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 or not rating gaps between the 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. I conclude that rating gaps are good proxies for the 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. The 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. The 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. The all-in rating contains information not only about a bank's own financial strength, but also about the external support a bank could receive from its parent holding institution and/or government authorities. A rating gap is the difference between the all-in and the stand-alone rating and they capture the possible external support these banks may receive. This paper investigates whether or not 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 that bank. Systemic risk is defined as the systemic importance of an individual bank; that is, the amount of influence a bank in distress has on the banking system as a whole.

This paper is motivated to explore whether or not the information contained in the rating gaps are useful in identifying too-big-to-fail (TBTF) or systemic important banks. Being TBTF has become a major policy issue since the 2008 financial crisis. Further, most governments have decided to offer subsidies to large financial institutions to avoid a collapse of their financial systems due to the failure of a financial institution such as Lehman Brothers. Subsidies to TBTF banks generate an externality cost to society and induce moral hazard problems within the banks. Thus, using public fund to save TBTF financial institutions may cause a resource misallocation in the economy. Regulators have the responsibility to supervise and monitor TBTF risks in the banking system on a regular basis. Rating gaps, in turn, could be conveniently used by regulators as proxies for systemic risk at a particular frequency since rating agencies frequently publish their ratings. Some authors suggest that since investors expect that TBTF financial institutions would be guaranteed to be bailed out, they can more easily have cheaper funding costs, compared to non-TBTF banks (Jacewitz and Pogach 2014). Investors will benefit by looking just at a simple indicator for systemic risk and distinguishing whether the funding discount they give to a TBTF bank is because of the financial strength of the bank itself or because of the potential support from their government.

To the full extent of TBTF-related studies, identifying which intuitions are TBTF should be the first step. The 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. The Bank for International Settlements (BIS) provides an indicator-based methodology for identifying 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 published official list of G-SIBs, studies related to the methodologies for identifying TBTF are still in demand and being developed. In the Bank of England's recent paper on implicit subsidies to TBTF, Siegert and Willison (2015) consider "Which banks are TBTF" as a core question for future studies.

Rating the gaps and sizes are two major approaches for measuring the chance that a TBTF bank may receive subsidies (Noss and Sowerbutts 2012). The chance that a bank will be saved is related to the importance of the bank to the banking system. Large banks; however, are not necessarily systemically important. As pointed out by Packer and Tarashev (2011, p. 42), the role of banks "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 using only the asset size to identify TBTF, using rating gaps as proxies for a bank's systemic importance has both pros and cons. Using rating gaps might be a less noisy method because the rating agency would 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 a flawed methodology for estimating the likelihood that a bank may receive external support. As conjectured by Siegert and Willison (2015), even though the ratings may be imprecise, if investors believe that a bank will be bailed out when in distress, by only taking the bank's rating at face value, then the bank will still enjoy benefits from the ex-ante expectation effects of being systemic important.

In exploring whether or not the rating gaps contain reliable information for systemic risk, this paper contributes to the literature by proposing several methods for calculating the rating gaps, and determining whether or not the rating gaps are positively related to a quantitative systemic risk measure, Co-independent Value at Risk (CoVar), which is presented by Andrian and Brunnermerier (2009). 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 accounts for the fact that systemic risk tends to be cyclical, falling in booms and rising in crises. This chapter focuses on whether or not the rating gaps capture the same risk as captured by quantitative systemic risk measures (CoVaR). The main finding is that they do, but only for large banks. The confirmation of the existing linkage between a bank's 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 a bank's systemic risk and can easily identify the TBTF banks.

This chapter is organized as follows: Section 2 provides a related literature review; Section 3 describes the methodology; Section 4 discusses the data and presents the summary statistics; Section 5 presents the results; and Section 6 is the conclusion.

2. Related Literature

Few papers investigate the information contained in bank ratings in terms of bank 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 or not being "too-big-to-fail" might 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 author goes on to conclude that large banks benefit from a significant increase in ratings. Nevertheless, neither Peresetsky and Karminsky (2008) nor Rime (2005) use a precise measure for systemic risk, instead employing 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 (it) is evidenced by co-movements (correlation) among most or all of the parts." In theory, a definition of systemic risk needs to be traced back to externalities that are caused by networking among the banks and fire-sale spillovers. Neither Peresetsky and Karminsky (2008) nor Rime (2005) use measures that deal with the externality character of systemic risk. Network effects can also lead to externalities, as emphasized by Allen, Babus and Carletti (2010). Banks connect to each other through their related businesses. Especially when developing modern financial innovations (e.g., derivatives and securitization), banks have become much more interconnected in terms of risk-sharing relationships than in earlier times. Inter-linkages in the banking system can exacerbate the possibility that a run on an individual bank can cause a broader 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, which usually employ complicated econometric models. They generally define systemic risk as systemic importance of an individual bank; that is, the amount of influence a bank in distress has on the banking system as a whole. In particular, Acharya et al. (2010) focus on high-frequency marginal expected shortfalls as a systemic risk measure. Adams et al. (2010) 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. Andrian and Brunnermerier (2009) 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, the CoVar in Andrian and Brunnermerier (2009) is designed to measure how a single bank's distress affects the whole banking system.

These econometric models provide quantitative measures of systemic risk. Many of the market participants; however, are probably unable to develop and utilize such sophisticated models and may simply rely on rating agencies for the 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. The stand-alone rating reflects a bank's own financial strength. The all-in rating contains information not only about a bank's own financial strength, but also the external support a bank might 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.

A few technical issues need to be considered when calculating the rating gaps. First, a map must be constructed to compare the all-in and stand-alone ratings. Fitch (2011) provides a rating map (Table 1) that gives the equivalent category for each all-in rating and stand-alone rating. My analysis uses the ratings from Fitch as Standard & Poor's published financial strength ratings only for banks in the Asia-Pacific region and Moody's only began assigning stand-alone ratings in 2007.

Second, the stand-alone ratings and the all-in ratings do not have a one-to-one mapping for a given stand-alone rating, so that multiple all-in ratings are present. 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,” order the assigned ratings so that they have a one-to-one relationship without any overlap.

The third consideration is that all ratings are provided as a set of characters, not as quantitative measures. To obtain numerical rating gaps, I need to translate these ratings into numbers, which depends on which method is used 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, “no gap” occurs and the GAP variable is recorded as 0. If the all-in rating is one category higher/lower than the equivalencies in Table 1, a small positive /negative gap occurs and the value for the GAP variable is +1/-1. If the all-in rating is two or more cells above/below, a large positive/negative gap occurs and the value for the GAP variable is +2/-2. For example, if the stand-alone rating is A and the all-in rating is AA+, GAP is 0, whereas, if the stand-alone rating is A/B and the all-in rating is AAA, then GAP is +1. Summary statistics for the GAP variable are shown in Table 5.

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

Similarly, optimist mapping moves the all-in ratings with overlaps up to the next higher rating category. That is, all-in ratings of 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, the stand-alone ratings are translated into ordered numbers from 0 to 8, in increments of 1. I design two possible ways for assigning numbers to the all-in ratings. The first is termed the "grid method," which assumes that the all-in ratings have the same numerical value as that of the equivalent stand-alone rating category. For example, under 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 is equal to 3, so BB and BB- are both equal to 3, and the rating gap is 0.

The second method for assigning values to all-in ratings is the "point method". All-in ratings are assigned values ordered from 0 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, four measures are constructed for calculating rating gaps: pessimist-grid, pessimist-point, optimist-grid, and optimist-point. The variable names and methods are listed in Table 4. Numerical gaps are shown in Tables 2 and 3.

3.2 Measuring Systemic Risk

Following Andrian and Brunnermerier (2009), I use a variable $\Delta CoVaR_q^{system|i}$ to measure systemic risk. Intuitively, $\Delta CoVaR_q^{system|i}$ can be seen as an individual bank *i* in distress and its asset return is at or below the bottom q% of its historical asset return distribution, the amount that the banking system's total asset return would be changed by the bank's distress is 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%, the return of the banking system is estimated to 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.,$\left(X^i \leq VaR_q^i\right) = q$, where X^i is the asset return of bank *i*. The market value of a 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 to 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 $C()$ occurring and bank *i*'s asset return being at or below X^i.

A special case occurs 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:

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

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

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

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

$\Delta CoVaR_q^i$ is obtained by using equation (5)

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

The next step is to construct a time series for *CoVaR* and *VaR*. Similar to Andrian and Brunnermerier (2010), I use a vector of state variables S_{t-1} to capture time variation in conditional moments of asset returns. The 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. Andrian and Brunnermerier (2009) find that the change in the three-month Treasury bill rate significantly explains the tails of the 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 maturities 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, representing 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 $\mathrm{X}_{\mathrm{t}}^{\mathrm{system}}$ 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 parameters $\widehat{\theta^{\iota}}$, $\widehat{\lambda^{\iota}}$, $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$ and $\hat{\gamma}^{system|i}$ from equations (6) and (7) are used to calculate:

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

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

Finally, I compute $\Delta CoVaR_t^{system|i}$ at the qth 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)[1]. Three data sources are used: 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, from Bloomberg. The quarterly data for a bank's book value of assets and book value of equity are from the FRY-9C reports. Both a bank's quarterly stock price and outstanding shares are from CRSP. To calculate the banking system's asset return, I begin with a pool of 589 banks. The final data set used to estimate the ordered probit model contains 1,819 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.

[1] The potential support to banks may come from two sources: their holding companies and the regulating authorities. Since all observations are of bank holding companies, for the banks in the sample, support resources are only from the regulating authorities. They could be FRB, SEC, or insurance regulators, and so on.

4.2 Summary Statistics

The summary statistics for the gaps and the gaps grouped by stand-alone ratings are listed in Tables 5 and 6, respectively. The summary statistics include some negative numbers, such as the minimum values for all five types of gaps. A negative external support could occur when the rating agency updates all-in ratings and stand-alone ratings at different times. 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 AA. So, the variable *PPGAP* is recorded as 0 for the second quarter of 1997 but as -1 for the third quarter.

The correlation matrix for the five rating gaps is shown in Table 9. The correlations between the 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 the four ratings gaps. Apparently, whether or not the overlaps in the ratings are ignored can make a big difference.

Overall, of 1,819 observations, 1,445 had non-zero values for *PGGAP*, 1,550 non-zero values for *PPGAP*, 788 non-zero values for *OGGAP*, 1,550 non-zero values for *OPGAP* and 219 non-zero values for *GAP*. Further, 21 of the values for *PGGAP* were non-negative, 126 were non-negative for *PPGAP*, 621 were non-negative for *OGGAP*, 1,064 were non-negative for *PPGAP*, and 30 were non-negative for *GAP*. Interestingly, most observations are concentrated on two or three values. Except for *PPGAP* and *OPGAP*, the other gaps show little variation, which can be seen in the histograms for the gaps (Figures 1 to 5), for both the full sample and the 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 7 and the summary statistics for all gap measures based on bank size are shown in Table 8.

For the *PGGAP* and *OGGAP* variables, the observations are clustered on four values. I tried each of the five rating gaps as the dependent variable in equation (11), with either the full sample or the sub-samples. As expected, due to lack of variation with three of the gap measures, results were obtained only for *OPGAP* and *PPGAP*. Therefore, I 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.

The variables in the final regression are described in Table 11, and in Table 12, I present the 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 that 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.

Both Δ*CoVar005* and Δ*CoVar001* are estimated variables based on equation (10). Δ*CoVar* describes 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 the historical asset return for the default thresholds), compared to when the bank's asset return is at its historical median. The mean for Δ*CoVar001* is -0.0231 and for Δ*CoVar005*, it is -0.0234. This means that, on average, when a bank is at a default threshold, the asset return of the banking system drops by 1.8%, compared to when the bank has asset returns equal to the median. The maximum value for Δ*CoVar005* is 0.2705 and for Δ*CoVar001*, it is 0.3678.

From 1994 to 2007, the VIX index in the sample varies from 11.38 to 40.95. The mean of the Dow Jones Real Estate index return is 0.02, which means that 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 the variables in the ordered probit model. The correlation between the all-in rating variable *RA* and the stand-alone variable *RI* is positive, and significant at the 1% level. This indicates that banks with higher stand-alone financial strength usually receive higher all-in ratings. Both Δ*CoVar005* and Δ*CoVar001* are negatively correlated with *OP/PP*, and significant at 1%. A negative Δ*CoVar* means that the bank's default causes the banking system asset return to drop. The lower the value of Δ*CoVar* for a bank, the higher the systemic importance of the bank. The negative correlation between *OP/PP* and Δ*CoVar* may be a sign that banks with higher systemic importance usually have a higher rating gap.

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.[2, 3]

The purpose of this chapter is to assess whether or not 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: $\tau < 0$ since $\Delta CoVaR_{i,t}^{system|i}(q)$ measures how much the asset return of the banking system may drop when a bank is in distress, compared to the asset return of the banking system when the 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

Tables 14 and 15 present the results of the ordered probit model, using the same group of control variables but two different independent variables, namely Δ*CoVar* at 1% and 5%.[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.

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2 I tried to include bank asset size as an explanatory variable; however, the model crashed when I ran the regressions. To examine whether or not asset size affects the relationship between systemic risk and rating gaps, I split the full sample into four subsamples based on quartile value of bank assets and then ran regressions on the four subsamples.

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

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

Testing the null hypothesis that the rating gaps are positively linked to systemic risk is equivalent to testing whether or not the coefficients on Δ*CoVar* are significantly negative. As seen in Tables 14 and 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 of a bank, 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 the 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, causing 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 Tables 14 and 15 and plotted in Figures 6, 7, and 8. For example, in the upper panel of Figure 6, the marginal effects of Δ*CoVar005* switch from being positive to being negative when $OP = 6$, and they then switch back to being positive when *OP= 12*. The summation of all the coefficients for all *OP* notches is naturally equal to 0 since the summation of all possibilities for a bank receiving a rating notch change must be zero.

The interpretation of the marginal effects of Δ*CoVar* seems complicated. Arguably, the exact interpretation is not important in this chapter as the main focus here is whether or not the rating gap is an easily constructed and useful proxy for measuring the systemic risk of a bank. The evidence suggests that it is.

Nevertheless, as Rime (2005) shows, the too-big-to-fail expectation boosts a bank's all-in ratings. Although all-in ratings may not necessarily be directly related to the external support, and the rating gaps may be a better measure for systemic support, Rime's (2005) conclusion implies that banks may not receive external support equally. Larger banks may enjoy more systemic support and the relationship between systemic risk and a bank's rating gap may shift the dependence on a bank's size.

5.2 Robustness Checks with Subsamples

To see whether or not the relationship between rating gaps and Δ*CoVar* 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 a bank's book value of assets. Table 16 presents the results for these subsamples. For each subsample, I run eight regressions corresponding to the relationships between *OP/PP* and Δ*CoVar001 and* Δ*CoVar005,* applying fixed and random effects. Note that when subsamples are used, some gap measures are seen to have zero observations.

To test whether or not the estimations that use the subsamples are consistent with the estimations that use the full sample, I conduct four LR tests when random effects are applied.[5] The null hypothesis is that a bank's behavior is the same for all four subsamples. The hypotheses are that the coefficients obtained using the four subsamples are all equal and equal to those obtained using the full subsample. The 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 pool all banks into one sample to do the estimation. The relationships between rating gaps and Δ*CoVar* may vary across banks, depending on which asset group they are in.

The relationships between rating gaps and Δ*CoVar* may vary across banks, depending on which asset quartile they are in. Nevertheless, the coefficient on Δ*CoVar005* is significant at 1%

[5] I do not test the results using fixed effects because some of the estimations collapse due the potential invariance in cross-section dummy variables.

and it is -8.57422 when the second quartile subsample is used and the dependent variable is *OP*. Also, the coefficients on Δ*CoVar001* and Δ*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 that the rating gap calculation method includes both *OP* and *PP*. That is, regardless of the investor being a pessimist or an optimist, the rating gaps are negatively related to a bank's Δ*CoVar*. This is consistent with the expectation that the coefficients on Δ*CoVar* are supposed to be negative. As least I am able to draw the conclusion that higher rating gaps are linked to higher systemic risk when a bank's book assets are greater than $83 billion.[6]

Not surprisingly, the rating gaps can be proxies for systemic risk only for large banks. Table 18 presents the mean of *OP, PP,* Δ*CoVar001, and* Δ*CoVar005* for the four subsamples in quartiles. It shows that, on average, banks in the higher asset quartile have larger rating gaps and a lower value for Δ*CoVar*, which suggests higher systemic risk. Large banks are likely to receive external support implicitly (funding discounts, in contrast to small banks) or explicitly (bailed out by governments). The evidence shows that TBTF banks receive higher implicit external support regardless of the TBTF banks being identified by their asset size or their rating gaps. Acharya et al. (2013) find that only the largest 10% of banks in their sample enjoy significant discounts on funding. The bond spread between the largest 10% and the remaining 90% of banks in their sample is about 30 basis points. Ueda and di Mauro (2013) show that, on average, an uplift in the rating gap led to a funding cost advantage of 60 basis points at the end of 2007 and 80 basis points at the end of 2009.

[6] All currencies are in $US.

6. Conclusion

The relationships between rating gaps and $\Delta CoVar$ may vary across banks, depending on which asset group they are in. Regardless of an investor being a pessimist or an optimist, higher rating gaps are linked to higher systemic risk when a bank's book assets are greater than $83 billion. Banks with higher rating gaps are coincidently large banks and large banks happen to be associated with higher systemic risk.

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

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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, gives the connections between stand-alone ratings and all-in ratings.

Table 1 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
E	0	CCC	0	0.7
		CC	0	0.3
		C	0	0

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

Table 2 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
A/B	7	AA-	7	7.6
		A+	7	7.3
		A	7	7
B	6	A-	6	6
B/C	5	BBB+	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 using the Optimist Method.

Table 3 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.

Table 4 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 5 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

Table 6 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 thousands of dollars.

Table 7 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.

Table 8 Correlation between Five Rating Gap Measures

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

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

Table 9 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 to fit the requirement as the dependent variables for the ordered probit model.

Table 10 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; the 21 gradations are from 1 to 21.
RI	Stand-alone ratings, transferred from characters into numbers; the 10 gradations are 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 captures the viability of the

	market.
HOUSING	The change in the Dow Jones United States Real Estate Industry Group Index, which represents Real Estate Investment Trusts (REIT) and other companies investing directly or indirectly in real estate through development, management or ownership, including property agencies. The Index is float-adjusted and market cap-weighted. The 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 the seven factors listed below.
LIQUIDITY	The difference between the three-month repo rate and the three-month bill rate, 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 with a maturity of ten years.
SPX	The quarterly equity market return from the SPX index.

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
Δ*CoVar005*	1819	-0.0234	0.0544	-0.2873	0.2705
Δ*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 the summary statistics for variables used to estimate CoVar and in the final ordered probit model.

Table 11 Correlation Matrix

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

	RI	*RA*	$\Delta CoVar005$	$\Delta CoVar001$	*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.

Table 14 Ordered Probit Regressions, ∆*CoVar 005*

	OP/Random	*OP*/Fixed	*PP*/Random
∆*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 the ordered probit regressions. The independent variables include ∆CoVar005, 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 ∆*CoVar005* are reported for every rating gap grade.The second column presents the results using *OP* as the dependent variable with a random effect applied to the panel data. The third column presents the results using *PP* as the dependent variable with a fixed effect applied. The last column presents the results using PP as the dependent variable with a random effect applied.
- Limdep cannot compute the fixed effect ordered probit 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 the ordered probit regressions. The independent variables include 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 grade.The second column presents the results using *OP* as the dependent variable with a random effect applied to the panel data. The third column presents the results using *PP* as the dependent variable with a fixed effect applied. The last column presents the results using PP as the dependent variable with a random effect applied.
- Limdep cannot compute the fixed effect ordered probit model when the dependent variable is *PP*.

Table 16 Results Obtained Using Subsamples

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

- This table presents results when regressions are run under subsamples. The full sample is divided into four subsamples by the quartile values of the bank book assets. For each subsample, I run eight regressions to see the relationship between *OP/PP* and Δ*CoVar001* and Δ*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. Δ*CoVar005*/Random stands for when Δ*CoVar005* is the major independent variable (other independent variables are the same as the full sample regressions) and a 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

	Δ*CoVar005/OP*	Δ*CoVar001/OP*	Δ*CoVar005/PP*	Δ*CoVar001/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 used to test whether or not the estimations using subsamples are the same as the estimation using the full sample.

Table 18 The Mean of *OP, PP,* Δ*CoVar001* and Δ*CoVar005* 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
Δ*CoVar001*	-0.0016	-0.0298	-0.0306	-0.0332
Δ*CoVar005*	-0.0019	-0.0284	-0.0304	-0.0326

- This table presents the mean of four variables: *OP*, *PP*, Δ*CoVar001*, and Δ*CoVar005* by quartile. It shows that, on average, banks in higher asset quartiles have larger rating gaps and present higher systemic risk.

Figure 1 ***OPGAP***

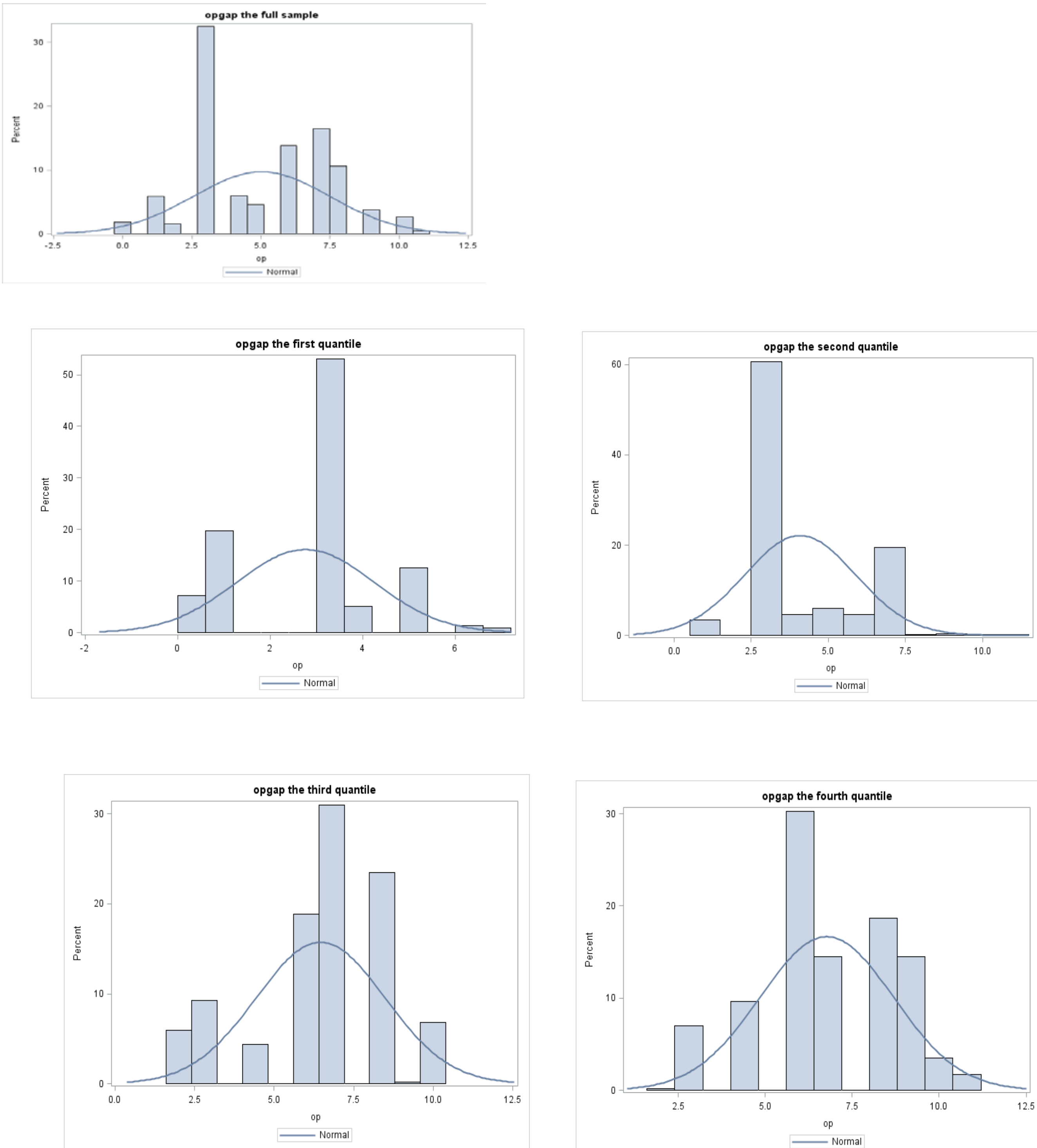


Figure 2 ***PPGAP***

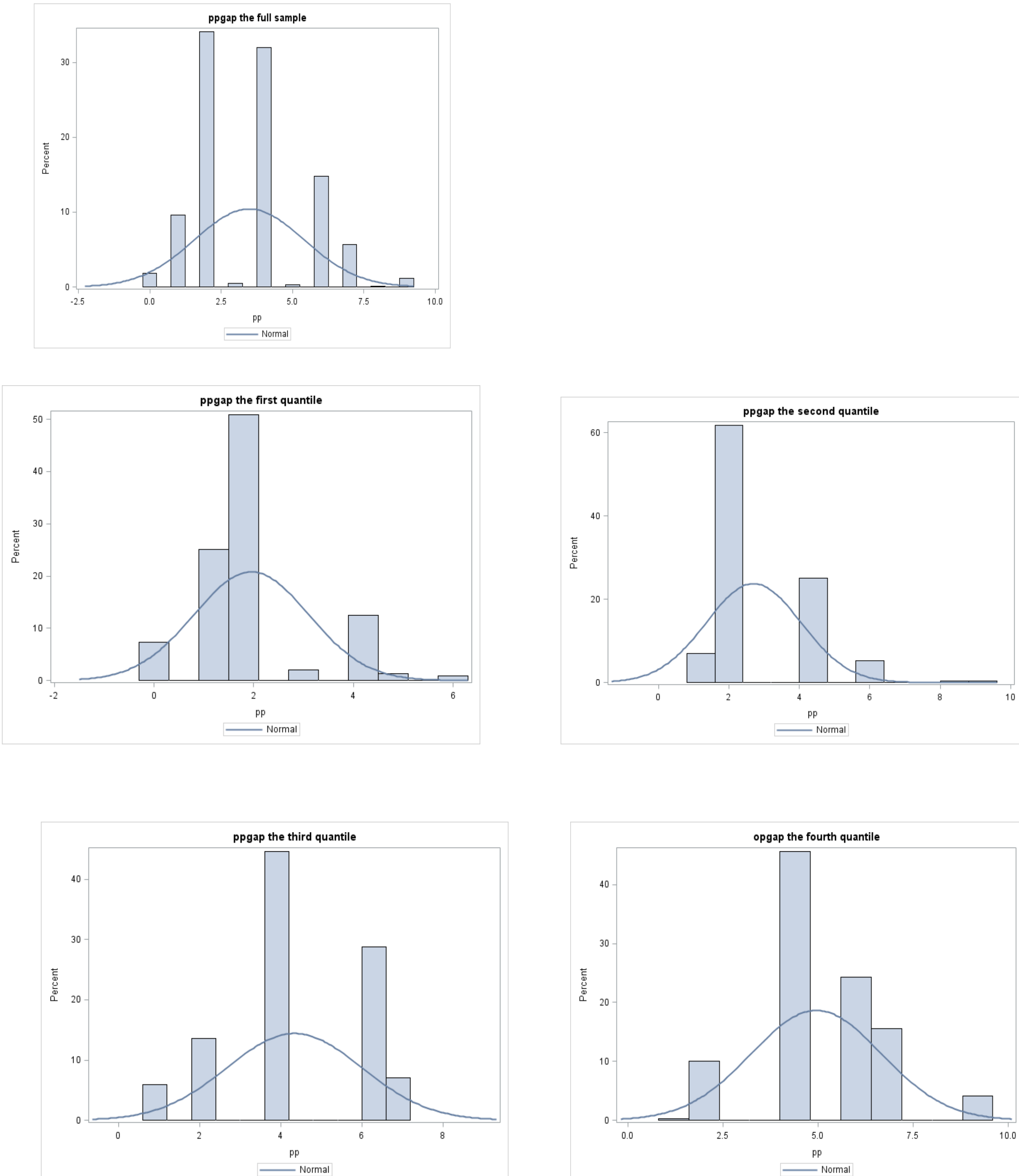
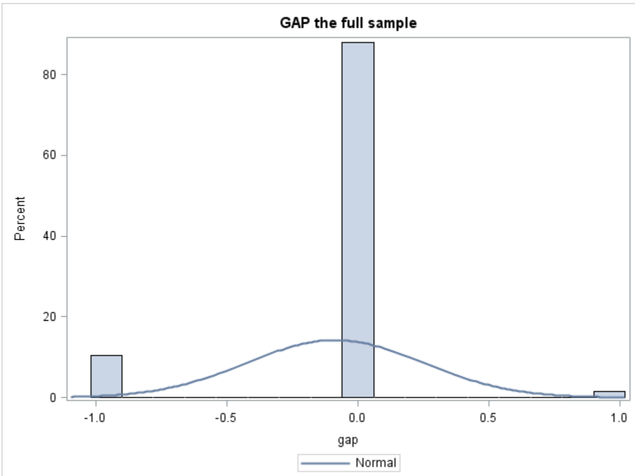


Figure 3 *GAP*


GAP the full sample
Percent
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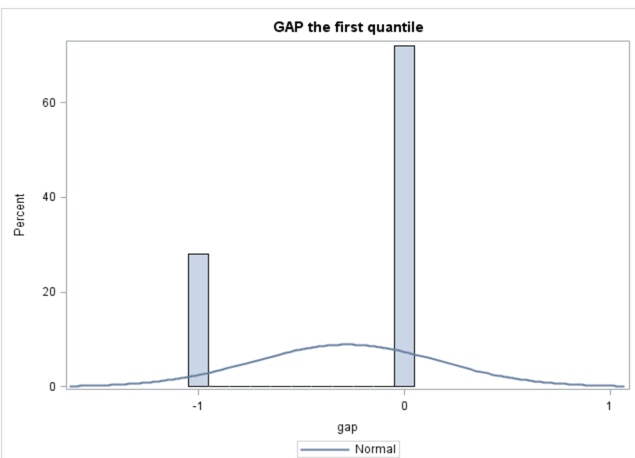
60
40
20
0
-1.0
-0.5
0.0
0.5
1.0
gap
Normal


GAP the first quantile
Percent
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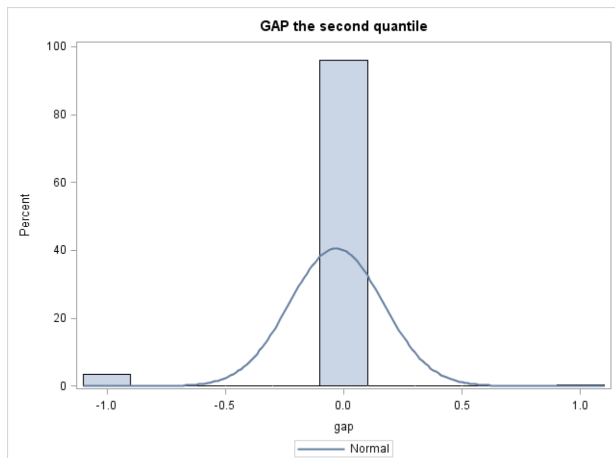
40
20
0
-1
0
1
gap
Normal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Percent
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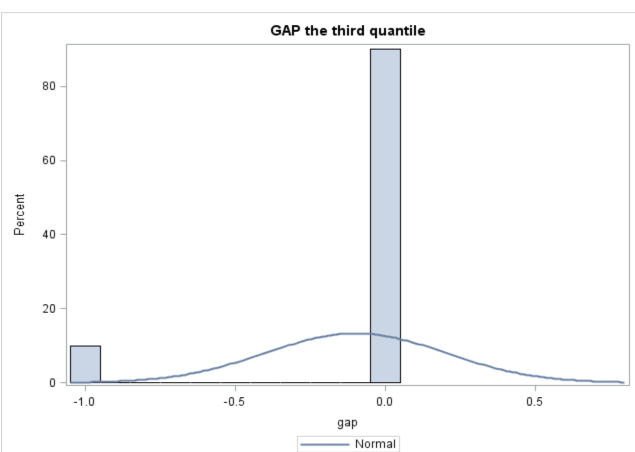
60
40
20
0
-1.0
-0.5
0.0
0.5
1.0
gap
Normal


GAP the third quantile
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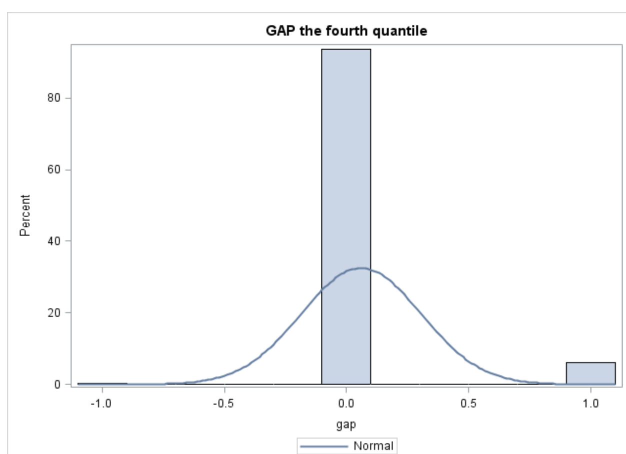
40
20
0
-1.0
-0.5
0.0
0.5
gap
Normal


GAP the fourth quantile
Percent
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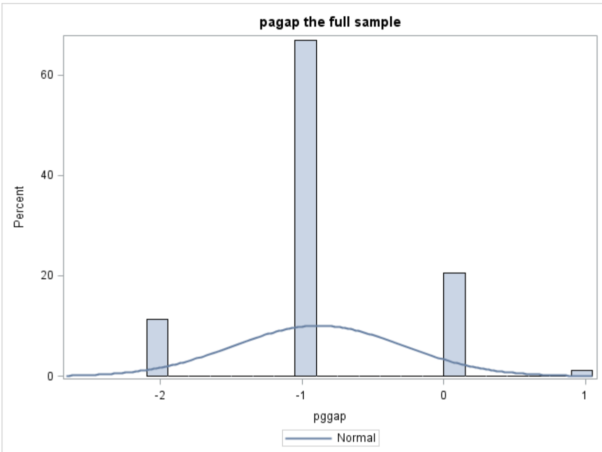
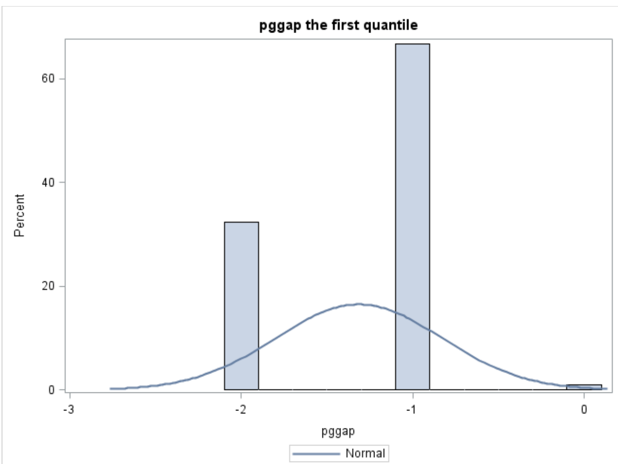
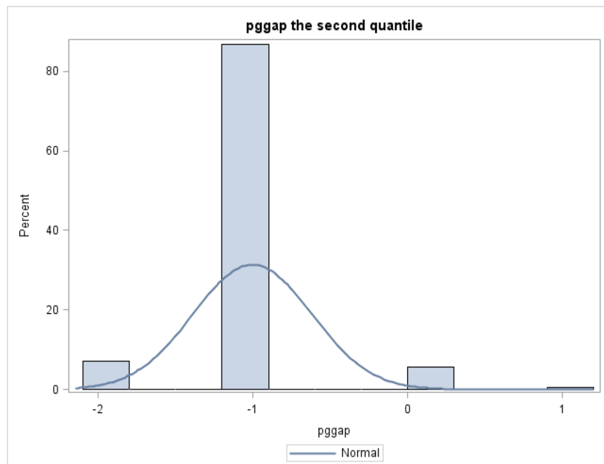
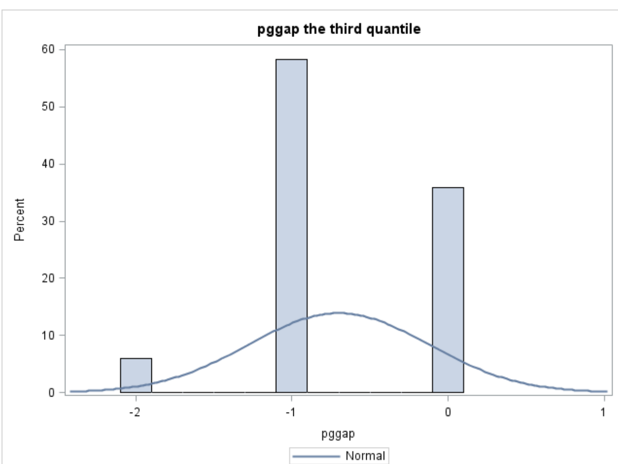
60
40
20
0
-1.0
-0.5
0.0
0.5
1.0
gap
Normal

Figure 4 *PGGAP*









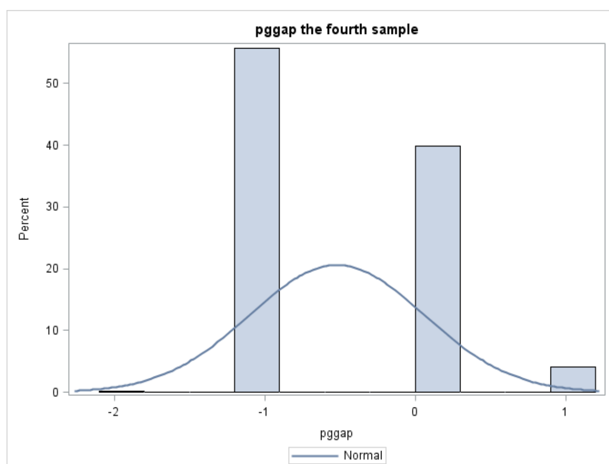
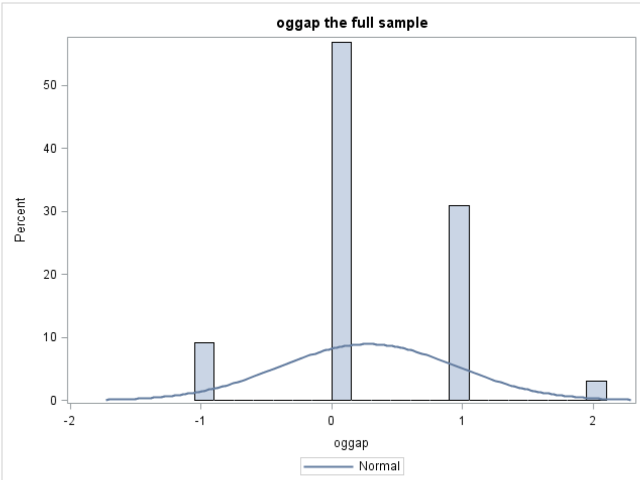
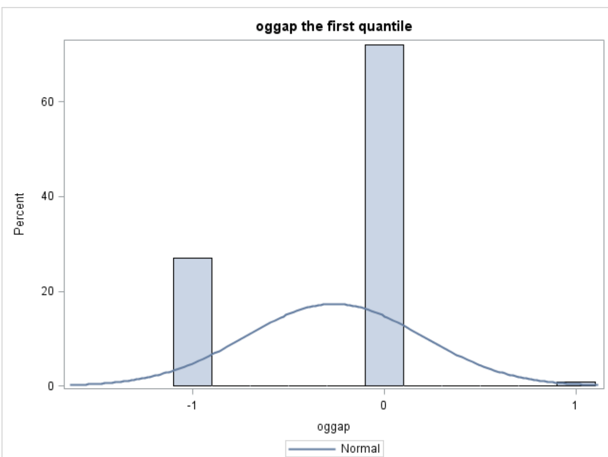
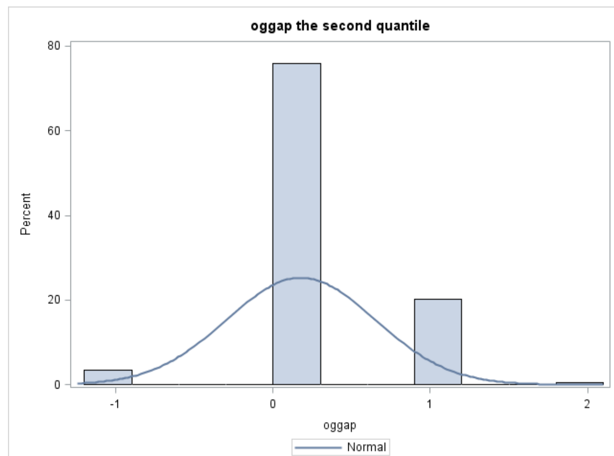
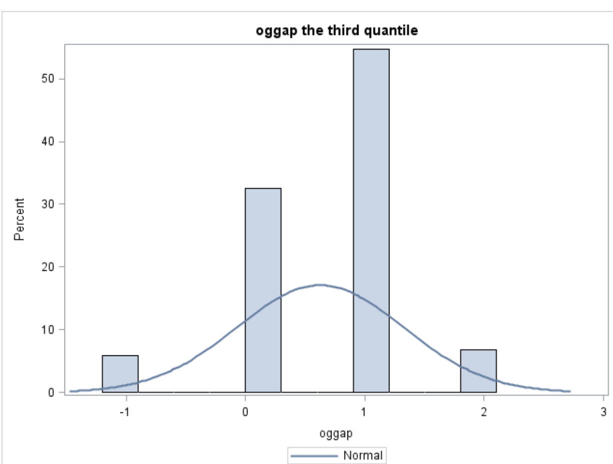


Figure 5 *OGGAP*









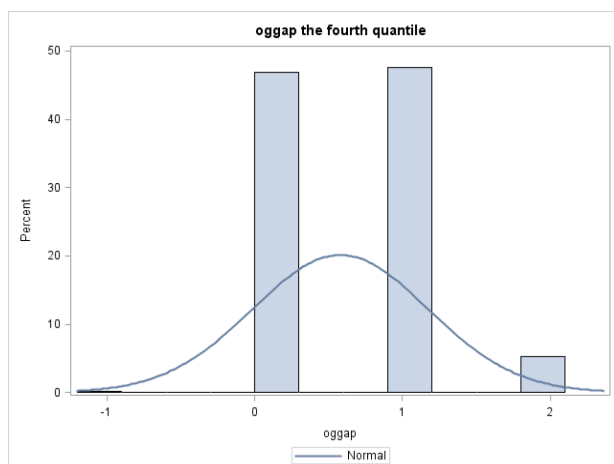
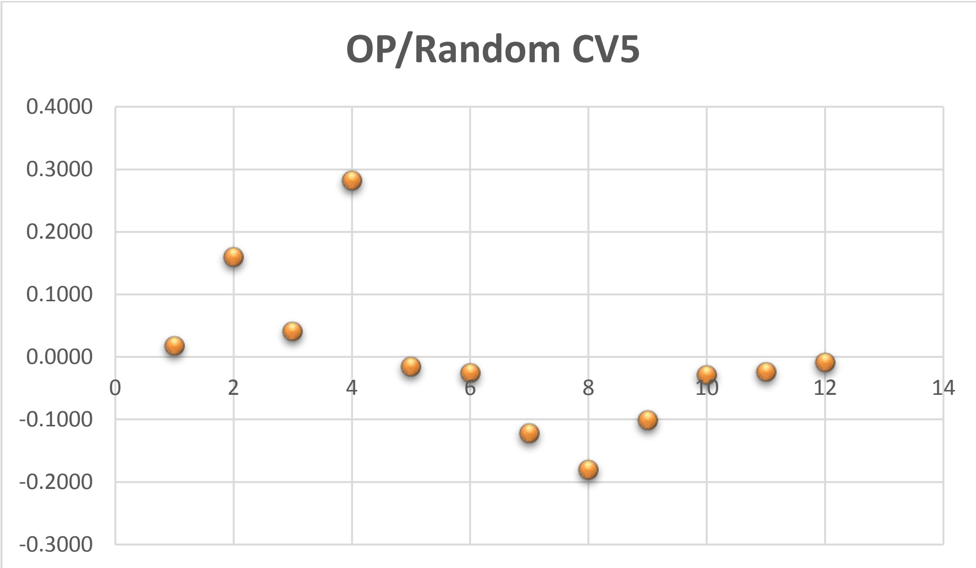


Figure 6 Marginal Effects/*OP-CV5*



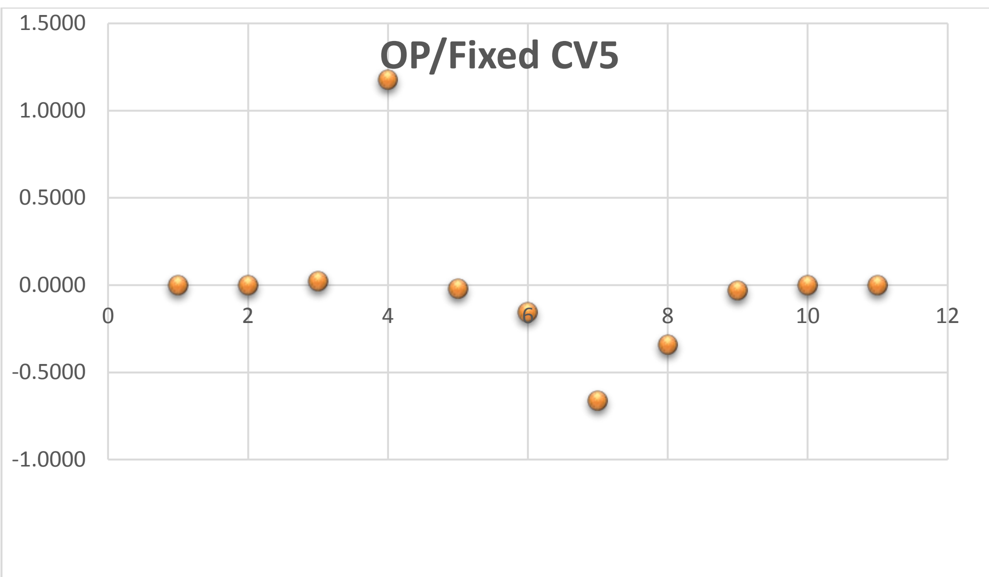
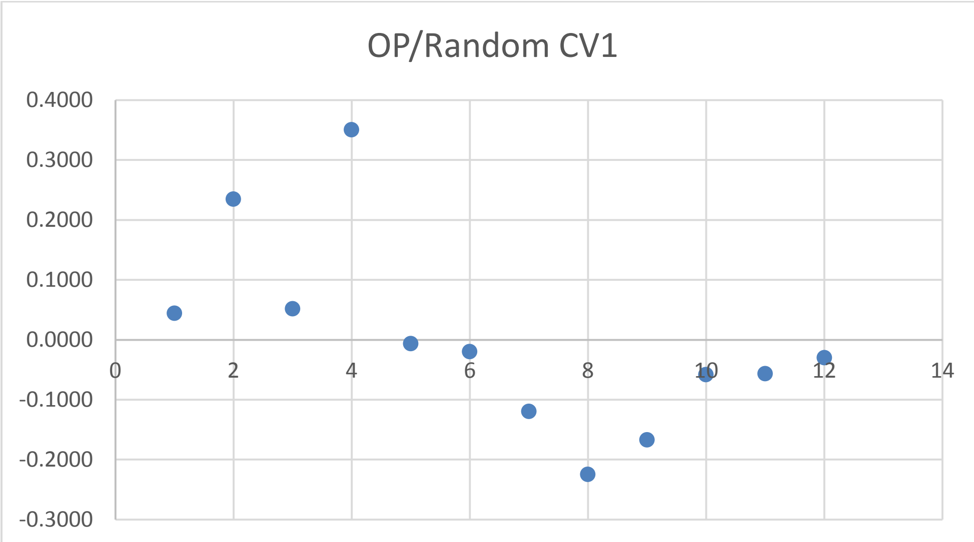


Figure 7 Marginal Effects/*OP-CV1*



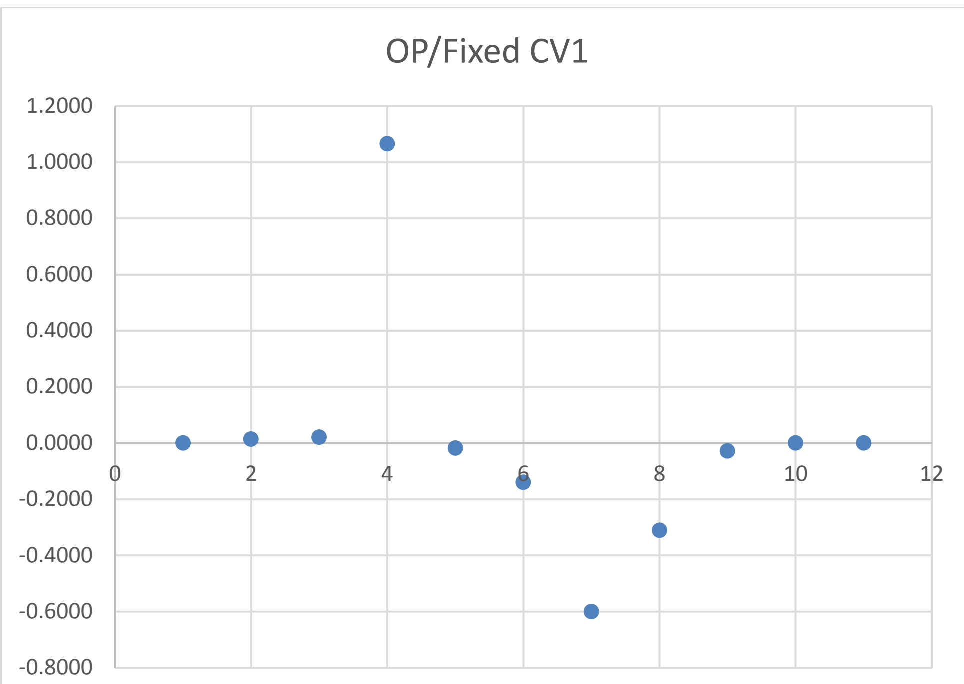


Figure 8 Marginal Effects/*PP*