

The Financial Premium Internet Appendix

Jens Dick-Nielsen* Peter Feldhütter†
Copenhagen Business School Copenhagen Business School

David Lando‡
Copenhagen Business School and CEPR

This version: March 21, 2025

Abstract

This Internet Appendix has further robustness checks and descriptions regarding the results in the main text.

*Department of Finance, Copenhagen Business School, Solbjerg Plads 3, A4.03, 2000 Frederiksberg
jdn.fi@cbs.dk

†Department of Finance, Copenhagen Business School, Solbjerg Plads 3, A4.07, 2000 Frederiksberg
pf.fi@cbs.dk

‡Department of Finance, Copenhagen Business School, Solbjerg Plads 3, A4.04, 2000 Frederiksberg
dl.fi@cbs.dk

A Including all bond maturities in the calculation of the financial premium

In the main text we restrict the sample of bonds to bonds with a remaining maturity less than 10.5 years because most financial bonds are in that maturity range as Figure A.1 shows. The estimated financial premium is very similar if we include all bond maturities as Figure A.2 shows.

B Historical default and recovery rates

In Section 5.1 in the main text we show that the financial premium is similar when we loss-adjust the credit spread by subtracting the historical loss rate. The historical default rates in the rolling sample in Table 7 are shown in Table B.1.

The table shows that there is no consistent pattern in the difference in historical default rates of financials vs industrials: for rating categories AAA, BBB, BB, B, and C industrial firms have higher average default rates than financial firms while for AA and A it is the other way around. ? show that historical default rates have large confidence bounds and therefore the differences are likely due to noise rather than differences in how rating agencies rate financial firms compared to industrial firms. Regardless, the table shows that default rates for financial firms are not higher than industrial firms on average – 60% (42/70) of the default rate point estimates are lower for financials.

C Default and credit loss prediction

In Section 5.1 we find a similar size of the financial premium when we subtract the historical loss rate from the bond spread. This approach is inherently backward-looking and as a further robustness test, we apply a forward-looking approach in this section.

In particular, if the default probability for a financial bond of a given rating is higher than that of an industrial bond, we expect that the rating of a financial bond predicts higher future default rates than the corresponding rating of an industrial bond. To test this,

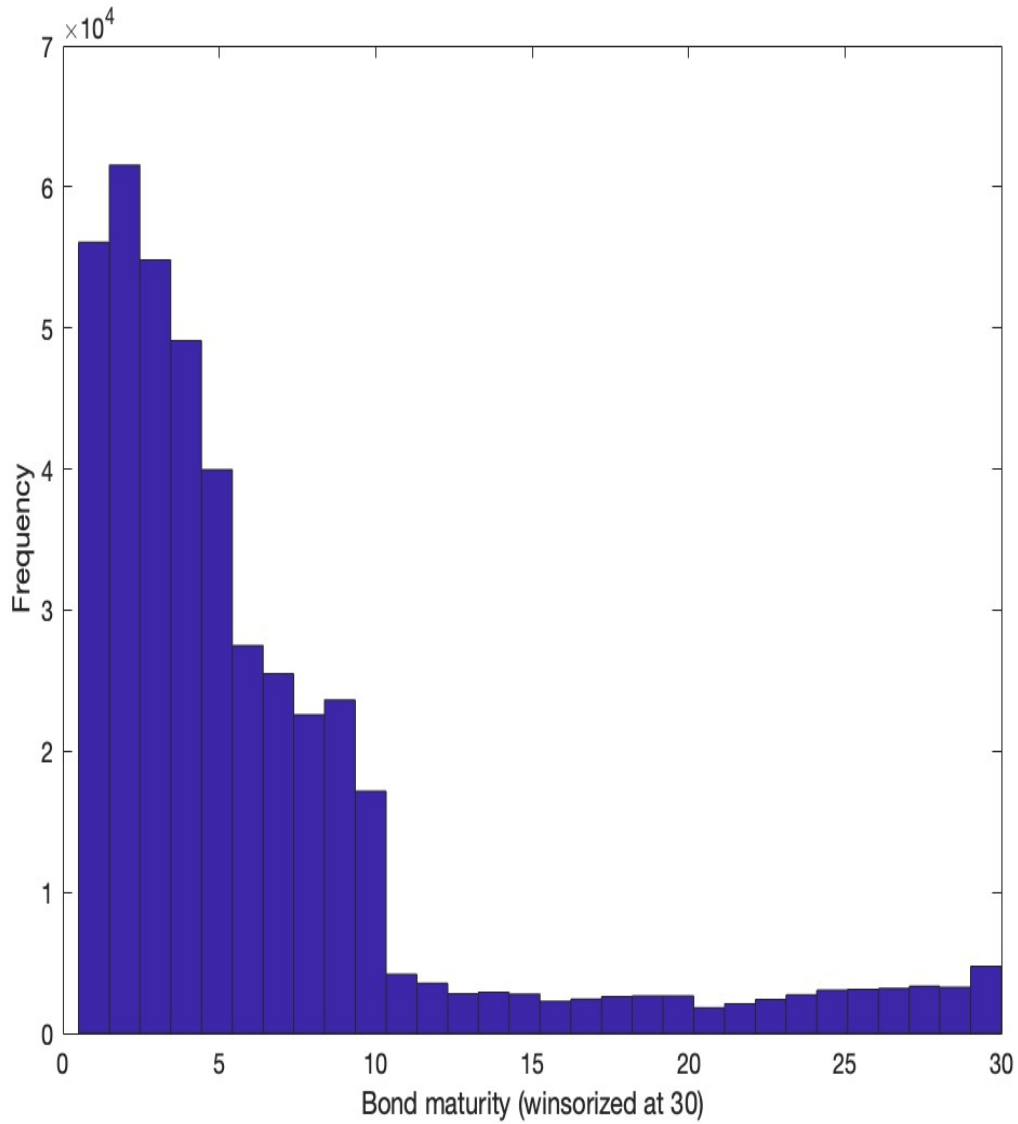


Figure A.1: *The distribution of maturity for financial bonds.* The figure shows the distribution of bond maturity for the financial bonds in our sample. The sample period is 1987–2020.

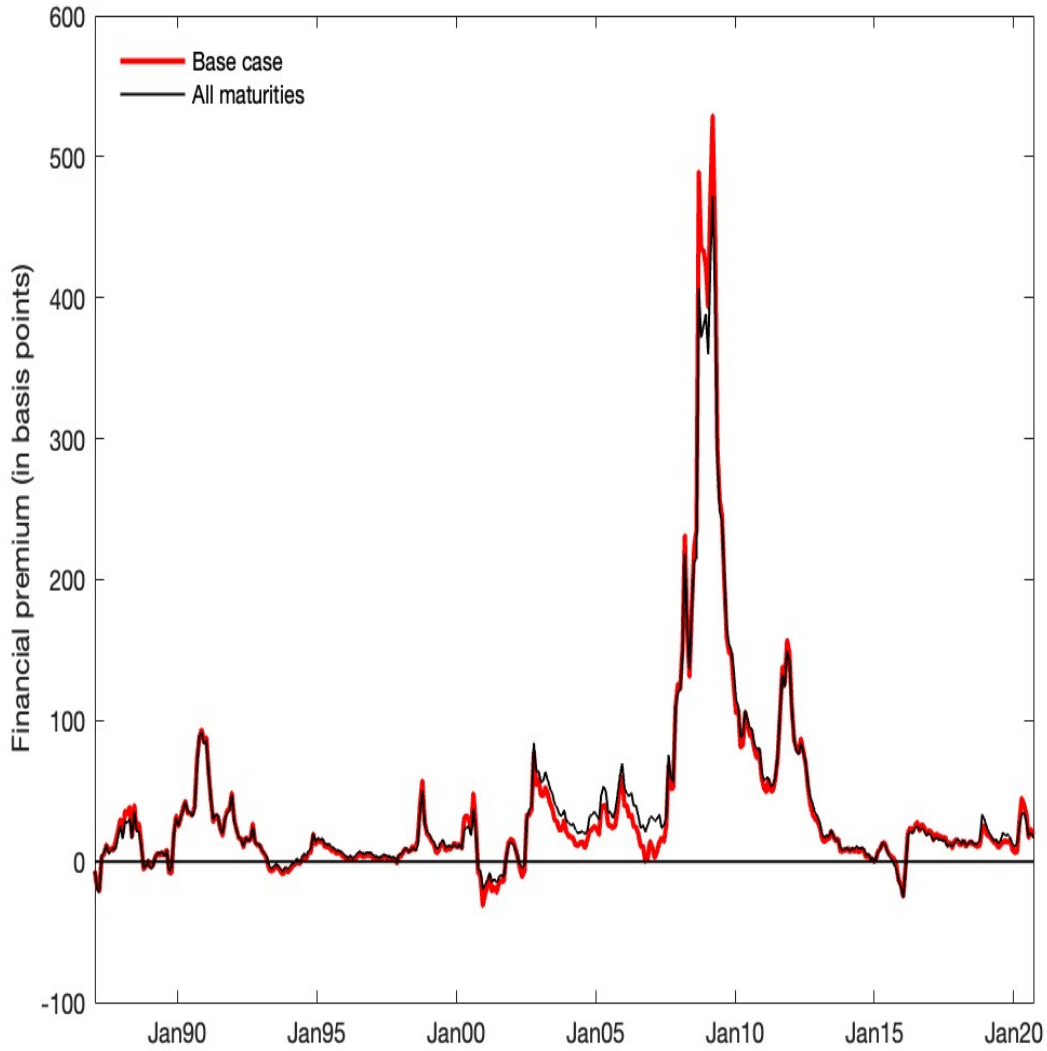


Figure A.2: *The financial premium using all maturities.* For each month in the sample, we estimate the financial premium φ from the regression $s_{ij} = \varphi 1_{fin,j} + \gamma' X_i + \mu_{mr} + \epsilon_{ij}$, where s_{ij} is the yield spread in the month of bond i issued by firm j , $1_{fin,j}$ is one (zero) if firm j is a financial (industrial) firm, X contains control variables and μ_{mr} is a rating-maturity fixed effect. The control variables are coupon, bond age, and $\log(\text{amount issued})$. The fixed effect maturity intervals are 0.5-1.5, 1.5-2.5, ..., 98.5-99.5, and 99.5-100.5 years while the fixed effect rating are at notch level (AAA, AA+, AA, ..., B, B-, C). The figure shows the time series of φ when using maturities less than 10.5 years ('Base case') and when using all maturities ('All maturities').

	horizon (years)										Ave.
	1	2	3	4	5	6	7	8	9	10	
AAA											
Industrial	0.00	0.00	0.00	0.08	0.23	0.42	0.60	0.75	0.92	1.10	0.41
Financial	0.02	0.07	0.07	0.07	0.08	0.10	0.12	0.15	0.19	0.23	0.11
AA											
Industrial	0.00	0.01	0.03	0.16	0.27	0.37	0.46	0.55	0.64	0.67	0.32
Financial	0.05	0.11	0.25	0.52	0.99	1.61	2.38	3.00	3.36	3.76	1.60
A											
Industrial	0.02	0.12	0.27	0.43	0.63	0.90	1.17	1.43	1.72	2.04	0.87
Financial	0.06	0.19	0.51	0.97	1.36	1.80	2.32	2.93	3.67	4.41	1.82
BBB											
Industrial	0.16	0.53	1.10	1.83	2.53	3.31	4.20	5.27	6.46	7.59	3.30
Financial	0.26	0.87	1.50	1.68	1.84	2.02	2.19	2.37	2.93	4.19	1.98
BB											
Industrial	1.32	3.41	5.73	8.31	11.06	13.83	16.43	18.92	21.37	23.79	12.42
Financial	0.94	2.77	4.06	4.68	5.10	5.29	5.86	6.47	7.13	8.01	5.03
B											
Industrial	5.30	10.32	15.19	19.42	23.71	27.66	31.40	34.88	38.15	42.75	24.88
Financial	6.87	11.83	14.76	19.40	21.31	19.54	20.48	22.19	24.43	27.38	18.82
C											
Industrial	7.09	11.84	16.20	20.21	24.53	27.87	30.86	34.93	39.83	42.76	25.61
Financial	5.74	6.22	6.95	7.87	8.98	9.94	11.24	13.15	15.92	17.91	10.39

Table B.1: *Average rolling industrial and financial default rates, 1970–2018.* For each year $T=1987, \dots, 2018$, we calculate the cumulative realized default rate for the period 1970– T and the table shows the cumulative realized default rate, averaged over T . 'Industrial firms' is the calculated default rate when using Moody's methodology and restricting the sample to the industrial category in their default database, with one change applied to their methodology: default rates from different cohorts are weighted equally instead of weighted by the cohort size. 'Financial firms' refers to the calculated default rate using all financial categories.

we record for each bond-month observation in our sample whether the bond subsequently defaults (value 1) or not (value 0).¹

Table C.1 Panel A shows linear regression results with default as the left-hand variable. We see in column (1) that rating is a strong predictor of default, but is not a stronger predictor for financial firms since the interaction term $\text{Rating} \times \text{Finance}$ is insignificant. Furthermore, column (2) shows that rating predicts higher default rates for bonds with longer maturity (the interaction term $\text{Rating} \times \text{Maturity}$ is significantly positive). This is expected since default rates increase with horizon. The interaction term $\text{Rating} \times \text{Maturity} \times \text{Finance}$

¹We use Mergent FISD's table ISSUE.DEFAULT to identify bond defaults and we use only bond-month observations where the bond matures before the end of the sample period.

is negative and statistically significant, showing that the predicted default rate is smaller for financial firms as the bond maturity increases. Column (3)-(5) shows similar results when we restrict the sample to investment grade, speculative grade, or outside the financial crisis 2007–2009.

Panel B shows the results of a logit regression.² Results are very similar to the results in Panel A with the only exception that the interaction Rating×Maturity×Finance becomes insignificant. Overall, we find no evidence that rating predicts higher default rates for financials firms compared to industrial firms.

In Panel C the left-hand variable is the credit loss. For a bond, the credit loss is zero in case of no default and equal to the first trading price after default if the bond defaults.³ We see very similar results to when we predict default rates: rating is a significant predictor of credit losses, the prediction is stronger for longer maturity bonds, but the effect is not stronger for financial bonds.

Overall, the results show no evidence that credit losses for financial bonds are higher than for industrial bonds.

D Calculation of bond betas

Betas in the model are with respect to overall market value as represented by V_m . The returns on V_m in this model are perfectly correlated with the state-price deflator and therefore the CAPM-relation holds using these betas. Because of the single-factor model structure, both the aggregate debt market and aggregate equity market would have a high correlation with the state-price deflator and be good proxies for V_m .

Table D.1 shows the regression in equation (12) in the main text. We see that the bond beta has a high explanatory power both when using the beta with respect to aggregate equity market (spec. (1)) – the specification reported in the main text – and aggregate bond market (spec. (2)). Specification (3) includes both betas, but since the correlation between

²In Panel A we cluster standard errors at the firm level. It is unclear how to adjust standard errors in the logit regression and we therefore retain the first bond-month observation of each issuer.

³The sample is substantially reduced in this case: There are 15,793 defaulted bonds in the sample, but we can only calculate the loss in 2,082 cases.

the betas is 93% the specification suffers from severe collinearity and it is not meaningful to interpret on the sign and significance of the coefficients.

E Accuracy of Vasicek loan portfolio approximation

The Vasicek approximation is incredibly accurate when the number of loans is in the hundreds of thousands or millions, as is the case for large commercial banks. To show that this approximation is not a source of concern, we include here in Figure E.1 a graph of the empirical distribution of default frequencies in a portfolio of (just) 1000 loans (based on 100.000 simulations) and the density of Vasicek’s large homogeneous portfolio approximation. The parameter choices underlying this graph are $p = 0.05$ and $\rho = 0.2$. The approximation is remarkably accurate, even for just 1000 loans, and for realistic portfolio sizes, the error becomes vanishingly small.

As a parenthetical remark, the approximation is widely used in the finance industry in the modeling of index CDS contracts, where the number of reference entities is just 125.

F Robustness of the financial premium for different recovery rates

In the model the financial premium is defined using the same fixed recovery for bank debt and for the firm debt with which bank debt is compared. In Appendix B.2 we examine the situation where the bank and the firm have the same loss rate λ but different combinations of default probability and recovery rate, $\lambda = (1 - R_b)p_b = (1 - R_f)p_f$. We show theoretically that the financial premium is positive whenever $R_b \leq R_f$, and we next argue that when $R_b > R_f$, it requires implausible parameters to get a negative financial premium.

In Figure F.1 we show the financial premium as a function of combinations of recovery rates where we keep the firm’s default probability fixed at $p_f = 3\%$ and for each recovery rate combination adjust the bank’s default probability p_b to match the expected loss on bank debt with that of firm debt, i.e. $p_b = \frac{(1-R_f)p_f}{1-R_b}$. We see that only with a bank recovery of 90% in combination with a firm recovery of 10% or less do we get a negative financial

premium. Such high levels of bank recovery rates correspond to unrealistically high bank default probabilities of 27% or more.

In Figure F.2 we keep the firm’s recovery rate fixed at 0.35, and vary the default probability of the firm and the recovery rate of the bank. It requires a large and unrealistic bank recovery rate of 0.9 in combination with high firm default probabilities for the financial premium to become negative.

G Default rate calculations

Moody’s provide an annual report with historical cumulative default rates and these are extensively used in the academic literature as estimates of default probabilities. The default rates are based on a long history of default experience for firms in different industries and different regions of the world. We follow Moody’s methodology for calculating cumulative default rates and in this Appendix we detail the calculation.

Assume that there is a cohort of issuers formed on date y holding rating z . The number of firms in the cohort during a future time period is $n_y^z(t)$ where t is the number of periods from the initial forming date (time periods are measured in months in the main text). In each period there are three possible mutually exclusive end-of-period outcomes for an issuer: default, survival, and rating withdrawal. The number of defaults during period t is $x_y^z(t)$, the number of withdrawals is $w_y^z(t)$, and the number of issuers during period t is defined as

$$n_y^z(t) = n_y^z(0) - \sum_{i=1}^{t-1} x_y^z(i) - \sum_{i=1}^{t-1} w_y^z(i) - \frac{1}{2}w_y^z(t). \quad (\text{G.1})$$

The marginal default rate during time period t is

$$d_y^z(t) = \frac{x_y^z(t)}{n_y^z(t)} \quad (\text{G.2})$$

and the cumulative default rate for investment horizons of length T is

$$D_y^z(T) = 1 - \prod_{t=1}^T [1 - d_y^z(t)]. \quad (\text{G.3})$$

The average cumulative default rate is

$$\bar{D}^z(T) = 1 - \prod_{t=1}^T [1 - \bar{d}^z(t)] \quad (\text{G.4})$$

where $\bar{d}^z(t)$ is the average marginal default rate⁴.

For a number of cohort dates y in a historical data set Y , Moody's calculate the average marginal default rate as a weighted average, where each period's marginal default rate is weighted by the relative size of the cohort

$$\bar{d}^z(t) = \frac{\sum_{y \in Y} x_y^z(t)}{\sum_{y \in Y} n_y^z(t)}. \quad (\text{G.5})$$

We label default rates based on equation (G.5) for *cohort-weighted* default rates. In the presence of macroeconomic risk as modelled in ? it is more robust to use *equal-weighted* default rates where the average marginal default rate is calculated as

$$\bar{d}^z(t) = \frac{1}{N_Y} \sum_{y \in Y} \frac{x_y^z(t)}{n_y^z(t)} \quad (\text{G.6})$$

where N_Y is the number of cohorts in the historical dataset Y . This is the default rate calculation we use in the main text.

⁴Note that this calculation assumes that marginal default rates are independent.

	All (1)	All (2)	Inv. (3)	Spec. (4)	Ex. crisis (5)
Panel A: Default, linear regression					
Constant	-0.0469*** [0.0085]	-0.0488*** [0.0084]	-0.0034 [0.0052]	-0.2814*** [0.0515]	-0.0488*** [0.0081]
Rating	0.0091*** [0.0012]	0.0055*** [0.0009]	0.0020** [0.0009]	0.0281*** [0.0043]	0.0090*** [0.0012]
Rating×Finance	-0.0006 [0.0010]	0.0013 [0.0010]	0.0000 [0.0008]	-0.0020 [0.0020]	-0.0011 [0.0009]
Rating×Maturity		0.0008*** [0.0001]			
Rating×Maturity×Finance		-0.0003** [0.0002]			
Observations	725184	725184	619912	105272	509806
Panel B: Default, logit regression					
Constant	-6.5382*** [0.3780]	-6.8532*** [0.4069]	-7.4342*** [0.9671]	-5.1311*** [0.8330]	-6.9474*** [0.4704]
Rating	0.3293*** [0.0299]	0.2658*** [0.0399]	0.4315*** [0.1090]	0.2327*** [0.0584]	0.3713*** [0.0363]
Rating×Finance	0.0091 [0.0212]	-0.0141 [0.0695]	-0.0134 [0.0399]	0.0153 [0.0244]	-0.0065 [0.0250]
Rating×Maturity		0.0124*** [0.0044]			
Rating×Maturity×Finance		0.0035 [0.0087]			
Observations	2563	2563	2042	521	1784
Panel C: Credit loss, linear regression					
Constant	-0.3503*** [0.1234]	-0.3694*** [0.1277]	0.0269 [0.0718]	-1.7929* [0.9839]	-0.2749** [0.1385]
Rating	0.0547*** [0.0150]	0.0323** [0.0139]	-0.0004 [0.0095]	0.1716** [0.0764]	0.0433** [0.0170]
Rating×Finance	0.0094 [0.0139]	0.0114 [0.0107]	0.0002 [0.0038]	0.0305 [0.0417]	0.0046 [0.0112]
Rating×Maturity		0.0053*** [0.0016]			
Rating×Maturity×Finance		0.0004 [0.0043]			
Observations	711473	711473	613630	97843	502028

Table C.1: *Default and credit loss prediction.* For each bond-month observation we record a binary default variable (1=default, 0=no default) if the bond subsequently defaults. Panel A shows linear regression results with the default variable as lefthand variable and standard errors clustered at the firm level. Panel B shows logit regression results with the default variable as the lefthand variable. In this case standard errors are unclustered and we keep only the first bond-month observation of each bond issuer. Panel C shows linear regression results with the credit loss as lefthand variable and standard errors clustered at the firm level. Credit loss is zero if the bond does not default and equal to the first bond price after default if the bond defaults. ‘Inv.’ (‘spec’) is the subsample of bond-months with an investment (speculative) grade rating and ‘ex. crisis’ is the subsample where the bond maturity is before June 1, 2007 or the bond yield observation date is after June 1, 2009. The sample period is 1987–2020.

	(1)	(2)	(3)
Bond excess beta wrt equity market	1208.06*** [225.94]		-618.65* [320.38]
Bond excess beta wrt bond market		397.71*** [36.96]	562.42*** [91.72]
Constant	-9.29 [10.12]	-0.48 [4.57]	7.74 [5.96]
R^2	0.68	0.89	0.92
N	18	18	18

Table D.1: *Financial premium and excess betas*. For each rating class and maturity group, we calculate the financial premium (in basis points) and financial excess beta and the table shows regression results with the financial premium as left-hand variable. 'Bond excess beta wrt equity market' is the excess beta where the bond beta for bond i at time t is calculated with respect to the aggregate equity market, while 'bond excess beta wrt bond market' is the excess beta where the bond beta for bond i at time t is calculated with respect to the aggregate corporate bond market. We restrict the data sample to bond-month observations where we observe both a spread and beta. The rating classes are AAA, AA, A, BBB, Speculative grade, and all ratings while maturities are 0.5–3.5 years (short), 3.5–7.5 years (medium), and 7.5–10.5 years (long). The sample period is 1987–2020. Standard errors are shown in brackets and '*', '**', and '***' indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Simulated portfolio with 1000 loans

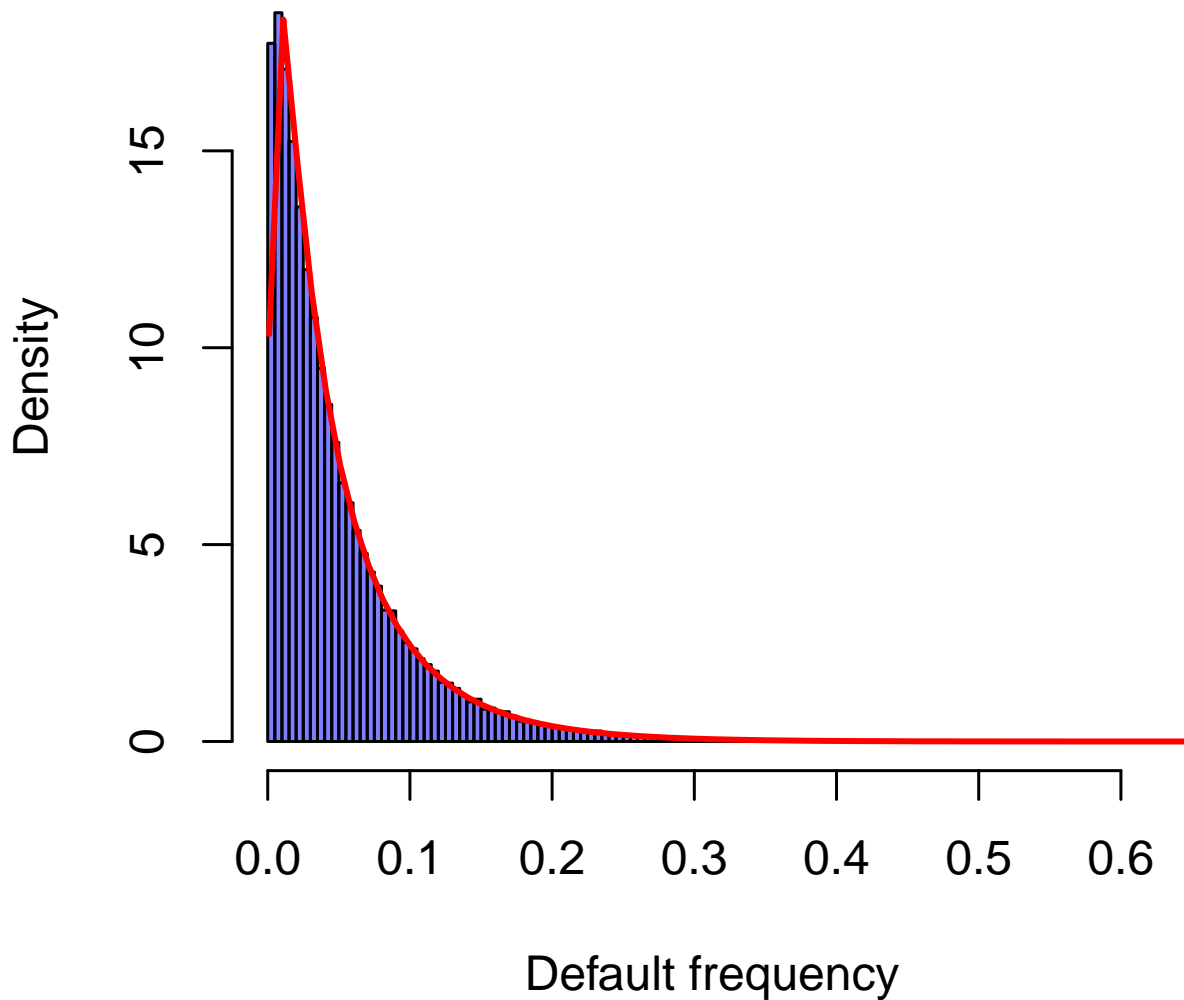


Figure E.1: *Accuracy of the Vasicek approximations.* The figure shows the empirical distribution of default frequencies in a portfolio of 1000 loans (based on 100.000 simulations) and the density of Vasicek's large homogeneous portfolio approximation. The parameter choices underlying this graph are $p = 0.05$ and $\rho = 0.2$.

Financial premium		Firm recovery									
		0	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9
Bank recovery	0	211	199	187	173	158	141	123	103	79	49
	0,1	198	188	176	164	150	135	118	98	76	47
	0,2	185	175	165	154	141	127	112	94	72	46
	0,3	169	161	153	143	132	119	105	89	69	44
	0,4	152	146	139	130	121	110	98	83	65	41
	0,5	133	128	123	116	109	100	89	76	60	39
	0,6	110	108	104	100	94	88	79	68	55	36
	0,7	82	82	82	80	77	72	67	59	48	32
	0,8	46	49	52	53	54	53	50	46	39	27
	0,9	-9	-1	6	13	18	22	25	26	25	19

Figure F.1: The table shows the financial premium as a function of combinations of recovery rates where we keep the firm's default probability fixed at 3% and for each recovery rate combination adjust the bank's default probability to match the expected loss on bank debt with that of firm debt.

Financial premium		Firm default probability						
		0,01	0,02	0,03	0,04	0,05	0,06	
Bank recovery	0,1	74	120	157	190	220	247	
	0,2	71	113	148	178	205	230	
	0,3	67	106	137	164	188	210	
	0,4	63	98	126	149	170	188	
	0,5	58	89	113	132	149	164	
	0,6	52	78	97	112	125	135	
	0,7	44	65	78	88	95	100	
	0,8	35	47	54	56	56	54	
	0,9	20	20	15	7	-3	-15	

Figure F.2: The table shows the financial premium when the firm's recovery rate is fixed at 0.35 and we vary the probability of default of the firm along with the recovery rate of the bank. The default probability of the bank is adjusted to make expected loss the same as for the firm.