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Credit risk and Interconnectedness: An asset pricing study

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Contents

0. Abstract	2
1. Intro	2
2. Literature review	3
3. Methodology	10
3.1. Credit risk factor.....	10
3.2. Interconnectedness	10
3.3. Composition of CRF	11
3.4. Sample.....	14
4. Asset Pricing Model	14
4.1. Construction of test portfolios	14
Table 2: Test portfolio descriptive statistics.....	15
5. Main asset pricing test.....	16
Table 3: Cross Sectional Regression	16
Goodness-for-fit Plots	17
6. Limitations.....	18
7. Additional regressions.....	18
Table 4: Time series regression betas – Alternative regression	19
Table 5: Cross sectional regression – Alternative regression.....	19
8. Conclusion.....	20
Appendix	22
Appendix 1: Bank Lending institutions.....	22
Reference list.....	23

0. Abstract

This study lay the foundation for merging two parallelly studied strains of academic literature asset risk factors and systemic banking risk, in order to create a measure incorporating credit risk in the banking sector and banking sector interconnectedness. The theoretical work accumulates to a proposed two factor model including a novel measure of interconnected credit risk and the traditional market factor. Despite the unsatisfactory statistical results, the theoretical foundation remains robust and the literature combining these twin brothers in the academic field of research is by a large unexplored. Thus, this paper's theoretical development is significant.

1. Intro

Academia has predominantly focused on ad hoc financial ratios and simple balance sheet items when researching asset prices, naturally due to ease of data accessibility. Consequently, asset pricing models have shed light on a variety of risk factors allowing practitioners to better analyse exposures to risk and given some evidence as to the origin of this risk. However, it has not to a satisfactory extent explained the origin of these factors relating them to unique sources of fundamental risk. Moreover, a vast number of studies have, in an attempt to fundamentally link the factors to economic variables, suggested credit risk to be influential. This research is aiming at combining credit risk of the banking sector weighted by interconnectedness. Thereby combining two distinct, though related, branches in the academia using a recently acknowledged measure of credit risk in the banking sector adjusting it to accommodate for a measure of interconnectedness. In awareness of the dispute among leading researchers with regards to factor models being consistent with efficient market hypothesis or not (Fama, 1970; Fama, 1991; Shiller, 2003), this paper is not aiming to make conclusive arguments on whether markets are efficient nor inefficient. Ultimately, this paper aim to present evidence describing the systemic risk of the banking sector in an asset pricing model incorporating credit risk and interconnectedness.

2. Literature review

Modern asset pricing models were first developed by the work of Markowitz (1959), Treynor (1961) Sharpe (1964), Lindtner (1965:a; 1965:b), Mossin (1966) and Tobin (1958) known as the Capital Asset Pricing Model (“CAPM”). CAPM present the expected return of an asset as a direct relationship between the beta and excess market return where, by definition, beta captures the systematic exposure to risk in its entirety. The model has been adopted by financial practitioners and greatly contributed to our understanding of asset return structures. It is, however, subject to limiting and unrealistic assumptions. Studies relaxing one or more assumptions have been presented in the literature suggesting a variety of alterations to CAPM (see Lindtner, 1969; Pratt, 1967; Black, Jensen and Scholes, 1972; Black, 1972). Even if academia presents compelling evidence rejecting the accuracy of CAPM it remains a powerful tool to assess and explain asset return structures although not presenting the whole truth. Fama and French (1993) published perhaps the most influential paper since the development of CAPM linking risk factors common to the bond market and equity market. The market, Book-to-Market equity (“BM”) and size factor (see Banz, 1981) are included in the asset pricing model where the market portfolio is found to also capture variations common for both stock returns and the two term structures. Thereby linking return structures in debt and equity markets.

Even though Fama and French (1995) argue for BM to proxy profitability, different competitive structures, products and customers will undoubtedly alter industrial characteristics including profit margins. Fama-French (1992) find a close relation between leverage and the BM factor, thus, suggesting BM might be associated to Chan and Chen’s (1991) distress risk. However, the authors do not rule out the possibility for capturing irrational behaviour. Regardless, negligence of industry specific characteristics, credit markets altering the foundation of profitability and source of funding are not fundamentally caused by accounting values or market

valuations given the reactive nature to economic events. On the contrary, economic shocks to industry specific assets or banking sector likely to drive asset return structures. Thus, the criticism is not that BM does not capture variation in stock returns, merely the lack of economically fundamental rational incorporated in the factor. Small businesses have in the past evidently yielded an abnormal return compared to large firms (Banz 1981). Thus, small firm investors must be exposed to risk uniquely priced in the market compared to investing in large, established firms. However, the size factor is not linked to a fundamental economic risk factor. For example it does not consider how influenced each sorted portfolio is by “fallen angels” or young, innovative companies (Chan and Chen, 1991). Thereby ignoring fundamental differences in the sample population as companies in sorted in the same sub sample might act independently of each other regardless of size. Furthermore, a legacy of large, failing firms is that their capital structure might remain the same, thus, are more exposed to tighter credit supply in the market. Consequently, one would expect small size risk premium to originate from factors relating to credit risk contrary to a value weighted market factor heavily dependent on successful, large firms (Chan and Chen, 1991). Therefore, it is evident that although size and BM have been found to possess financial distress information in the past literature later studies questions this. Fama and French (2008) accept the limitations of their three-factor model in particular with regards to momentum, financial distress and net stock issuance¹.

Of other factors presented by academia, momentum (Jegadeesh and Titman, 1993) is the most puzzling. Avramov et al. (2007) find that the momentum is in fact exclusive for samples characterising high credit risk. Their portfolios sorted by momentum reveal, in the subsamples of both extremes, all companies are of the lowest or second to lowest credit quality by rank. Importantly, the authors find momentum as a measure of credit rating rather than information

¹ See Ikenberry, Lakonishok, and Vermaelen, 1995; Loughran and Ritter, 1995; Daniel and Titman, 2006; Pontiff and Woodgate, 2008 for research on net stock issuance as this is beyond the scope of this research.

uncertainty as momentum across credit groups are not explained by information uncertainty. Chordia and Shivakumar (2002) find that momentum returns are also strongly linked to business cycles. The authors argue momentum only to occur during economic expansion whereas in recession the effect disappears. Therefore, momentum might be capturing a credit risk premium.

Credit risk in various measures is subject to a vast academic literature studies (Duffie and Singleton, 1997; Altman and Saunders, 1998). Vassalou and Xing (2004) are, however, first to use Merton's (1974) option pricing model to study how default risk increases the cost of debt financing for individual firms as the respective default risk increase. Thus, as distance to default increase cost of debt financing should increase for all firms. Although market capitalisation is directly impacting the measure of default risk, it is not obvious as to what extent return structure is driven by default risk given the subordinate nature of equity to debt. If default risk is sufficiently high, a favourable change in default risk might not get reflected in expected cash flow attributable to equity holder. On the contrary, an adverse change in default risk for a sufficiently low default risk might not get reflected in pricing the value of equity. Moreover, the traditional default spread is arguably not actually capturing default risk directly as systemic market risk is very pronounced (Elton, 2001; cited in Vassalou and Xing, 2004). Dichev (1998) finds firms with high bankruptcy risk do not return a premium on this risk. Moreover, high bankruptcy risk is associated with high BM, however, the extreme high bankruptcy risk is related to low BM. Default risk is to be associated with both extremes when sorting portfolios is also in accordance with Avramov et al. (2007) discovery when studying the momentum factor. Furthermore, Pereira and Rua (2018) present evidence on how distance to default in the banking sector is linked to credit supply to the wider economy and bankruptcy filings. The authors provide evidence specifically capturing a measure of financial distress for the banking

sector as opposed to the wider economy and thereby specify the effects of changes in creditworthiness of the sector on the wider economy.

Kiyotaki and Moore (1997) introduce a model in which lenders have to incur losses on their loans in the case of debt issuance not being secured. This distinction of debt highlights an interesting aspect of credit effects on firms as in a deteriorating market, high leverage can create a destructive spiral of reducing free cash flows and collateral value of assets. Moreover, if one firm in the industry experience the value of their assets is decreasing, the whole industry is likely experiencing the same, thereby enhancing the price pressure on firms in need of liquidating assets. Firm specific events can cause firms to face unsustainable levels of debt and therefore fail. However, only economic shock to the industry can deteriorate asset values to the extent that additional pressure on asset prices is experienced. If an adverse shock to credit supply is imposed in isolation, asset value of the borrowing industry is arguably not impacted directly. However, highly leveraged companies dependent on rolling over debt will face difficulties threatening to reduce industry output. Because industry assets are unaffected, firms with a conservative debt burden or new entrants can pursue acquisitions of the struggling firms mitigating output disruption and negative ripple effects in the market. This is also true for banks as proposed by Acharya (2009) where failure of one bank can have two opposing effects. Firstly, spill over effects as reduction in total supply of funds are reduced impacting funds available for investments. Secondly, remaining banks with financial and strategic capacity can exploit the situation by expansion. Nevertheless, the author finds the negative effects to exceed the positive supporting the argument of industrial asset return correlations and the literature on contagion.

Contagion in the banking sector is a central topic in the literature on systemic risk predominantly studied in parallel to asset pricing models. Kaufman (1994) argues contagion is

more likely in the banking sector and that failure of a bank has higher potential to adversely affect the wider economy due to its vital role in facilitating credit funding the economy. Firstly, due to the mismatch between long-term lending and short-term funding of banks adverse changes in cost of funds will spread faster in the financial sector (Kaufman, 1994). Secondly, industry specific shocks are more likely in the banking sector compared to other industries due to lack of information by creditors (depositors). Hence, contagion is assumed to spread wider within the industry for adverse shocks. Past research suggests similarity among lending portfolios is a crucial source of information contagion (Diamond, 1984; Calomiris and Kahn, 1991). However, it is not found to significantly impact bankruptcy rates historically, rather incapable management, small and undiversified banks and restrictive Fed policies (Kaufman, 1994). Lastly, due to lower than non-bank capital ratios and the economic importance of deposits, adverse shocks to banks might logically result in higher creditor losses. The economic importance of deposits is natural due to it predominantly being held privately by a majority of people in the economy and represents the most liquid part of consumer wealth. If losses are incurred on deposits, this will spill over to consumption in the following period, thus, other industries are most likely to experience a lagged adverse effect in sales (Kaufman, 1994).

Contagion can appear in three channels (Furfine, 2003). Firstly, ripple effects in payments systems or interbank lending markets. Freixas et al. (2000) studies the interbank structures with regards to lending among banks and how central banks facilitate liquidity in this market. The authors find that interbank lending reduce cost of holding liquid assets under normal market conditions. However, the structural flow of funds might also reduce incentives for an inefficient bank to fail as it can gain access to funding from the interbank credit lines. Thus, the interbank lending market reduces incentives for discipline. Freixas et al. (2000) suggest this is a reason for central banks to intervene by regulating the market. However, if appropriate measures of interconnectedness can be incorporated in a systemic credit risk factor in an asset pricing model

the market can effectively price the fluctuations in interconnectedness. Thereby, discipline is reinstated in the market without reducing the benefits of the interbank lending market. Secondly, exposure to the same failing or non-performing asset specific to an industry might cause banks to face difficulties simultaneously (Furfine, 2003; Aharony and Swary, 1983). The characteristic similarity in lending portfolios of banks will expose these respective banks to the same industry specific assets (Acharya, 2009). Therefore, in accordance with Kiyotaki and Moore (1997), if the industry in question experiences an adverse shock in its ability to generate cash flows or if collateral value of the asset diminished, it has the potential to incur losses on the lenders as well. Acharya (2009) finds correlation of banking assets increasing the incentives to trade away this risk, thus, spreading the banking risk to other financial sectors. Thirdly, uncertainty of how single credit events can spread through the financial markets. Furfine (2003) suggests the first origin of contagion likely is not sufficient to describe a systemic threat, although the uncertainty during a single credit event might exacerbate the magnitude. Hence, lack of knowledge or experience can unsettle markets sufficiently resulting in contagion. Acharya (2009) argues that this information contagion effect will incentivise banks to engage in correlating investments, increase exposure to similar assets, to limit the additional cost of bad news to other banks. Chen (1999) present a model describing how incentives of informed depositors are to withdraw before information is revealed in the case where the news of another bank's failing is spreading due to uninformed depositors knowingly are at disadvantage and will therefore act early. Therefore, credit conditions of individual banks must be considered in relation to the banking system when evaluating systemic credit risk.

Ultimately, banks have been unaware or underestimated the true effects of interconnectedness. Cifuentes et al. (2005) suggest individual financial institutions are not incorporating the external effects it has on other firms. Hence, the optimal amount of liquid assets held by the institution might exceed its actual holdings from a systemic point of view. This is evident in Acharya and

Skeie (2011) where banks are shown to pay excessive premiums for liquidity in times of crisis. Additionally, Cifuentes et al. (2005) contend regulations, particularly minimum capital requirements, might even have an undesirable spill over effect as assets are marked to market introducing channels for contagion. On the contrary, the authors argue that liquidity requirements can potentially mitigate contagion risk substituting the need for capital buffers. Furthermore, Cifuentes et al. (2005) argues that banking interconnectedness and the contagion is in fact not solely credit risk, merely the interaction of credit risk, market risk and counterparty risk and academia have in recent times published several methods for how to measure this complex interaction. Cai et al. (2018) present a measure for interconnectedness by correlating lending exposures. They find diversification of lending portfolio to be the primary driver of banking interconnectedness. By correctly pricing interconnectedness when measuring credit risk of the banking sector, incentives for banks to engage in risk-shifting activities and correlated investment strategies have the possibility to decrease regulatory subsidies. This is in accordance with Rochet and Tirole's (1996) argument where centralised government monitoring is offsetting the benefits of having a decentralised lending industry monitoring each other. The authors argue in a peer-monitoring system banks' capital should shift from the current short-term funding focus to more long-term focus as banks are responsible for any loss incurred by interbank linkages. However, introducing market discipline through pricing and sharing the risk among market participants can also have adverse effects. The argument for pricing interconnectedness will not close the three above-mentioned channels of contagion, rather mitigate moral hazard issues of exploiting governmental subsidies. In other words, pricing interconnectedness can at best mitigate too-big-to-fail or too-significant-to-fail problems by reducing governmental interaction in failing banks shifting cost of default from tax payers to the industry.

3. Methodology

3.1. Credit risk factor

The credit risk factor (“CRF”) originate from the banking factor presented by Pereira and Rua (2018), where the distance to default (“DD”) of commercial banks are shown to be a priced risk factor when controlling for the market beta. However, this study applies some adjustments to their banking factor. Among others, the banking system is defined as the globally systemically significant banks receding in the US rather than all commercial banks and weighted by banks’ interconnectedness contrary to size. Lastly, while the banking factor is defined as the periodical change in DD, the CRF is also taking into consideration the previous period DD.

3.2. Interconnectedness

Interconnectedness weights are based on Cai et al. (2018) creating proxies of banks’ lending portfolios using the loan facilities originated by each respective bank split by industry of the borrowing company. This follows three steps where the first is computing the distance between each bank monthly. All loan facilities are assigned to each respective lead credit arranger. If there are multiple lead credit arrangers, or unidentified, total loan facility is split in equal proportion to each lending bank. All facilities are then linked to a borrowing company before the corresponding two-digit SIC code is used to distinguish the lending exposures by industry. Unlike Cai et al. (2018), this article will not divide the US market into geographic locations. All facilities are split as per issuing month by bank before each banks’ loan issuance is summed for the past 12 months per industry on a rolling basis. Following, the weight for each banks’ loan issuance per industry per rolling 12 months is computed. The distance between each bank’s lending portfolio, denoted by l , is defined as the sum of all squared differences by industrial facility origination, denoted by j , per month multiplied with $\frac{1}{\sqrt{2}}$ in order to standardise the scores between [0,1].

$$Distance_{(i,k,t)} = \frac{1}{\sqrt{2}} \times \sqrt{\sum_{j=1}^J (l_{(i,j,t)} - l_{(k,j,t)})^2} \quad (1)$$

Second step is to compute each individual bank's interconnectedness score, where the sum of all interconnectedness scores equals the bank system's interconnectedness levels. The interconnectedness of each bank i is computed as;

$$I_{(i,k,t)} = \left(1 - \sum x_{(k,t)} \times Distance_{(i,k,t)}\right) \times 100 \quad (2)$$

Where x is the weight of the opposing bank relative to all banks identified in the system based on their total assets and k is other banks in the system. Lastly, the CRF weights are computed as the simple proportionate contribution to the systemic interconnectedness by each bank defined by

$$w_{(i,t)} = \frac{I_{(i,t)}}{\sum I_{(i,t)}} \quad (3)$$

3.3. Composition of CRF

Similar to Pereira and Rua (2018), the DD is based on Merton's (1974) model. The point of default is defined as assets equal debt. Most prudent would be to use the market value of debt, however, accounting data is used as it is easier obtainable. Consequently, debt is equal to total liabilities reported on a quarterly basis. Market capitalisation is on the contrary readily available. Accordingly, asset value is equal to the sum of total liabilities and market capitalisation. Thus, both equity and debt holders' continuous claim to each banks' assets are taken into consideration when computing the DD. Further, the drift is computed based on the monthly log returns from the past 12 months and on a rolling basis. The volatility is adjusted according to Bharath and Shumway (2008) where

$$\sigma_{(asset,t)} = 0.05 + 0.25 \times \sigma_{(equity,t)} \quad (4)$$

and computed on a rolling basis using the past 12 months market capitalisation fluctuations.

$$Adjusted\ DD_t = \sum_{i=1}^I \frac{\left(\ln\left(\frac{A_{(i,t)}}{D_{(i,t)}}\right) + \left(r_{(i,t)} - \left(\frac{\sigma_{(i,t)}^2}{2}\right)\right) \times T\right) \times w_{(i,t)}}{\sigma_{(i,t)} \times \sqrt{T}} \quad (5)$$

$$CRF_t = \frac{Adjusted\ DD_t}{Adjusted\ DD_{t-1}} - 1 \quad (6)$$

Lastly, in order to limit outlier problems when DD is approximating zero, the CRF range is capped to \pm two times the mean from zero. This is only adjusting for 15 out of 336 data points, thereby deemed reasonable and not impacting the economic interpretations of the results.

3.3.1. Interpretation of CRF

The economic interpretation of CRF is naturally close to the banking factor by Pereira and Rua (2018). Their paper provides evidence on how credit supply to non-financial is affected by DD of the banking sector whereas demand for credit is unrelated to the financial soundness of the banking sector. New to academic literature is the inclusion of interconnectedness allowing CRF to emphasize the risk of contagion to the financial system. Although Cai et al. (2018) describe large banks in general as more interconnected due to their inability to differentiate their syndicated lending base, this interconnectedness weight is more nuanced in comparison to asset data. DD of each bank will shed light on the financial state of one lender, whereas the interconnectedness of the bank is describing a specific bank's importance in relation to other lenders. Nevertheless, asset size remains a decisive factor when weighting aggregate DD because interconnectedness weights are directly dependent on size. Moreover, CRF is by definition the percentage change from past period to the current period, whereas the banking factor is the change from one period to the next. Thus, CRF is designed to distinguish between relatively modest changes in good times as less important contrary to changes bad states, which will be enhanced. The logic being investors cares more about the credit risk when bad turn worse compared to when good states turn a little less good (Allen and Gale, 2005; He and Krishnamurthy, 2013).

3.3.2. Causality

The rolling loan origination with two lags yields the highest correlation to Adjusted DD (Table 1). The coefficient of 22.25 for the loan origination is significant, p-value = 0.0275, and insignificant alpha. Therefore, increase in lending activities appear to be positively related to DD. Generally, strong financial institutions are associated with good states of the economy and inversely with banks' tightening credit standards (Pereira and Rua, 2018). Thus, Adjusted DD is a proxy for good states in the economy and CRF the speed and direction. Arguably, the lagged effect on Adjusted DD might demonstrate the positive effects of increased business opportunities on banks' credit worthiness. It is also logically assumed the lagged correlation of lending data to Adjusted DD can be related to Pereira and Rua's (2018) co-movement of banks' credit tightening versus their DD measure where loan officer opinions are used to illustrate the correlation between DD and banks' lending practices. These opinions are naturally forward looking, thus, the effect measured by loan origination will therefore lag in time. Additionally, it is curious to observe a reversal effect in the data. As for why this is the case is beyond this study, however, market conditions can be a suggested reason. I.e. debt is only available in periods of time when risk-averse debt investors and lenders are optimistic about the future.

Table 1: Aggregate DD versus Rolling 3 month loan origination

	β	S.E.	R ²	F/df	p-value
Aggregate DD - 0 Lags	0.0003	0.0003	0.0037	1.2278	0.2686
α	0.0188	0.0083		334	0.0236
Aggregate DD - 1 Lag	(0.0006)	0.0003	0.0141	4.7766	0.0295
α	0.0175	0.0082		333	0.0346
Aggregate DD - 2 Lags	0.0001	0.0003	0.0004	0.1182	0.7312
α	0.0192	0.0083		332	0.0212
Rolling 3 months Loan Origination US - 0 Lags	11.1523	10.0648	0.0037	1.2278	0.2686
α	(1.8033)	1.5325		334	0.2401
Rolling 3 months Loan Origination US - 1 Lag	21.1288	10.0368	0.0131	4.4316	0.0360
α	(1.9848)	1.5294		333	0.1953
Rolling 3 months Loan Origination US - 2 Lags	22.2541	10.0479	0.0146	4.9053	0.0275
α	(2.0053)	1.5326		332	0.1916

Aggregate DD versus lagged Rolling 3 months Loan Origination US							
	0 Lag	1 Lag	2 Lag	3 Lag	4 Lag	5 Lag	6 Lag
ρ	0.0605	0.1146	0.1207	(0.0124)	(0.0493)	(0.1495)	0.0253

3.4. Sample

The data is collected from the WRDS database relying on Compustat, CRSP and WRDS-Reuters DealScan. The time range for this research is limited to 1990 to 2017 limited by the available data, particularly in relation to interconnectedness. In total 145 503 loan facilities were documented of which 65 473 was linked to the eight banks defined in the system exceeding 50% of the loan issuance amount identified. The interconnectedness computation takes into consideration major M&A events in the relevant period for consistent treatment of assets and loan origination. Appendix 1 lists the defined banking system including legacy banks used when computing interconnectedness weights. As banks report on a quarterly basis the data will not allow for accurately computing DD monthly. Compustat also provided the share prices and number of shares outstanding on a daily basis. From this, monthly log returns, drift and volatility were computed for the computation of Adjusted DD.

4. Asset Pricing Model

The proposed asset pricing model include two factors: the market return in excess of risk free (“MKT^e”) and CRF. The expected excess return and time series regression is given by the following two equations:

$$E(R_{i,t}^e) = \beta_{i,MKT^e} \times \lambda_{MKT_t^e} + \beta_{i,CRF} \times \lambda_{CRF_t} \quad (7)$$

$$R_{i,t}^e = \alpha_i + \beta_{i,MKT^e} \times MKT_t^e + \beta_{i,CRF} \times CRF_t + \varepsilon_{it} \quad (8)$$

The CRF beta is expected to be positive yielding a risk premium for firms exposed to the state of the financial system. Increased lending activities is describing an economic environment where firms face attractive investment opportunities, thus, firms yield higher returns when the financial system is strengthening and vice versa.

4.1. Construction of test portfolios

The test portfolios are constructed regressing the log returns of the 500 largest firms in the US each month. Following, all firms are ranked then sorted, based on CRF and market betas, into

5 portfolios each of increasing exposure to the respective beta. All betas are computed on a rolling 24 month basis accepting varying risk exposures through time. Subsequently, 25 test portfolios are created from the five-by-five set of single sorted beta portfolios. There are 1940 companies in this sample, however, not all have available return data for the entire period. Thus, companies without return data for the past 24 months are excluded when computing portfolio returns. Furthermore, the returns are equally weighted.

Table 2: Test portfolio descriptive statistics

CRF: Single sorted portfolios					
	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF
Avg. Return	0.293	0.473	0.398	0.616	0.563
Median	0.532	0.911	0.703	1.327	0.934
S.E.	3.752	5.227	5.783	5.278	3.884
Skew	(0.387)	(0.391)	(1.087)	(0.978)	(0.731)
Kurtosis	0.945	2.026	5.618	3.083	2.755
CAPM B	0.598*	1.038*	1.226*	1.106*	0.672*
CAPM A	(0.100)	(0.210)	(0.409)*	(0.112)	0.120
CRF B	0.020*	0.013*	(0.000)	(0.012)*	(0.020)*
*p-value < 0.05					
CAPM α					
	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF
HiMkt	(0.1872)	(0.2422)	(0.3417)	(0.1931)	(0.0769)
	.0484	.0116	.0001	.0196	.3688
2 Qnt	(0.2439)	(0.2989)	(0.3985)	(0.2499)	(0.1336)
	.0187	.0063	.0001	.0099	.1532
3 Qnt	(0.2334)	(0.2884)	(0.3879)	(0.2393)	(0.1231)
	.0324	.0166	.0010	.0277	.2289
4 Qnt	(0.1343)	(0.1893)	(0.2888)	(0.1402)	(0.0240)
	.2770	.1757	.0392	.2743	.8440
LoMkt	0.1924	0.1374	0.0379	0.1865	0.3028
	.1526	.3646	.7987	.1750	.0225
Average excess returns					
	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF
	0.292	0.382	0.345	0.454	0.427
	0.292	0.382	0.344	0.453	0.427
	0.338	0.428	0.390	0.499	0.473
	0.422	0.512	0.474	0.583	0.557
	0.561	0.650	0.613	0.722	0.696
*monthly portfolio returns in excess of risk free rate					
CRF β					
	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF
HiMkt	0.0103	0.0068	0.0002	(0.0058)	(0.0097)
	.0000	.0000	.8136	.0000	.0000
2 Qnt	0.0101	0.0066	(0.0000)	(0.0060)	(0.0100)
	.0000	.0000	.9786	.0000	.0000
3 Qnt	0.0100	0.0065	(0.0001)	(0.0061)	(0.0100)
	.0000	.0000	.9561	.0000	.0000
4 Qnt	0.0095	0.0060	(0.0006)	(0.0066)	(0.0106)
	.0000	.0000	.6701	.0000	.0000
LoMkt	0.0096	0.0062	(0.0004)	(0.0064)	(0.0104)
	.0000	.0001	.7803	.0000	.0000
Mkt β					
	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF
	0.7285	0.9484	1.0427	0.9824	0.7656
	.0000	.0000	.0000	.0000	.0000
	0.8142	1.0340	1.1283	1.0680	0.8512
	.0000	.0000	.0000	.0000	.0000
	0.8680	1.0879	1.1822	1.1219	0.9051
	.0000	.0000	.0000	.0000	.0000
	0.8451	1.0650	1.1593	1.0990	0.8822
	.0000	.0000	.0000	.0000	.0000
	0.5595	0.7794	0.8736	0.8134	0.5965
	.0000	.0000	.0000	.0000	.0000

Table 2 display the time series descriptive statistics of the test portfolios. Surprisingly, return figures are, contrary to expectations, increasing with lower betas. In particular, portfolios sorted on market beta appear to be influenced by size as size is decreasing with beta, which is consistent through time. This characteristic is not true for the CRF sorted portfolios. However,

high and low beta single sorted portfolios are both made up of large companies contrary to 2nd, 3rd and 4th quintile, which are all comparable with regards to total market capitalisation. Table 2 also display 15 out of 25 CAPM alphas yield significant statistics implying CAPM being insufficient to explain the return structure of these portfolios. Generally, alphas are negative except for combinations of low market beta, which has positive alphas. Moreover, alphas seem to be increasing in statistical significance with both CRF and market beta. In terms of magnitude, higher alphas tend to increase with market beta. Consequently, firms capturing higher market risk also appear to possess additional risk characteristics not detected by the market risk factor. The bottom two tables are the times series coefficients and the corresponding p-values from the below asset pricing test.

5. Main asset pricing test

First, each test portfolio is regressed in time series to estimate the full sample betas. Subsequently, the cross-sectional regression of portfolio average returns on the previously estimated betas yield excess risk premiums.

$$\bar{R}_i^e = \lambda_{MKT^e} \times \beta_{i,MKT^e} + \lambda_{CRF} \times \beta_{i,CRF} + \epsilon_i \quad (10)$$

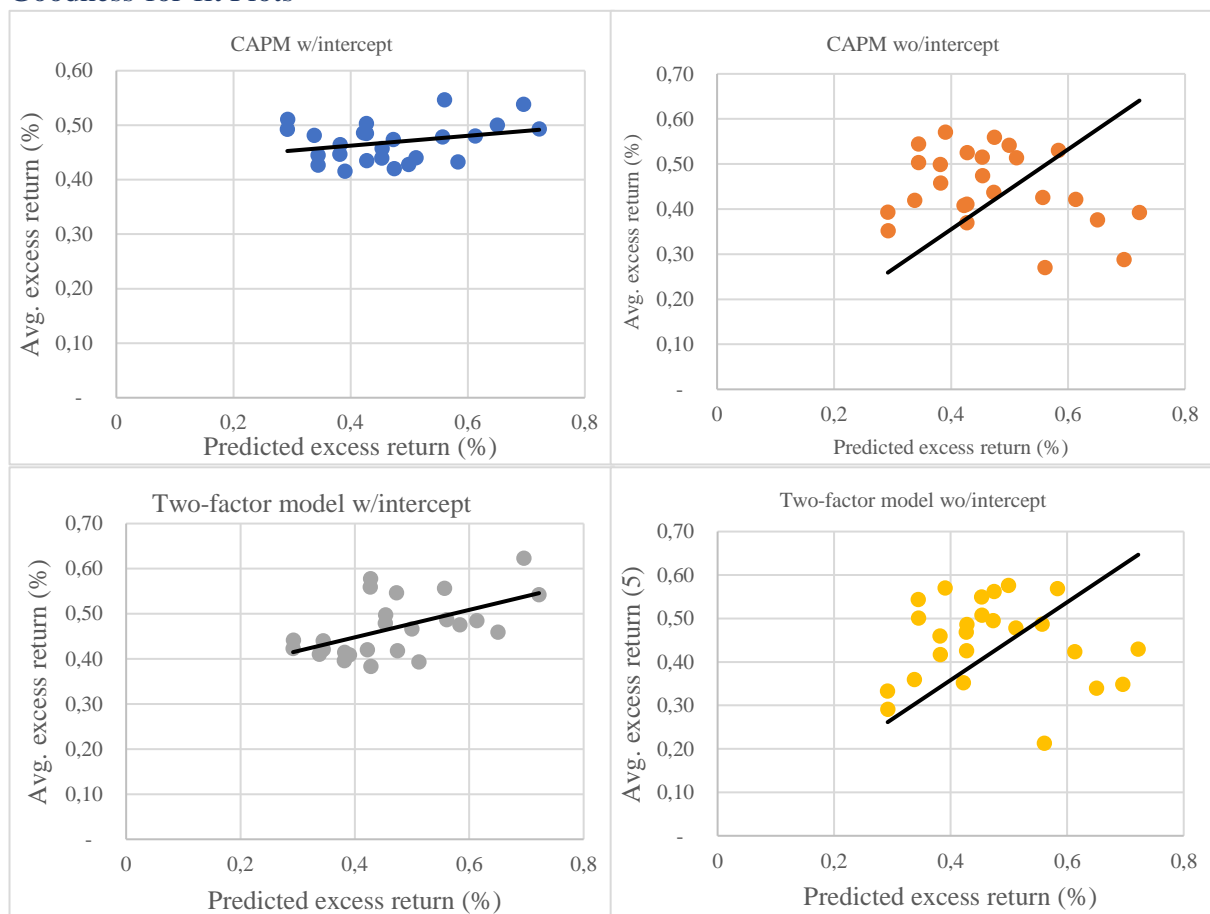
Table 3: Cross Sectional Regression

	Intercept	λ_{mkt}	λ_{crf}	X ² test	
				Statistic	p-value
Coefficients	0.6638	(0.2103)			
S.E.	0.1310	0.1389		0.6401	1.0000
t Stat	5.0674	(1.5138)			
Coefficients		0.4825			
S.E.		0.0351		1.8280	1.0000
t Stat		13.7556			
Coefficients	0.6894	(0.2382)	(7.2357)		
S.E.	0.1176	0.1247	2.7838	0.4962	1.0000
t Stat	5.8642	(1.9104)	(2.5992)		
Coefficients		0.4815	(5.8665)		
S.E.		0.0345	4.3435	1.7706	1.0000
t Stat		13.9587	(1.3507)		

Table 3 show the cross-sectional regression outputs. First, CAPM is found to perform badly when allowing for an intercept. However, the second case where theory is forced on the data, CAPM yields a significant monthly risk premium of 0.48% (5.45% p.a.). The same procedure

is done for the two-factor model. If intercept is allowed, market factor yields a negative excess premium, albeit not statistically different from zero. CRF, on the contrary, yields a statistically significant and strongly negative risk premium. The alpha is also highly significant at 0.69% per month. The story repeats itself once theory is forced on the data fixing intercept to zero. The market risk premium is “corrected” to 0.48% per month, however, the CRF is now insignificant. The goodness-for-fit plots (5.2.) illustrate the dispersion in the data set. Contrary to the ideal cluster of data point forming a 45-degree line, the predicted versus average excess return plots tends towards a flatter line with data point scattered to the sides of the best-fitted line. Ultimately, this research finds no evidence to the proposed model in the data and must therefore reject the CRF factor.

Goodness-for-fit Plots



6. Limitations

A significant limitation to this measure of interconnectedness is the neglect of investment banking activities. This is mitigated by scaling the interconnectedness by asset size, however, it is naïve to argue this fully correct the issue. Moreover, lending is only one out of three channels for systemic contagion defined in literature. Hence, it is unlikely this measure will capture the full extent of interconnectedness. Financial innovations have allowed banks to engage in risk-shifting practices on a wide scale which can have severe implications in the financial system, acutely illustrated by the bail-out of AIG during the financial crisis. This research is restricted by a narrow definition of the banking system. Thus, further research is encouraged to expand the inclusion of other commercial banks and insurance companies. Furthermore, data is limited to S&P 500 companies. It is important to be aware of this bias towards larger companies as it is reasonable to assume these firms are less dependent on bank lending by accessing public debt markets. Moreover, size is identified as a distinct characteristic in the constructed portfolios. Thus, inclusion of a wider range of companies is likely to improve the data set. Lastly, all asset pricing models are at risk of biased results due to omitted variables. This study does not claim to present the ideal asset pricing model accepting the possibility for other factors related and unrelated to credit risk also systemically important when describing asset price structures.

7. Additional regressions

To further investigate the return structure of the 25 test portfolios, Carhart's (1997) four-factor model is used to test an alternative model on the data following the same procedure as the main asset pricing test. First the time series betas are estimated followed by the cross-sectional regression of the average excess portfolio return run on the estimated betas.

Table 4: Time series regression betas – Alternative regression

Mkt β						HML β				
	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF
HiMkt	0.7482	0.9495	1.0224	0.9626	0.7851	0.2261	0.3184	0.2971	0.2012	0.1855
	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
2 Qnt	0.8206	1.0219	1.0948	1.0350	0.8574	0.2813	0.3736	0.3523	0.2564	0.2407
	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
3 Qnt	0.8715	1.0728	1.1458	1.0860	0.9084	0.3518	0.4441	0.4228	0.3269	0.3112
	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
4 Qnt	0.8483	1.0496	1.1226	1.0628	0.8852	0.4336	0.5259	0.5046	0.4087	0.3929
	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
LoMkt	0.5666	0.7679	0.8408	0.7810	0.6034	0.4749	0.5672	0.5459	0.4500	0.4342
	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
SMB β						Mom β				
	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF	HiCRF	2 Qnt	3 Qnt	4 Qnt	LoCRF
HiMkt	(0.0274)	0.0935	0.1732	0.1504	0.0492	(0.0430)	(0.0756)	(0.0942)	(0.0658)	0.0182
	.3235	.0002	.0000	.0000	.0631	.0222	.0000	.0000	.0000	.3081
2 Qnt	0.0301	0.1510	0.2308	0.2079	0.1067	(0.0787)	(0.1114)	(0.1299)	(0.1015)	(0.0175)
	.2996	.0000	.0000	.0000	.0001	.0001	.0000	.0000	.0000	.3473
3 Qnt	0.0982	0.2190	0.2988	0.2760	0.1747	(0.0784)	(0.1111)	(0.1296)	(0.1012)	(0.0172)
	.0008	.0000	.0000	.0000	.0000	.0001	.0000	.0000	.0000	.3712
4 Qnt	0.1929	0.3138	0.3936	0.3707	0.2695	(0.0578)	(0.0904)	(0.1090)	(0.0805)	0.0034
	.0000	.0000	.0000	.0000	.0000	.0081	.0001	.0000	.0002	.8770
LoMkt	0.2002	0.3211	0.4009	0.3780	0.2768	(0.0573)	(0.0899)	(0.1085)	(0.0801)	0.0039
	.0000	.0000	.0000	.0000	.0000	.0162	.0003	.0000	.0005	.8709

Interestingly, momentum appear to yield negative beta for the 25 test portfolios. The exceptions are among portfolios characterising low CRF betas, all of which are statistically insignificant. Furthermore, HML betas report consistently higher magnitude in comparison to SMB and all factor betas follow similar patterns strengthening in magnitude for combinations of third quintile sorted portfolios. Lastly, SMB yield insignificant betas for portfolios of high and low CRF betas in combination with high market beta.

Table 5: Cross sectional regression – Alternative regression

	Intercept	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{mom}	X ² test	
						Statistic	p-value
Coefficients	0.7307	(0.4101)	1.1366	(0.2536)	0.4824		
S.E.	0.0841	0.0816	0.1265	0.1462	0.2960	9.5278	0.9962
t Stat	8.6883	(5.0255)	8.9825	(1.7342)	1.6297		
Coefficients		0.2479	0.5110	0.7349	2.0594		
S.E.		0.0648	0.2219	0.1958	0.4985	0.3081	1.0000
t Stat		3.8272	2.3031	3.7526	4.1310		

When running the cross section of the four-factor model allowing for an intercept, only market and SMB yield significant risk premiums in addition to the significant intercept. In line with the main asset pricing test, the market yields a negative risk premium of 0.41% per month. SMB's risk premium is reported at 1.14% per month which confirms previous indications of size characteristics to be influential in this data set. In the case where intercept is set to zero, all

four factors yield a significant risk premium. Momentum yield an abnormal 2.06% per month in contrast to HML, SMB and the market factor yielding 0.73%, 0.51% and 0.25% respectively. Lastly, the former cross-sectional regression's strong significance and magnitude of the intercept imply yet uncovered risk factors important to explain the asset pricing structure of the constructed portfolios. Thus, although all four factors of Carhart's model yield strong significance when forced on the data the intercept suggest this is not sufficient.

8. Conclusion

This paper finds strong theoretical foundations for banking interconnectedness and credit risk to be tied together. Until recent credit risk has often been treated in isolation with the logical implication of no impact on the wider financial ecosystem. However, systemic risk in the financial sector is more complex. Thus, treating credit risk and interconnectedness in silos will not enable a true representation of risk. Undoubtedly, the positive effects of such measure on market discipline and efficient asset pricing are highly attractive when considering the aftermath of the last financial crisis. The too-big-to-fail issue regulators, authorities and tax-payers face can improve in the case where a reliable measure of systemic risk in the financial system is developed by imposing market discipline where the market participants bear the costs. Thereby, mitigating the need for regulators interfering with markets and unintended consequences of regulations. The two strains of literatures are widely studied in separation and advanced models for measuring either source of risk has been present for many years. This study, inspired by Pereira and Rua (2018) and Cai et al. (2018), combine two successful measures of credit risk and interconnectedness. Regretfully, this yielded unsatisfactory results, however, limitations to the methods used are several and future research can greatly improve either the measure or add to the rational leading to more precise and successful data. Regardless, this paper should remain academic and regulatory interest as the motivation of this study is well founded in established literature. Moreover, the potential economic benefits of the

development of a successful measure combining credit risk and interconnectedness in the financial sector should prove sufficient motivating further research in this field.

Appendix

Appendix 1: Bank Lending institutions

Bank of America (BoA)	Bank of New York Mellon	Citibank	Goldman Sachs	JP Morgan	Morgan Stanley	State Street	Wells Fargo
BoA International Ltd	Bank of New York	Citibank	Goldman Sachs & Co	JP Morgan & Co	MS Senior Funding Inc	State Street Bank & Trust	Wells Fargo & Co
BoA National Trust & Savings	Bank of New York Co Inc [BNY]	Citicorp Investment Bank Ltd (UK)	Goldman Sachs Credit Partners LP Goldman Sachs Capital Partners	JP Morgan Securities Inc	MS Dean Witter & Co		Wells Fargo Bank Wells Fargo Realty Advisors Funding
BoA Texas	Barclays Bank of New York	Citicorp	Goldman Sachs Mtg Co	JP Morgan Delaware	MS Group		Wells Fargo HSBC Trade Bank
BoA Illinois	Mellon Bank	Citicorp Savings		JP Morgan Australia Ltd	MS & Co International		
BoA Canada	Mellon Bank (East)	Citicorp USA Inc		Chase Manhattan Bank	MS Mortgage Capital		Wells Fargo - Texas
BoA Nevada	Mellon Bank Canada	Citicorp Real Estate Citicorp North America Inc		Chase Manhattan Asia Ltd	MS Capital Partners		Wachovia Bank Wachovia Bank of North Carolina
BoA Oregon	Mellon Financial Services Corp	Citicorp International Plc		Chase Manhattan Bank of Canada	MS Dean Witter & Co Dean Witter Realty Yield Plus LP		
BoA Arizona	Mellon Bank Corp	Citicorp Securities Markets		Chase Manhattan Corp			Wachovia Bank of Georgia Wachovia Bank of South Carolina
BoA	BNY Capital Markets	Citicorp Savings of Florida		Chase Manhattan Investment Bank Ltd	Dean Witter Dean Witter Discover & Co		Wachovia Corp
Merrill Lynch & Co Inc	Israel Discount Bank of New York Inc	Citicorp International Plc		Chemical Bank			
Merrill Lynch Capital Corp	BNY Financial Corp (Canada) Bank of New York Commercial Corp	Citicorp Venture Capital Ltd		Chemical Bank of Canada			
ML Interfunding		Citibank of Canada		Chemical Bank New Jersey NA			
ML Business Financial Services Inc		Citicorp Leasing Inc		Chase Securities			
ML International Bank Ltd				Chase Commercial Corp			
ML Capital Markets				Chase Lincoln First Bank			
ML Capital Partners				Chase Investment Bank Ltd			
ML Business Capital				Chase Bank of Florida			
ML Mortgage Investors				Chemical Securities			
ML International & Co				Chemical Securities Asia			
Fleet Financial Corp				JPM Co			
Fleet Financial Group Inc				Bear Stearns Cos			
BankBoston NA				Bear Stearns & Co			
BankBoston Capital				Morgan Guaranty Trust			
BankBoston Corp				First Chicago NBD Corp			
Fleet Bank NA				Manufacturers Hanover Trust			
Fleet Bank							
Fleet Bank of Massachusetts							
Fleet Bank of Maine							
Fleet Bank of New York							

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