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Can Higher Capital Discipline Bank Risk: Evidence from a Meta-Analysis

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Received: 23 July 2019; Accepted: 15 August 2019; Published: 20 August 2019



Abstract: Capital regulation has been among the most important tools for regulators to maintain the credibility and stability of the financial systems. However, the question whether higher capital induce banks to take lower risk remains unanswered. This paper examines the effect of capital on bank risk employing a meta-analysis approach, which considers a wide range of empirical papers from 1990 to 2018. We found that the negative effect of bank capital on bank risk, which implies the discipline role of bank capital, is more likely to be reported. However, the reported results are suffered from the publication bias due to the preference for significant estimates and favored results. Our study also shows that the differences in the previous studies' conclusions are primarily caused by the differences in the study design, particularly the risk and capital measurements; the model specification such as the concern for the dynamic of bank risk behaviors, the endogeneity of the capital and unobserved time fixed effects; along with and the sample characteristics such as the sample size, and whether banks are bank holding companies or located in high-income countries.

Keywords: bank capital; bank risk; meta-analysis; Bayesian model-averaging; capital regulation

1. Introduction

Three decades have passed since the first introduction of the Basel I Accord in 1988. Since then, capital regulation has been among the most important tools for regulators to maintain the credibility and stability of the financial systems. The capital regulation emphasizes the role of capital in disciplining the bank risk such that it requires banks to hold an adequate amount of capital to cover their risk. Over time, the accord has been regularly revised to enhance the quality of banking supervision and further ensure the credibility and stability of the international banking system. The latest version of Basel Accord—Basel III—is a response of the regulators to the massive failure of the banking system during the global financial crisis of 2007–2009. The new framework gives more focus on the role of capital by strengthening the regulatory capital base in both quality and quantity and introducing new minimum requirements for the non-risk-based capital (the leverage ratio), the common equity tier 1 capital, the capital conservation buffers as well as the capital surcharges for global systemically important banks (G-SIB) (BIS 2018). The average total capital to asset ratio of banks across countries has gradually increased from just 8.55% in 2000 to 10.31% in 2015. The average risk-weighted regulatory capital ratio also raises from 13.3% to 16.95% during the same period (World Bank 2018). While it is favorable for banks to have more capital, there remains debates on whether higher capital induce banks to take lower risk.

There have been two opposing views on the effect of capital on bank risk. One stream believes that capital represents the shareholders' benefits. Thus, it will motivate banks to manage risk properly and efficiently. Consequently, banks tend to take less risk given the higher level of capital. This stream is often

regarded as the “moral hazard hypothesis” (Admati et al. 2013; Gale 2010). The other stream, which is often referred as the “regulatory hypothesis”, argues that capital is costly, the enforcement of regulatory actions such as capital requirements increase the cost of capital (regulatory cost). Hence, they are induced to increase their risks to generate higher return (Altunbas et al. 2007; Shrieves and Dahl 1992).

Given different views on the effect of bank capital, numerous studies have relied on empirical evidence to solve the puzzle. Our survey of the literature yields around 100 empirical studies (until August 2018) studying the effect of bank capital on bank risk. However, the findings are inconclusive. These findings are important to the Basel Committee (who acts as the primary global standard setter for the prudential regulation of banks) and central banks’ governors for policy design to maintain the stability of the banking and financial system. Therefore, this study investigates empirical research on the impact of bank capital on bank risk to identify (1) whether bank capital increase or reduce bank risk; and (2) why there are variations in previous studies’ conclusions.

For that purpose, we employ a meta-analysis method. Since the term first coined by Glass in 1976 (Glass 1976), the meta-analysis has gained popularity and widely adopted in psychological research and major review articles in many fields, including finance and banking. These studies focus on controversial topics such as bank efficiency (Aiello and Bonanno 2016, 2018), bank competition and stability (Zigraiova and Havranek 2016), financial development and economic growth (Valickova et al. 2015), and the policy impact (Fidrmuc and Lind 2018; Gechert 2015). Meta-analysis is useful for review articles by providing a systematic review of the literature and not suffering from potential selective bias as qualitative literature surveys (Glass 1976; King and He 2005).

Our meta-dataset comprises 910 observations from 89 papers during the period from 1990 to 2018. We found that the negative effect of bank capital on bank risk, which implies the discipline role of bank capital, is more likely to be reported. However, the reported results are suffered from the publication bias due to the preference for significant estimates and favoured results. Our study also shows that the differences in the previous studies’ conclusions are primarily caused by the differences in the study design, particularly the risk and capital measurements; the model specification such as the concern for the dynamic of bank risk behaviors, the endogeneity of the capital and unobserved time fixed effects; along with and the sample characteristics such as sample size, and whether banks are bank holding companies or located in high-income countries. Even using the same risk measurements, the effect also varies due to the different model settings and samples.

Our study contributes to the literature in several ways. First, to the best of our knowledge, our study is the first to apply a meta-analysis to investigate the effect of bank capital on bank risk. Second, the study covers a comprehensive empirical literature over the past three decades. Third, rather than estimating the variations in the effect of bank capital on bank risk using the traditional fixed and random effect models, we apply Bayesian model-averaging techniques to address the model uncertainty. Fourth, our study is useful for academics in researching the way to constrain bank risk and for policy makers to design a proper banking regulation to promote the financial stability.

The remainder of the paper is structured as follows. Section 2 describes the data and methods used in the study. Section 3 reports the results. Section 4 conducts some further analysis including regressions for different risk measurements as well as calculating the “benchmark” and “best-practice” estimates for different risk measurements and samples. Finally, Section 5 concludes the paper with implications for future research and policy makers.

2. Data and Methodology

2.1. Data

Our data comes from previous papers that investigate the effect of bank capital on risk. We searched for all articles and working papers from online databases including Web of Science, ABI, Scopus, ScienceDirect Elsevier, JSTOR, Wiley Online Library, Crossref, Taylor & Francis, Springer, HAL, and Palgrave Macmillan. Searching key words are “bank”, “risk”, and “capital” in the title. Publication

date is restricted to range from 1990 to 2018, since studies on the topic increase significantly after the introduction of Basel I standard in 1988. Initially, we obtained 268 results. Then, we manually searched the top journals in finance (These are A* journals in finance (code 1502) in the ABDC journal list 2018, available at <http://www.abdc.edu.au/master-journal-list.php>), checked the reference lists in the found articles, and searched the Google Scholar database so that we did not omit important articles. We retrieved an additional 49 papers. We finish searching on 17 August 2018 with a total of 317 papers.

Then, we skimmed these papers and applied some criteria to obtain the final dataset. For this purpose, the paper should: (i) conduct empirical analysis; (ii) be written in English; (iii) estimate the coefficient β in equation (1); and (iv) have enough information to apply meta regression analysis (coefficient β and its standard deviations, or p -value). After filtering, our dataset comprised of 89 papers with 910 observations. The full list of surveyed papers is provided in Appendix A.

Specifically, papers considered should empirically examine the following model:

$$Risk_{it} = \alpha + \beta Capital_{it} + \sum_{k=1}^K \gamma_k X_{kit} + \varepsilon_{it} \tag{1}$$

where i is a bank index, t is a time index, and X is a set of control variables. The interest is in the coefficient β , which reflects the effect of bank capital on risk.

2.2. Standardized Effect Sizes

Given the broad scope of the measures for bank risk and the measurement units of regression variables in the literature, it is imperative that we re-compute the individual estimates (reported coefficient β) to a common metric. We transform the reported estimates into partial correlation coefficients (PCCs) as follow:

$$PCC_{ij} = \frac{t_{ij}}{\sqrt{t_{ij}^2 + df_{ij}}} \tag{2}$$

where t_{ij} and df_{ij} are t -statistic and degree of freedom of the reported estimates j th in study i th, respectively. PCC represents the statistical strength of the relationship between bank capital and risk (Since ZSCORE has reverse interpretation with other risk measurements. That is, higher ZSCORE implies lower risk. Thus, all betas and t -statistics in studies using ZSCORE are multiplied with (-1) before calculating PCC to be consistent with other measurements).

For cases that standard errors (se) of estimates β are reported instead of t -statistics, we derive t -statistics from the following equation:

$$t = \frac{\hat{\beta}_{ij}}{se(\hat{\beta})_{ij}} \tag{3}$$

If p -values of estimates β are reported rather than its standard errors, we obtain the t -statistics from estimates β and the number of observations using Excel two-tailed inverse function of the Student's t -distribution (T.INV.2T) with the sign corresponding to the sign of β .

The standard errors of PCCs are denoted as follows:

$$SEPCC = \sqrt{\frac{(1 - PCC_{ij})}{df_{ij}}} \tag{4}$$

Figure 1 displays the distribution of the effects of bank capital on risk. Before standardizing, the estimates varied greatly from -800 to 200 percentage point (Figure 1a) but distribute more normally and ranged from -1 to 1 after standardizing (Figure 1b).

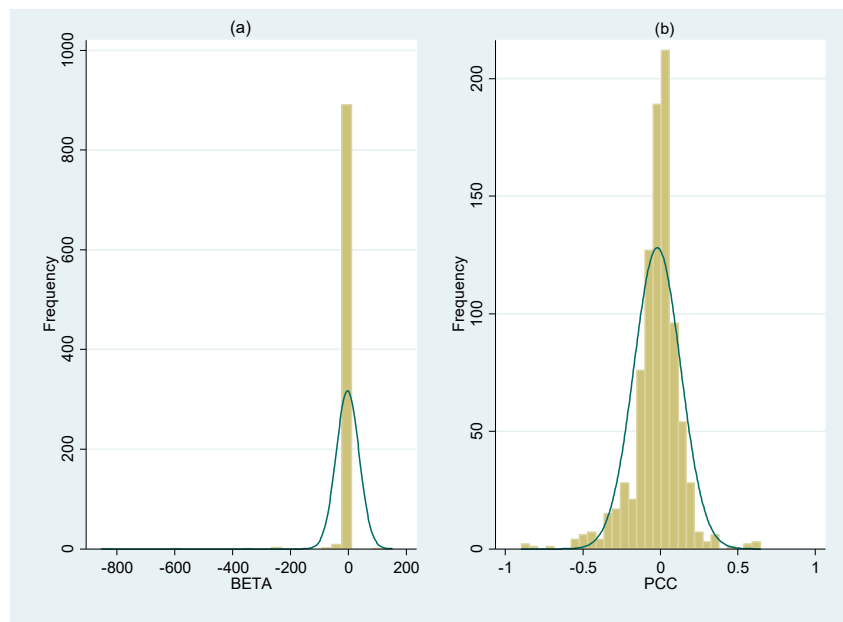


Figure 1. Distribution of the reported (a) and standardized effects (b) of bank capital on risk.

Table 1 shows that PCC varies substantially across countries. There is both positive and negative evidence on the relationship between bank capital and risk. This explains a large number of studies conducting cross-country analysis. Among the countries, the U.S attracts the most interest of the researchers. Both mean and median of all reported studies are negative and suggest a discipline role of bank capital. That is, higher capital induces banks to operate safely and take less risk.

Table 1. Standardized effects of bank capital on risk (partial correlation coefficient—PCC) across countries.

Country	Observations	Studies	Mean	S.D	Min	Max	Median
Bangladesh	20	3	−0.252	0.087	−0.370	−0.071	−0.284
Brazil	3	1	0.084	0	0.084	0.084	0.084
Canada	7	1	0.100	0.014	0.078	0.120	0.099
China	36	6	−0.122	0.245	−0.803	0.164	−0.073
Egypt	7	1	0.186	0.064	0.112	0.255	0.159
France	4	1	0.066	0.241	−0.181	0.284	0.081
India	35	6	−0.125	0.191	−0.500	0.457	−0.146
Indonesia	4	1	−0.218	0.081	−0.285	−0.100	−0.243
Italy	5	1	−0.010	0.034	−0.054	0.017	0.013
Jamaica	4	1	−0.009	0.071	−0.11.	0.051	0.012
Japan	8	3	0.068	0.121	−0.171	0.218	0.105
Jordan	6	1	0.010	0.144	−0.210	0.203	−0.013
Lebanon	2	1	−0.109	0.019	−0.122	−0.095	−0.109
Luxembourg	4	1	−0.345	0.356	−0.873	−0.130	−0.189
Malaysia	3	2	0.079	0.423	−0.212	0.565	−0.116
Pakistan	12	2	−0.063	0.266	−0.331	0.355	−0.092
Russian Federation	6	1	0.023	0.026	−0.001	0.065	0.016
Switzerland	12	2	0.104	0.05	0.007	0.166	0.128
Tunisia	13	5	−0.075	0.270	−0.488	0.210	0.015
UK	10	1	−0.053	0.025	−0.072	−0.007	−0.066
US	241	20	−0.018	0.106	−0.503	0.213	0
Vietnam	2	1	−0.487	0.296	−0.697	−0.278	−0.487
Cross-country	466	32	0.003	0.127	−0.895	0.646	0.008
Total	910	89	−0.021	0.154	−1.000	0.646	−0.001

2.3. Publication Bias

Before further analysis, it is necessary to check for publication bias in our reported estimates. Publication bias refers to the probability of a favoured result to be reported (Rosenthal 1979) and has been detected in many empirical economics studies (Doucouliagos and Stanley 2013). Given the controversies over capital regulation, it is likely in our study that capital regulation supporters tend to report a negative and significant effect of capital on risk, while others, primarily academic researchers, prefer a positive or insignificant result. The bias is non-trivial and can inflate the average estimates (Field and Gillett 2010).

The publication bias can be detected using funnel plot (Light and Pillemer 1984). The funnel plot graphs the estimated effects on the x-axis and their precision on the y-axis. The top of the funnel contains the most precise estimates that are close to the true effect. Without publication bias, the estimates should be randomly distributed, and the funnel is symmetric. In contrast, asymmetrical or hollow funnel indicates the presence of publication bias (Egger et al. 1997). Figure 2 depicts the funnel plot of standardized effects of capital on risk (PCC) against its precision. The funnel is not symmetric and suggests the existence of publication bias in the reported estimates. In addition, there are more negative than positive estimates. This either implies a discipline effect of capital on bank risk-taking, or in other words, there is more evidence supporting capital regulation to be reported.

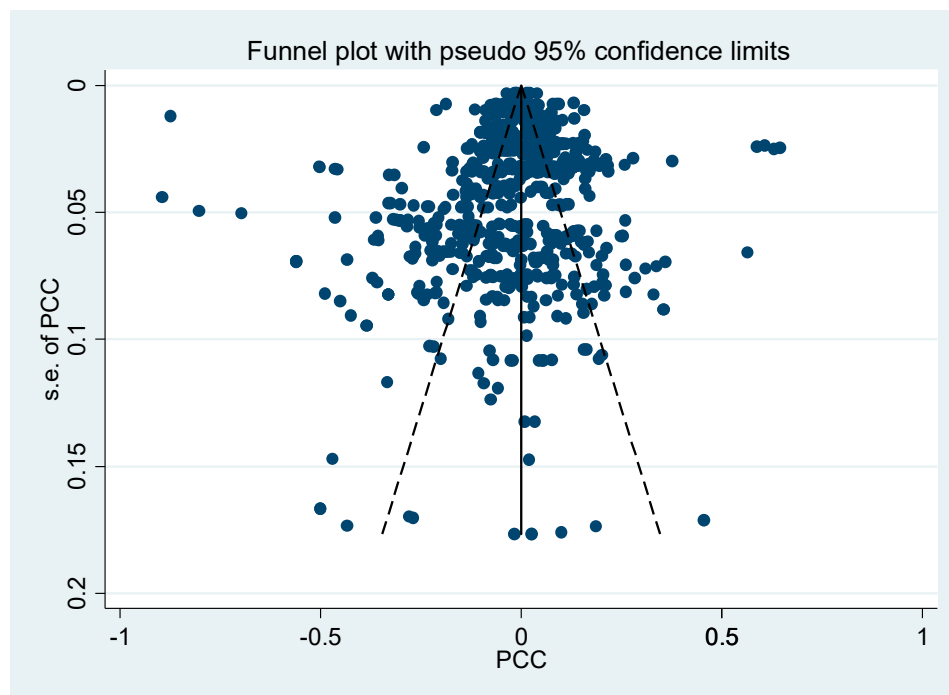


Figure 2. Funnel plot of standardized effects of capital on risk (PCC). Note: The vertical line shows the estimation of the population effect size. The two diagonal lines are the 95% confidence interval of the estimation.

Since the interpretation of funnel plot is subjective, we statistically test for publication bias using funnel asymmetry test. Two common methods for funnel asymmetry test are Begg and Mazumdar’s rank correlation test (hereafter, Begg test), and Egger’s regression test (hereafter, Egger test). Begg test reports the rank correlation (Kendall’s tau) between the standardized effect size and its precision. A Tau statistic deviating from zero will suggest the presence of publication bias (Sterne et al. 2000). On the other hand, Egger test regresses the standardized effect size against its precision, as follows:

$$t_{ij} = \frac{PCC_{ij}}{SEPCC_{ij}} = \beta_0 + \beta_1 \frac{1}{SEPCC_{ij}} + \vartheta_{ij} \tag{5}$$

where, t_{ij} is the standardized effect size, $\frac{1}{SEPCC_{ij}}$ is the precision of effect size, β_0 measures the asymmetry, β_1 is the true effect of the population, and ϑ_{ij} is the error term. The larger the deviation of β_0 from zero, the more pronounced the asymmetry, and more severe the bias (Egger et al. 1997).

Both the Begg and Egger tests in Table 2 confirms the presence of publication bias as suggested in the funnel plot in Figure 2.

Table 2. Funnel asymmetry test for publication bias.

	Begg Test		Egger Test	
	z	p-Value	β_0	p-Value
Bias	-3.48	<0.0001	-0.454	0.039
Observation	910		910	

However, there are factors other than publication bias that can cause asymmetry, such as true heterogeneity, data irregularities, poor study design (Egger et al. 1997). Peters et al. (2008) suggest the use of a contour-enhanced funnel plot to differentiate asymmetry due to publication bias from other factors. It displays areas of statistical significance, which is derived from the estimated effect sizes and their standard errors, on a funnel plot. If there are missing studies in areas of statistical non-significance (for example, p -value > 0.1), the publication bias causes the asymmetry. Conversely, it might be due to other factors. The contour-enhanced funnel plot in Figure 3 shows that published studies are found not only in the areas of statistical significance (shaded area) but also in areas of statistical non-significance (white area). Thus, publication bias is not the only cause of asymmetry.

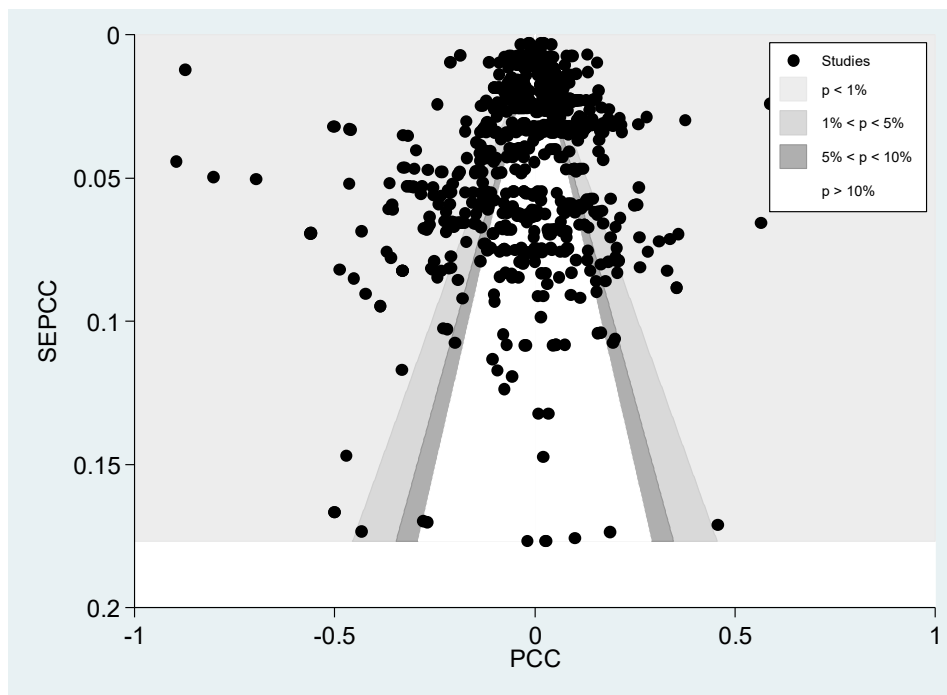


Figure 3. Contour-enhanced funnel plot of standardized effects of capital on risk (PCC).

2.4. Meta-Regression Analysis

To investigate whether the effect of capital on risk is affected by study characteristics, we employ a multivariate meta-regression analysis. It is a powerful method to assess and explore the

variability of reported results by the synthesizing of empirical evidence (Stanley and Jarrell 1989). Our meta-regression model is as follows:

$$PCC_{ij} = \gamma_0 + \sum_{k=1}^K \gamma_k D_{kij} + u_{kij} \tag{6}$$

where, D_{kij} are independent variables k th describing study characteristics; γ are coefficients to be estimated; u_{kij} is error term. We codify the study characteristics that potentially affect PCC variation into seven groups. These groups include measurement of risk variable, measurement of capital variable, study model, estimation method, sample characteristics, and publication quality.

The summary of these variables in Table 3 shows that the effect of bank capital on risk (PCC) varies across risk measurements. An average negative effect of bank capital on risk is reported in studies using RWATA, MARKET, and PROFIT_VOL as risk measurement. Whereas, when risk is referred to as CREDIT and Z-SCORE, the effect is positive. Among risk measurements, credit (CREDIT) and market risks measurements (MARKET) are the most frequently used. Similarly, the effect of bank capital on risk also varies across measurements and transformation of capital. Regulatory total capital (CAP) and Equity (EQUITY) are popular measurements of capital. Except for studies using Tier 1 ratio (TIER1) as capital measurement, all other studies report a negative effect of bank capital on risk. Almost half of estimations consider the endogeneity of capital (ENDO) and unobserved time fixed effects (TIME_EFFECT). These models are estimated with different methods, varying from the simple Ordinary Least Square (EST_OLS) to Instrumental Variables estimation (EST_IV) or dynamic model estimation (EST_DYN). Despite different models and methods used, there is a persistent average negative effect of capital on risk. Annual data (ANNUAL_DATA) are mostly used. Most studies are conducted in high-income countries (HIGH). In addition, a negative PCC, on average, is reported in most countries. Noteworthy, journal articles (JNAL), especially those published in high quality journals (PUB_QUAL), tend to report negative estimates.

Table 3. Main variables in meta-regression analysis.

Variable	Label	Description	N	Mean PCC	S.D
Dependent variable	PCC	Standardized effect of bank capital on risk	910	−0.019	0.151
	RWATA	Dummy variable, equal 1 if risk is measured as Risk-weighted assets over Total assets	132	−0.003	0.163
Measurement of RISK variable	CREDIT	Dummy variable, equal 1 if risk is measured as Non-performing loan ratio, loan loss reserve/provision ratio, Risk-weighted loans over assets, Distance to Default	325	0.012	0.146
	MARKET	Dummy variable, equal 1 if risk is measured as total market risk, idiosyncratic risk, specific risk, systematic risk, market risk	226	−0.034	0.110
	ZSCORE	Dummy variable, equal 1 if risk is measured as Z-score	105	0.125	0.200
	PROFIT_VOL	Dummy variable, equal 1 if risk is measured as standard deviation of bank profitability (ROA, ROE)	95	−0.031	0.119
	RISK_OTHER	Dummy variable, equal 1 if less frequent measurements of risk are used (Reference Group)	43	0.066	0.126
	RISK_DIF	Dummy variable, equal 1 if RISK is measured in first differences	202	0.007	0.127

Table 3. Cont.

Variable	Label	Description	N	Mean PCC	S.D	
Measurement of CAPITAL variable	CAP	Dummy variable, equal 1 if the numerator in capital measurement is Total Regulatory Capital	324	−0.022	0.153	
	TIER1	Dummy variable, equal 1 if the numerator in capital measurement is Tier 1 Regulatory Capital	190	0.006	0.129	
	EQUITY	Dummy variable, equal 1 if the numerator in capital measurement is Equity	341	−0.029	0.156	
	CAP_TA	Dummy variable, equal 1 if the denominator in capital measurement is Total Assets	507	−0.003	0.157	
	CAP_RWA	Dummy variable, equal 1 if the numerator in capital measurement is Risk-weighted Assets (Reference group)	383	−0.037	0.137	
	CAP_OTHER	Dummy variable, equal 1 if less frequent measurements of capital are used (Reference Group)	64	−0.014	0.159	
Model	NONLN	Dummy variable, equal 1 if capital is quadratic or interacted with other variables	133	0.008	0.105	
	DYN	Dummy variable, equal 1 if the dynamic of risk is considered	301	−0.033	0.154	
	ENDO	Dummy variable, equal 1 if the endogeneity of capital is considered	410	−0.019	0.143	
	TIME_EFFECT	Dummy variable, equal 1 if Time effect is considered	449	−0.024	0.121	
	VAR_NO ^a	Number of explanatory variables in the model	910	9.841	4.413	
Estimation Method	EST_OLS	Dummy variable, equal 1 if estimation method is pooled OLS	218	−0.017	0.156	
	EST_PANEL	Dummy variable, equal 1 if estimation method is Fixed Effects, Random Effects, Least Square Dummy Variables	230	−0.013	0.156	
	EST_IV	Dummy variable, equal 1 if estimation method is Instrumental Variables estimation	214	−0.004	0.155	
	EST_DYN	Dummy variable, equal 1 if estimation method is Dynamic Panel Data estimation	201	−0.049	0.139	
	EST_OTHER	Dummy variable, equal 1 if less frequently method is used (Reference Group)	81	0.0004	0.113	
Sample Characteristics	SAMPLE ^a	The logarithm of the total number of observations used	910	6.981	1.639	
	DATA_ANNUAL	Dummy variable, equal 1 if annual data is used, 0 if higher frequency data is used	780	−0.021	0.157	
	BHC	Dummy variable, equal 1 if only bank holding companies are examined	204	−0.032	0.104	
	COM	Dummy variable, equal 1 if only commercial banks are examined	246	−0.042	0.16	
	TYPE_OTHER	Dummy variable, equal 1 if other bank types or a mix of banks are examined (Reference Group)	664	−0.011	0.146	
	HIGH	Dummy variable, equal 1 if the study is conducted in high income countries	445	−0.014	0.121	
	UPPER	Dummy variable, equal 1 if the study is conducted in upper income countries	59	−0.072	0.225	
	LOW	Dummy variable, equal 1 if the study is conducted in lower and low-income countries	102	−0.117	0.217	
	Publication Characteristics	JNAL	Dummy variable, equal 1 if the study was published as a journal article, 0 if the study is a working paper	815	−0.016	0.154
		PUB_QUAL	Dummy variable, equal 1 if the study was published in a journal indexed in ISI, SSCI, or ranked in ABDC list, 0 otherwise	629	−0.01	0.152
CITE ^a		The logarithm of the number of Google Scholar citations normalized by the difference between 2018 and the year the study first appeared in Google Scholar	910	0.573	0.484	

Notes: ^a For continuous variables, their means and standard deviations are reported instead.

There are a large number of potential factors of PCC variation. This causes model uncertainty problem and affects the study inference. Therefore, we apply Bayesian model-averaging techniques, specifically the Bayesian model-averaging (BMA) and the weighted-average least-squares (WALS) estimators to address the model uncertainty and identify potential factors of PCC. Both estimators

consider all possible combinations of explanatory variables and estimate the parameters of interest as a weighted average of conditional estimates of each model. The BMA approach combines prior beliefs on the uncertain variables of the model with the additional information from the data and weights these individual regressions using the posterior model probabilities (PMP). The relevance important of a variable is reflected in the posterior inclusion probability (PIP), which is calculated by summing PMP of all models consisting the variable (Leamer 1978). A variable is robust if it has a PIP value at least 0.50 (Raftery 1995).

However, the BMA estimator encounters the computational burden proportional to the dimension of the model space, the difficulty in choosing the prior distribution where no prior information is available, as well as the unbounded risk related to the chosen priors (Magnus et al. 2010). Therefore, the WALS estimator is an alternative to the BMA since it relies on preliminary orthogonal transformations of the uncertain regressors and their parameters. WALS has proved useful with equivalent estimations to BMA (De Luca et al. 2018, Magnus et al. 2010). A variable is robustly correlated with the dependent variable if the absolute t-ratio is greater than 1 (Magnus et al. 2010).

3. Results

Table 4 reports the estimations of Equation (6) employing both BMA and WALS estimators. Our model comprises 29 explanatory variables and result a model space of 2^{29} models. With a small to moderate (less than 20) number of variables, the BMA calculation can be completed within one hour. However, when the number of explanatory variables is large (more than 20), it can take up to thousand years (Luca and Magnus 2011). Therefore, we use the Markov chain Monte Carlo (MCMC) samplers, which gather results on the most important part of the posterior model distribution and approximate it as closely to the actual posterior distribution as possible. The quality of the MCMC approximation depends on the number of draws of the MCMC samplers. We set this number at 1 million. Figure A1 in the Appendix B shows that the correlation between iteration counts and analytical PMPs for the 5000 best models is 0.997. This indicates a good convergence of MCMC samplers. For the WALS estimator, we follow (Einmahl et al. 2011) to use Subbotin prior instead of the Gaussian and Laplace due to its less fat and thicker tails distribution. For robustness, we also report the Ordinary Least Square (OLS) estimation to see how the estimations without model uncertainty consideration differ.

Table 4 shows that the most robust determinants in BMA estimator are risk measurements (MARKET, ZSCORE, and RISK_DIF), capital measurements (EQUITY and CAP_TA), model setting (DYN and TIME_EFFECT), data characteristics (SAMPLE), and publication characteristics (PUB_QUAL and CITE). The WALS estimator confirms the importance of these variables except for TIME_EFFECT and PUB_QUAL. It also emphasizes the importance of risk and capital measurements by suggesting the robustness of PROF_VOL, CAP and TIER1. In addition, the endogeneity in the empirical model (ENDO), the larger number of explanatory variables (VAR_NO), the sample for bank-holding companies (BHC), high-income countries (HIGH) and the publication in journals (JNAL) are also important determinants. The estimations in BMA and WALS are quite similar. Disregarding the model uncertainty, the OLS regression comprises a larger set of variables than BMA estimator but quite different from the WALS. This suggests the superior and necessary of model uncertainty consideration.

The effect of capital on risk (PCC) will be negative if the dependent variable uses market measures of risk (MARKET) or profit volatility (PROF_VOL), but positive if the risk is referred to as the bank insolvency (ZSCORE). In addition, the effect is positive if risk is measured in first differences (RISK_DIF). This suggests that the risk measurement is important for the result inference. The capital measurement also affects the conclusion. If the capital is measured as total regulatory capital (CAP) or equity (EQUITY), the effect will be negative. Conversely, if the capital is measured as Tier capital (TIER1) or standardized by the total assets (CAP_TA), instead of the risk-weighted assets, the effect will be positive. Among 15 potential factors affecting PCC, half of them are from the risk and capital measurements. The effects of these factors are also large compared to other explanatory variables.

Table 4. Bayesian model averaging regression.

Variables	BMA			WALS			OLS		
	Coef.	SE	PIP	Coef.	SE	t	Coef.	SE	P > t
RWATA	−0.0228	0.0267	0.4798	−0.0673	0.0218	0.22	−0.0213	0.0337	0.5280
CREDIT	0.0034	0.0105	0.1275	−0.0274	0.0187	0.46	−0.0082	0.0261	0.7530
MARKET	−0.0427 ^a	0.0234	0.8428	−0.0590 ^b	0.0187	1.29	−0.0376	0.0262	0.1510
ZSCORE	0.1362 ^a	0.0185	1.0000	0.0954 ^b	0.0209	4.55	−0.1287 ^{***}	0.0349	0.0000
PROFIT_VOL	−0.0012	0.0067	0.0539	−0.0556 ^b	0.0214	1.61	−0.0404	0.0273	0.1390
RISK_DIF	0.0605 ^a	0.0241	0.9344	0.0692 ^b	0.0184	2.62	0.0653 ^{***}	0.0196	0.0010
CAP	−0.0070	0.0140	0.2427	−0.0117 ^b	0.0201	1.16	0.0315	0.0203	0.1200
TIER1	0.0020	0.0079	0.0883	0.0098 ^b	0.0213	1.19	0.0336 [*]	0.0200	0.0940
EQUITY	−0.0656 ^a	0.0165	0.9970	−0.0587 ^b	0.0221	1.55	−0.0428 ^{**}	0.0204	0.0360
CAP_TA	0.0991 ^a	0.0149	1.0000	0.0760 ^b	0.0138	5.28	0.1018 ^{***}	0.0180	0.0000
NONLN	−0.0008	0.0048	0.0443	−0.0325	0.0145	0.78	−0.0122	0.0153	0.4250
DYN	−0.0769 ^a	0.0135	1.0000	−0.0664 ^b	0.0134	3.31	−0.0535 ^{***}	0.0156	0.0010
ENDO	−0.0002	0.0025	0.0266	−0.0058 ^b	0.0133	1.15	−0.0260 [*]	0.0153	0.0890
TIME_EFFECT	−0.0391 ^a	0.0147	0.9543	−0.0400	0.0113	0.34	−0.0102	0.0157	0.5170
EST_OLS	−0.0004	0.0032	0.0308	0.0207	0.0198	0.68	0.0158	0.0212	0.4560
EST_PANEL	0.0005	0.0035	0.0401	0.0379 ^b	0.0169	2.09	0.0450 ^{**}	0.0177	0.0110
EST_IV	0.0078	0.0157	0.2430	0.0433	0.0214	0.76	0.0245	0.0207	0.2380
EST_DYN	0.0001	0.0025	0.0226	0.0406	0.0220	0.13	0.0168	0.0256	0.5120
VAR_NO	0.0000	0.0002	0.0230	0.0019 ^b	0.0011	1.11	0.0016	0.0013	0.2200
SAMPLE	0.0057 ^a	0.0052	0.6172	0.0119 ^b	0.0036	3.05	0.0129 ^{***}	0.0049	0.0080
DATA_ANNUAL	−0.0001	0.0030	0.0247	−0.0052	0.0161	0.42	0.0025	0.0172	0.8840
BHC	−0.0085	0.0158	0.2699	−0.0316 ^b	0.0173	1.99	−0.0319	0.0211	0.1300
COM	−0.0015	0.0064	0.0756	−0.0178	0.0117	0.65	−0.0044	0.0164	0.7890
HIGH	−0.0005	0.0036	0.0417	0.0057 ^b	0.0118	2.28	0.0287 ^{**}	0.0133	0.0310
UPPER	0.0157	0.0251	0.3312	0.0587	0.0180	0.11	0.0080	0.0296	0.7870
LOW	0.0007	0.0122	0.0199	0.0866	0.0753	0.49	0.0391	0.0954	0.6820
JNAL	−0.0001	0.0033	0.0230	0.0042 ^b	0.0162	1.95	0.0360 [*]	0.0209	0.0850
PUB_QUAL	0.0310 ^a	0.0193	0.7940	0.0349	0.0108	0.89	−0.0188	0.0172	0.2740
CITE	0.0191 ^a	0.0199	0.5489	0.0245 ^b	0.0119	6.00	0.0838 ^{***}	0.0159	0.0000

Notes: BMA estimation uses the MCMC samplers. WALS estimation employs the Subbotin prior ($\eta = 0.5$). ^a denotes a PIP larger than 0.5. ^b denotes a t absolute value larger than 1. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors in OLS regression.

Another source of PCC variation is the model setting. If the model is concerned about the dynamic of bank risk behaviors (DYN), the endogeneity of the capital (ENDO) and unobserved time fixed effects (TIME_EFFECT), the reported coefficients will be negative. Against our expectation, the estimation method does not alter the effect of capital on risk, except for the panel data estimation (EST_PANEL). The sample and publication characteristics affect PCC in the same way that the reported effects are positive. However, studies on bank-holding companies (BHC) will report a negative PCC.

4. Further Analysis

4.1. Different Risk Measurements

Results in Table 4 suggest that the effect of capital on risk varies with the risk measurements. Figure 4 displays the distribution of PCC across different risk measurements. Even using the same measurement, PCCs still vary. There is evidence of both positive and negative effects of capital on risk. Therefore, we re-estimate Equation (6) on different risk measurements to examine the underlying factors of these variations.

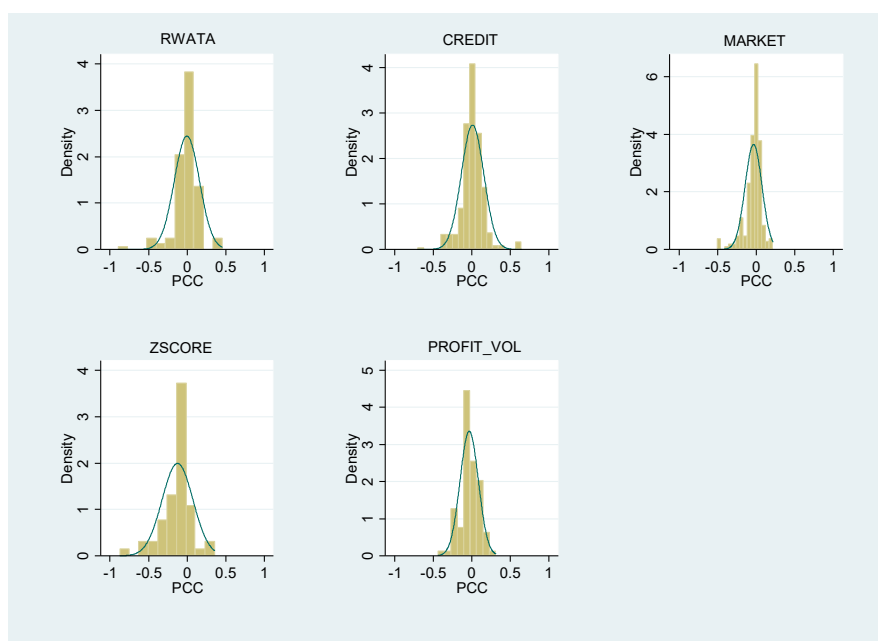


Figure 4. The PCC distribution by risk measurements.

Table 5 reports the WALS estimation on different risk measurements. EQUITY and LOW are omitted in the RWATA estimation to avoid the multicollinearity since there are few studies employing the EQUITY measurement and no studies are carried out in low and lower-income countries. Similarly, LOW is omitted in MARKET and ZSCORE estimations. In addition, most ZSCORE studies are journals, thus, JNAL is omitted in the ZSCORE estimation.

Table 5 shows that the determinants of PCC variations and their effects across risk measurements are similar to the total sample in Table 4 despite some slight differences. Specifically, measurement by regulatory capital (CAP) and Tier 1 capital (TIER1) will have positive effect on the reported PCC of credit risk (CREDIT) and market risk (MARKET), while exert negative influences on other risk measurements. The consideration of endogeneity (ENDO) and time fixed effects (TIME_EFFECT) will lead to positive reported PCC for RWATA and ZSCORE. When risk is regarded as market risk (MARKET), a panel model setting will result a negative PCC. Whereas, when risk is referred as ZSCORE, the larger the sample, the more negative the PCC is. Studies in high income countries will have a negative effect on PCC of credit risk (CREDIT) and ZSCORE. In addition, the effect of publication characteristics also varies across risk measurements.

Table 5. WALS Estimations on Different Risk Measurements.

	RWATA		CREDIT		MARKET		ZSCORE		PROFIT_VOL	
	Coef.	t	Coef.	t	Coef.	t	Coef.	t	Coef.	t
RISK_DIF	−0.0440	0.57	0.1090 *	3.89	−0.1180 *	1.09	0.1270 *	1.63	0.0730	0.60
CAP	−0.0410	0.67	0.0210	0.84	0.1430 *	4.57	−0.0900 *	1.20	−0.1200 *	1.38
TIER1	−0.0300	0.45	0.0370 *	1.34	0.1300 *	4.27	−0.0270	0.34	−0.1890	0.79
EQUITY			−0.0500 *	1.93	0.0390	0.65	−0.1500 *	1.83	−0.1890 *	2.00
CAP_TA	0.1130 *	2.51	0.0940 *	4.40	−0.0230	0.35	0.0730 *	1.22	0.0750 *	1.49
NONLN	0.0400 *	1.03	−0.0110	0.45	−0.1120 *	3.57	−0.1130 *	1.89	0.1670 *	1.65
DYN	−0.1630 *	2.79	−0.0740 *	4.20	0.0440	0.58	−0.0820 *	1.31	−0.0910 *	1.06
ENDO	0.1300 *	1.47	−0.0440 *	1.99	−0.0280 *	1.05	0.1910 *	2.91	−0.1570 *	1.97
TIME_EFFECT	0.0470 *	1.00	−0.0470 *	2.81	0.0040	0.19	0.0100	0.25	−0.1160 *	1.03
EST_OLS	0.1020	0.98	−0.0150	0.55	−0.0270	0.53	−0.0430	0.50	−0.0640	0.34
EST_PANEL	0.0440	0.47	0.0420 *	1.84	−0.0650 *	1.28	0.0310	0.41	0.0790	0.41
EST_IV	−0.0540	0.62	0.0220	0.79	0.0580 *	1.16	−0.1080 *	1.36	0.1540 *	1.04
EST_DYN	−0.0140	0.17	0.0160	0.51	−0.0210	0.37	−0.1980 *	2.20	0.1440 *	1.05
VAR_NO	−0.0030	0.54	0.0050*	2.66	−0.0030 *	1.79	0.0220 *	3.26	0.0110 *	1.76
SAMPLE	0.0010	0.08	0.0290*	4.87	−0.0040	0.64	−0.0190 *	1.22	0.0080	0.63
DATA_ANNUAL	−0.2740 *	3.06	0.0370	0.81	−0.1430 *	3.66	−0.0030	0.05	0.0300	0.19
BHC	−0.2450 *	2.50	−0.0010	0.03	−0.1180 *	4.06	−0.0510	0.73	0.1700	0.71
COM	0.1320 *	2.35	−0.0590 *	3.25	0.1440 *	3.00	−0.0970 *	1.85	0.0110	0.23
HIGH	0.0190	0.39	−0.0330 *	1.74	0.0500 *	1.44	−0.1050 *	1.86	0.0020	0.04
UPPER	−0.1170 *	1.04	0.0390 *	1.42	−0.0380	0.54	0.0880 *	1.80	0.0030	0.06
LOW			0.1990 *	1.69					0.0420	0.74
JNAL	0.0550	0.47	0.0030	0.13	0.2310 *	2.06			−0.0870	0.29
PUB_QUAL	0.1910 *	2.25	−0.0280 *	1.36	−0.1530 *	5.17	0.2390 *	4.83	−0.0420	0.61
CITE	−0.1550 *	1.40	0.0670 *	3.77	0.0240	0.49	−0.3370 *	5.56	0.1920	0.61
Constant	0.0700	0.40	−0.2990 *	3.52	−0.0020	0.02	0.1910 *	1.28	−0.1540	0.84
N	132		325		226		105		95	

Notes: WALS estimation employs the Subbotin prior ($q = 0.5$). * denotes an absolute t value larger than 1.

Apart from these factors, the variation in the estimation of risk measurements is further affected by the non-linearity of model (NONLN), the instrumental variable estimation (EST_IV), the sample characteristics such as whether data is annual, whether banks are bank-holding companies or commercial banks, as well as whether banks are located in upper income countries (UPPER).

4.2. Benchmark and Best-Practice Results

To gain further insights into how the effects of capital on bank risk should be regarding different determinants of the total sample and risk measurements, we calculate the “benchmark” and “best-practice” results from these estimations. The “benchmark” results are computed from the coefficients of non-robust determinants and their sample means and thus, it implies the average study in the field (Feld et al. 2013). Whereas, the “best-practice” results are derived from the robust determinants and represents the best practice in the field. Its purpose is to correct the potential effect of wrongly specified studies (DouCouliagos 2016).

Table 6 presents the “benchmark” and “best-practice” estimates for different risk measurements and samples. The “benchmark” effect of the capital on the bank’s risk-weighted assets (RWATA) is approximately 0.095. This effect is higher for bank-holding companies (BHC), but lower for commercial banks (COM), and banks in high- and upper-income countries. However, considering the scale of the capital measurement (CAPTA), the model specification (NONLN, DYN, ENDO, TIME_EFFECT), data characteristics (DATA_ANNUAL), bank types (BHC, COM), country development (UPPER), and publication characteristics (PUB_QUAL, CITE) (see Table 5), the “best practice” effect turns negative at -0.0518 . Nevertheless, the positive effect is persistent across BHC and UPPER samples. Similarly, we also found a substantial difference in the effect of capital on the market risk (MARKET) between the benchmark and best-practice estimates. In addition, this effect also varies across sub-samples (Table 6). Therefore, careful treatments for the capital measurements (CAP, TIER1), model design (NONLN, ENDO), estimation techniques (EST_PANEL, EST_IV), the control variables (VAR_NO), data characteristics (DATA_ANNUAL), bank types (BHC, COM) and country development (HIGH) should be considered in estimating the effect of capital on the bank’s market risk.

The effects of capital on the credit risk (CREDIT), insolvency risk (ZSCORE) and profit volatility (PROFIT_VOL) in the benchmark and best-practice estimates are of the same sign. This suggests that the studies on these risks are quite consistent. The estimates for PROFIT_VOL change greatly across samples in both benchmark and best practice results and suggests the importance of the selected sample. That is, the bank-holding companies or commercial banks, banks in high-income countries or upper income (see Table 6).

Table 6. Predicted Benchmark and Best Practice Results across Risk Measurements and Samples.

	Benchmark Results					Best Practice				
	Total	BHC	COM	HIGH	UPPER	Total	BHC	COM	HIGH	UPPER
RWATA	0.095145	0.12521	0.062582	0.089907	0.057983	−0.05177	0.141112	−0.09247	−0.04699	0.031717
CREDIT	−0.25384	−0.26528	−0.24567	−0.25831	−0.24554	−0.04857	−0.04393	−0.03629	−0.02123	−0.09672
MARKET	−0.01142	−0.02494	−0.01238	−0.01647	0.001743	0.004052	0.088588	−0.03307	−0.04116	0.034949
ZSCORE	0.173826	0.191152	0.188451	0.162209	0.190169	0.129122	0.295267	0.171561	0.275456	0.167132
PROFIT_VOL	−0.04567	−0.12419	−0.09766	−0.02968	−0.0726	−0.18316	−0.24249	−0.17905	−0.20342	−0.16056

Notes: Benchmark results are computed from the intercept, the coefficients of variables with absolute *t*-values less than 1 from Table 5, and their sample means.

5. Conclusions

This paper examines the effect of capital on bank risk using a meta-analysis approach. From a wide range of empirical papers from 1990 to 2018, we found that there is both positive and negative evidence on the relationship between bank capital and risk. Nevertheless, there are more negative effect to be reported. This suggests the discipline role of the capital on the bank risk.

Both funnel plots and formal funnel tests indicate the existence of the publication bias, which the significant and negative effects are more likely to be reported. This finding is not surprising since the capital regulation has gained an increasing importance recently and these negative reported effects give support to the regulation.

Nevertheless, the publication bias is not the only source of the variation. Our Bayesian Model Averaging estimations show that the reported effect of capital on bank risk is affected by the risk measurements, capital measurements, the model specification, and the sample characteristics. Even using the same risk measurements, the effect may also vary due to the different model setting and samples.

These results have significant academic and practice implications. Specifically, the researchers should consider various risk and capital measurements for the most precise estimations of the capital effect. In addition, they should carefully design the model by taking into account the non-linear effect of the capital, the dynamic of bank risk, the potential endogeneity of the capital, and the unobserved time effects since the results are sensitive to these specifications. It is preferable to have a large dataset and control for as most variables as possible. However, in such case, the attention should be paid to the sample characteristics since the risk behavior may not be homogeneous across samples.

These empirical results act as a guideline for the capital regulation in addition to the considerations for the macro-impacts. Our results also indicate that the effect of capital varies with risk types. Therefore, the regulators should consider the risk of interest, for example, the bank-specific risk or the systemic risk in designing the capital regulation. In addition, the effect of capital on risk is different across countries given their different contexts. Therefore, it is important for the regulators to consider their national markets and condition to have proper policies. In this regard, the common minimum requirements under the current Basel III framework would not be appropriate.

We acknowledge the limitations of meta-analysis in terms of the overreliance on statistics and potential sampling bias. However, there is no perfect method and meta-analysis using statistics are still superior comparing to qualitative methods such as narrative review and descriptive review. In our study, we tried to minimize these limitations' effect by including the most papers as possible by searching wide and various databases and considering working papers in addition to published articles. We are also concerned about the quality of these papers by considering the quality of journals and number of citations. The study focuses on the quantitative review of research only while theoretical papers on mathematical models, qualitative research, secondary data analysis, interviews, and case studies are omitted. Therefore, in the future, a narrative review of these articles will be a perfect complement for the current study to provide a full overview of the impact of bank capital on bank risk.

Author Contributions: Conceptualization, methodology, formal analysis, writing—original draft preparation, Q.T.T.N.; data collection and preparation, S.T.B.N.; writing—review and editing, Q.V.N.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. List of Surveyed Studies

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Appendix B

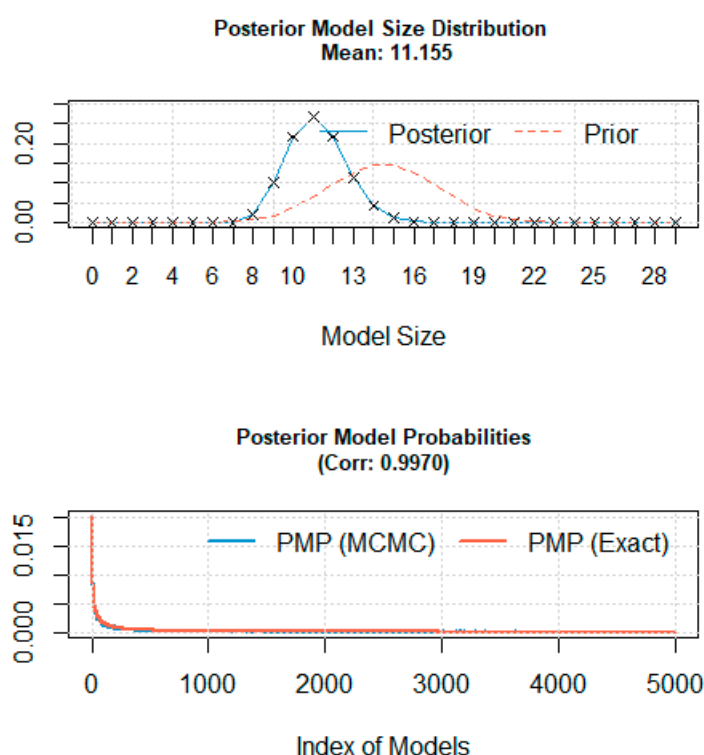


Figure A1. BMA Posterior Model Size Distribution and Probabilities.

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