Andrew G Haldane: The dog and the frisbee

Speech by Mr Andrew G Haldane, Executive Director, Financial Stability, Bank of England, and Mr Vasileios Madouros, Economist, Bank of England, at the Federal Reserve Bank of Kansas City's 366th economic policy symposium, "The changing policy landscape", Jackson Hole, Wyoming, 31 August 2012.

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(1) Introduction

Catching a frisbee is difficult. Doing so successfully requires the catcher to weigh a complex array of physical and atmospheric factors, among them wind speed and frisbee rotation. Were a physicist to write down frisbee-catching as an optimal control problem, they would need to understand and apply Newton's Law of Gravity.

Yet despite this complexity, catching a frisbee is remarkably common. Casual empiricism reveals that it is not an activity only undertaken by those with a Doctorate in physics. It is a task that an average dog can master. Indeed some, such as border collies, are better at frisbee-catching than humans.

So what is the secret of the dog's success? The answer, as in many other areas of complex decision-making, is simple. Or rather, it is to keep it simple. For studies have shown that the frisbee-catching dog follows the simplest of rules of thumb: run at a speed so that the angle of gaze to the frisbee remains roughly constant. Humans follow an identical rule of thumb.

Catching a crisis, like catching a frisbee, is difficult. Doing so requires the regulator to weigh a complex array of financial and psychological factors, among them innovation and risk appetite. Were an economist to write down crisis-catching as an optimal control problem, they would probably have to ask a physicist for help.

Yet despite this complexity, efforts to catch the crisis frisbee have continued to escalate. Casual empiricism reveals an ever-growing number of regulators, some with a Doctorate in physics. Ever-larger litters have not, however, obviously improved watchdogs' Frisbee-catching abilities. No regulator had the foresight to predict the financial crisis, although some have since exhibited supernatural powers of hindsight.

So what is the secret of the watchdogs' failure? The answer is simple. Or rather, it is complexity. For what this paper explores is why the type of complex regulation developed over recent decades might not just be costly and cumbersome but sub-optimal for crisis control. In financial regulation, less may be more.

Section 2 sets out the reasons why that might be, drawing on examples from outside economics and finance. Section 3 contrasts that thinking with the rapidly rising-tide of financial regulation. Sections 4 to 6 consider some experiments to assess whether less could be more in financial systems. Section 7 draws out some public policy implications.

(2) When less is more

Mainstream economics and finance is dominated by models of decision-making under risk. Modern macroeconomics has its analytical roots in the general equilibrium framework of Kenneth Arrow and Gerard Debreu (Arrow and Debreu (1954)). In the Arrow-Debreu framework, the probability distribution of future states of the world is known by agents. Risk can be securitised and thereby priced and hedged.

Modern finance has its origins in the portfolio allocation framework of Harry Markowitz and Robert Merton (Markowitz (1952), Merton (1969)). This Merton-Markowitz framework assumes a known probability distribution for future market risk. This enables portfolio risk to be calculated and thereby priced and hedged.

Together, the Arrow-Debreu and Merton-Markowitz frameworks form the bedrock of modern macroeconomics and finance. They help explain patterns of behaviour from consumption and investment to asset pricing and portfolio allocation. This has been a well-trodden path for the past 50 years.

The path less followed has been to study optimal choice under uncertainty – the inability to form priors on the distribution of future outcomes – rather than risk (Knight (1921)). Neither the Arrow-Debreu nor Merton-Markowitz frameworks admit such uncertainty. Instead, modern macro and finance has been built on often stringent assumptions about humans' state of knowledge and cognitive capacity.

For the past 40 years, the most popular of those informational assumptions has been rational expectations (Muth (1961)). That, too, has dominated modern macro and finance for a generation. In its strongest form, rational expectations assumes that information collection is close to costless and that agents have cognitive faculties sufficient to weight probabilistically all future outturns.

Those strong assumptions about states of knowledge and cognition have not always been at the centre of the economics profession. Many of the dominant figures in 20th century economics – from Keynes to Hayek, from Simon to Friedman – placed imperfections in information and knowledge centre-stage. Uncertainty was for them the normal state of decision-making affairs.

Hayek's Nobel address, "The Pretence of Knowledge", laid bare the perils of over-active policy if we assumed omniscience (Hayek (1974)). For Friedman, lack of knowledge justified a k% monetary policy rule (Friedman (1960)). For physicist Richard Feynman: "It is not what we know, but what we do not know which we must always address, to avoid major failures, catastrophes and panics." Through Arrow-Debreu and Merton-Markowitz, economists may have failed to heed Feynman's catastrophe warning.

Despite occupying a small corner of the profession, decision-making under uncertainty has begun to attract recent interest (Hansen and Sargent (2010)). That is in part recognition of the limitations of the rational-expectations-cum-general-equilibrium framework for capturing key elements of the current crisis (Kirman (2010)). More positively, it may also be because it yields powerful, and in some cases surprising, insights.

Take decision-making in a complex environment. With risk and rational expectations, the optimal response to complexity is typically a fully state-contingent rule (Morris and Shin (2008)). Under risk, policy should respond to every raindrop; it is fine-tuned. Under uncertainty, that logic is reversed. Complex environments often instead call for simple decision rules. That is because these rules are more robust to ignorance. Under uncertainty, policy may only respond to every thunderstorm; it is coarse-tuned.

Herbert Simon, the father of decision-making under uncertainty, believed human behaviour followed simple rules. More than that, it was precisely because humans operated in a complex environment that they sought such simple behavioural rules. "Human beings, viewed as behaving systems, are quite simple. The apparent complexity of our behavior over time is largely a reflection of the complexity of the environment in which we find ourselves."[1]

[1] Simon (1972).

Simon used the word "heuristics" to describe these simple rules. These heuristics were not plucked from the ether. Rather they were evolutionary responses, honed in the light of experience passed down generationally from the past (nature) or accumulated locally in the present (nurture). Neurological and experimental research has since lent support to Simon's thinking (for example, Selten (2001)).

In the 1970s and 1980s, Daniel Kahneman and Amos Tversky used heuristics as a means of explaining violations of the rational expectations axioms, often drawn from psychological experiments (Kahneman and Tversky (1974)). Like Simon, these simple rules of thumb had neurological roots. Kahneman and Tversky's work laid the foundations for behavioural economics (for example, Camerer (2003)).

Part of the attraction of these approaches is that they fit the decision-making facts. In many real-world settings heuristics are the rule, not the exception. This is not confined to Frisbee-catching dogs (Gigerenzer (2007)) – though heuristic decision-making is found throughout the animal world, in complex decisions such as the choice of mate. It has also been found to be true in many aspects of human decision-making, from finding a soulmate to finding a checkmate (Gigerenzer (2007)).

So why are such simple rules of thumb ubiquitous? And what are their implications?

(a) The costs of cognition

The simplest explanation is that collecting and processing the information necessary for complex decision-making is costly, perhaps punitively so. Fully defining future states of the world, and probability-weighting them, is beyond anyone's cognitive limits. Even in relatively simple games, such as chess, cognitive limits are quickly breached. Chess grandmasters are unable to evaluate fully more than 5 chess moves ahead. The largest super-computers cannot fully compute much beyond 10 moves ahead (Gigerenzer (2007)).

Most real-world decision-making is far more complex than chess – more moving pieces with larger numbers of opponents evaluated many more moves ahead. Simon coined the terms "bounded rationality" and "satisficing" to explain cost-induced deviations from rational decision-making (Simon (1956)). A generation on, these are the self-same justifications being used by behavioural economists today. For both, less may be more because more information comes at too high a price.

(b) Ignorance can be bliss

There is a second, quite different, rationale for simple decision rules. This does not rely on the sub-optimality of satisficing behaviour. Instead it states that heuristics may be the optimising response to a complex environment. Disregarding information can make not only for cheaper but also for better decisions. Ignorance can be bliss (Gigerenzer (2010)).

Oscar Wilde said of cynics that they knew the price of everything and the value of nothing.[2] Autistic savants have an acute case of this problem. Often, they combine prodigious memory skills (knowing "the price of everything") with serious deficiencies in value judgements (understanding "the value of nothing"). They are penny-wise and pound-foolish.

These neurological traits are linked. Too great a focus on information gathered from the past may retard effective decision-making about the future. Knowing too much can clog up the cognitive inbox, overload the neurological hard disk. One of the main purposes of sleep – doing less – is to unclog the cognitive inbox (Wang et al (2011)). That is why, when making a big decision, we often "sleep on it".

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[2] Wilde (1893).

"Sleeping on it" has a direct parallel in statistical theory. In econometrics, a model seeking to infer behaviour from the past, based on too short a sample, may lead to "over-fitting". Noise is then mistaken as signal, blips parameterised as trends. A model which is "over-fitted" sways with the smallest statistical breeze. For that reason, it may yield rather fragile predictions about the future.

Experimental evidence bears this out. Take sports prediction. In principle, this should draw on a complex array of historical data, optimally weighted. That is why complex, data-hungry algorithms are used to generate rankings for sports events, such as the FIFA world rankings for football teams or the ATP world rankings for tennis players. These complex algorithms are designed to fit performance data from the past.

Yet, when it comes to out-of-sample prediction, these complex rules perform miserably. In fact, they are often inferior to simple alternatives. One such alternative would be the "recognition heuristic" – picking a winning team or player purely on the basis of name-recognition. This simple rule out-performs the ATP or FIFA rankings (Serwe and Frings (2006), Scheibehenne and Broder (2007)). One good reason beats many.

It is not just sports prediction. Experimental evidence has found the same to be true across a range of other activities. Among physicians diagnosing heart attacks, simple decision trees beat a complex model.[3] Among detectives locating serial criminals, simple locational rules trump complex psychological profiling.[4] Among investors picking stocks, simple passive strategies outperform complex active ones.[5] And among shopkeepers understanding spending patterns, repeat purchase data out-predict complex models.[6]

Applying complex decision rules in a complex environment may be a recipe not just for a cock-up but catastrophe. In "Natural Accidents", sociologist Charles Perrow demonstrated how catastrophe was more likely to strike in complex, interconnected – "tightly coupled" – systems (Perrow (1984)). Drawing on experience from a variety of real world systems – nuclear power plants, oil rigs, aircraft navigation systems – Tim Harford (2011) illustrates how complex control of a complex environment has often been calamitous.

The general message here is that the more complex the environment, the greater the perils of complex control. The optimal response to a complex environment is often not a fully state-contingent rule. Rather, it is to simplify and streamline (Gigerenzer (2010)). In complex environments, decision rules based on one, or a few, good reasons can trump sophisticated alternatives. Less may be more.

In Isaiah Berlin's famous essay "The Hedgehog and the Fox" (Berlin (1953)), the fox knew many things, the hedgehog one big thing. Philosophers continue to debate their relative merits. But sports fans, doctors and detectives have made their choice. They think the hedgehog has the upper paw. Selective unclogging of the cognitive inbox can make for better decisions.

(c) Weighting may be in vain

John von Neumann and Oskar Morgenstern established that optimal decision-making involved probabilistically-weighting all possible future outcomes (von Neumann and Morgenstern (1944)). Multiple regression techniques are the statistical analogue of von Neumann-Morgenstern optimisation, with behaviour inferred by probabilistically-weighting explanatory factors.

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3 Gigerenzer and Kurzenhäuser (2005).

4 Snook et al (2005).

5 DeMiguel et al (2007).

6 Wübben and von Wangenheim (2008)).

In an uncertain environment, where statistical probabilities are unknown, however, these approaches to decision-making may no longer be suitable. Probabilistic weights from the past may be a fragile guide to the future. Weighting may be in vain. Strategies that simplify, or perhaps even ignore, statistical weights may be preferable. The simplest imaginable such scheme would be equal-weighting or "tallying". Gigerenzer and Brighton (2009).[7]

In complex environments, tallying strategies have been found to be superior to risk-weighted alternatives. Take avalanche prediction. Avalanches are difficult to predict, as they are drawn from a fat-tailed (Power Law) distribution. Yet simple tallying of a small number of avalanche indicators has been found capable of predicting over 90% of historical accidents. It has also been found to be superior to more complex decision methods (McCammon and Hägeli (2007)).

A similar finding has emerged from studies of asset prices. They too are drawn from a fat-tailed distribution. When investing across N assets, the Merton-Markowitz portfolio strategy would weight by risk and return. A far simpler strategy would equally-weight all assets – a 1/N rule. In out-of-sample trials, the 1/N rule outperforms complex optimising alternatives, including Merton-Markowitz (DeMiguel et al (2007)). Indeed, Markowitz himself pursued a 1/N, rather than Markowitz, strategy when investing for retirement.

(d) Small samples and simple rules

The choice of optimal decision-making strategy depends importantly on the degree of uncertainty about the environment – in statistical terms, model uncertainty. A key factor determining that uncertainty is the length of the sample over which the model is estimated. Other things equal, the smaller the sample, the greater the model uncertainty and the better the performance of simple, heuristic strategies.

Small samples increase the sensitivity of parameter estimates. They increase the chances of inaccurately over-fitting historical data. This risk becomes more acute, the larger the parameter space being estimated. Complex models are more likely to be over-fitted. And the parametric sensitivity induced by over-fitting makes for unreliable predictions about the future. Simple models suffer fewer of these parametric excess-sensitivity problems, especially when samples are short.

Experimental evidence again bears out that conclusion. For example, simple rules have been shown to outperform complex ones when tracking serial criminals, provided the number of committed crimes in a sequence is in single figures (Snook et al (2005)).

Investment strategies tell a similar story. Simple tallying rules, like 1/N, outperform complex strategies, like mean-variance, unless the sample size is very large. In the study by DeMiguel et al (2007), the sample threshold at which complex rules out-perform simple ones is in excess of 3000 months (around 250 years) of data. Less is more, at least without much (much) more data.

(d) Complex rules and defensive behaviour

There is a final, related but distinct, rationale for simple over complex rules. Complex rules may cause people to manage to the rules, for fear of falling foul of them. They may induce people to act defensively, focussing on the small print at the expense of the bigger picture.

Studies of the behaviour of doctors illustrate this pattern (Gigerenzer and Kurzenhäuser (2005)). Fearing misdiagnosis, perhaps litigation, doctors are prone to tick the boxes. That may mean over-diagnosing drugs or over-submitting patients to hospital. Both are defensive actions, reducing risks to the doctor. But both are a potential health hazard to the patient. For

[7] Gigerenzer and Brighton (2009).

example, submitting patients to hospital increases significantly their risk of secondary infection. Hospitals are, after all, full of sick people.

Doctors unencumbered by a complex rulebook will have fewer incentives to act defensively. They may also be better able to form their own independent judgements when diagnosing medical problems, using their accumulated experience. That ought to more closely align a doctor's risk incentives with their patient's. The same is likely to be true of other professions, from lawyers to policemen to bank supervisors.

Of course, simple rules are not costless. They place a heavy reliance on the judgement of the decision-maker, on picking appropriate heuristics. Here, a key ingredient is the decision-maker's level of experience, since heuristics are learned behaviours honed by experience. A dog will outperform a puppy at frisbee-catching because it has had time to fine-tune its "gaze heuristic". An expert baseball player or cricketer will outperform a novice sportsman for the same reason. So too will an experienced doctor or detective or fund manager or shopkeeper.

These are "Five Commandments" of decision-making under uncertainty. That description is apt. Like disease detection, frisbee catching, sports prediction and stock-picking, living a moral life is a complex task. The Ten Commandments are heuristics to help guide people through that moral maze, the ultimate simple rules. They have proven remarkably robust through the millennia. Less has been more.

(3) Finance – more is more?

The response to the financial crisis by banks and regulators has been swift and sizeable. Gaps in risk management have been filled, deficiencies in regulation plugged, errors by regulators corrected. This is a self-healing and familiar response. Past crises have also been met by a combination of more risk management, more regulation and more regulators. More has been more.

(a) The Tower of Basel

The foundations for today's financial regulatory framework were laid in the 1980s. The Basel Accord of 1988 was a landmark. It was the first-ever genuinely international prudential regulatory agreement. For the first time in financial history, a minimum standard had been established for all internationally-active banks. Yet despite its breadth, the Basel I agreement was only 30 pages long.[8]

This brevity came courtesy of focussing on a limited set of credit risks measured at a broad asset class, rather than individual exposure, level. Only five different risk weights were defined under Basel I, varying from zero to 100%. Calculating regulatory capital ratios was possible using pad and pen.

In taking this simplified approach, the Basel Committee fully recognised its limitations. It was recognised that the role of regulatory rules was not to capture every raindrop. Rather, they served as a backstop to banks' own risk assessments. Basel rules were there to support, not supplant, commercial risk decisions.

During the 1990s, the bluntness of the risk judgements embodied in Basel I came increasingly to be questioned – and arbitraged. Basel I was perceived as lacking risk-sensitivity, at least by comparison with the new wave of credit and market risk models emerging at the time. Change came in 1996 with the Market Risk Amendment.[9] This

[8] Basel Committee on Banking Supervision (1988).

[9] Basel Committee on Banking Supervision (1996).

introduced the concept of the regulatory trading book and, for the first time, allowed banks to use internal models to calculate regulatory capital against market risk.

With hindsight, a regulatory rubicon had been crossed. This was not so much the use of risk models as the blurring of the distinction between commercial and regulatory risk judgements. The acceptance of banks' own models meant the baton had been passed. The regulatory backstop had been lifted, replaced by a complex, commercial judgement. The Basel regime became, if not self-regulating, then self-calibrating.

A revised Basel Accord, Basel II, was agreed in 2004. It followed closely in the footsteps of the trading book amendment. Internal risk models were allowed as a means of calibrating credit risk. Indeed, not so much permitted as actively encouraged, with internal models designed to deliver lower capital charges. By design, Basel II served as an incentive device for banks to upgrade their risk management technology.

As a by-product, there was a step change in the granularity of the Basel framework. Risk exposures were no longer captured at a broad asset class level. And risk weights on these exposures were no longer confined to five buckets. That meant greater detail and complexity. Reflecting these changes, Basel II came in at 347 pages – an order of magnitude longer than its predecessor.[10]

The ink was barely dry on Basel II when the financial crisis struck. This exposed gaping holes in the agreement. In the period since, the response has been to fill the largest of these gaps, with large upwards revisions to the calibration of the Basel framework. Agreement on this revised framework, Basel III, was reached in 2010. In line with historical trends the documents making up Basel III added up to 616 pages, almost double Basel II.[11]

The length of the Basel rulebook, if anything, understates its complexity. The move to internal models, and from broad asset classes to individual loan exposures, has resulted in a ballooning in the number of estimated risk weights. For a large, complex bank, this has meant a rise in the number of calculations required from single figures a generation ago to several million today (Haldane (2011)).

That increases opacity. It also raises questions about regulatory robustness since it places reliance on a large number of estimated parameters. Across the banking book, a large bank might need to estimate several thousand default probability and loss-given-default parameters (Table 1). To turn these into regulatory capital requirements, the number of parameters increases by another order of magnitude.

It is close to impossible to determine with complete precision the size of the parameter space for a large international bank's banking book. That, by itself, is revealing. But a rough guess would put it at thousands, perhaps tens of thousands, of estimated and calibrated parameters. That is three, perhaps four, orders of magnitude greater than Basel I.

If that sounds large, the parameter set for the trading book is almost certainly larger still. To give some sense of scale, consider model-based estimates of portfolio Value at Risk (VaR), a commonly-used technique for measuring risk and regulatory capital in the trading book. A large firm would typically have several thousand risk factors in its VaR model. Estimating the covariance matrix for all of the risk factors means estimating several million individual risk parameters. Multiple pricing models are then typically used to map from these risk factors to the valuation of individual instruments, each with several estimated pricing parameters.

Taking all of this together, the parameter space of a large bank's banking and trading books could easily run to several millions. These parameters are typically estimated from limited

[10] Basel Committee on Banking Supervision (2004).

[11] Basel Committee on Banking Supervision (2010). This refers to the sum of Basel II, Basel II.5 and Basel III and covers liquidity, leverage and risk-based capital requirements.

past samples. For example, a typical credit risk model might comprise 20-30 years of sample data – barely a crisis cycle. A market risk model might comprise less than five years of data – far less than a crisis cycle.

Regulatory complexity has also found its way into the numerator of the capital ratio – the definition of capital. Under Basel I, the focus was on common equity capital, with restrictions on non-equity instruments. Progressively, a complex undergrowth of new non-equity capital instruments began to emerge. Additional "tiers" of regulatory capital, and tiers within tiers, were added.

In the end, it did all end in tears. During the crisis, investors lost confidence in non-equity capital instruments. Basel III simplified the definition of core regulatory capital, basing it around a common equity Tier 1 definition. Yet measuring capital remains a complex task. The numerator of the capital ratio adds dozens, perhaps hundreds, of parameters to the complexity quotient.

This degree of complexity complicates greatly the task for investors pricing banks' financial instruments. For example, serious concerns have been expressed about the opacity of the Basel risk weights and their consistency across firms (Haldane (2011), Le Leslé and Avramova (2012)). Their granularity makes it close to impossible to account for differences across banks. It also provides near-limitless scope for arbitrage.

This degree of complexity also raises serious questions about the robustness of the regulatory framework given its degree of over-parameterisation. This million-dimension parameter set is based on the in-sample statistical fit of models drawn from short historical samples. If previous studies tell us it may take 250 years of data for a complex asset pricing model to beat a simple one, it is difficult to imagine how long a sample would be needed to justify a million-digit parameter set.

(b) The legislative blanket

Basel Accords are non-statutory. But since the 1980s, the trend has been towards underpinning these non-statutory agreements with national legislation or additional rule-making. At first, this was simple. The 30 pages of Basel I were translated into 18 pages in the US and 13 pages in the UK. By the time of Basel III, the domestic documentation topped 1,000 pages in both countries.

Viewed over an historical sweep, this pattern is even more striking. Contrast the legislative responses in the US to the two largest financial crises of the past century – the Great Depression and the Great Recession. The single most important legislative response to the Great Depression was the Glass-Steagall Act of 1933. Indeed, this may have been the single most influential piece of financial legislation of the 20th century. Yet it ran to a mere 37 pages.

The legislative response to this time's crisis, culminating in the Dodd-Frank Act of 2010, could not have been more different. On its own, the Act runs to 848 pages – more than 20 Glass-Steagalls. That is just the starting point. For implementation, Dodd-Frank requires an additional almost 400 pieces of detailed rule-making by a variety of US regulatory agencies.

As of July this year, two years after the enactment of Dodd-Frank, a third of the required rules had been finalised. Those completed have added a further 8,843 pages to the rulebook. At this rate, once completed Dodd-Frank could comprise 30,000 pages of rulemaking. That is roughly a thousand times larger than its closest legislative cousin, Glass-Steagall. Dodd-Frank makes Glass-Steagall look like throat-clearing.

The situation in Europe, while different in detail, is similar in substance. Since the crisis, more than a dozen European regulatory directives or regulations have been initiated, or reviewed, covering capital requirements, crisis management, deposit guarantees, short-selling, market abuse, investment funds, alternative investments, venture capital, OTC derivatives, markets in financial instruments, insurance, auditing and credit ratings.

These are at various stages of completion. So far, they cover over 2000 pages. That total is set to increase dramatically as primary legislation is translated into detailed rule-writing. For example, were that rule-making to occur on a US scale, Europe's regulatory blanket would cover over 60,000 pages. It would make Dodd-Frank look like a warm-up Act.

(c) The regulatory response

The density and complexity of financial regulation has had predictable consequences for the scale and scope of regulatory resources. One metric for that would be the number of human resources devoted to financial regulation. In the UK up until the late-1970s, bank supervision was performed by the Bank of England on an informal basis, with a team of around 30 employees. Even when the Bank was given statutory responsibility in 1979, fewer than 80 people were engaged in the supervision of financial firms.

In the period since, the number of UK financial supervisors has increased dramatically, rising almost forty-fold (Chart 1). In response to the current crisis, regulatory numbers are set to rise further. Over the same period, the number of people employed in the UK financial services sector has risen fractionally. In 1980, there was one UK regulator for roughly every 11,000 people employed in the UK financial sector. By 2011, there was one regulator for every 300 people employed in finance.

The pattern in the US, looked at over a longer historical sweep, is broadly similar. The FDIC and SEC were set up as part of the regulatory response to the Great Depression. In 1935, together with the OCC and supervisors housed in the Federal Reserve banks, they had combined regulatory resources of around 4,500 people. There was one regulator for every three banks in the US (Chart 2). Today, the combined regulatory resources of the FDIC, OCC, Federal Reserve banks and SEC is closer to 18,500 people. That is three regulators for every US bank.

As numbers of regulators have risen, so too have regulatory reporting requirements. In the UK, regulatory reporting was introduced in 1974. Returns could have around 150 entries. In the Bank of England archives is a memo to George Blunden, who was to become Deputy Governor, on these proposed regulatory returns. Blunden's handwritten comment reads: "I confess that I fear we are in danger of becoming excessively complicated and that if so we may miss the wood from the trees".[12]

Today, UK banks are required to fill in more than 7,500 separate cells of data – a fifty-fold rise. Forthcoming European legislation will cause a further multiplication. Banks across Europe could in future be required to fill in 30–50,000 data cells spread across 60 different regulatory forms. There will be less risk of regulators missing the wood from the trees, but only because most will have needed to be chopped down.

In the US, regulatory reporting has a history going back to the early 19th century. Nationally-chartered banks began to submit quarterly returns after the formation of the OCC in 1863. In 1869, following a legislative amendment, these became "call reports", so named because banks were asked to report on surprise dates to prevent window-dressing. The Federal Reserve Act of 1913 required all state-chartered member banks to file reports with the OCC and in 1917 responsibility for collecting these passed to the Federal Reserve. By 1930, these reports might contain around 80 entries.

Today, regulatory reporting is on an altogether different scale. Since 1978, the Federal Reserve has required quarterly reporting by bank holding companies. In 1986, this covered 547 columns in Excel, by 1999, 1,208 columns. By 2011, it had reached 2,271 columns. Fortunately, over this period the column capacity of Excel had expanded sufficiently to capture the increase.

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[12] Bank of England Archive number 7A222/2.

Taken together, the emerging picture is of a steadily-rising regulatory tower. New floors have been added in response to each crisis episode. Extra filing cabinets have been ordered and installed to house the explosion in regulatory returns. And many new skulks of supervisory foxes (together with the occasional hedgehog) have been installed on the upper floors.

The costs of constructing and maintaining this regulatory skyscraper are not trivial. A recent study by McKinsey estimates the compliance costs of Basel III. For a midsize European bank, these are put at up to 200 full-time jobs.[13] Given that Europe has around 350 banks with total assets over €1 billion, this translates into over 70,000 new full time jobs to comply with Basel III requirements.

The picture in the US is similar. Dodd-Frank rulemaking in the 12 months after its enactment covered thirty new rules or less than 10% of the total. A survey of the Federal Register showed that complying with these new rules would require an estimated 2,260,631 labour hours every year, equivalent to over 1,000 full-time jobs.[14] Scaling this up, the compliance costs of Dodd-Frank will run to tens of thousands of full-time positions.

Of course, the costs of this regulatory edifice would be considered small if they delivered even modest improvements to regulators' ability to avert future financial crises. The public policy question is – will they? In financial regulation, is more more or is more less? To begin to answer that, consider a set of empirical experiments on the performance of regulatory rules, simple and complex.

(4) Risk-weighting capital – simple or complex?

The primary source of complexity in the Basel framework is granular, model-based risk-weighting. Heightened risk-sensitivity of the regulatory framework was intended to improve the detection of bank weakness. But if the financial environment is uncertain, complex risk-weighting may be sub-optimal. As when predicting Alpine avalanches or Wimbledon winners, simpler weighting measures may be more robust.

This is a testable proposition. To do so, we take a sample of about 100 large, complex global banks, defined as those with total assets over $100 billion at end-2006.[15] These large banks are likely to hold a diverse array of assets and to use complex, internal models to calibrate regulatory capital against these assets. So at least in principle, risks to these banks should be better captured by granular, risk-sensitive capital measures. Von Neumann-Morgenstern principles, with probabilistic-weighting, ought to apply.

Consider the relative performance of two measures of capital in predicting bank failure during the course of the crisis: the Basel Tier 1 regulatory capital ratios with assets risk-weighted and simple leverage ratios with assets equally-weighted – a 1/N rule. To predict bank failure, a definition is needed. We use the classification scheme of Laeven and Valencia (2010), defined as those institutions that went into resolution or which required government intervention. In the sample, that amounts to 37 banks.

Chart 3 plots the Basel risk-based capital ratios for the sample of global banks on an ascending scale, distinguishing "failed" and "surviving" banks. There is little visual correlation between levels of regulatory capital and subsequent bank failure. That is confirmed in Chart 4 which, in the left-hand panel, compares levels of risk-based capital in failed and surviving banks. These are not statistically significantly different.

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[13] Härle et al (2010).

[14] Financial Services Committee (2010).

[15] This analysis draws on the preliminary results of research being undertaken by Gerd Gigerenzer and Sujit Kapadia.

Chart 5 plots the simple leverage ratio for the same set of banks. Visually, the pattern now seems more systematic, with lower leverage ratios associated with failing banks. The right-hand panel in Chart 4 confirms that. The pre-crisis leverage ratio of failing banks was statistically significantly lower than surviving banks at the 1% significance level, by on average 1.2 percentage points.

For a set of the world's most complex banks, simple-weighted measures appear to have greater pre-crisis predictive power than risk-weighted alternatives. Running a simple horse-race of the two capital measures in a logit regression confirms the dominance of the simpler measure (Table 2). Measures of risk-weighted capital are statistically insignificant, while the leverage ratio is significant at the 1% level. Contrary to the risk-sensitivity doctrine, less appears to have offered more.

These results are robust to the inclusion of a broader set of macro factors, such as GDP growth and credit (Table 3). Using different methods and samples, other studies support the predictive superiority, or at least equivalence, of leverage over capital ratios (IMF (2009), Demirguc-Kunt et al (2010), Estrella et al (2000)).

A second source of regulatory complexity is the definition of capital. Table 4 considers the predictive performance of a selection of measures of capital for a sub-set of banks. Two key conclusions emerge. First, simpler measures of accounting capital based on equity capital (core Tier 1) outperform broader, more complex, measures. Second, simple market-based measures of banks' equity dominate accounting measures in their crisis-predictive performance. Simple, once again, beats complex.

Put another way, consider a straight horse-race between the most complex measure of banks' capital position (the Basel Tier 1 ratio) and the simplest (the market value of equity relative to unweighted assets). The explanatory power of the simple measure is about 10 times greater than the complex measure. However well they perform in theory or in sample, complex capital rules do not appear to have performed well in practice and out-of-sample. That is a sobering message for the architects of the Tower of Basel.

(5) Predicting bank failure – simple or complex?

In theory, the choice of optimal regulatory rule depends importantly on the environment. The simpler the environment, the more robust are likely to be sophisticated regulatory rules. To assess that, consider a sample of simpler banks – FDIC-insured banks in the US. This covers 8,500 institutions, the majority small regional banks. How well did solvency metrics, simple and complex, perform in predicting pre-crisis failure among this very different bank cohort?

Charts 6 and 7 plot the pre-crisis Tier 1 capital and leverage ratios of these banks, with the failed institutions again identified, while Table 5 shows the results of a formal logit regression. Failure is defined here as those banks entering receivership. Since 2007, this totals 442 institutions, almost all of which had assets below $100 billion.

Both solvency metrics enter with the right sign: lower capital and leverage ratios signal a higher probability of bank failure in a univariate regression. In general, however, the ranking of the solvency metrics is reversed. Risk-based capital ratios are significant at the 1% level, while the leverage ratio is not significant at the 10% level.

There are two potential explanations for this finding. One is that, during the sample period, US banks were already subject to a leverage ratio. This may have encouraged them to seek higher-risk assets which would tend to be better reflected in risk-based capital ratios. An alternative explanation, consistent with the complexity literature, is that risk-based rules are more robust in an easier to calibrate risk environment.

Which explanation is more likely? Some insight can be provided by assessing whether, even in a simple environment, a complex predictive rule outperforms a simple one. To assess that, consider a wider range of potential predictors of bank failure than just capital. A natural starting point would be the well-known CAMEL (capital, asset quality, management, earnings and liquidity) indicators of bank strength. These are a commonly-used performance metric, including by bank supervisors.[16]

Table 6 presents the results of a logit regression of US bank failure using the CAMEL indicators as predictors. All five CAMEL measures are correctly signed, although not all are statistically significant. The in-sample fit suggests an important explanatory role for the CAMEL measures. When fitting bank failure from the past, many indicators dominate the few.

But how would this model have performed out-of-sample in situations where information was partial? As one way of exploring that question, consider estimating the model using a subset of the sample of banks and using that sub-set to predict bank failure for the remainder of the sample. This can be done for a sequence of random samples of varying sizes.[17] The size of these samples proxies the degree of information imperfection – the smaller the sample, the greater the model uncertainty.

These random bank samples of varying sizes are used to re-estimate a set of models of bank failure. These range from the complex (the multi-indicator CAMEL model) to the relatively simple (only one of each of the CAMEL indicators) to the very simple (a constant – similar to the 1/N rule). The out-of-sample predictive performance of these restricted-sample models can then be considered.

Charts 8 and 9 show the performance of the different models estimated across two sample sizes (100 and 1000 banks). Lower values imply better model performance. With a sample of 100 banks, the complex model performs poorly. It is out-performed by every one of the single-indicator models. Indeed, it is even out-performed by the constant. The sample mean beats the CAMEL-estimated model as a bank failure predictor for a small-enough sample.

Expanding the sample to 1000 banks, the complex model now out-performs the simplest rule. But it still falls short of the performance of a model which comprises a single liquidity indicator. Chart 10 summarises the performance of three of the models (complex CAMEL, single liquidity indicator and 1/N) for samples of varying sizes. The complex model performs worst of all for smallish samples. And even with 1000 banks, the complex CAMEL model under-performs the single liquidity indicator.

This evidence suggests that, even among simple banks in a simple environment, imperfections in information can mean that less is more. As when tracking serial killers or serial shoppers, one good reason may be enough.

(6) Modelling financial risks – simple or complex?

The final set of experiments looks at modelling risk in financial markets. This is relevant to how banks themselves might estimate risk to their asset portfolios through their internal

[16] The definitions of these variables are as follows: capital is the risk-based Tier 1 ratio; asset quality is proxied by loans past due as a per cent of total loans; management is proxied by the cost to income ratio, with lower values pointing to greater efficiency and, in principle, better managerial quality; earnings is measured by the return on assets; and liquidity is defined as US government bonds, cash and deposits with banks as a per cent of total assets.

[17] Specifically, from the overall sample of about 8,500 banks, we pick random sub-samples of 100, 250, 500, 1,000 and 4,279 observations. We estimate the models using the smaller sub-samples and use the parameters to predict failure out-of-sample for the remaining 4,279 observations in the dataset. To minimise the risk that our results are distorted by the specific choice of sub-sample, we repeat this exercise 10,000 times. So, for example, we end up looking at the out-of-sample performance of 10,000 estimated models using samples of 100 observations. Throughout, we reject sub-samples if there are no observations of bank failures.

models. It enables us to ask what size of time-series sample is needed before less-is-more effects dissipate. It also enables us to assess the effects of expanding the range of assets on the choice of simple versus complex rules.

Imagine a hypothetical financial asset which follows a well-defined stochastic process. Assume that the underlying asset price data are generated by a GARCH (3,3) process. It is well-known that asset prices in general, and stock prices in particular, can exhibit GARCH-like features (Bollerslev (1987), Lamoureux and Lastrapes (1990)). This particular specification describes, in broad terms, the historical distribution of daily stock prices returns in the US over the past 80 or so years, though it clearly under-estimates the fatness of the tails (Chart 11).

The true model is known, but not to outside investors. To manage their assets, investors use a model to forecast return volatility. The success of these models is measured by their out-of-sample prediction errors. These errors can be further decomposed into two components: bias (deviations of estimated values from their "true" value) and variance (the degree of variation across the set of estimators). The second component captures model uncertainty.

The models used by investors are assumed only to vary by their degree of parametric complexity. In particular, the models are assumed to range from the parsimony of a GARCH (1,1) to the complexity of a GARCH (5,5). Clearly, both simpler and more complex specifications are possible, as are different dimensions of complexity. By generating random samples from the underlying stochastic process, the out-of-sample performance of these different models can be compared.[18]

Charts 12 to 17 show the estimated mean squared prediction errors (MSPE) from the different models, together with their breakdown into bias and variance. This MSPE is shown using different-sized data samples for estimation of the model, ranging from 20 days (one month) to 250,000 days (one millennium).

When sample sizes are small, simpler models are unambiguously superior (Charts 12 to 13). With highly imperfect information, adding model complexity simply increases prediction errors. Indeed, in this hypothetical setup, for samples smaller than around two years, the simple model does better even than the true model. Simple does not just defeat complex; it trumps the truth.

As the sample size expands, model uncertainty decreases and prediction errors fall. The performance of the complex models begins to improve relative to the simple ones. In general, prediction errors converge to a U-shaped pattern centred on the true model, with models which are either too simple or too complex inferior. This is a standard statistical finding.

But it is only at sample sizes in excess of 100,000 days (400 years) that estimates of the "true" model outperform a much simpler one. Moreover, the simple model is only materially worse than complex models when the sample size rises to around 250,000 days (1,000 years). According to this experiment, the sample sizes which would be necessary for complex models to outperform much simpler ones are very large indeed.

This experiment is only illustrative, as it is based on a hypothetical distribution. By drawing on actual financial market data, it is possible to assess more precisely the impact of model complexity and sample size on out-of-sample performance. Consider first a portfolio of three commodities using monthly data from 1890.

[18] Specifically, we generate 100,000 random series of data from the underlying process. We use these series to forecast conditional volatilities and then compare these with actual conditional volatilities.

Determining the risk of this portfolio in a Value-at-Risk (VaR) framework involves estimates of asset volatilities and correlations. We consider three models to estimate the variance-covariance matrix of returns which vary in complexity from the simple (a sample average covariance matrix (MA)) to the relatively simple (an exponentially-weighted covariance matrix (EWMA)) to the complex (a multivariate GARCH(1,1)).

Using historical samples of different sizes, these models are used to generate forecasts of VaR over the period 1970–2010. These VaR estimates can be compared with actual losses over this period. We report the ratio of actual to expected VaR violations – the "violation ratio" – at the 95% confidence interval. The closer this ratio is to unity, the better the performance of the model.

The violation ratios are shown in Chart 18. The simpler moving-average models materially outperform the complex GARCH model when samples are around 20–30 years. The performance of the complex models improves as the sample size is increased. But even with a sample size of three-quarters of a century, the simple models perform at least as well as the complex one.

Another dimension to complexity is the number of assets in a portfolio. So consider a different portfolio of 200 equities since 1973. To reduce the risk that the results are portfolio-specific, we construct the maximum number of combinations of portfolios of different sizes (ranging between two and 100 assets per portfolio) using daily returns.

For each of these sets of portfolios, we forecast VaRs for the period 2005–2012 using the EWMA and GARCH models. To keep things simple, these models are all estimated over a common sample period. The expected losses can then be compared with actual losses, allowing "violation ratios" for portfolios of differing sizes to be calculated.

The results are summarised in Chart 19. For very simple portfolios of two or three assets, the performance of the simple and complex models is not so different. As the number of assets increases, however, the simple model progressively out-performs the complex one. That is a direct result of the uncertainties associated with over-fitting the complex model relative to the simple one.

The message from these experiments is clear and consistent. Complexity of models or portfolios generates robustness problems when understanding a complex financial system over plausible sample sizes. More than that, simplicity rather than complexity may be better capable of solving these robustness problems.

(7) Public policy – more or less?

In forgone output, financial crises can be as costly as wars. The public policy issue, then, is whether the war on crises is best waged with the weapons of the past. Einstein wrote that: "The problems that exist in the world today cannot be solved by the level of thinking that created them". Yet the regulatory response to the crisis has largely been based on the level of thinking that created it. The Tower of Basel, like its near-namesake the Tower of Babel, continues to rise.

An alternative point of reference when regulating a complex system would be to simplify and streamline the control framework. Based on the evidence here, this might be achieved through a combination of five, mutually-supporting policy measures: de-layering the Basel structure; placing leverage on a stronger regulatory footing; strengthening supervisory discretion and market discipline; regulating complexity explicitly; and structurally re-configuring the financial system.

(a) Reconstructing the Tower of Basel

The quest for risk-sensitivity in the Basel framework, while sensible in principle, has generated problems in practice. It has spawned startling degrees of complexity and an over-reliance on probably unreliable models. The Tower of Basel is at risk of over-fitting – and over-balancing. It may be time to rethink its architecture.

A useful starting point might be to take a more sceptical view of the role and robustness of internal risk models in the regulatory framework. These are the main source of opacity and complexity. With thousands of parameters calibrated from short samples, these models are unlikely to be robust for many decades, perhaps centuries, to come. It is close to impossible to tell whether results from them are prudent.

One simple response to that concern may be to impose strict limits, or floors, on model outputs. These would provide a binding regulatory backstop. There are precedents for such an approach. At the introduction of Basel II, temporary floors were introduced into aggregate capital requirements, set at 80% of Basel I requirements. And under the Collins amendment to the Dodd-Frank Act, banks using internal models will be subject to a 100% floor based on the simpler standardised approach.[19]

But these measures only take us so far. Regulatory-imposed floors do little by themselves to simplify the underlying regulatory architecture. Only by removing internal models from the regulatory framework can this be achieved. As an alternative foundation stone, simplified, standardised approaches to measuring credit and market risk, on a broad asset class basis, could be used. Indeed, there have been already been small steps in this direction. A consultation document on the fundamental review of the trading book issued in May this year proposed a greater role for standardised approaches.[20]

This would be a turning back of the clock, restoring the regulatory framework as a backstop to commercial risk management. Legal rules and regulatory rules have followed a similar historical path. In response to crisis events and case law, both have evolved into a complex tapestry. In his book "Simple Rules for a Complex World", Richard Epstein suggests this legal tapestry can be unravelled into six basic threads (Epstein (1995)). The same unravelling ought to be possible in banking.

(b) Leverage versus capital

The Basel III framework will introduce for the first time an internationally-agreed leverage ratio – a 1/N rule. That is good news from a robustness perspective. Less good is the fact that there will be a clear hierarchy of solvency rules, with the frontstop provided by a risk-weighted capital ratio and with the leverage ratio serving as backstop. In the hierarchy, leverage will be second-in-line.

At least for the world's largest and most complex banks – the ones for which Basel was designed – that hierarchy is difficult to justify. On the evidence presented here, the hierarchy should if anything be reversed, with the leverage ratio playing the frontstop role given its simplicity and superior predictive performance. The more complex the bank, the stronger is this case.

The case against leverage ratios is that they may encourage banks to increase their risk per unit of assets, reducing their usefulness as an indicator of bank failure – a classic Goodhart's Law. Indeed, that was precisely the rationale for seeking risk-sensitivity in the Basel framework in the first place. A formulation which would avoid this regulatory arbitrage, while preserving robustness, would be to place leverage and capital ratios on a more equal footing. That is why, in its recommendations on macroprudential instruments, the Bank of England's Financial Policy Committee has given capital and leverage ratios equal billing.[21]

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[19] Wall Street Reform and Consumer Protection Act, Section 171.

[20] Basel Committee on Banking Supervision (2012).

[21] Bank of England (2012).

The evidence presented here suggests that there may also be a case for reconsidering the measurement of equity capital. Basing this on market values rather than accounting cost is not only simpler, but appears superior as a guide to banks' dynamic viability. Certainly, adding market-based indicators of capital adequacy to regulators' and investors' indicator set would seem worthwhile.[22]

On calibration, at present Basel III rules prescribe a 3% leverage ratio – that is, banks' equity can in principle be leveraged up to 33 times. Most banks would say a loan-to-value ratio of 97% was imprudent for a borrower. A 3% leverage ratio means banks are just such a borrower. For the world's largest banks, the leverage ratio needed to guard against failure in this crisis would have been above 7%. The leverage ratio that would have minimised Type I and II crisis errors is around 4%. Both lie well above the current Basel backstop.

(c) Pillars 1, 2 and 3

The Tower of Basel is underpinned by three pillars: Pillar 1 (regulatory rules); Pillar 2 (supervisory discretion); and Pillar 3 (market discipline). To date, the weight borne by these three pillars has been heavily unbalanced, with most of the strain taken by Pillar 1. Simplifying Pillar 1 rules would help rebalance the Basel scales. That would not only strengthen Pillar 1, but could simultaneously strengthen Pillars 2 and 3.

A rebalancing away from prescriptive rules provides greater scope for supervisory judgement, Pillar 2. In other professions, such as medicine, prescriptive rules have generated a wood-from-trees problem. They have also caused defensive, backside-covering behaviour. Both may have increased risk in the system.

What is true of doctors is almost certainly true of bank supervisors. In the pre-crisis period, being required to monitor many small, rule-based risks may have caused supervisors to overlook potentially life-threatening ones. This ticked-box approach failed to save the banks, just as in medicine it fails to save lives. Supervision suffered the same fate as the autistic savant – penny-wise but pound-foolish.

Breaking free of that psychological state calls for a fresh approach, one which is less rules-focussed, more judgement-based. That alternative approach to financial supervision is beginning to be recognised. For example, this approach will underpin the Bank of England's new supervisory model when it assumes prudential regulatory responsibilities next year (Bank of England and FSA (2011)).

Accompanying this will be a streamlined approach to regulatory reporting in the UK. In line with US reporting from the 1860s, more regulatory data will be available "on call". In future, the limits of Excel will hopefully no longer be tested. This will reduce the complexity quotient, making easier the wood-and-trees task for supervisors. It will also hopefully streamline compliance costs for both regulator and regulated.

This approach does not come without risks. As when catching a frisbee or a criminal, catching crises relies on a lengthy sample of past experience. Good supervision means developing well-honed rules of thumb. So one of the secrets to making this new supervisory approach a success will be the accumulated experience of supervisory staff. That means having staff with a nose for a crisis (like a hedgehog) as well as ears and eyes (like a fox).

Therein lies a dilemma. Galbraith observed that: "There can be few fields of human endeavour in which history counts for so little as in the world of finance."[23] A full crisis cycle might last 20–30 years. A systemic crisis might only occur once or twice a century. Among

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[22] A number of authors have proposed basing contractual triggers in banks' debt instruments on market-based measures of capital adequacy (Calomiris and Herring (2011), Flannery (2010)).

[23] Galbraith (2008).

risk managers, typical levels of experience are significantly less than a full crisis cycle. The same is true among bank supervisors. Historically, financial supervision has been long foxes and short hedgehogs.

Ever-expanding numbers of regulators will not solve this problem – if anything, that may cause average levels of experience to fall, not rise. Nor will ever-expanding amounts of regulatory reporting – if anything, that breeds more complexity, not less. A strong case can be made for a reversal of the historical trajectory in which “more is more”. This strategy has comprehensively, and repeatedly, failed the crisis test.

This calls for a different supervisory direction of travel. Practically, that may mean fewer (perhaps far fewer), more (ideally much more) experienced supervisors, operating to a smaller, less detailed rulebook. That would reduce the risk of self-defeating defensive supervisory actions. It would mean being brave enough to allow less to deliver more.

Market discipline, Pillar 3, would also be strengthened by simplified regulatory rules and practices. For investors today, banks are the blackest of boxes. One area of conspicuous darkness is banks’ risk weights. More than half of all investors do not understand or trust banks’ risk weights (Barclays Capital (2012)). Their multiplicity and complexity have undermined transparency and, with it, market discipline.

Greater simplicity and consistency of risk weight information would help restore discipline. In 2009, the UK Financial Services Authority (FSA) asked banks to estimate the capital they would hold against a common hypothetical portfolio.[24] Repeating that exercise internationally would shed some sunlight on international banks’ capital treatment, helping restore market discipline.

Beyond risk weights, there is a case for re-considering the wider disclosure agenda. Here again, more is not necessarily more. The explosion in banks’ reporting over the past decade has not conspicuously helped in pricing bank risk. Important detail is often lost in the thicket of figures, with investors and regulators seeking the needle in the rising haystack of information. Cutting back the thicket, re-sizing the haystack, could actually enhance transparency and bolster market discipline.

(d) Taxing complexity

Until recently, complexity had not been penalised by the regulatory framework. To the contrary, by providing an explicit capital incentive to pursue internal models, the Basel framework effectively provided a subsidy to complexity. Conceptually, that is difficult to justify. Complexity has externality-type properties, making risk more difficult to monitor and manage, not less.

Rather than subsidising it, there is a conceptually coherent case for taxing complexity within the regulatory framework. A degree of progress has already been made on this front. For example, the capital surcharge to be levied on the world’s most systemically important institutions has been calibrated with half an eye on the complexity and connectivity of banks’ balance sheets.[25] And the recovery and resolution plans being drawn up for these same firms may, as a by-product, simplify corporate structures in banking.

But there is a case for tackling complexity directly and at source. Recent events have re-demonstrated the problems that arise in risk-managing large, complex financial firms with multiple models and management information systems. They make the world’s largest banks, arguably, too big to manage. At present, no explicit regulatory charge is levied on

[24] Financial Services Authority (2010).

[25] Basel Committee on Banking Supervision (2011).

those complexity externalities. Doing so would help protect the system against failure, while providing explicit incentives to simplify balance sheets.

What is true within firms is also true across them. Cross-system complexity has exploded over recent decades due to the growth in opaque, intra-financial system chains of exposure. That complexity externality is currently largely unrecognised and un-priced by regulatory rules. Indeed, under the current Basel rules intra-financial system exposures carry a much lower capital charge than exposures outside the financial sector.[26] From a system-wide complexity perspective, this may be the wrong relative risk-ranking.

(e) Structural change

Over the past 30 years or so, the regulatory direction of travel has been towards pricing risk in the financial system, rather than prohibiting or restricting it. In the language of Weitzman, regulators have pursued price over quantity-based regulation (Weitzman (1974)). That makes sense when optimising in a risky world.

It may make less sense when optimising in an uncertain world. Quantity-based restrictions may be more robust to mis-calibration. Simple, quantity-based restrictions are the equivalent of a regulatory commandment: "Thou shalt not". These are likely to be less fallible than: "Thou shalt provided the internal model is correct". That is one reason why Glass-Steagall lasted for 60 years longer than Basel II.

Quantity-based regulatory solutions have gained currency during the course of the crisis. In the US, the Volcker rule is a quantity-based regulatory commandment: "Thou shalt not engage in proprietary trading". In the UK, the Independent ("Vickers") Commission on Banking has also proposed structural, quantity-based reforms: "Thou shalt not co-mingle retail deposit-taking and investment banking".

Yet even these notionally simple, structural proposals run some risk of backdoor complexity. For example, the consultation document accompanying Volcker already runs to 298 pages. Were these proposals to become mired in detail, they risk sinking, like the Tower of Basel, into the swamp. This is not because these proposals go too far but because they may not go far enough. These reform efforts have too many commas, semi-colons and sub-clauses. They would benefit from a few more full stops.

That logic suggests cleaner solutions than are currently being implemented, if not than are currently being contemplated. Strict size limits and forced separation of commercial and investment banking are two frequently cited such radical options (Haldane (2010), Fisher (2011), Johnson and Kwak (2010)). The debate on them has waxed and waned on both sides of the Atlantic. A stalemate has been reached.

Having risen to a peak of almost three in 1928, the largest US banks' price-to-book ratios had by 1931 plummeted to below one. They remained close to these levels for several years afterwards (Chart 20). This discount implied that investors in the bank could improve their wealth by selling-off the banks' assets separately. Investor pressures to separate began to mount.

In response, a number of banks began selling off their equity brokerage affiliates, including the two largest banks, Chase National Bank and National City Bank in 1933. A number of banks delisted their shares. This response, led by the market, paved the way for the passage of Glass-Steagall in 1933. As Fuller (2009) puts it: "Divorce made a virtue of necessity and cursed and condemned bankers jumped at the opportunity to demonstrate their virtue". The market was leading where regulators had feared to tread.

[26] Bank of England (2011).

Today, the situation is not so dissimilar. As then, many of the world's global banks have fallen from heady heights to trade at heavy discounts to the book value of their assets. If anything, the discounts to book value are even greater today than in the early 1930s (Chart 20). As then, this conjunction is stirring market pressures to separate. Bankers today, many cursed and condemned, could make a virtue of necessity. The market could lead where regulators have feared to tread.

(8) Conclusion

Modern finance is complex, perhaps too complex. Regulation of modern finance is complex, almost certainly too complex. That configuration spells trouble. As you do not fight fire with fire, you do not fight complexity with complexity. Because complexity generates uncertainty, not risk, it requires a regulatory response grounded in simplicity, not complexity.

Delivering that would require an about-turn from the regulatory community from the path followed for the better part of the past 50 years. If a once-in-a-lifetime crisis is not able to deliver that change, it is not clear what will. To ask today's regulators to save us from tomorrow's crisis using yesterday's toolbox is to ask a border collie to catch a frisbee by first applying Newton's Law of Gravity.

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Table 1:

Approximate number of estimated parameters for a typical large international bank[(a)(b)]

	Probability of default	Loss given default	Number of models	Range of parameters
Retail mortgages	10–15	10–15	40	400–600
Credit cards	10–15	3	15	100–140
SME retail	10–15	3	6	40–50
Wholesale	5–15	5–15	100	500–1500
SME corporate	5–15	5–15	2	10–30

(a) Number of parameters required to determine credit risk capital charges under the internal ratings-based approach.

(b) The number of parameters used to estimate PD and LGD, as well as the number of models used for each portfolio, have been estimated based on a large representative UK bank, so they are a broad approximation only. To calculate the range of total parameters we have assumed that half the models are used to estimate PD and the other half are used to estimate LGD.

Table 2:

Risk-based capital versus leverage for major global banks

Variable	Model 1	Model 2	Model 3
Leverage ratio	–0.37 *** (0.13)		–0.35*** (0.13)
Risk-based capital ratio		–0.16 (0.11)	–0.07 (0.11)

Notes: For all models, the dependent variable is “failure”. Standard errors are shown in brackets.

(*) Significant at the 10% level

(**) Significant at the 5% level

(***) Significant at the 1% level

Table 3:

Risk-based capital versus leverage for major global banks

Variable[(a)]	Model 1	Model 2
Leverage ratio	–0.53 *** (0.19)	
Risk-based capital ratio		–0.09 (0.12)
GDP	–0.82 *** (0.24)	–0.89 *** (0.24)
Current account	–0.04 (0.05)	0.04 (0.04)
Credit-to-GDP	0.001 (0.006)	–0.002 (0.006)

(a) "GDP" is defined as average GDP growth over the period 2007–2011; "current account" is defined as the current account balance as a per cent of GDP in 2007; and "credit-to-GDP" is defined as the stock of bank lending to the domestic private sector as a per cent of GDP in 2007.

Notes: For all models, the dependent variable is "failure". Standard errors are shown in brackets.

(*) Significant at the 10% level

(**) Significant at the 5% level

(***) Significant at the 1% level

Table 4:

Horse-race between different indicators of bank solvency for major global banks[(a)]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
T1 Risk-based	–0.23 (0.20)						0.97 (1.47)
T1 Leverage		–0.55 *** (0.18)					–0.48 (2.04)
CT1 Risk-based			–0.44 * (0.25)				–1.52 (1.36)
CT1 Leverage				–0.70 *** (0.23)			1.22 (1.99)
Market risk-based					–0.08 (0.05)		0.13 (0.11)
Market leverage						–0.20 *** (0.06)	–0.35 * (0.20)
McFadden R^2	0.023	0.177	0.070	0.203	0.071	0.216	0.317

(a) Regression based on a smaller sample (45 global banks). This is because of missing information on market capitalisation (where banks were not publicly listed) or on consistent pre-crisis estimates of Core Tier 1 capital.

Notes: For all models, the dependent variable is "failure". Standard errors are shown in brackets.

(*) Significant at the 10% level

(**) Significant at the 5% level

(***) Significant at the 1% level

Table 5:

Risk-based capital versus leverage, FDIC-insured banks[(a)]

Variable	Model 1	Model 2	Model 3
Leverage ratio	–0.01 (0.01)		0.27*** (0.03)
Risk-based capital ratio		–0.06*** (0.01)	–0.22*** (0.03)

(a) Sample excludes outlier banks with very large risk-based capital and leverage ratios. Excluded observations account for approximately 0.5% of the entire sample.

Notes: For all models, the dependent variable is "failure". Standard errors are shown in brackets.

(*) Significant at the 10% level

(**) Significant at the 5% level

(***) Significant at the 1% level

Table 6:

CAMEL-based determinants of bank failure for FDIC-insured banks[(a)]

Variable	Coefficient
Risk-based capital ratio	–0.04*** (0.01)
Asset quality	0.05 (0.03)
Efficiency ratio	0.001 (0.001)
Return on assets	–0.16** (0.07)
Liquid asset ratio	–0.07*** (0.01)
McFadden R^2	0.075
Likelihood Ratio (Chi-square)	261.12***

(a) Sample excludes outlier banks with very large risk-based capital and leverage ratios. Excluded observations account for approximately 0.5% of the entire sample.

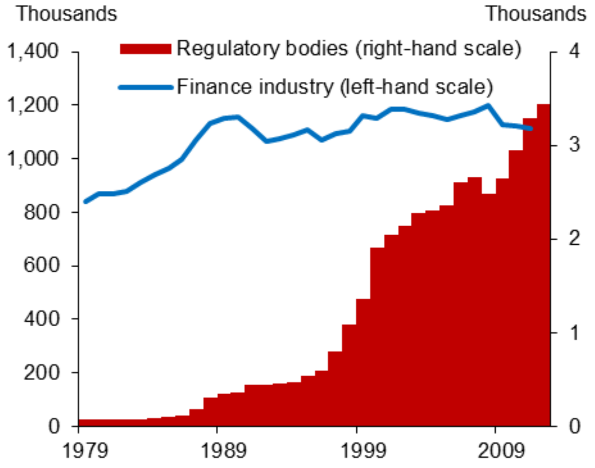
Notes: For all models, the dependent variable is "failure". Standard errors are shown in brackets.

(*) Significant at the 10% level

(**) Significant at the 5% level

(***) Significant at the 1% level

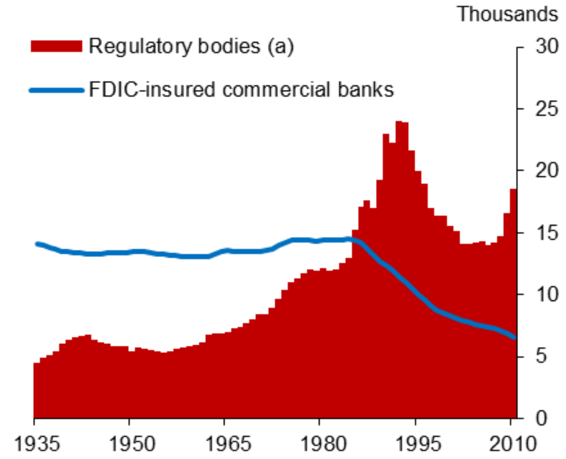
Chart 1: Number of employees in UK regulatory bodies and the finance industry, 1979–2012[(a)]



Source: Bank of England, Securities and Investment Board, Financial Services Authority annual reports, Capie (2010), Office for National Statistics and Bank calculations.

(a) Prior to 1997, data cover staff employed in banking supervision at the Bank of England and staff employed at the Securities and Investment Board. Thereafter, data cover staff employed at the Financial Services Authority. Where data are not available, they are interpolated.

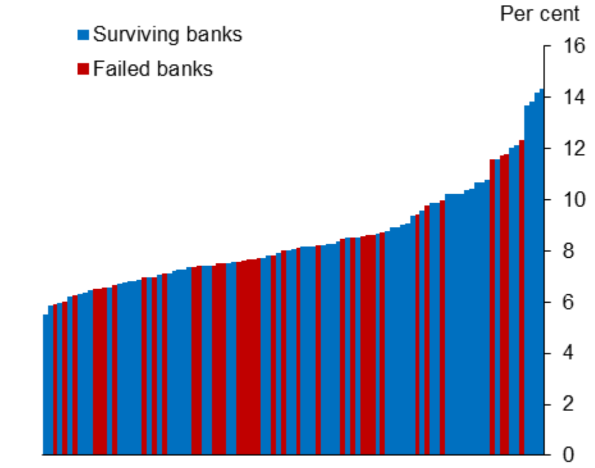
Chart 2: Number of employees in US Federal regulatory bodies and number of commercial banks, 1935–2010[(a)]



Source: Federal Deposit Insurance Corporation (FDIC), Board of Governors of the Federal Reserve, Office of the Comptroller of the Currency (OCC), Securities and Exchange Commission (SEC) annual reports, FDIC (1984), Budget of the US government and Bank calculations.

(a) Covers staff employed at the FDIC, the OCC, the SEC and the Federal Reserve System (bank supervision and regulation area only). Where data are unavailable, they are interpolated. For the Federal Reserve System, there is no information on the number of employees in the area of bank supervision regulation prior to 1984. It is assumed that the proportion of staff employed in that area remained constant at its average level between1984 and 2010.

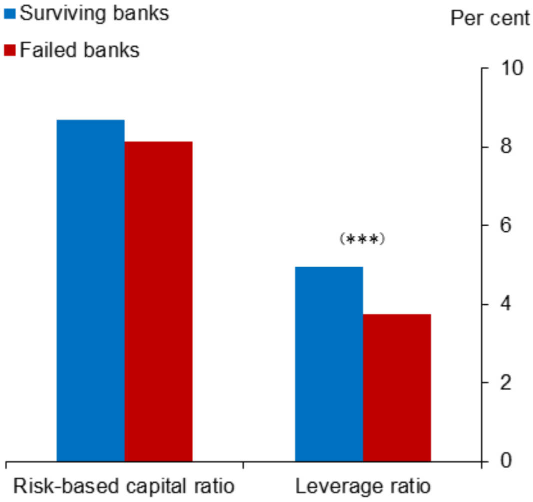
Chart 3: Risk-based capital ratios of major global banks, end-2006[(a)]



Source: Capital IQ, SNL, published accounts, Laeven and Valencia (2010).

(a) The classification of bank failure is based on Laeven and Valencia (2010), updated to reflect failure or government intervention since August 2009.

Chart 4: Average solvency ratios of major global banks, end-2006[(a)(b)]



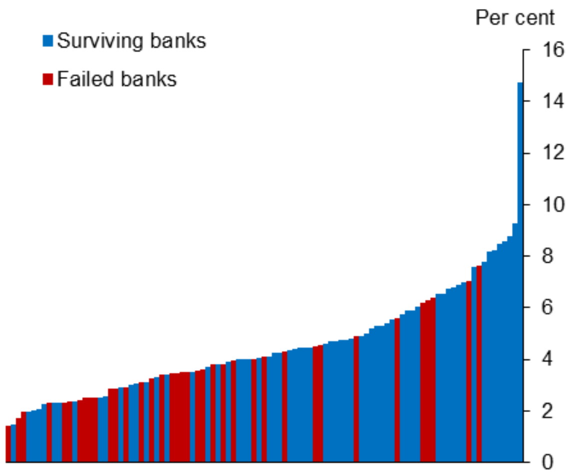
Source: Capital IQ, SNL, published accounts, Laeven and Valencia (2010) and Bank calculations.

(***) Denotes null hypothesis of mean equality rejected at the 1% significance level.

(a) The classification of bank distress is based on Laeven and Valencia (2010), updated to reflect failure or government intervention since August 2009.

(b) For the purposes of the leverage ratio calculation, total assets have been adjusted on a best-efforts basis to achieve comparability between institutions reporting under US GAAP and IFRS.

Chart 5: Leverage ratios of major global banks, end-2006[(a)(b)]

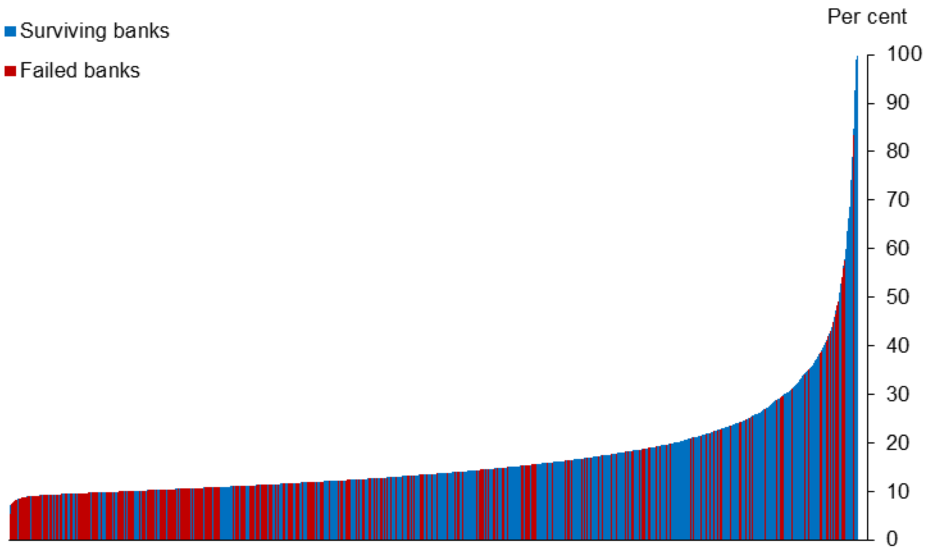


Source: Capital IQ, SNL, published accounts, Laeven and Valencia (2010) and Bank calculations.

(a) The classification of bank distress is based on Laeven and Valencia (2010), updated to reflect failure or government intervention since August 2009.

(b) Total assets have been adjusted on a best-efforts basis to achieve comparability between institutions reporting under US GAAP and IFRS.

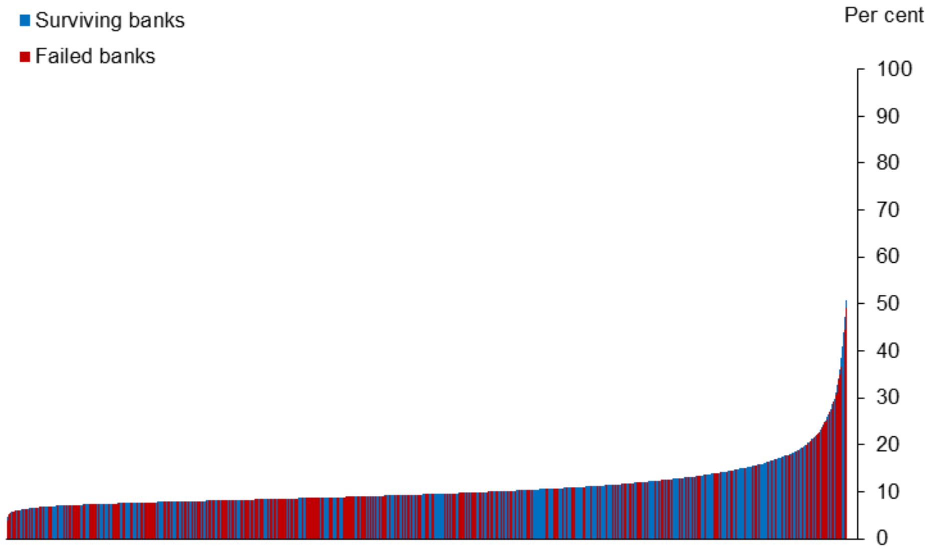
Chart 6: Risk-based capital ratios of FDIC-insured banks, end-2006[(a)]



Source: FDIC and Bank calculations.

(a) Sample has been truncated to remove outlier observations with very large risk-based capital ratios.

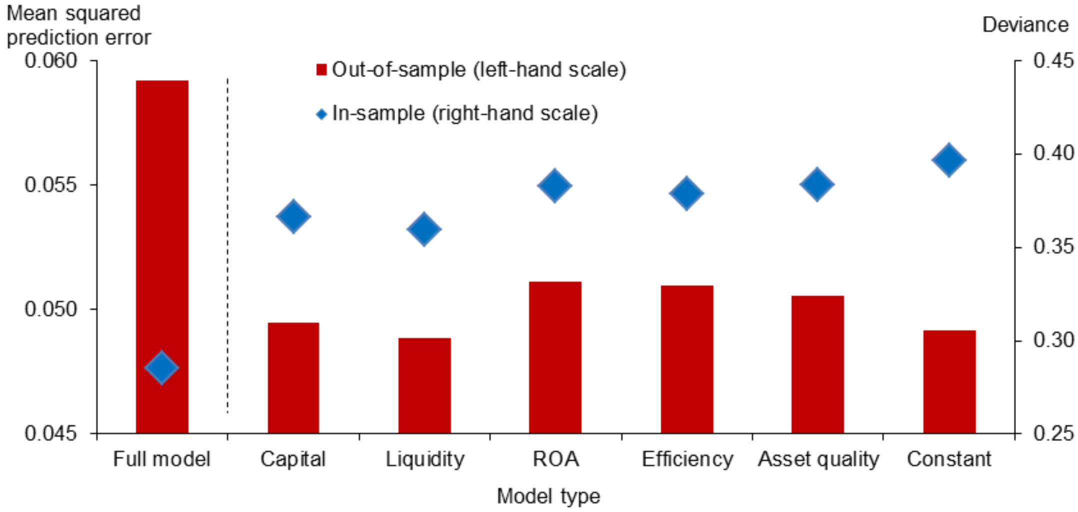
Chart 7: Leverage ratios of FDIC-insured banks, end-2006[(a)]



Source: FDIC and Bank calculations.

(a) Sample has been truncated to remove outlier observations with very large leverage ratios.

Chart 8: In- and out-of-sample performance of different models of bank risk (100 observations)[(a)(b)(c)]



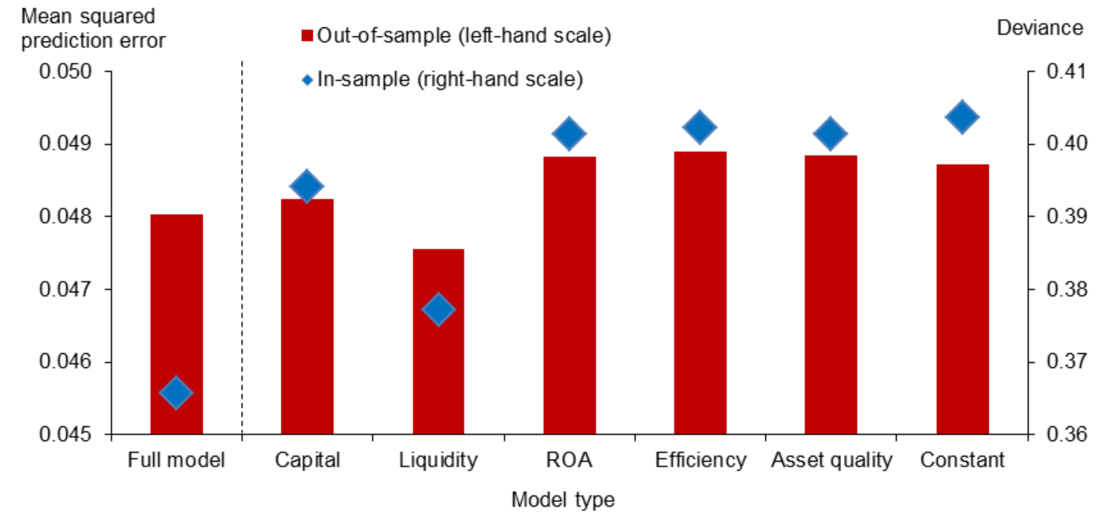
Source: FDIC and Bank calculations.

(a) Different models estimated using 10,000 random samples of 100 observations each. Samples are rejected if there are no observations of bank failure. The different models are used to predict bank failure for approximately 4,300 banks out-of-sample.

(b) In-sample performance is measured by deviance and out-of-sample performance by the mean squared prediction error. For both statistics, a lower number implies better performance.

(c) The data set excludes outlier banks with very large risk-based capital and leverage ratios. Excluded observations account for approximately 0.5% of the entire sample.

Chart 9: In- and out-of-sample performance of different models of bank risk (1000 observations)[(a)(b)(c)]



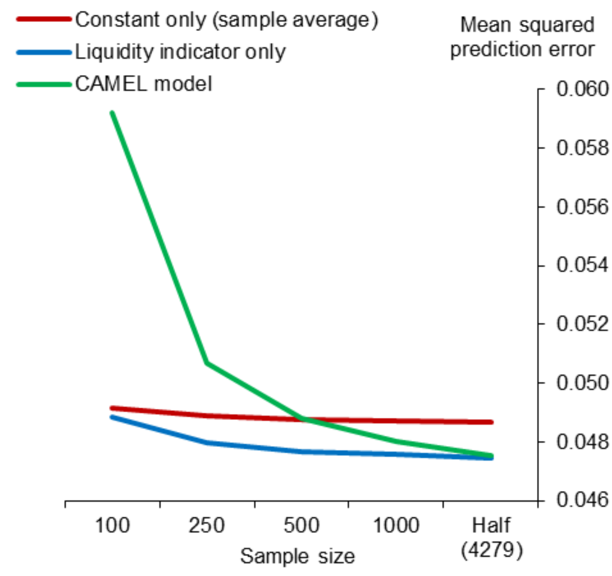
Source: FDIC and Bank calculations.

(a) Different models estimated using 10,000 random samples of 1,000 observations each. Samples are rejected if there are no observations of bank failure. The different models are used to predict bank failure for approximately 4,300 banks out-of-sample.

(b) In-sample performance is measured by deviance and out-of-sample performance by the mean squared prediction error. For both statistics, a lower number implies better performance.

(c) The data set excludes outlier banks with very large risk-based capital and leverage ratios. Excluded observations account for approximately 0.5% of the entire sample.

Chart 10: Summary of out-of-sample model performance[(a)(b)]

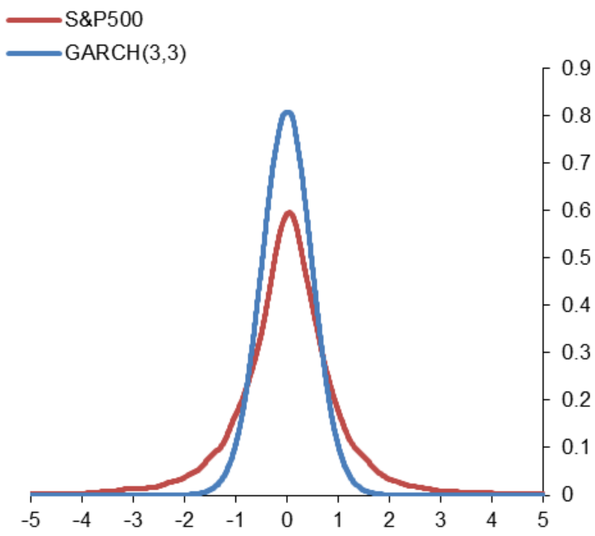


Source: FDIC and Bank calculations.

(a) Different models estimated using 10,000 random samples of different size. Samples are rejected if there are no observations of bank failure. The different models are used to predict bank failure for approximately 4,500 banks out-of-sample.

(b) Out-of-sample performance is measured by the mean squared prediction error. A lower number implies better performance.

Chart 11: Distribution of daily stock price returns, 1928–2012[(a)]



Source: Bloomberg and Bank calculations.

(a) GARCH innovations are normally-distributed.

Charts 12–17: Mean Squared Prediction Errors (MSPE) and Decomposition[(a)(b)]

Chart 12: Sample size = 20

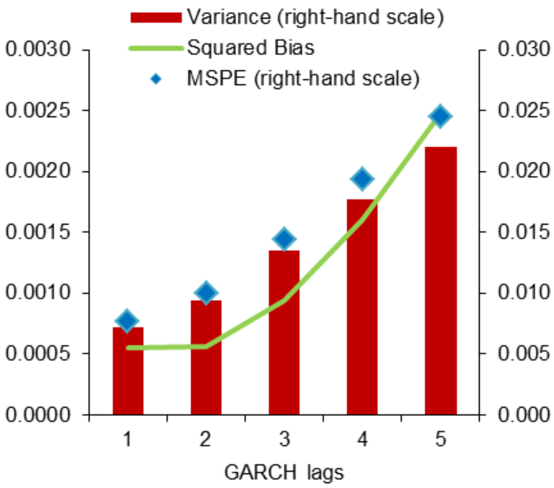


Chart 13: Sample size = 500

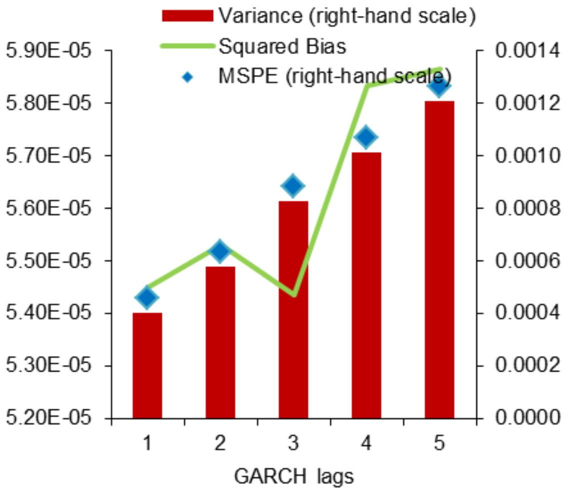


Chart 14: Sample size = 2500

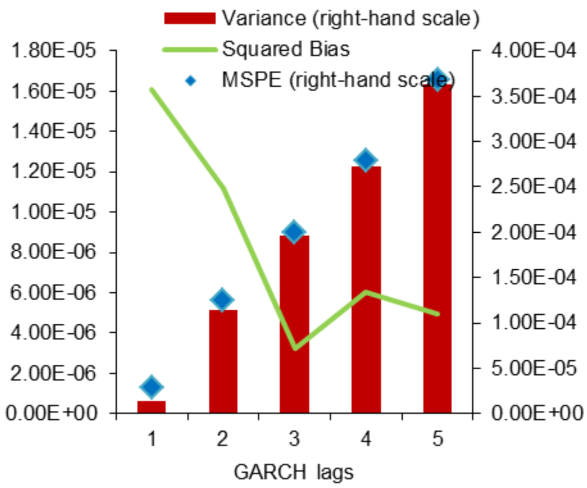


Chart 15: Sample size = 25,000

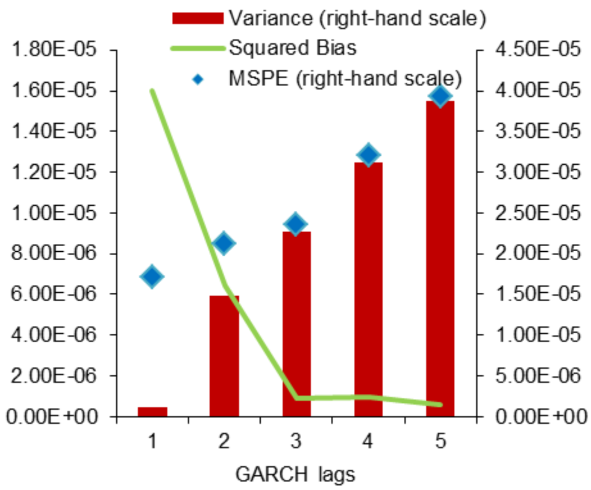


Chart 16: Sample size = 100,000

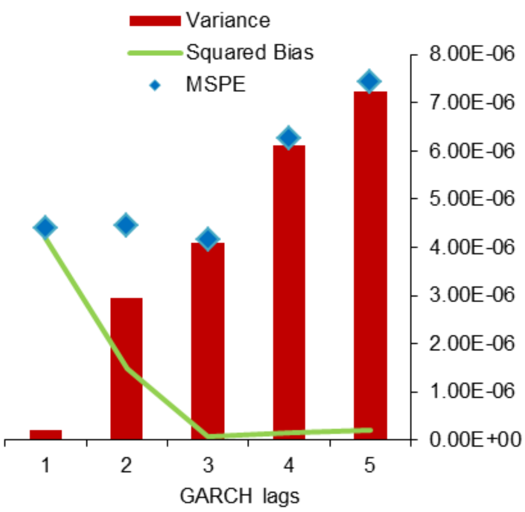
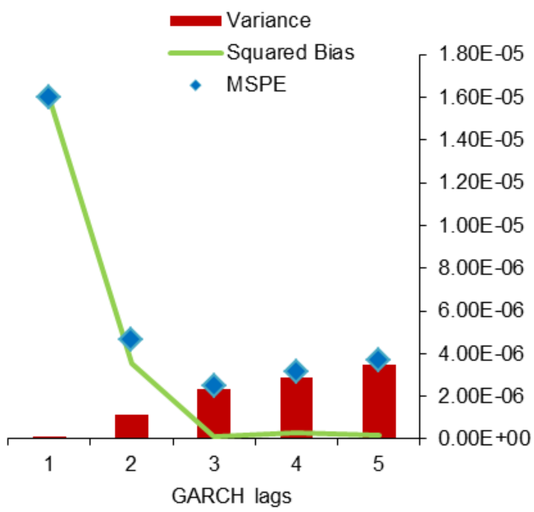


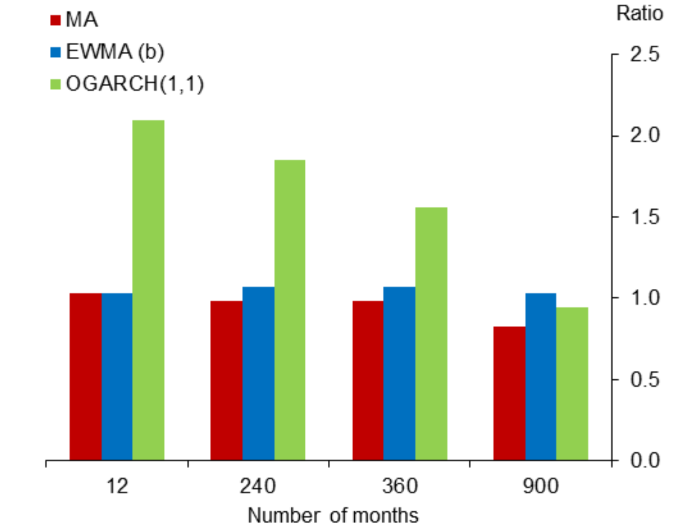
Chart 17: Sample size = 250,000



Source: Bank calculations.

(a) MSPE equals the sum of the squared bias and variance.
(b) Data generating process: GARCH (3,3) with normally-distributed innovations.

Chart 18: VaR violation ratios for portfolio of commodities[a]

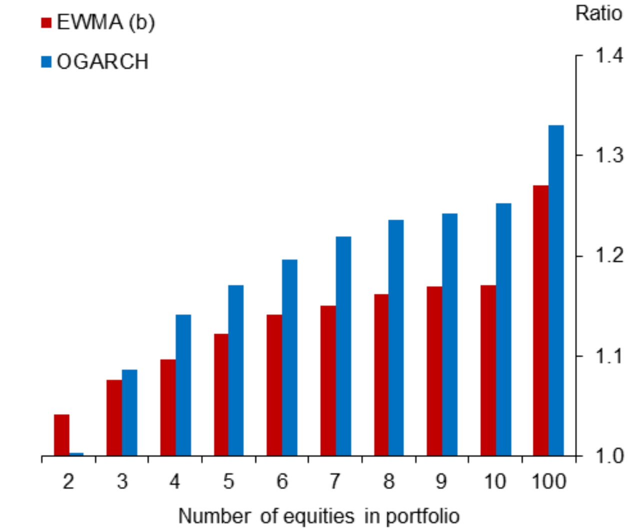


Source: Global Financial Data and Bank calculations.

(a) Equally-weighted portfolio of silver, wheat and hogs. Validation period starts in 1970. 95% VaR using monthly returns.

(b) EWMA: lambda = 0.94.

Chart 19: VaR violation ratios for portfolios of equities[a]

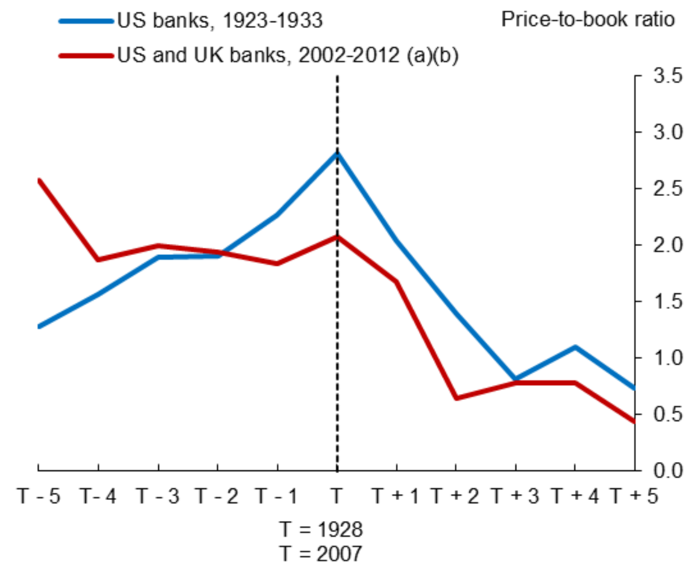


Source: Global Financial Data and Bank calculations.

(a) For each k-sized portfolio, the result shown is the average of 100 random k-sized combinations of equities out of a universe of 210 stocks in the S&P 500. Validation period starts in 2005. 95% VaR using daily returns.

(b) EWMA: lambda = 0.94.

Chart 20: Evolution of bank price to book ratios, historical and present day[a][b]



Source: Thomson Reuters Datastream, Calomiris and Wilson (2004) and Bank calculations.

(a) Sample includes Bank of America, Barclays, Bank of Ireland, Citigroup, Goldman Sachs, HSBC, JP Morgan Chase & Co., Lloyds Banking Group, Morgan Stanley, National Australia Bank, Northern Rock, Royal Bank of Scotland and Santander.

(b) 2012 data to date.