Predicting Market Risk with Density Combination: An Introduction

David Ardia
Institute of Financial Analysis, University of Neuchâtel, Switzerland

Jeremy Kolly
Finance, Insurance and Real Estate Department, Laval University, Québec, Canada;
Department of Management, University of Fribourg, Switzerland;
E-mail: jeremy.kolly.1@ulaval.ca

Abstract

Density forecast combination is a useful tool for risk managers to reduce model risk. We present up-to-date methodologies in the field, discuss key issues, and provide some illustrations.

Keywords

density forecast combination, censoring, incomplete model set, risk model contribution, skew Student-*t* distribution, pool risk forecasts

JEL classification: C53, G32.

1 Introduction

Model risk refers to the possibility of relying on a misspecified model. Increasing model complexity, regulation, financial accidents, and competitiveness are reasons that lead today's financial institutions to manage model risk (Krishnamurthy, 2014). However, it remains a difficult exercise in financial risk management, as illustrated in Daníelsson (2008). In this paper, we show how density forecast combination can be used to reduce the model risk embedded in market risk predictions. Only a few contributions have considered this issue up to now (see Gatarek *et al.*, 2014; Opschoor *et al.*, 2015), although exploiting expected gains in forecast accuracy stemming from combination is a useful research avenue for financial practitioners (Chua *et al.*, 2013).

Bayesian model averaging is a natural way to get rid of model uncertainty (Leamer, 1978). However, it operates in a rigid framework and postulates that one of our risk models is true, which is often unrealistic. We present the optimal pooling method (Hall and Mitchell, 2007; Geweke and Amisano, 2011, 2012) to produce weights of different density aggregation rules. This method is very flexible and accommodates the fact that all risk models are generally wrong. Furthermore, we consider an extension proposed in Opschoor *et al.* (2015), where weights give more importance to left-tail events.

Besides reducing model risk, density combination is also a device for risk decomposition. It enables us to identify the contribution of individual models to a given risk measure such as the expected shortfall. Such decomposition can be used to compare risk models and to improve density combinations. We propose a first simple attempt in this direction.

2 Combination methods

Consider a model set of cardinality K, where each model is able to produce a one-step-ahead density forecast $p_{t,k}(y_{t+1})$ for the future outcome y_{t+1} given data up to time t. As explained in Kascha and Ravazzolo (2010), two rules emerged in the literature to aggregate these density forecasts. The first is the linear pool:

$$p_{t,lin}(y_{t+1}) \equiv \sum_{k=1}^{K} w_{t,k} p_{t,k}(y_{t+1}), \qquad (1)$$

where the weight vector $w_t \equiv (w_{t,1}, \ldots, w_{t,K})'$ depends on data up to time t and meets the conditions $\sum_{k=1}^{K} w_{t,k} = 1$ and $w_{t,1}, \ldots, w_{t,K} \geq 0$ to ensure that (1) is a valid density. The second rule is the logarithmic pool:

$$p_{t,log}(y_{t+1}) \equiv \frac{\prod_{k=1}^{K} p_{t,k}(y_{t+1})^{w_{t,k}}}{\int_{-\infty}^{\infty} \prod_{k=1}^{K} p_{t,k}(y_{t+1})^{w_{t,k}} dy_{t+1}}, \qquad (2)$$

where the denominator enables (2) to integrate to one and where the weights sum to one and are non-negative for convenience. Note that the logarithm of the kernel of (2) is equal to a weighted average of logarithmic individual density forecasts. Logarithmic pools are generally unimodal, unlike linear ones, and present less dispersion (Genest and Zidek, 1986).

When the K models produce Bayesian predictive densities and when we aggregate them with a linear pool whose weights are posterior model probabilities, we obtain a natural and formal framework to account for model uncertainty called Bayesian model averaging (BMA) (Leamer, 1978, ch. 4; see Hoeting *et al.*, 1999 for an introduction). However, we fall outside this framework when we consider non-Bayesian density forecasts or logarithmic pooling. Moreover, BMA may not be adequate for incomplete model sets, as illustrated in Section 3. In this paper we rather rely on the optimal pooling (OP) method to form pool weights. First appearing in Hall and Mitchell (2007), this approach was fully developed by Geweke and Amisano (2011, 2012), who present it as an alternative to BMA when all models are misspecified. The OP weights result from the following problem:

$$w_t^{OP-c} \equiv \underset{w_t}{\arg\max} \sum_{s=t_0}^{t} \ln p_{s-1,c}(y_s), \tag{3}$$

subject to the usual constraints on the weights where t_0 has to be chosen empirically and where $p_{s-1,c}(y_s)$ is either the linear or the logarithmic pool with the elements of w_t as weights. In (3), the objective function sums the pool log score from time t_0 to time t. It is noteworthy that the OP weights depend on the rule used to aggregate density forecasts. Methods where the weights are obtained by averaging some measures of model fit do not possess this property.

In a risk management context, it can be relevant to produce weights that give more importance to extreme outcomes such as large losses. This can be achieved in the OP method by considering the censored scoring rule of Diks *et al.* (2011) instead of the logarithmic one as proposed in Opschoor *et al.* (2015). The censored OP (COP) weights are then given by:[1]

$$w_t^{COP-c} \equiv \underset{w_t}{\arg\max} \sum_{s=t_0}^{t} I\{y_s < q_{t_0:t}^{\beta}\} \ln p_{s-1,c}(y_s) + I\{y_s \geq q_{t_0:t}^{\beta}\} \ln \int_{q_{t_0:t}^{\beta}}^{\infty} p_{s-1,c}(y_s)dy_s, \tag{4}$$

where $I\{\cdot\}$ is an indicator function taking the value one when the event in brackets occurs and zero otherwise, and where $q_{t_0:t}^{\beta}$ is the empirical β-quantile computed over the sample $y_{t_0:t} \equiv (y_{t_0}, \ldots, y_t)'$. Defining the censoring bound this way allows the analyst to directly control the number of uncensored observations used to form the weights. It is worthwhile presenting the specific form taken by the objective function in (4) for the two aggregation rules we consider. For the linear pool, the COP weights simply follow from

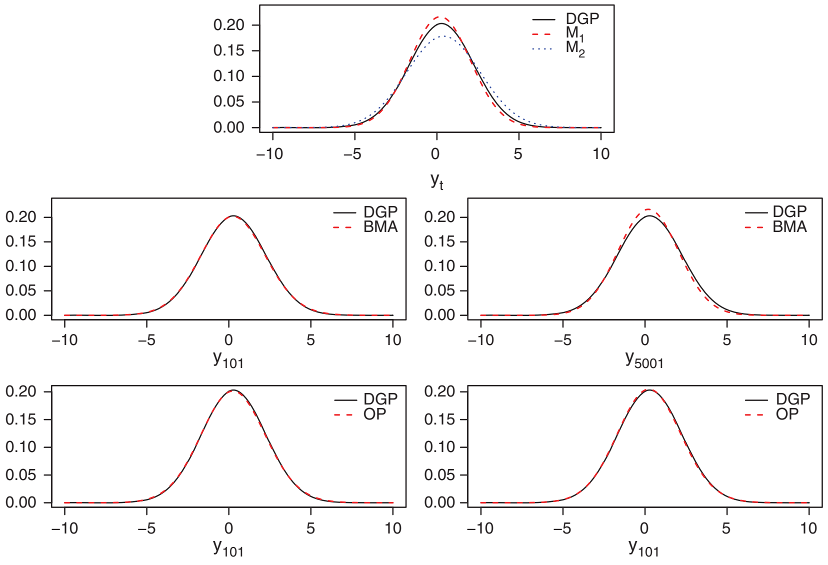
$$w_t^{COP-lin} \equiv \underset{w_t}{\arg\max} \sum_{s=t_0}^{t} \ln \sum_{k=1}^{K} w_{t,k} \times \left[I\{y_s < q_{t_0:t}^{\beta}\} p_{s-1,k}(y_s) + I\{y_s \geq q_{t_0:t}^{\beta}\} \int_{q_{t_0:t}^{\beta}}^{\infty} p_{s-1,k}(y_s)dy_s \right],$$

and for the logarithmic pool, they are obtained from the more cumbersome expression

$$w_t^{COP-log} \equiv \underset{w_t}{\arg\max} \sum_{s=t_0}^{t} I\{y_s < q_{t_0:t}^{\beta}\} \sum_{k=1}^{K} w_{t,k} \ln p_{s-1,k}(y_s) + I\{y_s \geq q_{t_0:t}^{\beta}\} \ln \int_{q_{t_0:t}^{\beta}}^{\infty} \prod_{k=1}^{K} p_{s-1,k}(y_s)^{w_{t,k}} dy_s - \ln \int_{-\infty}^{\infty} \prod_{k=1}^{K} p_{s-1,k}(y_s)^{w_{t,k}} dy_s,$$

where computational difficulties arise from repeated integrations of the logarithmic pool kernel.

Figure 1: Illustration of the model set incompleteness issue.



3 Model set incompleteness

An illustration presented in Kolly (2014, ch. 4) is reproduced here to justify the use of OP-type methods. We consider a time series governed by the following data-generating process (DGP): $y_t \sim$ i.i.d. $N(0.29, 3.86)$ and assume the following two models: M_1: $y_t \sim$ i.i.d. $N(0.2, 3.4)$ and M_2: $y_t \sim$ i.i.d. $N(0.4, 5)$. These densities are given in the top panel of Figure 1. We now want to predict y_{101} and y_{5001} with the BMA and OP methods. To implement BMA, we compute the posterior model probabilities of M_1 and M_2 assuming equal prior model weights from the 100 and 5000 first realizations of the series. The resulting probabilities for M_1 and M_2 are respectively 0.63 and 0.37 for the first sample and 1 and 0 for the second. The middle panels of Figure 1 show the one-step-ahead linear pools that can be formed with these weights. We observe that on the basis of 100 realizations, BMA offers a closer approximation to the DGP density than M_1 or M_2 but that in the large sample case it selects M_1, although this is not the DGP. This occurs because BMA supposes that the DGP belongs to the model set under study or, in other words, that this model set is complete. Such an assumption would obviously be questioned by a risk manager. Eklund and Karlsson (2007) propose forming BMA weights with predictive instead of marginal likelihoods, which implies a slower convergence to a single model. Nevertheless, the completeness assumption remains.

The situation is different with the OP method. We compute the OP weights for a linear pool of M_1 or M_2 with the same samples as BMA. These weights are respectively equal to 0.61 and 0.39 for the smaller sample and to 0.70 and 0.30 for the larger one.[2] The bottom panels of Figure 1 present the OP density in each case. We see in the large-sample case that OP does not select a single model and provides a good approximation to the DGP density. This illustrates that OP does not make the completeness assumption and that it may be appropriate to use it when we think of working with an incomplete model set, as is generally the case in financial risk management.

---

[1] Note that Gatarek *et al.* (2014) develop a BMA framework based on censoring.

[2] Note that the BMA and OP weights obtained with 100 realizations may substantially vary from one simulation to another, whereas with 5000 realizations the BMA weights are always 1 and 0 and the OP weights remain roughly the same.

4 Pool risk measures

Market risk is often measured with the value-at-risk (VaR) and the expected shortfall (ES). In our framework, the VaR is defined as the α-quantile of the (unknown) distribution of the return y_{t+1} given data up to time t, while the ES is the mean of this distribution conditional on y_{t+1} being below the VaR. The risk level $\alpha \in (0, 1)$ is generally set to low values such as 0.01 or 0.05. Assuming a particular model for the data, these risk measures can be written as:

$$\mathrm{VaR}^{\alpha}_{t,k} \equiv \inf \left\{ y_{t+1} \in \mathbb{R} : \int_{-\infty}^{y_{t+1}} p_{t,k}(y)dy \geq \alpha \right\},$$

$$\mathrm{ES}^{\alpha}_{t,k} \equiv E_{t,k}(y_{t+1} | y_{t+1} < \mathrm{VaR}^{\alpha}_{t,k}) = \frac{1}{\alpha} \int_{-\infty}^{\mathrm{VaR}^{\alpha}_{t,k}} y_{t+1} p_{t,k}(y_{t+1}) dy_{t+1}.$$

Considering instead a model combination, we obtain from the linear pool:

$$\mathrm{VaR}^{\alpha}_{t,lin} \equiv \inf \left\{ y_{t+1} \in \mathbb{R} : \sum_{k=1}^{K} w_{t,k} \int_{-\infty}^{y_{t+1}} p_{t,k}(y)dy \geq \alpha \right\},$$

$$\mathrm{ES}^{\alpha}_{t,lin} \equiv E_{t,lin}(y_{t+1} | y_{t+1} < \mathrm{VaR}^{\alpha}_{t,lin}) = \frac{1}{\alpha} \sum_{k=1}^{K} w_{t,k} \int_{-\infty}^{\mathrm{VaR}^{\alpha}_{t,lin}} y_{t+1} p_{t,k}(y_{t+1}) dy_{t+1}, \quad (5)$$

and from the logarithmic pool:

$$\mathrm{VaR}^{\alpha}_{t,log} \equiv \inf \left\{ y_{t+1} \in \mathbb{R} : \int_{-\infty}^{y_{t+1}} \prod_{k=1}^{K} p_{t,k}(y)^{w_{t,k}} dy \geq \alpha\gamma \right\},$$

$$\mathrm{ES}^{\alpha}_{t,log} \equiv E_{t,log}(y_{t+1} | y_{t+1} < \mathrm{VaR}^{\alpha}_{t,log}) = \frac{1}{\alpha\gamma} \int_{-\infty}^{\mathrm{VaR}^{\alpha}_{t,log}} y_{t+1} \prod_{k=1}^{K} p_{t,k}(y_{t+1})^{w_{t,k}} dy_{t+1},$$

where γ is the integrating constant in (2).

5 Risk model contribution

In portfolio risk management, the Euler decomposition can be used to assess the holdings' contribution to the overall portfolio risk (see, e.g., Keel and Ardia, 2011). In our context, it can be relevant to identify how individual models contribute to pool risk, but the Euler decomposition does not apply to the pool risk measures presented in Section 4. We notice, however, that the expected shortfall of the linear pool can easily be decomposed. In (5), we define the contribution of the kth model as:

$$c_{t,k} \equiv \frac{w_{t,k}}{\alpha} \int_{-\infty}^{\mathrm{VaR}^{\alpha}_{t,lin}} y_{t+1} p_{t,k}(y_{t+1}) dy_{t+1},$$

where $\sum_{k=1}^{K} c_{t,k} = \mathrm{ES}^{\alpha}_{t,lin}$ and where dividing $c_{t,k}$ by $\mathrm{ES}^{\alpha}_{t,lin}$ gives us the percentage contribution of the kth model to $\mathrm{ES}^{\alpha}_{t,lin}$. Decompositions for other pool risk measures are a topic for further research.

To illustrate the above decomposition, suppose that the return of a security is modeled either by a mixture of two Student-t distributions:

$$M_1 : \quad p_1(y_t) = \omega t(y_t; \mu_1, \sigma_1, \nu_1) + (1 - \omega) t(y_t; \mu_2, \sigma_2, \nu_2),$$

where $t(y; \mu, \sigma, \nu)$ is a Student-t density with $\mu \in \mathcal{R}$, $\sigma > 0$, $\nu > 0$ and where $\omega \in [0,1]$, or by a skew Student-t distribution à la Fernández and Steel (1998):

$$M_2 : \quad p_2(y_t) = \frac{2\xi}{(\xi^2 + 1)} \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{\pi\nu}\sigma}$$

$$\times \left[1 + \frac{1}{\nu}\left(\frac{y_t - \mu}{\sigma}\right)^2 (\xi^{-2} I\{y_t \geq \mu\} + \xi^2 I\{y_t < \mu\})\right]^{-\frac{\nu+1}{2}},$$

where $\xi > 0$.

Each model can be considered separately, but we can also combine them with an equally weighted linear pool. A plot of these densities with arbitrary parameter values is given in the left panel of Figure 2. The right panel of Figure 2 shows the

Figure 2: Model densities (left panel) and risk contributions at various risk levels (right panel).

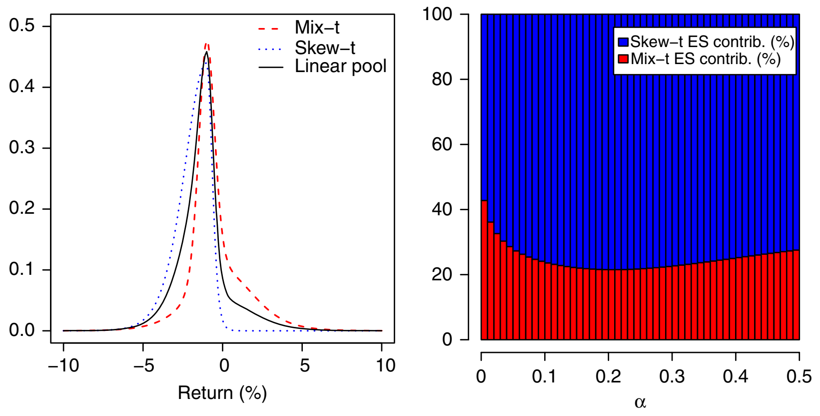
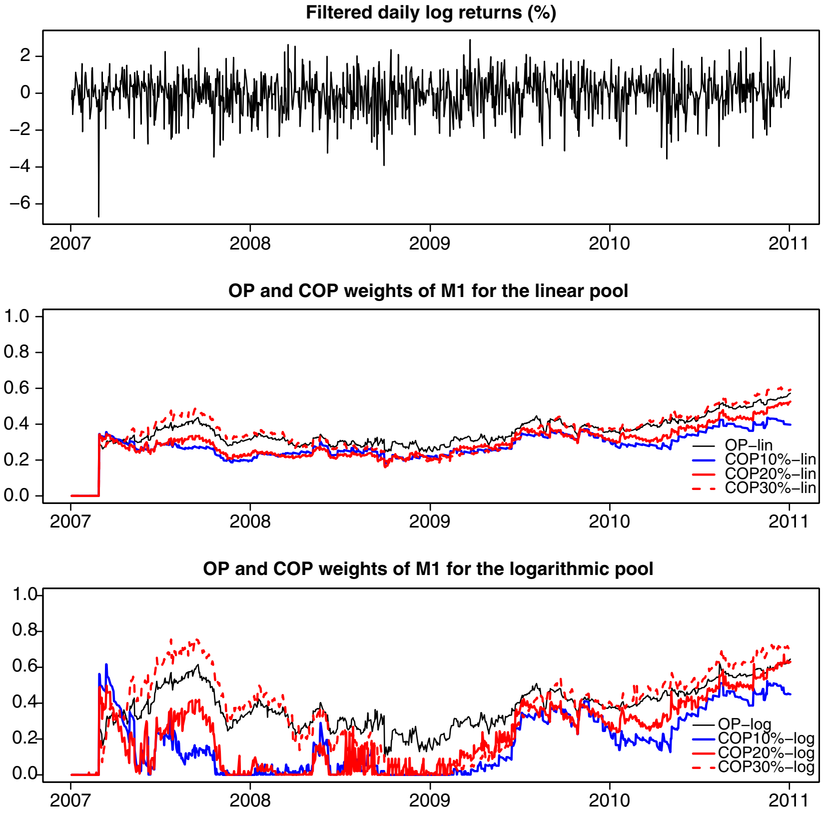


Figure 3: Filtered returns (top panel) and OP and COP weights of the mixture of Student-*t* distributions for the linear pool (middle panel) and for the logarithmic pool (bottom panel) over the forecasting period.



contributions to the linear pool ES at various risk levels. We see that the contribution of the mixture of Student-*t* distributions is generally lower than that of the skew Student-*t* distribution, but that it strongly increases in the left-tail. Therefore, the mixture of Student-*t* distributions could compete with the skew Student-*t* distribution as a risk model. Note also that the contributions are very different from model weights, which are equal to one-half.

Model contribution plots can be viewed as diagnostic tools providing precious insights to improve model combinations for the purpose of risk management. In our illustration, M_1 (the mixture of Student-*t* distributions) is complementary to M_2 (the skew Student-*t* distribution) as a risk model. Furthermore, these plots can also be used to compare risk models. Indeed, the right panel of Figure 2 would lead us to retain M_2 in a model selection exercise.

6 An empirical application

We illustrate now, through a backtesting experiment, the variation of single risk forecasts and compare them with the pooling approaches. For simplicity, we perform the backtest on daily GARCH-filtered log-returns y_t of the S&P500 index. This allows us to focus on higher moments of the conditional distribution of log-returns. Extension to full estimation is straightforward. Our forecasting experiment goes from January 3, 2007 to January 3, 2011 (1009 observations). Over this period, we consider one-day-ahead density forecasts obtained from M_1 and M_2 presented in Section 5 and from linear and logarithmic pools of these models. We use rolling windows of 755 observations updated every 20 trading days to compute maximum likelihood parameter estimates and set t_0 in combination methods to January 3, 2006.

Figure 4: One-day-ahead VaR forecasts for (filtered) returns over the forecasting period.

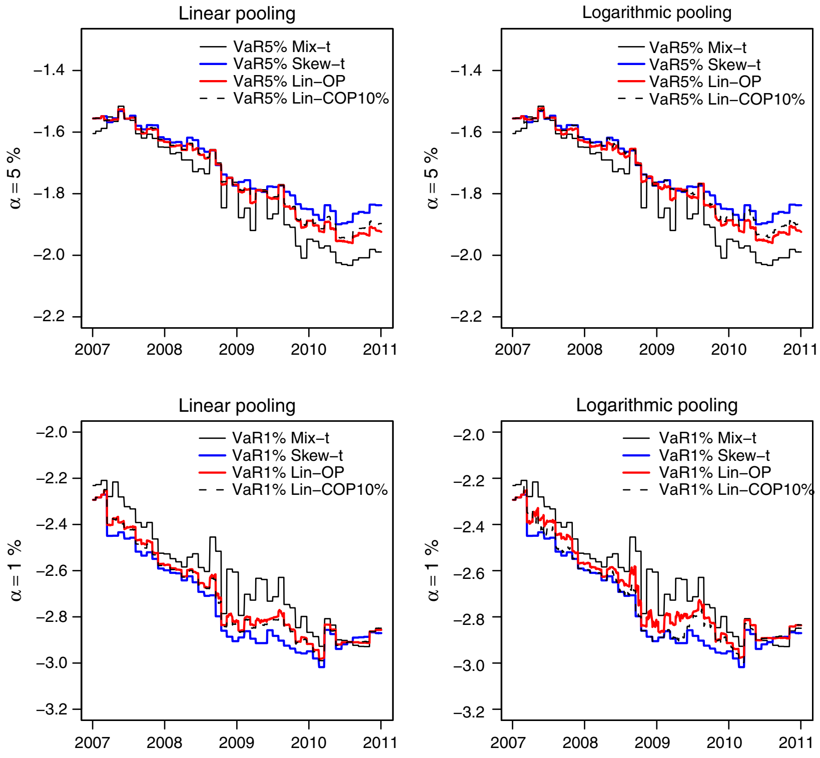
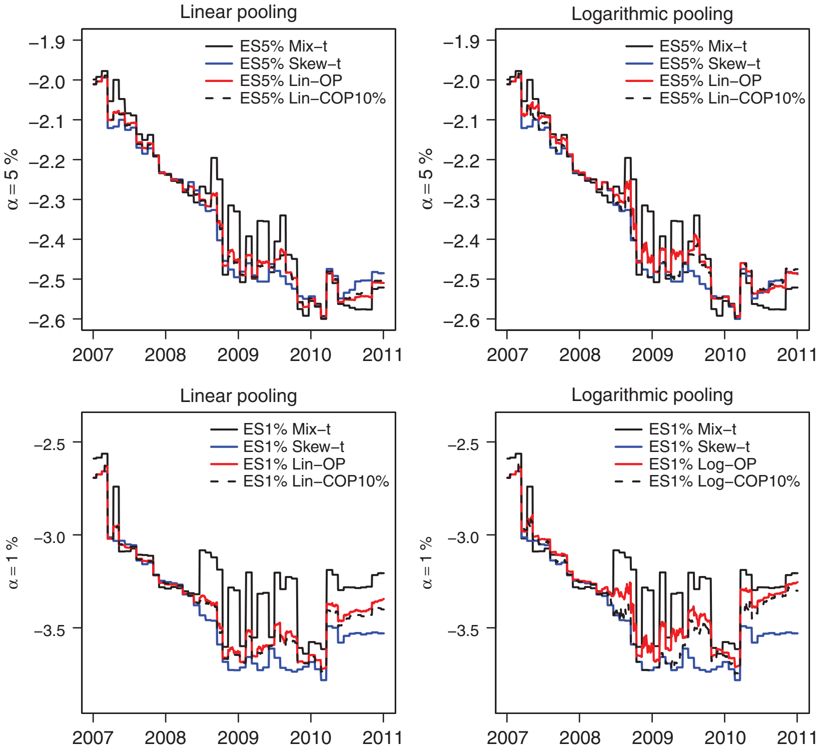


Figure 5: One-day-ahead ES forecasts for (filtered) returns over the forecasting period.



The top panel of Figure 3 displays the (filtered) returns over the forecasting period. A large outlier can be observed at the beginning of 2007. The middle and bottom panels of Figure 3 present the evolution of OP and COP weights of M_1 (the mixture of Student-*t* distributions) in the linear and logarithmic pool cases, respectively. The COP weights rely on the 10, 20, and 30 percent empirical quantiles. We observe that the weights for the logarithmic pool are more volatile than those for the linear pool. Note that the COP weights tend to be smaller when the censoring bound is low whatever the pooling rule. Furthermore, the OP and COP weights start to be different from zero at the beginning of the forecasting period, simultaneously with the occurrence of the lowest filtered return in the whole sample. This suggests that M_1 is helpful for capturing extremes.

Figure 4 displays the evolution of one-day-ahead VaR forecasts at the 5 percent and 1 percent risk levels. Figure 5 displays the same plot for ES forecasts. We only present results with 10 percent quantile as censoring bound. We see that the VaR and ES estimates tend to increase (in absolute value) until 2010, when they start to diminish (in absolute value). Combination risk forecasts do not evolve stepwise because the weights are updated daily. We observe that combination risk forecasts are less volatile than those from the mixture of Student-*t* distributions. Note that combination risk forecasts are generally between those from the two individual distributions. We performed some coverage tests for VaR forecasts, but the results do not allow model discrimination and are thus not reported here.

Acknowledgments

The authors are grateful to Lennart Hoogerheide for helpful remarks. David Ardia thanks IFM2 Montreal for financial support. Jeremy Kolly thanks the Department of Management at Fribourg University (Switzerland) as well as the Swiss National Science Foundation for financial support, and the Department of Finance, Insurance and Real Estate at Laval University for its hospitality. The views expressed in this paper are those of the authors only. They are solely responsible for any remaining errors or shortcomings.

David Ardia is Assistant Professor of Finance at the University of Neuchâtel, Switzerland. Previously he was senior analyst at aeris CAPITAL AG and head of research at Tolomeo Capital AG, two Swiss-based asset managers. In 2008 he received the Chorafas Prize for his book *Financial Risk Management with Bayesian Estimation of GARCH Models*, published by Springer. He is the author of several scientific articles and statistical packages. He holds an MSc in applied mathematics, an MAS in finance, and a PhD in Bayesian econometrics.

Jeremy Kolly is a postdoctoral researcher in financial econometrics at Laval University, Québec, Canada. He carried out his PhD thesis at University of Fribourg (Switzerland) on the prediction of the US unemployment rate using combinations of time-series models. He also holds a BA in management and an MA in economics from University of Fribourg.

REFERENCES

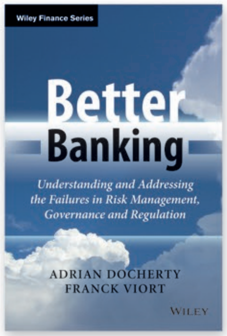
Chua, C.L., Suardi, S., and Tsiaplias, S. 2013. Predicting short-term interest rates using Bayesian model averaging: Evidence from weekly and high frequency data. *International Journal of Forecasting* 29(3), 442–455.
Daníelsson, J. 2008. Blame the models. *Journal of Financial Stability* **4**(4), 321–328.
Diks, C., Panchenko, V., and van Dijk, D. 2011. Likelihood-based scoring rules for comparing density forecasts in tails. *Journal of Econometrics* **163**(2), 215–230.
Eklund, J. and Karlsson, S. 2007. Forecast combination and model averaging using predictive measures. *Econometric Reviews* **26**(2–4), 329–363.
Fernández, C. and Steel, M.F.J. 1998. On Bayesian modeling of fat tails and skewness. *Journal of the American Statistical Association* **93**(441), 359–371.
Gatarek, L.T., Hoogerheide, L.F., Hooning, K., and van Dijk, H.K. 2014. Censored posterior and predictive likelihood in Bayesian left-tail prediction for accurate value at risk estimation. Tinbergen Institute Discussion Paper.
Genest, C. and Zidek, J.V. 1986. Combining probability distributions: A critique and an annotated bibliography. *Statistical Science* **1**(1), 114–135.
Geweke, J. and Amisano, G. 2011. Optimal prediction pools. *Journal of Econometrics* **164**(1), 130–141.
Geweke, J. and Amisano, G. 2012. Prediction with misspecified models. *American Economic Review* **102**(3), 482–486.
Hall, S.G. and Mitchell, J. 2007. Combining density forecasts. *International Journal of Forecasting* **23**(1), 1–13.
Hoeting, J.A., Madigan, D., Raftery, A.E., and Volinsky, C.T. 1999. Bayesian model averaging: A tutorial. *Statistical Science* **14**(4), 382–417.
Kascha, C. and Ravazzolo, F. 2010. Combining inflation density forecasts. *Journal of Forecasting* **29**(1&2), 231–250.
Keel, S. and Ardia, D. 2011. Generalized marginal risk. *Journal of Asset Management* **12**(2), 123–131.
Kolly, J. 2014. Predicting the US unemployment rate using Bayesian model averaging. PhD thesis, Fribourg University (Switzerland). Available at: doc.rero.ch/record/232699.
Krishnamurthy, S. 2014. Quantifying model risk. Wilmott **69**, 56–59.
Leamer, E.E. 1978. *Specification Searches: Ad hoc inference with nonexperimental data*. New York: Wiley.
Opschoor, A., van Dijk, D., and van der Wel, M. 2015. Combining density forecasts using censored likelihood scoring rules. Tinbergen Institute Discussion Paper.

Book Club

Share our passion for great writing – with Wiley's list of titles for independent thinkers ...

Better Banking

Adrian Docherty and Franck Viort



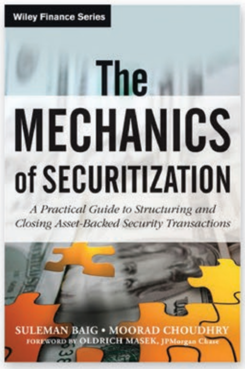
Better Banking gives readers a clear and thorough run-through of some of the key concepts and developments in banking, to enable the reader to understand better this vital yet perilous industry. Without excessive detail or jargon, the authors explain the most important issues in risk management, regulation and governance and build a comprehensive description of how failings in these areas resulted in the current financial crisis. In order to make the diagnosis clear, they also illustrate their descriptions with a series of informative case studies. The book revolves around a critique of the current regulatory developments, which the authors feel will be ineffective in fixing the structural flaws in banking. Crucially, and as the title of the book suggests, they set out their own series of proposals to contribute to the development of a better, safer and more effective banking industry.

9781118651308 • Hardback • 376 pages
December 2013 • ~~£40.00 / €48.00~~ £24.00 / €28.80

The Mechanics of Securitization

A Practical Guide to Structuring and Closing Asset-Backed Security Transactions

Moorad Choudhry



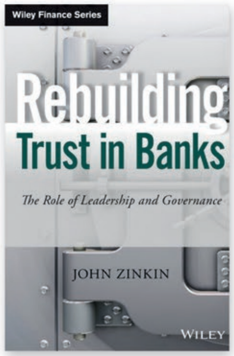
This book specifically analyzes and describes the process by which a bank successfully implements and closes a securitization transaction in the post subprime era.
This book begins with an introduction to asset-backed securities and takes you through the historical impact of these transactions including the implications of the recent credit crisis and how the market has changed.

9780470609729 • Hardback • 182 pages
March 2013 • ~~£65.00 / €76.00~~ £39.00 / €45.60

Rebuilding Trust in Banks

The Role of Leadership and Governance

John Zinkin



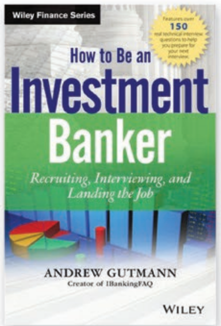
Since 2008, the global financial industry has lurched from crisis to crisis, calamity to calamity, resulting in an epic loss of public trust in banking and financial institutions. *Rebuilding Trust in Banks* argues that this series of disasters have usually been the result failures of leadership and governance, combined with unenforced systems of checks and balances. Often, leaders lose their way, believing their own hype and buying into their own propaganda. The more successful these leaders are initially the greater their self-confidence grows along with the certainty that they're right. The result is a dangerous hubris with no countervailing power to stop or change reckless, unethical, or self-interested strategies. This book offers a solution, with useful benchmarks for corporate governance and a global perspective.

9781118550380 • Hardback • 320 pages
January 2014 • ~~£50.00 / €60.00~~ £30.00 / €36.00

How to Be an Investment Banker

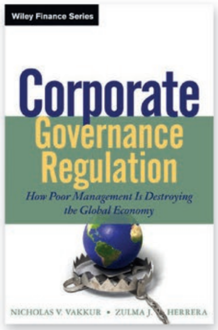
Recruiting, Interviewing, and Landing the Job

Andrew Gutmann



For undergraduates and MBA students, this book offers the perfect preparation for the demanding and rigorous investment banking recruitment process. It features an overview of investment banking and careers in the field, followed by chapters on the core accounting and finance skills that make up the necessary framework for success as a junior investment banker. The book then moves on to address the kind of specific technical interview and recruiting questions that students will encounter in the job search process, making this the ideal resource for anyone who wants to enter the field.

9781118487624 • Hardback • 448 pages • May 2013 • ~~£50.00 / €60.00~~ £30.00 / €36.00



Corporate Governance Regulation

How Poor Management Is Destroying the Global Economy

Nicholas V. Vakkur and Zulma J. Herrera

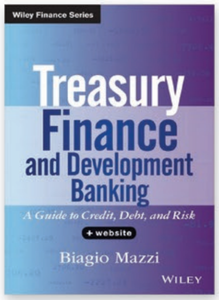
Modern history persuasively demonstrates the inexorable link that binds comprehensive regulation to the global economy. This important book, rather than simply recount a litany of corporate governance failures, persuasively explains *why*, despite policymakers' best intentions, regulation has failed in the modern era. An objective study intended for a diverse readership, *Corporate Governance Regulation* unveils the underlying, root causes of regulatory failure. The result: A compelling and original analysis, broadly suited for a global audience of all backgrounds.

9781118496374 • Hardback • 269 pages • March 2013 • ~~£50.00 / €60.00~~ £30.00 / €36.00

Treasury Finance and Development Banking

A Guide to Credit, Debt, and Risk

Biagio Mazzi



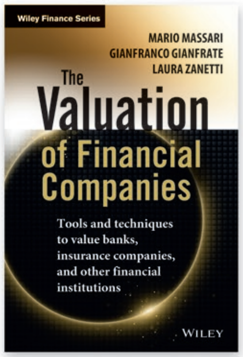
The purpose of this book is to analyze credit from the beginning—the point at which any borrowing entity (sovereign, corporate, etc.) decides to raise capital through its treasury operation. To describe the debt management activity, the book presents examples from the development banking world which not only presents a clearer banking structure but in addition sits at the intersection of many topical issues (multi-lateral agencies, quasi-governmental entities, Emerging Markets, shrinking pool of AAA borrowers, etc.).

9781118729120 • Hardback • 336 pages • November 2013 • ~~£57.50 / €68.00~~ £34.50 / €40.80

The Valuation of Financial Companies

Tools and Techniques to Measure the Value of Banks, Insurance Companies and other Financial Institutions

Mario Massari, Gianfranco Gianfrate and Laura Zanetti



This book presents the main valuation approaches that can be used to value financial institutions. By sketching 1) the different business models of banks (both commercial and investment banks) and insurance companies (life, property and casualty and reinsurance); 2) the structure and peculiarities of financial institutions' reporting and financial statements; and 3) the main features of regulatory capital frameworks for banking and insurance (ie Basel III, Solvency II), the book addresses why such elements make the valuation of financial institutions different from the valuation of non-financial companies.

9781118617335 • Hardback • 256 pages
February 2014 • ~~£60.00 / €72.00~~ £36.00 / €43.20

SAVE 40%

When you subscribe to *WILMOTT magazine* you will automatically become a member of the **Wilmott Book Club** and you'll be eligible to receive 40% discount on specially selected books in each issue when you order direct from **www.wiley.com** - just quote promotion code **WBC40** when you order. The titles will range from finance to narrative non-fiction.

For further information, call our **Customer Services Department on 44 (0)1243 843294**, or visit *www.wileyeurope.com/go/wilmott*