firm fixed effects, industry times quarter and state time quarter dummies. Each of these is included to capture firm time invariant unobserved heterogeneity, and shocks to the industry and the geographical area where the firm is located. $DumExposed_i$ is a dummy equal to one if the firm's lender is exposed to the shock and $Post_t$ is a dummy equal to one every period after the shock. The specification allows for the inclusion of firm time varying characteristics.

The parameter of interest, β, represents the differential effect of the shock across firms with exposed and unexposed lenders. To the extent that changes in the demand for credit of the firm that are not absorbed by industry and region shocks are uncorrelated with the matching of firms to their banks, the financial transmission effect is identified.

In the particular example at hand, the defaults started to take place in the second quarter of 2002. I will estimate the above specification using only two quarters of data to avoid introducing biases due to serial correlation in the data (Bertrand, Duflo and Mullainathan (2004)). In other words, the $Post_t$ dummy is in fact a dummy equal to one when the observation corresponds to the second quarter of 2002 (Dum2002-Q2 in the tables).

B. A Measure of Financial Transmission

Table IV presents the estimated parameters of equation 1 using leverage as the dependent variable. The first column shows the results using a subsample that excludes all firms in the Communications industry (SIC 48) and introducing no controls or dummies. The parameter of interest is negative and significant at the 1% level. The magnitude, 0.054, implies that on average the leverage of firms with lenders exposed to the shock declined by more than 5 percentage points relative to the leverage of firms that borrowed from unexposed lenders.

The next two columns show this result remains unaltered when industry shocks are absorbed and when state dummies are included. The specification cannot be estimated using the full set of dummies in equation 1, because the limited sample of firms implies there would be more dummies than observations. Instead, in columns 4 and 5 I estimate the parameters again but excluding from the sample all firms that are located in the same state as any of the four defaulted firms. This assures that the result is not driven by regional shocks that are common to the defaulted firms.

Finally, column 5 shows the estimates when firm fixed effects are included. The point estimate of β remains negative, but drops in magnitude by two thirds and becomes statistically insignificant. This suggests that unobserved firm heterogeneity is in part driving the previous estimates.

It is useful to discuss what the potential sources of firm heterogeneity. This heterogeneity cannot be driven by industry or location, given that these factors have been controlled for in the baseline specification. The unobserved heterogeneity cannot be correlated with other observable firm characteristics either, since Table III showed that the two groups of firms were indistinguishable in terms of size and capital structure. The only source of heterogeneity that remains unaccounted for is related to firm matching with their lenders. In fact, unobserved bank heterogeneity would appear into specification 1 confounded with the firm heterogeneity.

This discussion highlights the importance of including firm fixed effects in this specification to rid of both firm and bank time invariant unobserved heterogeneity. It also suggests that one should look at heterogeneous financial transmission effects across different types of lenders, to which I proceed in the next section.

C. Other Outcomes

I estimate specification 1 again using the proportion capital expenditures to assets as a measure of firm investment. It is reassuring that the point estimates of the parameter of interest, shown in Table V, are negative across all specifications which is consistent with the financial transmission hypothesis. However, the magnitudes are small and the estimates are insignificant at the standard levels for all but the specification with no controls. A similar pattern of negative but insignificant estimates is obtained when adjusted stock returns are used as the dependent variable in specification 1.

The insignificance of the effect on firm investment and return may be due to the lack of power of the test to detect small changes in the magnitudes. It could also be due to the fact that firms exposed to the shock are large public firms (average assets $6.5 billion) with access to financing from alternate sources. In either case, the results suggest that although there is an effect on the supply of credit of banks exposed to the shock, the effects on investment are small.

III. Financial Transmission and Bank Characteristics

Several bank characteristics have been associated to the financial transmission channel in the existing empirical and theoretical literature on banking. Empirical papers in the lending channel literature following Kashyap and Stein (2000) have suggested that lending by large banks and banks with substantial holdings of liquid assets is less likely to be affected by shocks to the balance sheet of the bank. More recently, the increased participation of financial institutions in credit derivative markets has originated a debate on the potential consequences on the risk exposure of banks (Carey and Stulz (2005)).

The previous section indicated that, on average, financial transmission effect of the Telecoms industry defaults on firm outcomes was not statistically distinguishable from zero. I now explore whether this average effect masks the existence of heterogeneous effects across banks with different characteristics. The main advantage of the empirical strategy of the paper is precisely that it allows the flexibility to estimate consistently the effect of the financial transmission channel in the cross section of banks and firms.

A. Including Bank Characteristics in the Baseline Specification

In order to estimate heterogeneous effects across different types of banks with specification 1, I continue to rank firms according to the characteristics of their lenders. I am interested in estimating whether the financial transmission of shock is smaller through banks that use credit derivatives more heavily. So I calculate the ratio of credit derivatives use to total assets and classify a bank as 'hedged' if it is in the highest quartile of the distribution of this ratio. As before, I define for every firm a dummy DumHedge which is equal to one if its main lender is classified as hedged. I follow the same procedure with bank assets to define DumLarge and DumLiquid, which are equal to one if a firm's main lender is in the top quartile of the distribution of assets and liquid assets/assets ratio respectively.

Using these new dummies I can estimate the following expanded version of specification 1:

$$\begin{gathered} Y_{it} = \alpha_i + \alpha_{Industry\times t} + \alpha_{State\times t} + \beta^{E}(DumExposed_i).Post_t + \\ + \beta^{H}(DumHedge_i).Post_t + \ + \beta^{EH}(DumExposed_i).(DumHedge_i).Post_t + \\ + \gamma Post_t + \gamma X_{it} + \varepsilon_{it} \end{gathered} \qquad \textbf{(2)}$$

The hedge lender dummy and the hedged lender dummy interacted with the exposed lender dummy have been added to the specification (interacted with the post-shock dummy). The coefficient of the interaction term represents the differential response to the shock by firms that borrow from banks that use credit derivatives more intensively.

Table VI shows the estimated parameters of specification 2 excluding from the sample of firm all firms in the Telecoms industry and in the same state of the defaulting firms. The first column presents the estimates with no control dummies. The estimate of the direct effect (β^{E}) is negative and significant as before, and the magnitude suggests that firms hose main borrower was exposed to the shock reduce leverage by 3 percentage points.

The point estimate of the differential effect of the financial transmission channel through bank that use credit derivatives is positive and has almost the same magnitude of the main effect although statistically insignificant. This time, the magnitude and significance of the main effect are robust to the inclusion on industry-quarter dummies, state dummies and firm fixed effects. This result suggests that neither firm nor bank heterogeneity are driving this estimate and that the defaults in fact had a negative impact on the supply of credit and firm leverage.

Moreover, the estimate of the differential effect through banks that use derivatives remains positive and surprisingly unaltered across specifications. This result, together with the fact that the inclusion of the hedge interaction makes possible to obtain a significant main effect indicate that the use of derivatives is a relevant determinant of the financial transmission of shocks.

This can be contrasted with the results in Table VII and Table VIII, where the interactions with DumLarge and DumLiquid have been included. The main effect is negative throughout all specifications and significant only in some of them. But the main effect is always insignificant in the specifications that control for firm heterogeneity. And the magnitude of the effect through large banks or banks with liquid assets changes magnitudes and sign across specifications.

IV. Conclusion

The empirical method developed in the paper allows identifying the financial transmission of shocks through the banking sector. It is flexible enough to allow identification consistently across different types of banks. The application of the methodology to the measurement of the financial transmission of the Telecommunications industry defaults in 2002 provided sensible results consistent with the expectations. The application also showed that the methodology may lack power to identify changes in firm investment and other outcomes, especially when identification is achieved through the effects on large public firms.

The next step in the research agenda involves exploiting the flexibility of the methodology to provide a broader empirical characterization of the financial transmission channel. This paper already began to explore the association of the magnitude of financial transmission and bank characteristics. One interesting avenue for further research involves looking at how the magnitude of the transmission of shocks varies with the business cycle and with the time series in general.

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Tables

Table I
Fraction of Bank Lending to the Largest Default Firms during 2002

		Fraction of Loan Portfolio to	
	stat	Defaulted firms	Communications Industry
2002q1	n	36	35
	Mean	0.0170	0.0459
	SD	0.1161	0.0504
	Median	0.0005	0.0088
2002q2	n	35	34
	Mean	0.0012	0.0170
	SD	0.1047	0.0419
	Median	0.0004	0.0066
2002q3	n	30	29
	Mean	0.0012	0.0177
	SD	0.0891	0.0357
	Median	0.0005	0.0077

Shares of lending for the 36 banks that had some debt outstanding with WorldCom Inc., Adelphia Communication, Global Crossing Ltd, McLeod Inc during the first quarter of 2002. These four firms defaulted during the second quarter of 2002.

Table II
Descriptive Statistics of Banks during the First Three Quarters of 2002, by Exposure to the Telecoms Defaults

Sample		Assets ($ million)	Deposits/ Assets	Equity/ Assets	Loan Portfolio Concentration (hhi)
All (n = 233)					
	Mean	40,000	0.743	0.093	0.454
	SD	122,000	0.112	0.030	0.394
	Median	4,063	0.764	0.085	0.317
Exposed to Default (n = 17)					
	Mean	234,000	0.624	0.086	0.050
	SD	216,000	0.082	0.017	0.015
	Median	165,000	0.644	0.083	0.044
Not Exposed (n=216)					
	Mean	24,700	0.750	0.094	0.485
	SD	96,600	0.109	0.031	0.392
	Median	3,332	0.767	0.085	0.385

HHI: Herfindahl index of loan portfolio concentration by industry, calculated using the imputed loans shares by industry with Dealscan.

Table III
Firm Descriptive Statistics (2002 Q1-Q3), by Lender Exposure to the Telecoms Industry Defaults, Credit Default Swaps and Liquid Assets

Firm Sample	Statistic	Assets ($ million)	Leverage	Investment/ Assets
1. All Firms (N = 1,891)				
	Mean	5,779	0.308	0.011
	SD	24,998	0.236	0.016
	Median	736	0.289	0.006
2. Lender Exposure to Telecoms Defaults				
High (N = 697)	Mean	6,482	0.297	0.011
	SD	25,837	0.223	0.033
	Median	801	0.278	0.007
Low (N = 1,194)	Mean	5,815	0.308	0.012
	SD	26,497	0.228	0.046
	Median	791	0.298	0.006
3. Lender Credit Default Swaps				
High (N = 1,116)	Mean	5,948	0.301	0.011
	SD	22,131	0.223	0.014
	Median	762	0.282	0.006
Low (N = 775)	Mean	5,536	0.318	0.012
	SD	28,641	0.253	0.018
	Median	678	0.297	0.007
4. Lender Liquid Assets				
High (N = 944)	Mean	7,955	0.329	0.011
	SD	30,213	0.261	0.014
	Median	1,165	0.308	0.006
Low (N = 947)	Mean	3,610	0.286	0.012
	SD	18,144	0.205	0.018
	Median	483	0.271	0.007

Table IV
Financial Transmission of the Telecommunications Industry Defaults on Firm Leverage

Dependent variable: Leverage	(1)	(2)	(3)	(4)	(5)
DumExposed x Dum2002-Q2	-0.054***	-0.046***	-0.045***	-0.056***	-0.016
	[0.011]	[0.011]	[0.010]	[0.013]	[0.019]
DumExposed	0.034*	0.031	0.033*	0.038**	
	[0.019]	[0.019]	[0.020]	[0.017]	
Dum2002-Q2	0.034***	0.062***	0.061***	0.096***	0.055***
	[0.011]	[0.020]	[0.020]	[0.013]	[0.019]
Constant	0.071***	0.004	0.028	0.027	0.072***
	[0.006]	[0.003]	[0.032]	[0.035]	[0.005]
Telecoms Industry excluded	Yes	Yes	Yes	Yes	Yes
Same state excluded	No	No	No	Yes	Yes
Industry-Quarter Dummies	No	Yes	Yes	Yes	Yes
State Dummies	No	No	Yes	Yes	No
Firm FE	No	No	No	No	Yes
Observations	3096	3088	3086	2382	2384
R-squared	0.007	0.071	0.078	0.081	0.719

Sample: First and second quarters of 2002. Baseline sample contains 1,590 firms that were matched with Dealscan and Compustat. Heteroskedasticity robust standard errors, clustered by firm, in brackets. *, **, and *** indicate that the estimated coefficient is significant at the 10%, 5% and 1% respectively.

Table V
Financial Transmission of the Telecommunications Industry Defaults on Firm Investment

Dependent variable: Investment/assets	(1)	(2)	(3)	(4)	(5)
DumExposed x Dum2002-Q2	-0.005**	-0.002	-0.002	-0.002	-0.001
	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]
DumExposed	-0.005	-0.005	0.001	-0.002	
	[0.003]	[0.004]	[0.002]	[0.004]	
Dum2002-Q2	0.016***	0.027*	0.028*	0.008***	0.007***
	[0.002]	[0.014]	[0.014]	[0.003]	[0.002]
Constant	0.012***	0.004***	0.014**	0.006	0.012***
	[0.000]	[0.001]	[0.007]	[0.006]	[0.000]
Telecoms Industry excluded	Yes	Yes	Yes	Yes	Yes
Same state excluded	No	No	No	Yes	Yes
Industry-Quarter Dummies	No	Yes	Yes	Yes	Yes
State Dummies	No	No	Yes	Yes	No
Firm FE	No	No	No	No	Yes
Observations	2923	2915	2913	2225	2227
R-squared	0.054	0.336	0.35	0.361	0.909

Sample: First and second quarters of 2002. Baseline sample contains 1,590 firms that were matched with Dealscan and Compustat. Heteroskedasticity robust standard errors, clustered by firm, in brackets. *, **, and *** indicate that the estimated coefficient is significant at the 10%, 5% and 1% respectively.

Table VI
Financial Transmission of the Telecoms Defaults on Firm Leverage, by Bank Usage of Credit Derivatives

Dependent Variable: Leverage	(1)	(2)	(3)	(4)
DumExposed x Dum2002-Q2	-0.028*	-0.031*	-0.032*	-0.029*
	[0.016]	[0.019]	[0.019]	[0.016]
DumExposed x DumHedge x Dum2002-Q2	0.023	0.026	0.026	0.026
	[0.021]	[0.019]	[0.019]	[0.022]
DumExposed	0.083	0.046	0.051	
	[0.054]	[0.056]	[0.058]	
Dum2002-Q2	0.006	0.007	0.006	0.01
	[0.006]	[0.006]	[0.007]	[0.007]
DumHedge	0.104***	0.090***	0.087***	
	[0.030]	[0.029]	[0.030]	
DumExposed x DumHedge	-0.081	-0.051	-0.05	
	[0.059]	[0.060]	[0.062]	
DumHedge x Dum2002-Q2	-0.015	-0.02	-0.02	-0.018
	[0.013]	[0.013]	[0.013]	[0.015]
Constant	0.214***	0.286***	0.243***	0.307***
	[0.022]	[0.026]	[0.077]	[0.002]
Industry-Quarter Dummy	No	Yes	Yes	Yes
State Dummy	No	No	Yes	No
Firm FE	No	No	No	Yes
Observations	2422	2410	2408	2422
R-squared	0.016	0.172	0.19	0.951

Sample: First and second quarters of 2002. Firm sample excludes all firms in the Telecoms industry and all firms located in the same state as WorldCom Inc., Adelphia Communication, Global Crossing Ltd, McLeod Inc. Heteroskedasticity robust standard errors, clustered by firm, in brackets. *, **, and *** indicate that the estimated coefficient is significant at the 10%, 5% and 1% respectively.

Table VII
Financial Transmission of the Telecoms Defaults on Firm Leverage, by Bank Size (Assets)

Dependent Variable: Leverage	(1)	(2)	(3)	(4)
DumExposed x Dum2002-Q2	-0.033	-0.053	-0.05	-0.016
	[0.045]	[0.047]	[0.046]	[0.057]
DumExposed x DumLarge x Dum2002-Q2	0.022	0.043	0.04	0.007
	[0.046]	[0.046]	[0.045]	[0.059]
DumExposed	0.198*	0.114	0.095	
	[0.102]	[0.095]	[0.087]	
Dum2002-Q2	0.003	-0.011	-0.011	0.004
	[0.008]	[0.016]	[0.016]	[0.010]
DumLarge	0.115***	0.092***	0.085**	
	[0.032]	[0.033]	[0.035]	
DumExposed x DumLarge	-0.187*	-0.108	-0.083	
	[0.105]	[0.097]	[0.089]	
DumLarge x Dum2002-Q2	-0.006	-0.015	-0.016	-0.007
	[0.012]	[0.015]	[0.015]	[0.015]
Constant	0.193***	0.272***	0.231***	0.307***
	[0.027]	[0.031]	[0.080]	[0.002]
Industry-Quarter Dummy	No	Yes	Yes	Yes
State Dummy	No	No	Yes	No
Firm FE	No	No	No	Yes
Observations	2422	2410	2408	2422
R-squared	0.016	0.17	0.189	0.951

Sample: First and second quarters of 2002. Firm sample excludes all firms in the Telecoms industry and all firms located in the same state as WorldCom Inc., Adelphia Communication, Global Crossing Ltd, McLeod Inc. Heteroskedasticity robust standard errors, clustered by firm, in brackets. *, **, and *** indicate that the estimated coefficient is significant at the 10%, 5% and 1% respectively.

Table VIII
Financial Transmission of the Telecoms Defaults on Firm Leverage, by Bank Liquid Assets

Dependent Variable: Leverage	(1)	(2)	(3)	(4)
DumExposed x Dum2002-Q2	-0.011	-0.015*	-0.015*	-0.012
	[0.008]	[0.009]	[0.009]	[0.009]
DumExposed x DumLiquid x Dum2002-Q2	0.008	0.011	0.01	-0.001
	[0.023]	[0.024]	[0.024]	[0.027]
DumExposed	0.039*	0.025	0.029	
	[0.022]	[0.022]	[0.023]	
Dum2002-Q2	0.01	-0.022**	-0.022**	0.002
	[0.007]	[0.009]	[0.009]	[0.007]
DumLiquid	0.045	0.048	0.052	
	[0.041]	[0.037]	[0.036]	
DumExposed x DumLiquid	-0.006	-0.009	-0.01	
	[0.049]	[0.046]	[0.045]	
DumLiquid x Dum2002-Q2	-0.016	-0.018	-0.017	-0.008
	[0.020]	[0.020]	[0.019]	[0.023]
Constant	0.260***	0.346***	0.298***	0.307***
	[0.015]	[0.022]	[0.073]	[0.002]
Industry-Quarter Dummy	No	Yes	Yes	Yes
State Dummy	No	No	Yes	No
Firm FE	No	No	No	Yes
Observations	2422	2410	2408	2422
R-squared	0.012	0.171	0.191	0.951

Sample: First and second quarters of 2002. Firm sample excludes all firms in the Telecoms industry and all firms located in the same state as WorldCom Inc., Adelphia Communication, Global Crossing Ltd, McLeod Inc. Heteroskedasticity robust standard errors, clustered by firm, in brackets. *, **, and *** indicate that the estimated coefficient is significant at the 10%, 5% and 1% respectively.