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Bank Rating Gaps as Proxies for Systemic Risk

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Abstract

Banks receive two types of ratings from major rating agencies: an "all-in" and a "stand-alone" rating. This paper investigates whether rating gaps between all-in ratings and stand-alone ratings could serve as a useful measure for the systemic risk of banks. Using US data from 1994 to 2007, the link between the rating gaps and a quantitative systemic risk measure, Co-independent Value at Risk (CoVar), is examined. The conclusion is that rating gaps are good proxies for systemic risk of large banks.

Keywords: Bank, Rating gaps, Systemic risk, CoVar

JEL classification codes: G21, G28

1. Introduction

Three major credit rating agencies, (Fitch, Moody's, and Standard & Poor's) each provide two types of ratings for individual banks: an "all-in" and a "stand-alone" rating. A stand-alone rating is referred to as an "individual rating" by Fitch, as a "bank financial strength rating" by Moody's, and as a "stand-alone credit profile" by Standard & Poor's. An all-in rating is referred to as a "long term issuer default rating" by Fitch, and an "issuer rating" by Moody's and Standard & Poor's. An all-in rating contains information about not only a bank's own financial strength itself, but also the external support a bank could receive from its parent holding institution and/or government authorities. A rating gap is the difference between an all-in and a stand-alone rating. Rating gaps capture the possible external support these banks may receive. This paper investigates whether the rating gap between an all-in and a stand-alone rating for a bank could serve as a useful measure for the systemic risk of the bank. Systemic risk is defined as systemic importance of an individual bank; that is, how much influence a bank in distress has on the banking system as a whole.

This paper is motivated to explore whether the information contains in the rating gaps are useful to identify too-big-to-fail (TBTF) or systemic important banks. TBTF has become a major policy issue since the 2008 financial crisis. Most governments decided to offer subsidies to large financial institutions in order to avoid the collapse of their financial systems due to the failure of a financial institution such as Lehman Brother. The subsidies to TBTF banks generate externality cost to the society and induce moral hazard problems within banks. Thus, using public fund to save TBTF financial institutions may cause resource misallocation in the economy. It is the responsibility of regulators to supervise and to monitor TBTF risks on the banking system on a regular base. Rating gaps are convenient for regulators to use as proxies for systemic risk at a certain frequency since rating agencies publish ratings frequently. Research suggests that since investors expect that TBTF financial institutions are guaranteed to be bailed out, it helps them to receive cheaper funding cost, comparing to non-TBTF banks (Jacewitz and Pogach, 2014). Investors will be benefited by just looking at a simple indicator for systemic risk and distinguish between whether the funding discount they give to TBTF is because of the financial strength of banks themselves or for the potential support from their governments.

To the full extent of TBTF related studies, to identify which intuitions are TBTF should be the first step. Financial Stability Board (FSB) published an official list of global systemic important banks (G-SIB) in 2011 and has updated the list every November since then. Bank for International Settlements (BIS) provides an indicator based methodology to identify G-SIBs, which "reflect[s] the size of banks, their interconnectedness, the lack of readily available substitutes or financial institution infrastructure for the services they provide, their global (cross-jurisdictional) activity and their complexity" (BIS, 2013). Despite the publication of the official list of G-SIBs, studies related to the methodologies to identify TBTF are still in demand and in development. In Bank of England's recent paper about implicit subsidies to TBTF, Siegert and Willison (2015) address "Which banks are TBTF" as one of the core questions for future studies.

Rating gaps and size are two major approaches to measure the chance that TBTF banks may receive subsidies (Noss and Sowerbutts, 2012). The chance whether a bank is to be saved is related to the importance of this bank to the banking system. However, large banks are not necessarily systemically important. As pointed out by Packer and Tarashev (2011, p42), "banks role as financial intermediaries and their importance for financial stability determine the degree of external assistance they receive and shape the risk factors to which they are exposed. Assessments of bank creditworthiness thus need to account for the degree of external support, gauge the degree of systemic risk and address the inherent volatility of banks' performance".

Compared to only using asset size to identify TBTF , using rating gaps as proxies for banks' systemic importance have both pros and cons. Rating gaps might be a less noisy method because the rating agency have considered multiple factors for systemic importance, including size, interconnection, complexity and so on. On the other side, rating gaps may be a noisy way if the rating agency uses flawed methodologies and mistakenly estimate the likelihood that a bank may receive external support. However, as conjectured by Siegert and Willison (2015), although the ratings may be imprecise, if investors believe in that the banks will be bailed out in distress anyway by taking the banks' rating face value only, these banks still enjoy benefits from the ex-ante expectation effects of being systemic important.

To explore whether rating gaps contain reliable information for systemic risk, this paper contributes to the literature in proposing several methods to calculate the rating gaps, and studying whether the rating gaps are positively related with a quantitative systemic risk measure, Co-independent Value at Risk (CoVar), which is presented by Adrian and Brunnermerier (2016). Intuitively, CoVar is designed to measure how a single bank's distress affects the whole banking system. The main advantage of CoVar, compared to other quantitative systemic risk measures, is that it takes into account the fact that systemic risk tends to be cyclical, falling in booms and rising in crises. This chapter studies whether rating gaps capture the same risk that quantitative systemic risk measures (CoVaR) do. The main finding is that they do, but only in large banks. The confirmation of the existing linkage between banks' systemic risk and their rating gaps provides a simple and readily available measure to assess the systemic importance of an individual bank. Instead of studying complicated quantitative models, policymakers and investors can use rating gaps as proxies for banks' systemic risk and easily identify those TBTF banks.

The chapter is organized as follows. Section 2 provides a related literature review. Section 3 describes the methodology. Section 4 discusses the data and presents summary statistics. Section 5 presents results and section 6 concludes.

2. Related Literature

Few papers study the information contained in bank ratings for banks' systemic risk. Peresetsky and Karminsky (2008) use an Ordered Logit model and quantile regressions to study which factors contribute to the unobserved external support contained in the Moody's All-in ratings. They conclude that the "external support" component can be largely predicted by public information factors, such as county-specific volatility of economic growth and a corruption index, bank size, capital adequacy, asset quality, efficiency, and profitability. Rime (2005) examines whether being "too-big-to-fail" could boost the expectations for credit ratings for certain banks from Moody's and Fitch. The author regresses all-in ratings on stand-alone ratings, bank asset size, and market share as proxies for "too-big-to-fail." The conclusion is that large banks do benefit from a significant increase in ratings. However, neither Peresetsky and Karminsky (2008) nor Rime (2005) use a precise measure for systemic risk, but rather employ indirect proxies for systemic risk.

Kaufman and Scott (2003) refer to systemic risk as "...the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by co-movements (correlation) among most or all the parts." In theory, a definition of systemic risk needs to trace back to externalities caused by networking among banks and fire-sale spillovers. Neither Peresetsky and Karminsky (2008) nor Rime (2005) uses measures that deal with the externality character of systemic risk. Network effects can lead to externalities, as emphasized by Allen, Babus and Carletti (2010). Banks connect to each other through their related businesses. Especially with the development of modern financial innovations, (e.g., derivatives and securitization), banks now are much more interconnected in terms of risk sharing relationships than in earlier times. Inter-linkages in the banking system can exacerbate the possibility of an individual bank run leading to a broader system bank run. The theoretical bank run literature has clearly shown that such possibilities can dramatically reduce social welfare (Bhattacharya and Gale (1987)).

In recent years, several systemic risk measures have been proposed. These measures usually employ complicated econometric models. Some define systemic risk as how a crisis affects an individual institution's capital adequacy. Acharya, Engle, and Richardson (2012), further refined by Brownless and Engle (2017), provide a measure so called Expected Capital Shortfall, which focuses on high-frequency marginal expected capital shortfall as the system as a whole experiencing a crisis. Acharya, Pedersen, Philippon, and Richardson (2017), develop Systemic Expected Shortfall, which measures an institution's tendency to be undercapitalized when the system as a whole is undercapitalized. On the reverse side, some define systemic risk as how an institution contributes to a systemic crisis. Adams et al. (2014) study risk spillovers among financial institutions, including hedge funds, using quantile regressions. Zhou (2009) provides an estimation methodology, termed CoVaR, which uses a multivariate Extreme Value Theory framework. Adrian and Brunnermerier (2016) present a modified CoVaR measure that takes into account the fact that CoVaR tends to be cyclical, falling in booms and rising in crises. Intuitively, CoVar in Adrian and Brunnermerier (2016) is designed to measure how a single bank's distress affects the whole banking system. This paper adopts CoVar by Adrian and Brunnermerier (2016) as the measure of systemic risk. As one of the motivations of this paper is to identify TBTF banks, which are the banks, by definition, important enough to cause a systemic catastrophe when they fail.

These econometric models provide quantitative measures of systemic risk. However, many market participants probably may not have the ability to develop and utilize such sophisticated models and may simply rely on rating agencies for their credit risk estimates of financial institutions. Policy makers and financial market supervision authorities thus, to some extent, ought to be aware of the information content of credit ratings for systemic risk. Since all three rating agencies publish both stand-alone and all-in ratings, it is surely convenient to take the gap between the two ratings as a measure of systemic risk.

3. Methodological Issues

3.1 Gap Calculation

The rating gap is the difference between the all-in rating and the stand-alone rating. A stand-alone rating reflects a bank's own financial strength. An all-in rating contains information about not only a bank's own financial strength, but also the external support a bank could receive from its parent company and government bodies in the event the bank's financial health is in jeopardy. The rating gap thus captures the external support a bank could receive if it were in distress.

There are some technical issues that have to be considered when calculating rating gaps. First, one must construct a map to compare the all-in and stand-alone ratings. Fitch (2011) provides a rating map which gives the equivalent category of each all-in rating and stand-alone rating.

The map is presented in Table 1. My analysis uses the ratings from Fitch because Standard & Poor's has published financial strength ratings only for banks in the Asia-Pacific region and Moody's only began assigning stand-alone ratings in 2007.

Table 1. Rating Mapping from Fitch (2011)

Stand-alone	All-in
A	AAA
	AA+
	AA
A/B	AA+
	AA
	AA-
	A+
B	AA-
	A+
	A
	A-
B/C	A
	A-
	BBB+
	BBB
C	BBB+
	BBB
	BBB-
	BB+
C/D	BBB+
	BB+
	BB
	BB-
D	BB
	BB-
	BB
	BB-
	B+
	B
	B-
D/E	B+
	B
	B-
	CCC
E	CCC
	CC
	C

- This map issued by Fitch, which gives the connections between Stand-alone ratings and All-in ratings.

Second, the stand-alone ratings and the all-in ratings do not have a one-to-one mapping for a given stand-alone rating. There are multiple all-in ratings. Moreover, a given all-in rating can be assigned to banks with different stand-alone ratings. To deal with these issues, I consider three approaches. First, the "rough mapping" approach ignores these issues and simply computes the gaps using the two ratings. The other two approaches, a "pessimist mapping" and an "optimist mapping", the assigned ratings are ordered so that they have a one-to-one relationship with no overlap.

The third consideration is that all ratings are provided as a set of characters, not quantitative measures. To obtain numerical rating gaps, I need to translate these ratings into numbers. The ways in which the various ratings and thereafter rating gaps are translated into numbers depending on which method is chosen to deal with the overlaps.

The rough mapping approach is used to construct a variable "GAP". If the stand-alone rating is the same as any of the listed all-in equivalencies in Table 1, there is "no gap" and the variable GAP is recorded as 0. If the all-in rating is one category higher/ lower than the equivalencies in Table 1, there is a small positive / negative gap and the value for the variable GAP is +1/ -1. If the all-in rating is 2 or more cells above/ below, there is a large positive/ negative gap and the value for the variable GAP is +2/ -2. For example, if the stand-alone rating is A and the all-in rating is AA+, GAP is 0, where as if the stand-alone rating is A/B and the all-in rating is AAA, then GAP is +1. Summary statistics for the variable GAP are shown in Table 5.

The pessimist mapping approach assumes that the rating agency overstates a banks' all-in rating and thus overlaps with all-in ratings in Table 1 are moved to the next lower level. For example, all-in ratings of AA+ and AA both are equivalent in Table 1 to stand-alone ratings of A and A/B. The pessimist mapping assumes the all-in ratings AA+ and AA are equivalent to stand-alone ratings of only A/B. The pessimist mapping is shown in Table 2.

Table 2. Pessimist Mapping

Stand-alone Letter Rating	Stand-alone Numerical Rating	All-in Letter Rating	All-in Grid Numerical Rating	All-in Point Numerical Rating
A	8	AAA	8	8
A/B	7	AA+	7	7.5
		AA	7	7
B	6	AA-	6	6.5
		A+	6	6
B/C	5	A	5	5.5
		A-	5	5
C	4	BBB+	4	4.5
		BBB	4	4
C/D	3	BBB-	3	3.5
		BB+	3	3
D	2	BB	2	2.5
		BB-	2	2
D/E	1	B+	1	1.7

		B	1	1.3
		B-	1	1
	0	CCC	0	0.7
E		CC	0	0.3
		C	0	0

- This map transfers ratings from letters into numbers by using the Pessimist Method.

Similarly, the optimist mapping moves all-in ratings with overlaps up to the next higher rating category. That is, all-in ratings AA+ and AA in the example are assumed to be equivalent to a stand-alone rating of A. The optimistic mapping is shown in Table 3.

For each of the pessimist and optimist mappings stand-alone ratings are translated into ordered numbers from 0 to 8, increasing in increments of 1. I design two possible ways to assign numbers to the all-in ratings. The first one is termed the “grid method”. This method assumes all-in ratings have the same numerical value as the equivalent stand-alone rating category. For example, under the optimist mapping, the rating gap would be the same for all-in ratings of BB and BB- as these are both in the same category for the stand-alone rating C/D. When translated into numbers, C/D equals to 3, so BB and BB- both equal to 3, and the rating gap is 0.

Table 3. Optimist Mapping

Stand-alone Letter Rating	Stand-alone Numerical Rating	All-in Letter Rating	All-in Grid Numerical Rating	All-in Point Numerical Rating
A	8	AAA	8	8.6
		AA+	8	8.3
		AA	8	8
		AA-	7	7.6
A/B	7	A+	7	7.3
		A	7	7
B	6	A-	6	6
B/C		BBB+	5	5.5
	5	BBB	5	5
C	4	BBB-	4	4.5
		BB+	4	4
C/D	3	BB	3	3.5
		BB-	3	3
D	2	B+	2	2.6
		B	2	2.3
		B-	2	2
D/E	1	CCC	1	1
E	0	CC	0	0.5
		C	0	0

- This map transfers ratings from letters into numbers by using the Optimist

The second method for assigning values to all-in ratings is the "point method". All-in ratings are assigned values ordered from to 8.6, but the increments vary depending on how many all-in ratings are equivalent to the same stand-alone rating.

In summary, in addition to the rough mapping for constructing rating gaps, there are four measures constructed for calculating rating gaps: pessimist-grid, pessimist-point, optimist-grid and optimist-point. The variable names and the methods are listed in Table 4. Numerical gaps are shown in Tables 2 and 3.

Table 4. Variable Name and Method

Variable	**Method**
GAP	Rough Rating
PGGAP	Pessimism-grid
PPGAP	Pessimism-point
OGGAP	Optimistic-grid
OPGAP	Optimistic-point

- This table indicates the method used to calculate the rating gap variables.

3.2 Measuring Systemic Risk

Following Adrian and Brunnermerier (2010), I use a variable, $\Delta CoVaR_q^{system|i}$, to measure systemic risk. Intuitively, $\Delta CoVaR_q^{system|i}$can be thought of as, when an individual bank *i* is in distress and its asset return is at or below the bottom q% of its historical asset return distribution, how much the banking system total asset return would be changed by the bank's distress compared to when the bank's asset return is at its median level. For example, in the first quarter of 1995, the estimated historical bottom 1% ($q = 1$) return of JPMorgan Chase is -23.76%. Conditional on JPMorgan Chase's return dropping by 23.76%, it is estimated that the return of the banking system will drop by 3.85%. That is, $\Delta CoVaR_1^{system|JPMORGAN} = 3.85\%$.

Note that VaR_q^i is defined as the qth quantile of the bank's asset return distribution, i.e.,$(X^i \leq VaR_q^i) = q$, where X^i is the asset return of bank *i*. The market value of bank's assets is denoted as A^i, where:

$$A^i = BA^i \times \frac{ME^i}{BE^i} \tag{1}$$

BA^i is bank *i*'s book value of assets, ME^i is its market value of equity, and BE^i is the book value of equity.

$C()$ is denoted as some event that causes the bank's asset return change to X^i. X^{system} is the market value weighted total asset return of the banking system. $CoVaR_q^{system|i}$ is the Value at Risk (VaR) of the banking system, conditional on the event $C()$ happens and bank *i*'s asset return is at or below X^i.

A special case is when $X^i = VaR_q^i$. That is, when bank *i*'s asset return is at its *q*th quantile historical level. The impact of Bank *i*'s distress on the system is defined as its systemic risk, which is

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{i|X^i=median^i} \quad (2)$$

Furthermore, I use quantile regressions to obtain $\hat{X}_q^{system}$

$$\hat{X}_q^{system} = VaR_q^{system}|X^i = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \quad (3)$$

$$CoVaR_q^{system|X^i=VaR_q^i} = VaR_q^{system}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \quad (4)$$

$\Delta CoVaR_q^i$ is obtained by using equation (1.5)

$$\Delta CoVaR_q^{system|i} = \hat{\beta}_q^i (VaR_q^i - VaR_{50\%}^i) \quad (5)$$

The next step is to construct time series for *CoVaR* and *VaR*. Similar to Adrian and Brunnermerier (2010), I use a vector of state variables S_{t-1} to capture time variation in conditional moments of asset returns. This state vector includes seven factors:

(i) The Chicago Board Options Exchange Market Volatility index (VIX), to capture the implied volatility in the stock market.

(ii) A short term liquidity risk measure, which is the difference between the three-month repo rate and the three-month T-bill rate.

(iii) The change in the three-month Treasury bill rate. Adrian and Brunnermerier (2010) find that the change in the three-month Treasury bill rate significantly explains the tails of financial sector asset returns.

(iv) The change in the slope of the yield curve, measured by the yield spread between the ten-year Treasury rate and the three-month T-bill rate.

(v) The change in the credit spread between BAA-rated bonds and the Treasury rate, both with maturity of ten years.

(vi) The quarterly equity market return using the S&P 500 index (SPX).

(vii) The change in the Dow Jones United States Real Estate Industry Group Index, represents Real Estate Investment Trusts (REIT) and other companies that invest directly or indirectly in real estate through development, management or ownership, including property agencies. This index is float-adjusted and market cap weighted.

I estimate time-varying X_t^i and $\mathrm{X}_t^{\mathrm{system}}$ as

$$X_t^i = \theta^i + \lambda^i S_{t-1} + \mu_t^i \tag{6}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} S_{t-1} + \varepsilon_t^{system|i} \tag{7}$$

The parameter $\widehat{\theta^i}$, $\widehat{\lambda^i}$, $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$ and $\hat{\gamma}^{system|i}$ from equation (6) and (7) are used to calculate:

$$VaR_t^i = \widehat{\theta^i} + \widehat{\lambda^i} S_{t-1} \tag{8}$$

$$CoVaR_t^{system|i} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} VaR_t^i + \hat{\gamma}^{system|i} S_{t-1} \tag{9}$$

Finally, I compute $\Delta CoVaR_t^{system|i}$ at the *q*th quantile for each bank:

$$\begin{aligned} \Delta CoVaR_t^{system|i}(q) &= CoVaR_t^{system|i}(q) - CoVaR_t^{system|i}(50\%) \\ &= \hat{\beta}^{system|i}(VaR_t^i(q) - VaR_t^i(50\%) \end{aligned} \tag{10}$$

4. Bank Data and Summary Statistics

4.1 Data

All observations in this paper are for bank holding companies (BHCs) (Note 1). There are three data sources: Bloomberg, the Federal Reserve Board (FRB) FRY-9C reports, and the Center for Research in Security Prices (CRSP) database. Fitch Ratings and the factors discussed above are recorded on a quarterly basis. They are from Bloomberg. Quarterly data for banks' book value of assets and book value of equity are from FRY-9C reports. Both banks' quarterly stock price and outstanding shares are from CRSP. To calculate the banking system asset return, I begin with a pool of 589 banks. The final data set used to estimate the Ordered Probit model contains 1819 quarterly observations for 54 banks with the number of observations for a bank ranging from 13 to 54. The sample period is from the third quarter of

1994 to the fourth quarter of 2007.

4.2 Summary Statistics

Table 5. Summary Statistics

Variable	**Mean**	**Maximum**	**Upper Quartile**	**Median**	**Lower Quartile**	**Minimum**
PGGAP	-0.8851	1	-1	-1	-1	-2
PPGAP	-0.6443	1.3	-0.5	-0.5	-1	-2
OGGAP	0.2793	2	1	0	0	-1
OPGAP	0.4974	2.3	1	0.5	0	-1
GAP	-0.0874	1	0	0	0	-1

- This table presents the summary statistics of the rating gap variables.

Table 6. Summary Statistics --- by Stand-alone Ratings

sa	**N Obs**	**Variable**	**Mean**	**Maximum**	**Upper Quartile**	**Median**	**Lower Quartile**	**Minimum**
0	1	*PGGAP*	1	1	1	1	1	1
		PPGAP	1.3	1.3	1.3	1.3	1.3	1.3
		OGGAP	2	2	2	2	2	2
		OPGAP	2.3	2.3	2.3	2.3	2.3	2.3
		GAP	1	1	1	1	1	1
1	2	*PGGAP*	0	0	0	0	0	0
		PPGAP	0.7	0.7	0.7	0.7	0.7	0.7
		OGGAP	1	1	1	1	1	1
		OPGAP	1.6	1.6	1.6	1.6	1.6	1.6
		GAP	0	0	0	0	0	0
2	23	*PGGAP*	-0.6522	0	0	-1	-1	-1
		PPGAP	-0.3522	0	0	-0.3	-0.7	-0.7
		OGGAP	0.3478	1	1	0	0	0
		OPGAP	0.6217	1	1	0.6	0.3	0.3
		GAP	0	0	0	0	0	0
3	12	*PGGAP*	-0.7500	1	-1	-1	-1	-1
		PPGAP	-0.3333	1	-0.5	-0.5	-0.5	-0.5
		OGGAP	0.2500	2	0	0	0	0
		OPGAP	0.6667	2	0.5	0.5	0.5	0.5
		GAP	0.0833	1	0	0	0	0
4	12	*PGGAP*	-0.6667	0	0	-1	-1	-1
		PPGAP	-0.6250	0	0	-1	-1	-1
		OGGAP	0.3333	1	1	0	0	0
		OPGAP	0.3750	1	1	0	0	0
		GAP	0	0	0	0	0	0

5	461	*PGGAP*	-1.0434	1	-1	-1	-1	-2
		PPGAP	-0.8590	1	-0.5	-1	-1	-2
		OGGAP	0.0347	2	0	0	0	-1
		OPGAP	0.1852	2.3	0.5	0	0	-1
		GAP	-0.1757	1	0	0	0	-1
6	785	*PGGAP*	-0.6981	1	0	-1	-1	-2
		PPGAP	-0.4847	1	0	-0.5	-1	-1.5
		OGGAP	0.5860	2	1	1	0	-1
		OPGAP	0.7396	2	1.3	1	0	-0.5
		GAP	-0.0318	1	0	0	0	-1
7	413	*PGGAP*	-0.9976	0	-1	-1	-1	-2
		PPGAP	-0.6525	0	-0.5	-0.5	-1	-2
		OGGAP	0.0993	1	0	0	0	-1
		OPGAP	0.5053	1	0.6	0.6	0.3	-1
		GAP	-0.0654	0	0	0	0	-1
8	110	*PGGAP*	-1.2545	-1	-1	-1	-2	-2
		PPGAP	-0.9909	-0.5	-0.5	-1	-1.5	-1.5
		OGGAP	-0.2545	0	0	0	-1	-1
		OPGAP	-0.0200	0.3	0.3	0	-0.4	-0.4
		GAP	-0.2545	0	0	0	-1	-1

- This table presents the summary statistics of the rating gap variables grouped by stand-alone ratings.

Summary statistics of the gaps and the gaps grouped by stand-alone ratings are listed in the Table 5 and the Table 6, respectively. There are negative numbers in the summary statistics. For example, the minimum values for all five types of gaps are negative. Negative external support could happen when the rating agency update all-in ratings and stand-alone ratings at different time. For example, the stand-alone rating for Wells Fargo & Company in the third quarter of 1997 switched from A/B to A but its all-in rating remained to AA. So the variable *PPGAP* is recorded as 0 for the second quarter of 1997 but as -1 in the third quarter.

The correlation matrix for the five rating gaps is shown in Table 7. The correlations between gaps are all positive and significant at 1%. The highest correlation is 0.9600, which is between the optimist-point gap and the pessimist-point gap. The correlations between GAP and the other four types of rating gaps are much lower than the correlations among these four ratings gaps. It seems that ignoring the overlaps in ratings or not does make a big difference.

Overall, out of 1819 observations there are 1445 non-zero values for *PGGAP*, 1550 for *PPGAP*, 788 for *OGGAP*, 1550 for *OPGAP* and 219 for *GAP*. Further, there are 21 non-negative values for *PGGAP*, 126 for *PPGAP*, 621 for *OGGAP*, 1064 for *PPGAP* and 30 for *GAP*. Interestingly, most observations are concentrated on two to three values. Except for *PPGAP* and *OPGAP*, the other gaps have little variation, which are showed by the histograms for the gaps are presented in Figures 1 through 5, both for the full sample and sub-samples. The sub-samples correspond to the quartiles of the book values of bank assets. The quartiles of book values of assets are listed in Table 8 and the summary statistics of all gap measures based on bank size are shown in Table 9.

Table 7. Correlation between Five Rating Gap Measures

	PGGAP	*PPGAP*	*OGGAP*	*OPGAP*	*GAP*
PGGAP	1				
PPGAP	0.9080 (0.0001)***	1			
OGGAP	0.8342 (0.0001)***	0.8623 (0.0001)***	1		
OPGAP	0.8391 (0.0001)***	0.9600 (0.0001)***	0.9285 (0.0001)***	1	
GAP	0.6268 (0.0001)***	0.5600 (0.0001)***	0.6422 (0.0001)***	0.5493 (0.0001)***	1

- This table shows the correlations among five types of rating gaps.

Table 8. Summary Statistics ---- Bank Book Assets in Dollars

Mean	**Maximum**	**Upper Quartile**	**Median**	**Lower Quartile**	**Minimum**
117,797,366	2,358,266,000	83,856,300	32,175,286	9,423,099	486,418

- This table presents the quartiles of bank book assets in thousand dollars.

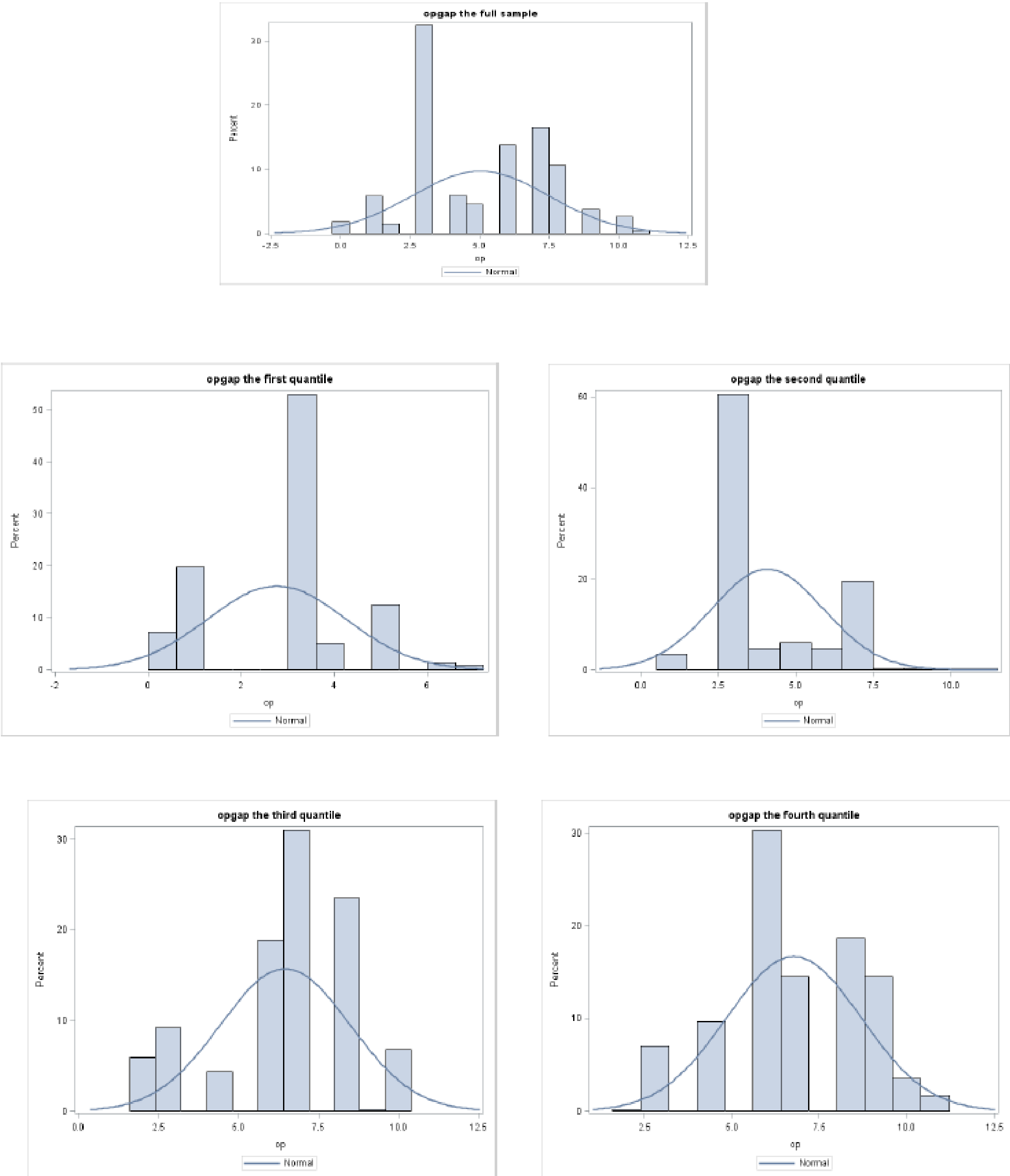


Figure 1. OPGAP

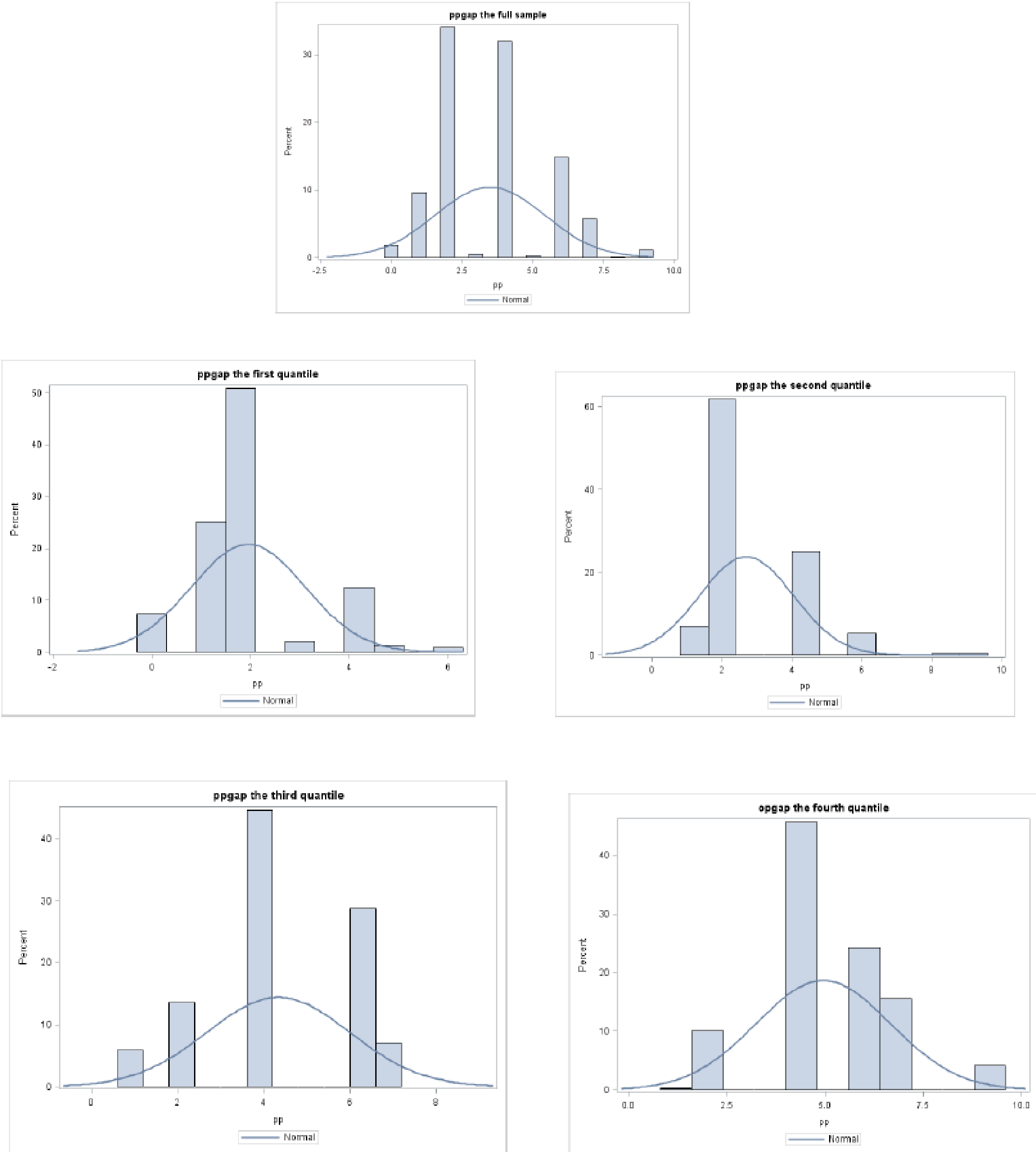


Figure 2. *PPGAP*

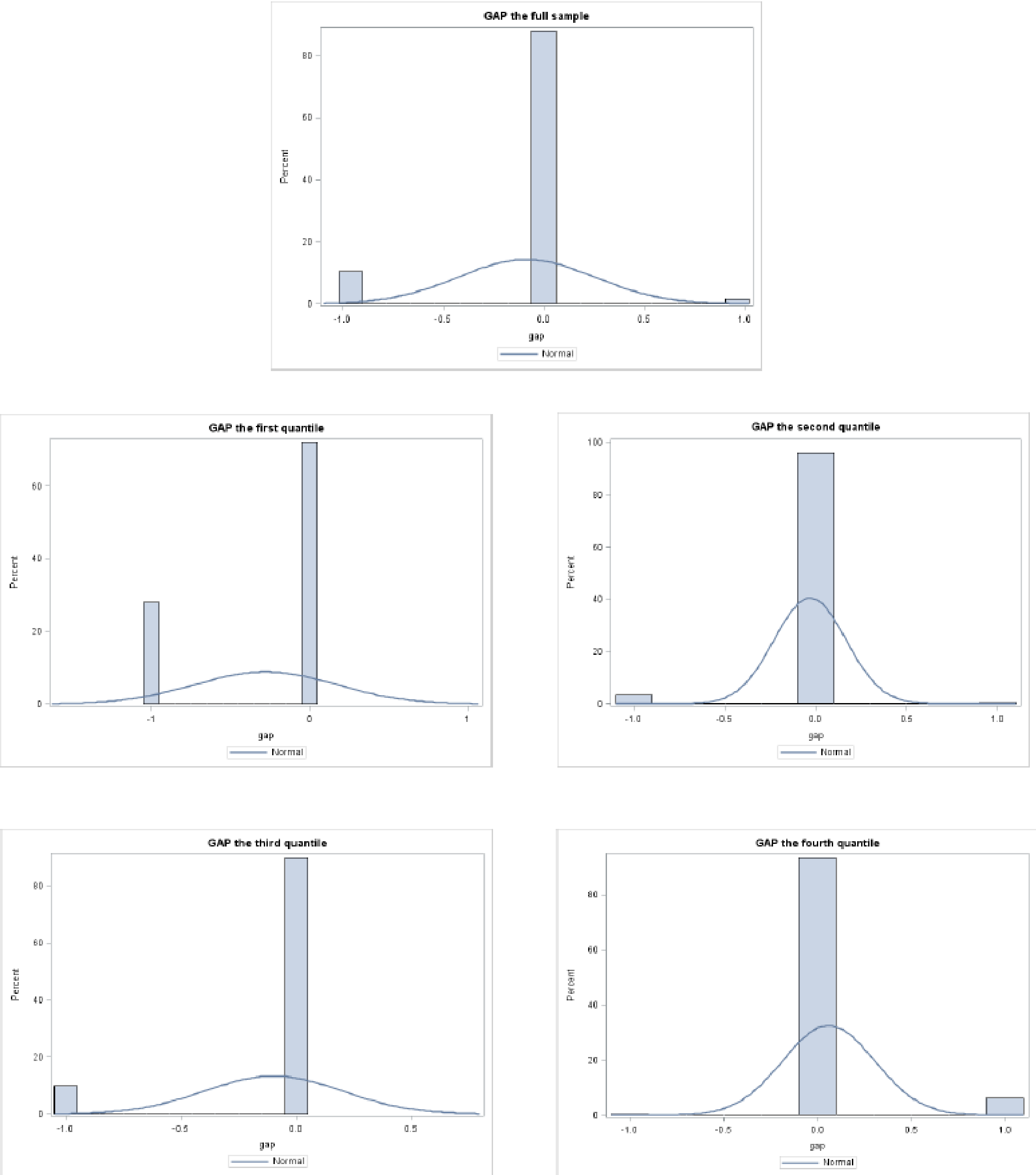

GAP the full sample
Percent
gap
Normal
GAP the first quantile
Percent
gap
Normal
GAP the second quantile
Percent
gap
Normal
GAP the third quantile
Percent
gap
Normal
GAP the fourth quantile
Percent
gap
Normal

Figure 3. *GAP*

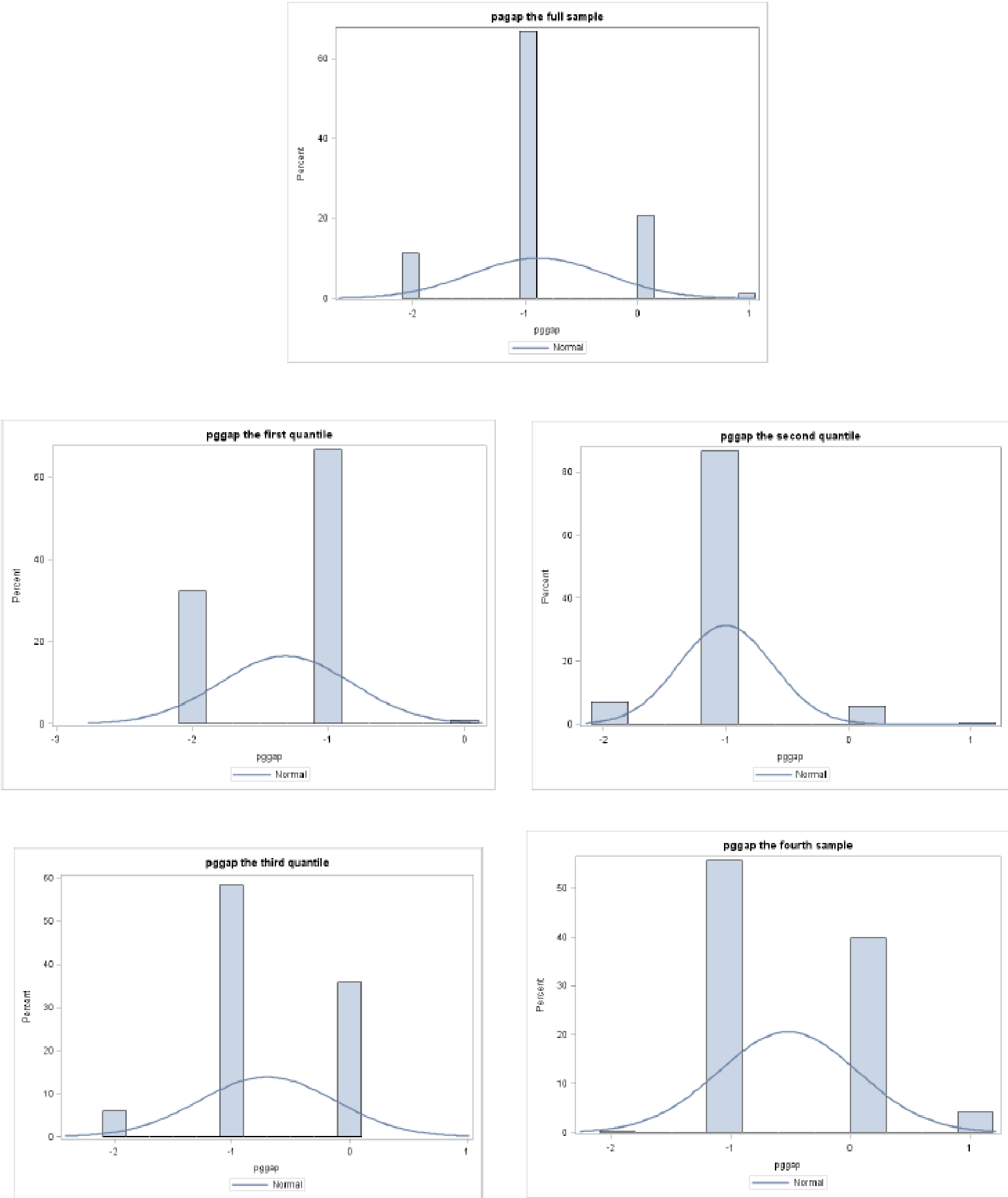


Figure 4. *PGGAP*

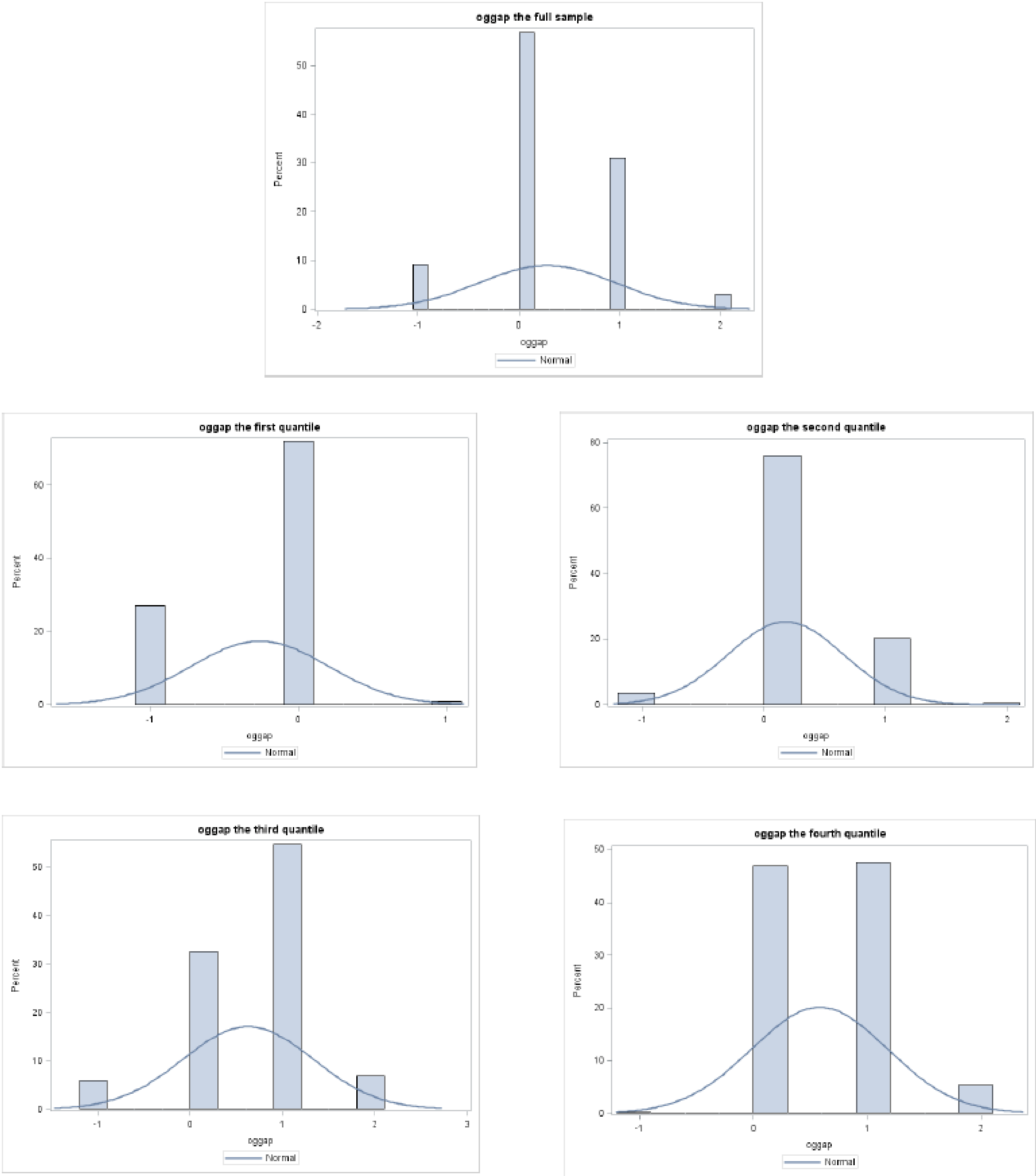


Figure 5. *OGGAP*

Table 9. Summary Statistics by Bank Size

	Variable	Mean	Maximum	Upper Quartile	Median	Lower Quartile	Minimum
First Quartile	*PGGAP*	-1.3150	0	-1	-1	-2	-2
	PPGAP	-1.1115	0	-1	-1	-1.5	-2
	OGGAP	-0.2621	1	0	0	-1	-1
	OPGAP	-0.0771	1	0	0	-0.5	-1
	GAP	-0.2797	0	0	0	-1	-1

Second Quartile	*PGGAP*	-1.0044	1	-1	-1	-1	-2
	PPGAP	-0.8402	1.3	-0.5	-1	-1	-1.5
	OGGAP	0.1758	2	0	0	0	-1
	OPGAP	0.2686	2.3	0.6	0	0	-0.5
	GAP	-0.0308	1	0	0	0	-1
Third Quartile	*PGGAP*	-0.7011	0	0	-1	-1	-2
	PPGAP	-0.4132	0.5	0	-0.5	-0.5	-1.5
	OGGAP	0.6242	2	1	1	0	-1
	OPGAP	0.8582	2	1.3	1	0.6	-0.4
	GAP	-0.0989	0	0	0	0	-1
Fourth Quartile	*PGGAP*	-0.5197	1	0	-1	-1	-2
	PPGAP	-0.2127	1	0	-0.5	-0.5	-1.5
	OGGAP	0.5789	2	1	1	0	-1
	OPGAP	0.9388	2.3	1.3	1	0.6	-0.4
	GAP	0.0592	1	0	0	0	-1

- This table presents summary statistics in four quartile groups by bank book assets.

For the variables *PGGAP* and *OGGAP* the observations are clustered on four values. I tried each of the five rating gaps as the dependent variable in equation (11), both by using the full sample and sub-samples. As expected, due to lack of variation with three of the gap measures, results were obtained only for *OPGAP* and *PPGAP*. I therefore use *PPGAP* and *OPGAP* for the final Ordered Probit regressions. Note that I translated *OPGAP* and *PPGAP* into integers starting from 0 to meet the programing requirement. The variables after translation are denoted *OP* and *PP*. The translation maps are presented in Table 10.

Table 10. Translating *OPGAP* into Integers

OPGAP	***OP***	***PPGAP***	***PP***
-1	0	-2	0
-0.5	1	-1.5	1
-0.4	2	-1	2
0	3	-0.7	3
0.3	4	-0.5	4
0.5	5	-0.3	5
0.6	6	0	6
1	7	0.5	7
1.3	8	0.7	8
1.6	9	1	9
2	10	1.3	9
2.3	11		

- This table shows how the *OPGAP* and *PPGAP* are translated into non-negative integers in order to fit the requirement as the dependent variables for the Ordered Probit Model.

Variables used in the final regression are described in Table 11. In Table 12, I present summary statistics for each variable. The all-in rating, *RA*, varies from 7 to 20. The highest all-in rating in the sample is AA+, while the lowest all-in rating is B. The mean of *RA* is 15.7005, which means the average all-in rating is about A- to A. The mean of the variable *RI* is 8.0022, which means that the average stand-alone rating is about B. The maximum value for *RI* is 10 and the minimum value is 2. The stand-alone rating varies from E to A in the sample.

Table 11. Descriptions of Variables and Notations

Variable Name	Description
X^i	The market value asset return of bank *i*.
X^{system}	The market value weighted total asset return of the banking system.
A^i	The market value asset of bank *i*.
BA^i	Bank *i*'s book asset value.
ME^i	Bank *i*'s market value of equity.
BE^i	Bank *i*'s book value of equity
C( )	Some event that causes the bank's asset return to change to X^i.
VaR_q^i	The *q*th quantile of the asset return X^i
$CoVaR_q^{system\|i}$	The *VaR* of the banking system, conditional on an event when bank i's asset return is at X^i.
$\Delta CoVaR_q^{system\|i}$	How much the system total market value asset return would be changed when bank *i*'s asset return is at its bottom *q*% of historical asset distribution compared to when the bank's market asset return is at its median level.
RA	All-in ratings, transferred from characters into numbers. There are 21 gradations, from 1 to 21.
RI	Stand-alone ratings, transferred from characters into numbers. There are 10 gradations, from 1 to 10.
Δ*CoVar005*	ΔCoVar estimation for each bank at 5%.
Δ*CoVar001*	ΔCoVar estimation for each bank at 1%.
VIX	The VIX index available on Bloomberg, which is to capture the viability of the market.
HOUSING	The change in the Dow Jones United States Real Estate Industry Group Index represents Real Estate Investment Trusts (REIT) and other companies that invest directly or indirectly in real estate through development, management or ownership, including property agencies. Index is float-adjusted and market cap weighted. Base price is 100 as of 12/31/91.
MKTA	Quarterly market asset return of a bank.
OP/OPGAP	Rating gaps calculated by using the optimist point method.
PP/PPGAP	Rating gaps calculated by using the pessimist point method.
PGGAP	Rating gaps calculated by using the pessimist grid method.

OGGAP	Rating gaps calculated by using the optimist grid method.
GAP	Rating gaps calculated by using the Rough Rating Method.
S	A state vector to capture time variation in conditional moments of asset returns, which contains seven factors listed below.
LIQUIDITY	The difference between the three-month repo rate and the three-month bill rate, is to capture short-term liquidity risk.
TBILL3M	The quarterly change in the three-month Treasury bill rate.
YIELD	The quarterly change in the slope of the yield curve, measured by the yield spread between the ten-year Treasury rate and the three-month bill rate.
CREDIT	The quarterly change in the credit spread between BAA-rated bonds and the Treasury rate, both in the maturity of ten years.
SPX	The quarterly equity market return from the SPX index.

- This table shows definitions for major variables.

Table 12. Summary Statistics---Major Variables

Variable	N	Mean	Std Dev	Minimum	Maximum
RI	1819	8.0022	1.0287	2	10
RA	1819	15.7108	2.3265	7	20
$\Delta CoVar005$	1819	-0.0234	0.0544	-0.2873	0.2705
$\Delta CoVar001$	1819	-0.0231	0.0576	-0.2873	0.3678
VIX	1819	19.2278	7.0160	11.3800	40.95
HOUSING	1819	0.0203	0.0761	-0.1538	0.1521
LIQUIDITY	1819	0.2556	0.1924	0.0200	0.78
TIBILL3M	1819	-0.0360	0.4637	-1.4350	0.77
YIELD	1819	-0.0140	0.5379	-1.0624	1.29
CREDIT	1819	0.0062	0.3484	-0.5750	0.9860
SPX	1819	-0.0082	0.0795	-0.1726	0.2141
MKTA	1819	0.0129	0.1906	-2.0612	1.1614
OP	1819	5.0192	2.4661	0	11
PP	1819	3.4849	1.9149	0	9

- This table shows summary statistics for variables used to estimate CoVar and in the final Ordered Probit Model.

Both $\Delta CoVar005$ and $\Delta CoVar001$ are estimated variables based on equation (10). $\Delta CoVar$ stands for how the asset return of the banking system would change in response to a particular bank at its default level (I use 1% and 5% of historical asset return for default thresholds), compared to when the bank's asset return is at its historical median. The mean for $\Delta CoVar001$ is -0.0231 and for $\Delta CoVar005$ it is -0.0234. This means on average, when a bank is at a default threshold, the asset return of the banking system drops by 1.8%, compared to when this bank has asset returns equal to the median. The maximum for value for $\Delta CoVar005$ is 0.2705 and for $\Delta CoVar001$ it is 0.3678.

From 1994 to 2007, the VIX index varies from 11.38 to 40.95 in the sample. The mean of the Dow Jones Real Estate index return is 0.02, means the average return in the real estate market is about 2% quarterly for 1994-2007. The mean of *MKTA* is 0.0129, that is, the average quarterly asset return of banks from 1994 to 2007 is about 1%.

In Table 13, I present the correlation matrix for variables used in the Ordered Probit model. The correlation between the all-in rating variable *RA* and the stand-alone variable *RI* is positive and it is significant at 1% level. This indicates that banks with higher stand-alone financial strength usually receive higher all-in ratings. Both $\Delta CoVar005$ and $\Delta CoVar001$ are negatively correlated with *OP/PP*, and significant at 1%. A negative $\Delta CoVar$ means that the bank's default causes the banking system asset return to drop. The lower the value of $\Delta CoVar$ for a bank, the higher the systemic importance of the bank. The negative correlation between *OP/PP* and $\Delta CoVar$ may be a sign that banks with higher systemic importance usually have higher rating gap.

Table 13. Correlation Matrix

	RI	*RA*	$\Delta CoVar005$	$\Delta CoVar001$	*VIX*	*Housing*	*LIQUIDITY*	*TIBILL3M*
RI	1.0000							
RA	0.8729 (0.0001)***	1.0000						
$\Delta CoVar005$	0.0378 (-0.1072)	-0.1007 (0.0001)***	1.0000					
$\Delta CoVar001$	0.0302 (-0.1987)	-0.1084 (0.0001)***	0.9824 (0.0001)***	1.0000				
VIX	0.0921 (0.0001)***	0.0881 (0.0002)***	-0.0950 (0.0001)***	-0.0863 (0.0002)***	1.0000			
Housing	-0.0161 (-0.4923)	-0.0355 -0.1301	0.0572 (0.0148)**	0.0511 (-0.0293)**	-0.4327 (0.0001)***	1.0000		
LIQUIDITY	0.0468 (-0.0461)**	0.1342 (0.0001)***	-0.0822 (0.0004)***	-0.0746 (0.0015)***	-0.1014 (0.0001)***	-0.2338 (0.0001)***	1.0000	
TBILL3M	-0.0135 (-0.5646)	0.0077 -0.7419	0.0609 (0.0094)***	0.0564 (0.0162)**	-0.5486 (0.0001)***	0.2376 (0.0001)***	-0.1989 (0.0001)***	1.0000

	RI	*RA*	*ΔCoVar005*	*ΔCoVar001*	*VIX*	*Housing*	*LIQUIDITY*	*TIBILL3M*
YIELD	-0.0023	-0.0237	-0.0318	-0.0337	0.1345	-0.1122	0.0409	-0.5665
	(-0.9231)	(-0.3116)	(-0.1755)	(-0.1511)	(0.0001)***	(0.0001)***	(0.0815)*	(0.0001)***
CREDIT	0.0165	0.0337	-0.0402	-0.0363	0.3680	-0.4083	0.3084	-0.2960
	(-0.482)	-0.1503	(0.0865)*	(-0.1215)	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
SPX	-0.0086	-0.0445	-0.0018	-0.0041	-0.0950	0.1562	0.0088	-0.0852
	(-0.7132)	(0.0577)*	(-0.9393)	(-0.8619)	(0.0001)***	(0.0001)***	-0.7090	(0.0003)***
MKTA	0.0431	0.0681	0.0142	0.0130	-0.0716	0.2429	-0.0502	0.0319
	(-0.066)*	(0.0037)***	(-0.5443)	(-0.5795)	(0.0022)***	(0.0001)***	(0.0322)**	-0.1740
OP	-0.0025	0.4664	-0.3346	-0.3336	0.0063	-0.0365	0.1903	0.0525
	(-0.9142)	(0.0001)***	(0.0001)***	(0.0001)***	(-0.7877)	-0.1192	(0.0001)***	(0.0253)**
PP	-0.0417	0.4506	-0.2750	-0.2768	0.0107	-0.0420	0.1887	0.0425
	(0.0754)*	(0.0001)***	(0.0001)***	(0.0001)***	(-0.6473)	(0.0736)*	(0.0001)***	(0.0698)*

	YIELD	*CREDIT*	*SPX*	*MKTA*	*OP*	*PP*
YIELD	1.0000					
CREDIT	-0.3638	1.0000				
	(0.0001)***					
SPX	0.1730	-0.0620	1.0000			
	(0.0001)***	(0.0082)*				
MKTA	0.0804	-0.2107	0.0553	1.0000		
	-0.0006	(0.0001)***	(0.0184)**			
OP	-0.0535	0.0341	-0.0883	0.0688	1.0000	
	(-0.0226)**	-0.1461	(0.0002)***	(0.0033)***		
PP	-0.0455	0.0378	-0.0764	0.0604	0.9600	1.0000
	(0.0526)**	-0.1069	(0.0011)***	(0.0100)***	(0.0001)***	

This table shows the correlation matrix of variables used to estimate CoVar and in the final Ordered Probit Model.

5. Ordered Probit Model

The systemic importance of a bank should be a continuous concept. However, the rating gaps are discrete. The rating gap between All-in and Stand-alone ratings can be seen as a proxy for the unobservable continuous real systemic importance of a bank, which is denoted by G_i^*. Following Kaplan and Urwitz's (1979) study of bond ratings, an Ordered Probit model is presented as:

$$G_{i,t}^* = \delta_i + \tau \Delta CoVaR_{i,t}^{system|i}(q) + \lambda MKTA_{i,t} + \theta_1 T_1 + \theta_2 T_2 + \cdots + \theta_t T_t + \omega_{i,t} \qquad (11)$$

$$P(rating_i = r) = P(C_{r-1} < G_i^* < C_r) \tag{12}$$

where $MKTA_{i,t}$ is the market asset return of each bank, $G_{i,t}^*$ is the observed rating gap between a bank's all-in rating and its stand-alone rating, and T_t are annual time dummies. (Note 2, Note 3)

The purpose of this chapter is to assess whether a rating gap is a useful proxy for a bank's systemic risk. This requires that rating gaps be positively related to systemic risk measures. In terms of equation (11), the hypothesis is: $\tau < 0$. This is because $\Delta CoVaR_{i,t}^{system|i}(q)$ measures how much the asset return of the banking system may drop because one of the banks is in distress, compared to the asset return of the banking system when this bank is not in distress. $\Delta CoVaR_{i,t}^{system|i}(q)$ is assumed to be a negative value by definition. Thus, the larger the systemic risk of a bank, the lower the value of $\Delta CoVaR_{i,t}^{system|i}(q)$.

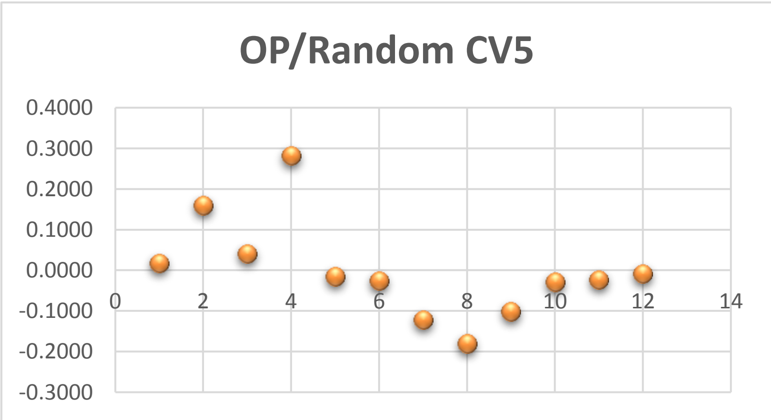
5.1 Full Sample Results

Table 14 and Table 15 present the results of the Ordered Probit model by using the same group of control variables but two different independent variables, namely Δ*CoVar* at 1% and 5% respectively. (Note 4) In both tables, the first and second columns present the results when using *OP* as the dependent variable. The only difference is that the results in the first column are obtained by using an Ordered Probit model in panel data with random effects, whereas the second column has fixed effects. The third column presents the results for *PP* as the dependent variable and the regression method is an Ordered Probit model in panel data with random effects.

To test the null hypothesis that the rating gaps are positively linked to systemic risk is equivalent to testing whether the coefficients on Δ*CoVar* are significantly negative. As showed in Table 14 and Table 15, coefficients on Δ*CoVar005* and Δ*CoVar001* are negative and significant at 1% in all regressions. This suggests that the rating gaps and banks systemic risk are significantly positively related. The more systemic importance the bank has, the higher the rating gap. For example, the coefficient on Δ*CoVar005* is -3.1663 when *OP* is the dependent variable. The marginal effect of ΔCoVar005 when fixed effect is applied, for example, when *OP=6*, is -0.6630 and significant at 1%. This means that when a bank is at its historical bottom 5% asset return level and it causes the asset return of the banking system to drop by 1%--the probability of the rating gap of this bank moving from 6 to 7 is 1.2%, holding other control variables constant. The estimated marginal effects of Δ*CoVar* for each gap notch are presented in Table 14 and 15 and are plotted in Figures 6, 7 and 8. For example, in the upper panel of Figure 6, the marginal effects of Δ*CoVar005* switch from positive to negative when $OP = 6$, and then switch back to positive when *OP= 12*. The summation of all the coefficients for all *OP* notches is naturally equal to 0. This is because the summation of all possibilities for a bank to receive a rating notch change must be zero.

It seems complicated to understand the interpretation of the marginal effects of $\Delta CoVar$. Arguably, the exact interpretation is not important for this chapter as the main focus here is whether the rating gap is an easy to construct and useful proxy for measuring the systemic risk of a bank. The evidence suggests it is.

However, as showed by Rime (2005), too-big-to-fail expectation boosts banks' all-in ratings. Although all-in ratings may not necessarily relate to the external support directly and rating gaps may be a better measure for systemic support, the conclusion of Rime (2005) implies that banks may not receive external support equally. Larger banks may enjoy more systemic support. The relationship between systemic risk and banks rating gap may shift depending on banks' size.



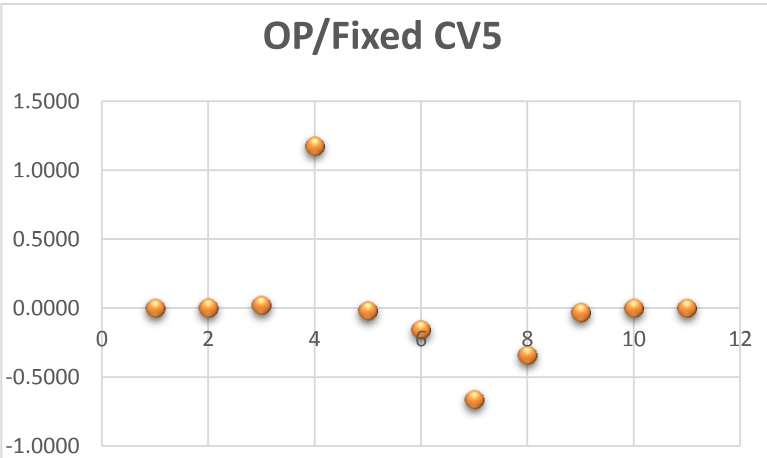
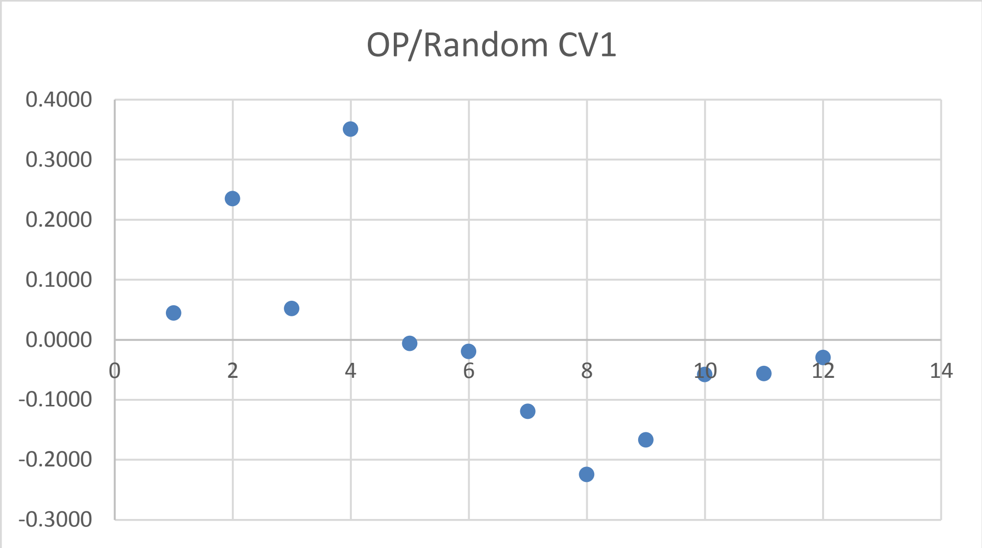


Figure 6. Marginal Effects/*OP-CV5*



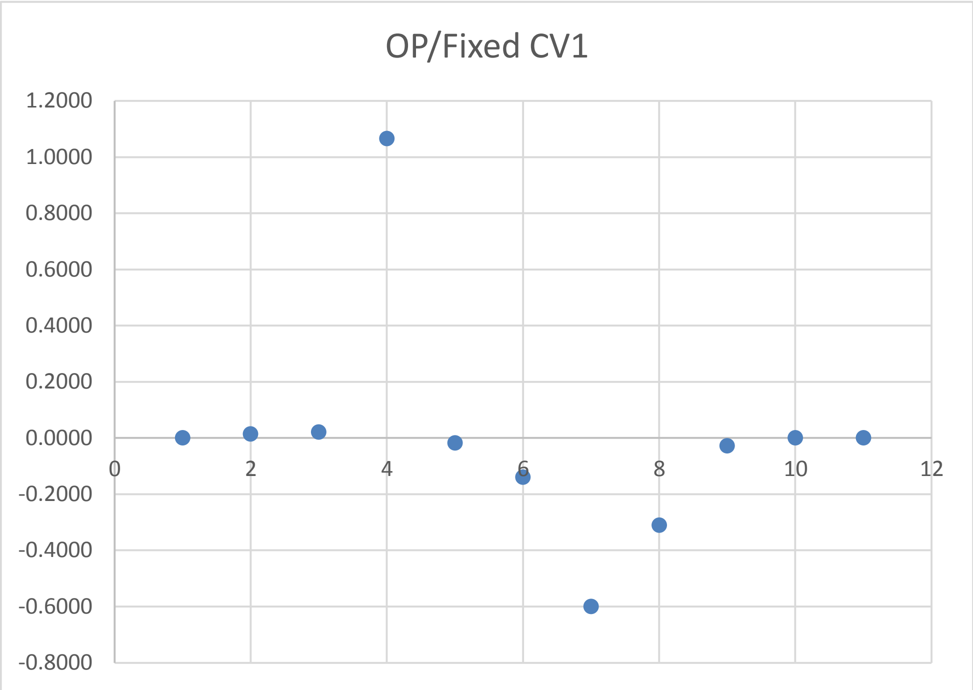
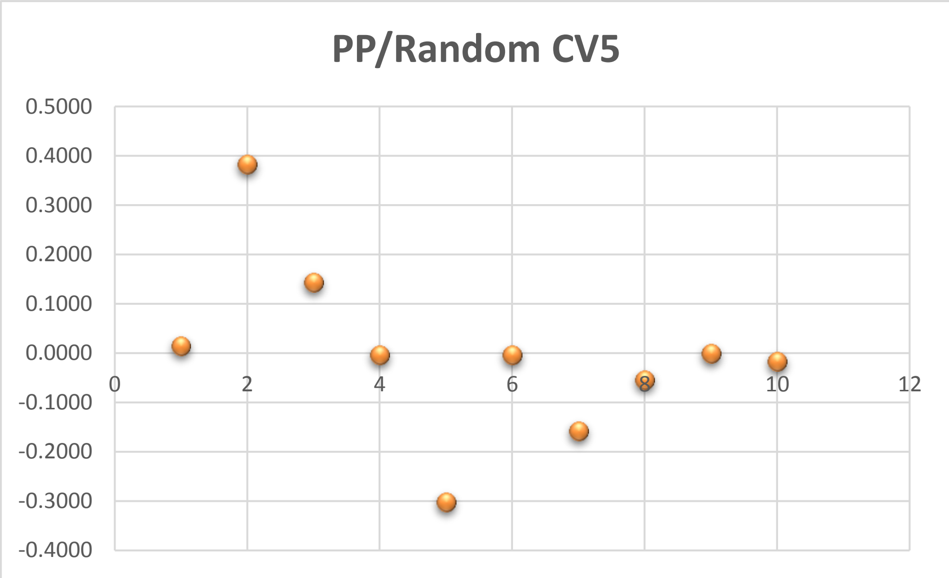


Figure 7. Marginal Effects/*OP-CV1*



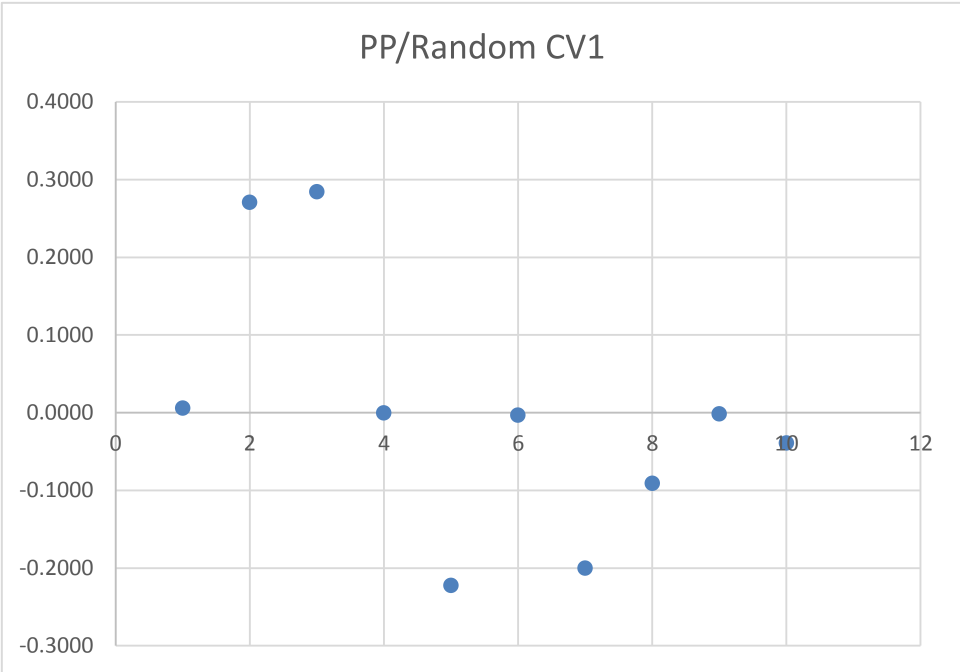


Figure 8. Marginal Effects/*PP*

Table 14. Ordered Probit Regressions, Δ*CoVar 005*

	OP/Random	*OP*/Fixed	*PP*/Random
Δ*CoVar005*	-2.4253	-3.0915	-3.0092
	(-2.98)***	(-3.67)***	(-3.94)***
MKTA	-0.0314	-0.0867	-0.0520
	(-0.13)	(-0.42)	(-0.20)
Y=0	0.0181	0.1886D-06	0.0148
	1.66*	(-0.57)	1.81*
Y=1	0.1601	0.0004	0.3829
	3.04***	0.39	3.51***
Y=2	0.0413	0.0222	0.1432
	1.17	0.84	1.58
Y=3	0.2827	1.1754	-0.0038
	1.86*	3.68***	(-0.25)
Y=4	-0.0151	-0.0206	-0.3027
	(-2.92)***	(-.10)	(--3.90)
Y=5	-0.0255	-0.1555	-0.0034
	(-2.60)***	(-1.29)	(-0.20)
Y=6	-0.1215	-0.6630	-0.1582
	(-2.61)***	(-3.61)***	(--3.94)***
Y=7	-0.1798	-0.3413	-0.0544
	(-2.32)**	(-1.58)	(-3.82)***
Y=8	-0.1007	-0.0312	-0.0010
	(-2.36)**	(-.93)	(-0.62)
Y=9	-0.0284	-0.0007	-0.0175
	(-2.50)***	(-.66)	(-2.97)***
Y=10	-0.0231	0.0000	N/A
	(-3.08)***	(-0.57)	
Y=11	-0.0081	N/A	N/A
	(-2.44)**		
Number of Observations	1819	1819	1819
Log Liklihood value	-2390.2785	-2164.5377	-1651.8039

- This table presents the results of Ordered Porbit regressions. The independent variables includes ΔCoVar005, MKTA, and a set of yearly dummies, which are presented in the first column. The coefficients on yearly dummies are not reported. Instead, the marginal effects of Δ*CoVar005* are reported for every rating gap grades.The second column presents the results by using *OP* as the dependent variable with random effect applied to the panel data. The third column presents the results by using *PP* as the dependent variable with fixed effect applied. The last column presents the results by using PP as the dependent variable with random effect applied.
- Limdep cannot compute the fixed effect ordered Porbit model when the dependent variable is *PP*.

Table 15. Ordered Probit Regressions, Δ*CoVar 001*

	OP/Random	*OP*/Fixed	*PP*/Random
Δ*CoVar001*	-3.6969	-2.8014	-2.9207
	(-5.20)***	(-3.49)***	(-3.93)
MKTA	-0.0520	-0.0869	-0.0482
	(-.20)	(-0.42)	(-0.18)
Y=0	0.0443	0.18196D-06	0.0054
	2.96***	(-0.57)	1.60
Y=1	0.2350	0.0136	0.2705
	4.81***	1.05	3.11***
Y=2	0.0518	0.0201	0.2840
	1.62	0.84	2.68
Y=3	0.3506	1.0647	-0.0006
	3.46***	3.49***	(-0.31)
Y=4	-0.0065	-0.0179	-0.2228
	-1.24	(-.10)	(-3.83)***
Y=5	-0.0197	-0.1402	-0.0036
	(-3.35)***	(-1.28)	(-0.20)
Y=6	-0.1196	-0.6004	-0.2003
	(-4.03)***	(-3.44)***	(-3.87)***
Y=7	-0.2248	-0.3106	-0.0914
	(-3.93)***	(-1.57)	(-3.77)***
Y=8	-0.1670	-0.0286	-0.0020
	(-4.05)***	(-0.93)	(-0.59)
Y=9	-0.0579	-0.0007	-0.0393
	(-4.13)***	(-0.67)	(-3.44)***
Y=10	-0.0567	0.0000	N/A
	(-6.24)***	(-0.57)	
Y=11	-0.0296	N/A	N/A
	(-4.35)***		
Number of Observations	1819	1819	1819
Log Liklihood	-2390.2785	-2164.6313	-1649.7160

- This table presents the results of Ordered Porbit regressions. The independent variables includes Δ*CoVar001*, *MKTA*, and a set of yearly dummies, which are presented in the first column. The coefficients on yearly dummies are not reported. Instead, the marginal effects of Δ*CoVar001* are reported for every rating gap grades.The second column presents the results by using *OP* as the dependent variable with random effect applied to the panel data. The third column presents the results by using *PP* as the dependent variable with fixed effect applied. The last column presents the results by using PP as the dependent variable with random effect applied.
- Limdep cannot compute the fixed effect ordered Porbit model when the dependent variable is *PP*.

Table 16. Results Obtained by Using Subsamples

		Coefficient on $\Delta CoVar$	Z-value	Log-likelihood Value
	$\Delta CoVar005$/Random	-4.03615	-1.16	-298.60188
	$\Delta CoVar005$/Fixed	-6.49294*	-1.92	-189.71264
	$\Delta CoVar001$/Random	-3.7349	-0.46	-281.6185
First/*OP*	$\Delta CoVar001$/Fixed	-4.1908	-1.25	-180.6571
	$\Delta CoVar005$/Random	-2.9802	-0.2	-209.9631
	$\Delta CoVar005$/Fixed	N/A		
	$\Delta CoVar001$/Random	0.8130	0.2	-209.0740
First/*PP*	$\Delta CoVar001$/Fixed	N/A		
	$\Delta CoVar005$/Random	-5.9937	-0.67	-279.2676
	$\Delta CoVar005$/Fixed	(-8.57422)***	-2.46	-178.6849
	$\Delta CoVar001$/Random	-2.8549	-0.47	-281.2752
Second/*OP*	$\Delta CoVar001$/Fixed	-4.2831	-1.29	-180.1973
	$\Delta CoVar005$/Random	-3.7877	-0.25	-206.5844
	$\Delta CoVar005$/Fixed	N/A		
	$\Delta CoVar001$/Random	-1.3241	-0.12	-208.8856
Second/*PP*	$\Delta CoVar001$/Fixed	N/A		
	$\Delta CoVar005$/Random	3.3948	0	-555.7051
	$\Delta CoVar005$/Fixed	3.1049	1.53	-477.2259
	$\Delta CoVar001$/Random	1.89153	0.08	-566.8492
Third/*OP*	$\Delta CoVar001$/Fixed	3.1195	1.54	-477.2087
	$\Delta CoVar005$/Random	1.1741	0.03	-444.0385
	$\Delta CoVar005$/Fixed	1.7802	0.86	-400.9266
	$\Delta CoVar001$/Random	1.1038	0.02	-444.0742
Third/*PP*	$\Delta CoVar001$/Fixed	1.7979	0.87	-400.9191
	$\Delta CoVar005$/Random	-6.3981	-.31	-676.6547
	$\Delta CoVar005$/Fixed	-6.48544***	-4.08	-636.1037
	$\Delta CoVar001$/Random	-6.44695	0.0	-675.52805
Fourth/*OP*	$\Delta CoVar001$/Fixed	-6.59749***	-4.28	-634.94961
	$\Delta CoVar005$/Random	-5.44806	-.17	-483.30478
	$\Delta CoVar005$/Fixed	-5.03459***	-2.97	-454.65444
	$\Delta CoVar001$/Random	-5.86028	-1.23	-483.33372
Fourth/*PP*	$\Delta CoVar001$/Fixed	-5.61198***	-3.44	-455.24416

- This table presents results when regressions are run under subsamples. The full sample are divided into four subsamples by the quartile values of the bank book assets. For each subsample, I run eight regressions in order to see the relationship between *OP/PP* and $\Delta CoVar001$ *and* $\Delta CoVar005$, applying fixed and random effects. For example, in the table First/OP stands for when *OP* is the dependent variable and the data is the subsample when bank book assets are in the first quartile. $\Delta CoVar005$/Random stands for when $\Delta CoVar005$ is the major independent variable (other independent variables are the same as the full sample regressions) and random effect is applied.

- I drop some yearly dummies in some of the regressions due to singularity.

Table 17. LR Tests for the Estimation Consistency in Subsamples and the Full sample

	ΔCoVar005/OP	*ΔCoVar001/OP*	*ΔCoVar005/PP*	*ΔCoVar001/PP*
LR χ^2 Value	1149.3536	2294.3021	612.06184	610.01016
Degree of Freedom	97	97	88	88

- This table presents the LR test χ^2 values. The LR tests are employed to test whether the estimations by using subsuamples are the same as the estimation by using the full sample.

Table 18. The Mean of *OP*, *PP*, *ΔCoVar001* and *ΔCoVar005* by Asset Quartile

Variable	**First Quartile Mean**	**Second Quartile Mean**	**Third Quartile Mean**	**Fourth Quartile Mean**
OP	2.7621	4.0857	6.4571	6.7675
PP	1.9493	2.6989	4.3363	4.9539
ΔCoVar001	-0.0016	-0.0298	-0.0306	-0.0332
ΔCoVar005	-0.0019	-0.0284	-0.0304	-0.0326

- This table presents the mean of four variables: *OP*, *PP*, *ΔCoVar001* and *ΔCoVar005* by quartile. It shows that on average, banks in higher asset quartile have larger rating gaps and present higher systemic risk.

5.2 Robustness Checks With Subsamples

In order to see if the relationship between rating gaps and *ΔCoVar* holds for banks of all sizes, I perform a "Chow" test of parameter equality. I split the full sample into four subsamples by using quartile values of book assets. Table 7 provides the minimum, lower quartile, medium and maximum of banks' book value of assets. Table 16 presents results for these subsamples. For each subsample, I run eight regressions corresponding to the relationships between *OP/PP* and *ΔCoVar001 and ΔCoVar005,* applying fixed and random effects. Note that when subsamples are applied, there are some gap measures with zero observations.

To test whether the estimations by using the subsamples are consistent with the estimation by using the full sample, I conduct four LR tests when random effects are applied. (Note 5) The null hypothesis is that banks behavior the same in all four subsamples. The hypotheses are that the coefficients obtained by using four subsamples are all equal and they are all equal to the ones obtained by using the full subsample. χ^2 values of the LR tests are presented in Table

17. At the 5% critical value, the null hypotheses are all rejected. That is, it may not be appropriate to pull all banks in one sample to do the estimation. The relationships between rating gaps and $\Delta CoVar$ may vary across banks, depending on which asset group they are in.

The relationships between rating gaps and $\Delta CoVar$ may vary across banks, depending on which asset quartile they are in. However, the coefficient on $\Delta CoVar005$ is significant at 1% and is -8.57422 when the second quartile subsample is used and the dependent variable is *OP*. Also, the coefficients on $\Delta CoVar001$ and $\Delta CoVar005$ are both negative and significant at 1% when banks are in the subsample of the fourth quartile bank asset and fixed effects are applied. Note the rating gap calculation method includes both *OP* and *PP*. That is, no matter an investor is a pessimist or an optimist, rating gaps are related to banks' $\Delta CoVar$ negatively. This is consistent with the expectation that the coefficients on $\Delta CoVar$ are supposed to be negative. As least I am able to draw the conclusion that higher rating gaps link to higher systemic risk when banks' book assets are greater than 83 billion dollars.

It is not surprising that the rating gaps can be proxies as systemic risk only for large banks. Table 18 presents the mean of *OP, PP,* $\Delta CoVar001$ *and* $\Delta CoVar005$ of four subsamples in quartiles. It shows that on average, banks in higher asset quartile have larger rating gaps and present lower value in $\Delta CoVar$, which suggests higher systemic risk. Large banks are likely to receive external support implicitly (funding discount comparing to small banks) or explicitly (bailed out by governments). Evidence shows that TBTF banks receive higher implicit external support no matter whether TBTF is identified by their asset size or their rating gaps. Acharya et al. (2014) find that only the largest 10% banks in their sample enjoy significant discount on finding. The bond spread between the largest 10% and the 90% rest of banks in their sample is about 30 basis point lower. Ueda and di Mauro (2013) show that on average, an uplift in rating gap leads to a funding cost advantage of 60 basis points at end of 2007 and 80 basis points at end-2009.

6. Conclusion

The relationships between rating gaps and $\Delta CoVar$ may vary across bank sizes. No matter an investor is a pessimist or an optimist, higher rating gaps link to higher systemic risk when banks' book assets are greater than 83 billion dollars. Banks with higher rating gaps are coincidently to be large banks. Large banks happen to be associated with higher systemic risk.

The analysis of this paper shows that $\Delta CoVar$, a precise measure for systemic risk, has a positive and significant relationship with rating gaps in large banks. The findings of this paper have important implications for both market participants and regulators. Instead of studying complicated quantitative models, they can use rating gaps as proxies for banks' systemic risk. The confirmation of a linkage between banks' systemic risk and their rating gaps provides great convenience for investors to assess banks' credit risk, and for regulators to easily identify banks with systemic importance.

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Notes

Note 1. The potential support to banks may come from two sources: their holding companies and regulating authorities. Since all observations are bank holding companies, for banks in the sample, support resource is only from regulating authorities. As stated in footnote 1, they might be FRB, SEC, insurance regulators and so on.

Note 2. I have tried to include bank asset size as an explanatory variable. However, the model crashed when I run the regressions. To exam whether asset size is a factor to affect the relationship between systemic risk and rating gaps, I then split the full sample into four subsamples based on quartile value of bank assets and run regressions on four subsamples.

Note 3. Quarterly dummies were also applied when both the full sample and the four sub-samples are used. However, due to multicollinearity, I am not able to obtain any results.

Note 4. For all regressions, I have tried both random effects and fixed effects. However, I fail to obtain any results when PP is the dependent variable with fixed effects estimation.

Note 5. I don’t test the results by using fixed effects because some of the estimation collapse due the potential invariance in cross-section dummy variables.