WHAT WE KNOW, DON'T KNOW AND CAN'T KNOW ABOUT BANK RISK: A VIEW FROM THE TRENCHES*

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<u>Abstract</u>: This paper seeks to put forward a framework, from the perspective of practitioners and policymakers, for how the known, unknown, and unknowable vary by risk type within banking. We define total bank risk in terms of earnings volatility, which can be broken down into five major classes of risk: market, credit, asset/liability, operational, and business risks. For our purposes, risk is "known" (K) if it can be enumerated, in the sense of being identified, and quantified; it is "unknown" (u) if the set of risks can be identified and enumerated but not meaningfully quantified; and it is "unknowable" (U) if the existence of the risk or set of risks is not predictable ex ante, let alone quantifiable. Based on these definitions, we position the five sources of bank risk within the K, u, U space based on evidence from industry practice and suggest that K decreases, and u and U increase, along a spectrum from market risk to credit risk, asset/liability risk, operational risk, and business risk. Using bank-level data we attempt to quantify or "size" both total bank risk and the contribution from each risk type based on a large sample of earnings volatility data for US bank holding companies over the 1986-2005 period. We find that a) total earnings volatility is protected by minimum regulatory capital requirements at implied credit rating levels ranging from about A- to BBB, depending on the sample; b) when allocating among the different risk types, market risk accounts for only about 5%, credit for almost half, structural interest rate risk for about 18%, and non-financial risks, including both operational and business risk, for about 30% of total risk; c) the diversification benefit, i.e. the difference between the whole and the sum of the parts, is about one-third. Not surprisingly, large banks also seem to experience fewer extreme adverse outcomes.

Keywords: risk measurement, risk management, capital adequacy
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1. Introduction

This paper addresses how the known (K), the unknown (u) and the unknowable (U) vary by risk type within banking. We propose that knowledge of risk differs systematically by risk type – with more, for example, being known about market risk than credit risk, and less being known about non-financial risks than financial risks. Understanding the nature of the differences across risk types and their relative contribution to total earnings volatility can shed light on the portion of the risk space within banking that is known and knowable – and hence manageable – versus unknown and unmanageable.

Our primary concern is to describe what practitioners – including risk managers and policymakers – know, don't know, and can't know about bank risk. Our focus is on a current snapshot of the banking industry, recognizing that the boundaries of K, u, and U shift over time. In particular, we look to evidence of contemporary industry practice to help position risks within our framework. An important indicator of current practice is the New Basel Capital Accord, or Basel II – the major international regulatory initiative to develop more risk-sensitive capital requirements for banks – which reflects a concerted attempt by regulators to codify "best practice" in banking as it relates to risk and capital measurement (BCBS 2001a, §99).

We start from the premise that risk is the potential for deviation from expected results, and that practitioners are particularly concerned with adverse deviation. Within this context, we define the known, the unknown, and the unknowable in terms that are closely related to the distinction made by Knight (1921, chapter 7) between risk and uncertainty[1]

[1] For further and more in-depth discussions of the definitions of the known, unknown and unknowable, see the chapter by Granger in this volume.

- A risk is known (K) if it can be identified and quantified ex ante. For a practitioner, risk quantification has developed a specific meaning: the ability to estimate downside tail risks or extreme loss events at high confidence levels associated with a bank's solvency standard. This concept is what underlies economic capital, the common denominator for risk measurement that has emerged within the banking industry. An economic capital approach to risk quantification is the basis on which capital requirements for credit, market, and operational risks are set under Basel II.
- A risk is unknown (*u*) if it belongs to a set of risks that can be identified but not meaningfully quantified at present. An example of an unknown risk might be the impact of reputation risk following the criminal indictment of a bank's CEO for fraud. While the general class of reputation risks can be identified, the consequences are likely to be too diffuse and fact-specific to be meaningfully quantified ex ante. Over time, it may be possible for reputation risks to be linked to causal factors and estimated discretely, in which case reputation risks will become more "known," but that is not the case given prevailing information and technology. For this reason, Basel II specifically excludes reputation risks from the category of "operational risks" for which banks must hold capital (BCBS 2005, §644).
- A risk is unknowable (*U*) if the existence of the risk or set of risks is not predictable, let alone quantifiable, ex ante. An example of a risk that was probably unknowable prior to 9/11 was the threat to businesses located in the World Trade Center that terrorists would fly aircraft into the twin towers, causing the buildings to collapse. Arguably, despite the 1993 bombing at the World Trade Center, this form of attack was not something that a bank risk manager could have anticipated (let alone quantified), even if the risk should have been foreseeable to some within the national security community. The discontinuity in the market for terrorism

insurance pre- and post-9/11 suggests that the insurance sector, at least, had not predicted the possibility of such an attack before 9/11.

Based on these concepts, the first part of this paper proposes a framework for positioning different sources of bank risk in the *K*, *u*, *U* space. Consistent with how risk is defined by practitioners, we define bank "risk" as deviation from expected earnings – or, equivalently, earnings volatility – and disaggregate risk into five main categories. The first three categories include market risk from trading activities, structural interest rate risk from asset/liability management, and credit risk, which together constitute the main sources of financial risk. The remaining two categories refer to sources of non-financial risk, and include operational risk and "business risk" – this last category being a catch-all for residual non-financial earnings volatility.

Given the available evidence, we rank order these risks based on two main characteristics: *quantification,* which reflects their ability to be measured, and *granularity*, which reflects their ability to be disaggregated. According to our ordering, market risk is the easiest risk to quantify and disaggregate, followed by credit risk, asset/liability risk, operational risk, and business risk. We argue that *K* increases as both the ability to measure and disaggregate risk increases; and conversely, that *u* and *U* increase as the ability to measure and disaggregate risk decreases. It follows that practitioners and policymakers "know" the most about market risk and the least about business risk. The boundary between what they know and don't know determines the portion of bank risk that currently is (or at least can be) managed. The portion of risk that is unknown is unmanaged, and the portion that is unknowable is largely unmanageable.[2]

The second part of the paper attempts to size the known versus unknown portions of risk through empirical research on bank earnings volatility. First, we ask how much bank risk is there in total? Our analysis establishes, using data for the 300+ U.S. bank holding companies that had total assets of at least $1bn (2005Q1 dollars) from 1986Q2 to 2005Q1, what the total level of earnings volatility (as reflected by quarterly deviation in returns on Basel I style risk-weighted assets) is at varying quantiles. The analysis include tail observations out to the 99.9% level corresponding to a 0.1% one-year default probability, the level to which the Basel II risk weights are calibrated. Significantly, we conclude that the current minimum Basel I required regulatory capital level of 8% for banks protects quarterly earnings volatility at roughly the 99.98% level – consistent with the quarterly default probability of an A- rated bond. If we consider a minimum of 6%, corresponding to a Tier 1 capital threshold, the commensurate quarterly earning volatility protection is 99.94%. We compare the quarterly analysis with annual data available back to 1981 and find that this 8% (6%) capital cushion corresponds to an annual default probability of 0.28% (0.49%), or a confidence level of 99.72% (99.51%), which is equivalent to the annual default rate of a BBB (BBB-) rated bond. For the largest banks, i.e. those with at least $10bn in assets (2005Q1 dollars), the 8% (6%) regulatory capital cushion is consistent with an annual default probability of 0.12% (0.37%), or a 99.88% (99.63%) confidence level, which maps to a A- (BBB) credit rating, though the large bank results are based on a much smaller sample.[3] To our knowledge, this is the first study to estimate the total amount of bank risk from a large pool of earnings volatility data.

Next, we estimate the relative contribution to bank earnings volatility from each of the five sources of risk identified in our taxonomy. We find that although the most is "known" about market risk, it contributes the least to bank earnings volatility – only 5% of total risk at the 99.9% level. Not surprisingly, credit risk is the major risk facing banks, accounting for about

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[2] This is not to say that risk that is unknown or unknowable cannot be transferred – to depositors, bondholders, the

half of total earnings volatility at the 99.9% level. But more surprisingly, by our measure asset/liability risk accounts for 18% and non-financial risks account for 30% of total risk, respectively, at the same confidence level. Based on the results of other studies, we split the 30% estimate of non-financial risk into 12% for operational risk and 18% for business risk – the category about which, according to our framework, the least is known. All of these risk proportions are robust to choice of tail quantile from 99% to 99.95%.

Finally we find that the diversification benefit, meaning the difference between the whole and the sum of the parts, is about one-third.

The last section of the paper draws some tentative implications of the empirical findings for both practitioners and policymakers. For practitioners, the historical focus on market and credit risk management – while not unimportant – only covers about half of total bank earnings volatility. Greater returns to risk management can be expected from progress in the other three categories of risk that are less well understood.

From a policy perspective, Basel II's three pillar framework has the flexibility to accommodate differences in how much we know, don't know and can't know about the distinct risk types. Pillar 1, which adopts a rules-based approach to setting minimum capital requirements, should focus on the more known risks such as market and credit risk, whereas Pillar 2, which relies on judgment-based supervisory reviews of a bank's overall risk profile, is better able to address the less well understood risk types. (Pillar 3, which stresses market discipline through improved disclosure, is meant to reinforce the first two pillars.) In this context, it is perhaps surprising that Basel II imposes a new Pillar 1 capital charge for operational risk, a relatively small source of earnings volatility about which we know comparatively little,

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FDIC, or insurers. It is to say, rather, that you can't actively, or consciously, manage what you don't know.

while leaving asset/liability risk as a matter for supervisory discretion under Pillar 2 and ignoring business risk altogether – even though asset/liability risk and business risk account for over one-third of total earnings volatility. For both practitioners and policymakers, the message may be to stop looking for keys under the lamppost. The search for improvements in risk management should focus on the sources of risk that are the least "known" and have the greatest impact on earnings volatility.

Two important caveats should be borne in mind when interpreting these findings. First, while the full sample used here, consisting of 300+ banks and extending back to 1981, has statistical advantages, it may obscure differences in risk profile between larger and smaller banks and may also fail to reflect structural changes over sample sub-periods. Some observers might point to the introduction of FDICIA in 1991 and the increasing use of improved risk management practices in the later 1990s as evidence of a "regime shift" toward lower risk within our sample period. Indeed, the largest banks are likely to make the most use of such risk management practices, as documented by Minton et al. (2005) and Purnanandam (2006), who report that large banks are much more active users of credit derivatives and interest rate derivatives.

Robustness checks confirm that large banks – defined as banks with assets greater than \$10bn in 2005 dollars – do experience fewer extreme adverse outcomes than smaller banks. Moreover, splitting the sample in 1993 reveals a significant difference between the first and second periods, both in terms of total risk and risk allocation. For instance, 99.9% VaR levels are more than double in the first period than in the second using quarterly data. This change in total risk is accompanied by a change in allocation. The more recent period shows a noticeable

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[3] The quarterly results do not differ by size.

shift away from credit risk and towards market, structural interest rate and non-financial risk as sources of earnings volatility. Nevertheless, despite the differences over the two time periods, we caution against relying too heavily on recent experience and basing conclusions on a benign but limited record.

Second, just as a bank's risk profile is, to a degree, endogenously determined by the state of our knowledge of risk, so too does it depend on the influence of government policies. The existence of a safety net such as deposit insurance or a lender of last resort may cause bank managers to take on more risk – or hold less capital – than is socially optimal; see Santos (2001) for a survey of this rich literature. Thus our empirical findings are conditioned on the presence of such a safety net in the U.S. banking system. For example, the FDIC assumes a major portion of the tail risk of banks' loss distribution. The shape of that distribution is governed by the risk taking behavior and capital levels of banks. Kuritzkes, Schuermann and Weiner (2005), using a bottom-up Merton-based approach, compute the implied solvency level of the bank insurance fund at the FDIC at the end of 2000, and find that it ranges from 99.85% (about a BBB+ rating) to 98.83% (about a BB rating) depending on the model and choice of parameters. Any policy conclusions drawn from our study need to recognize that bank capital levels and earnings volatility are not exogenously determined, but reflect the institutional features of the banking system.

2. Positioning Bank Risks Along the *K, u, U* Spectrum

2.1. Risk Measurement, Earnings Volatility, and Economic Capital

Among practitioners, risk in banking is typically defined in terms of earnings volatility (Rajan 2005). Earnings volatility creates the potential for loss. Losses, in turn, need to be funded, and it is the potential for loss that imposes a need for banks to hold capital. Capital provides the balance sheet cushion that absorbs (downside) earnings volatility and prevents a firm from becoming insolvent (Berger, Herring, and Szegö 1995).

The link between earnings volatility and capital is central to the way risk is measured in banking. Increasingly, risk is measured in terms of value-at-risk (VaR) or, equivalently, economic capital – the amount of capital needed to protect against earnings volatility at a prescribed confidence interval.[4] The reason for measuring risk at a stated confidence interval is that volatility, by itself, is insufficient to describe the whole distribution of earnings. Two distributions with dramatically different shapes and differing amounts of downside risk can have the same volatility. VaR scales the volatility to a specified confidence interval so as to create a common currency for risk that allows different risk factors to be directly compared. This is illustrated in Figure 1, where the stylized earnings (or loss) distributions for different bank risks are shown to have very different shapes, but, assuming a common time horizon, can each be measured in equivalent terms at the same confidence interval. Moreover, the standalone amounts for these risks can be aggregated (although, because of diversification effects, not by simple addition) to create a single loss distribution for the bank overall (Kuritzkes, Schuermann and Weiner 2003, Rosenberg and Schuermann 2006).

[4] We will use VaR and economic capital somewhat interchangeably. Strictly speaking this is appropriate only if the risks are scaled to a common horizon, typically one year. See, for instance, the discussion in Jorion (2001, ch. 16).

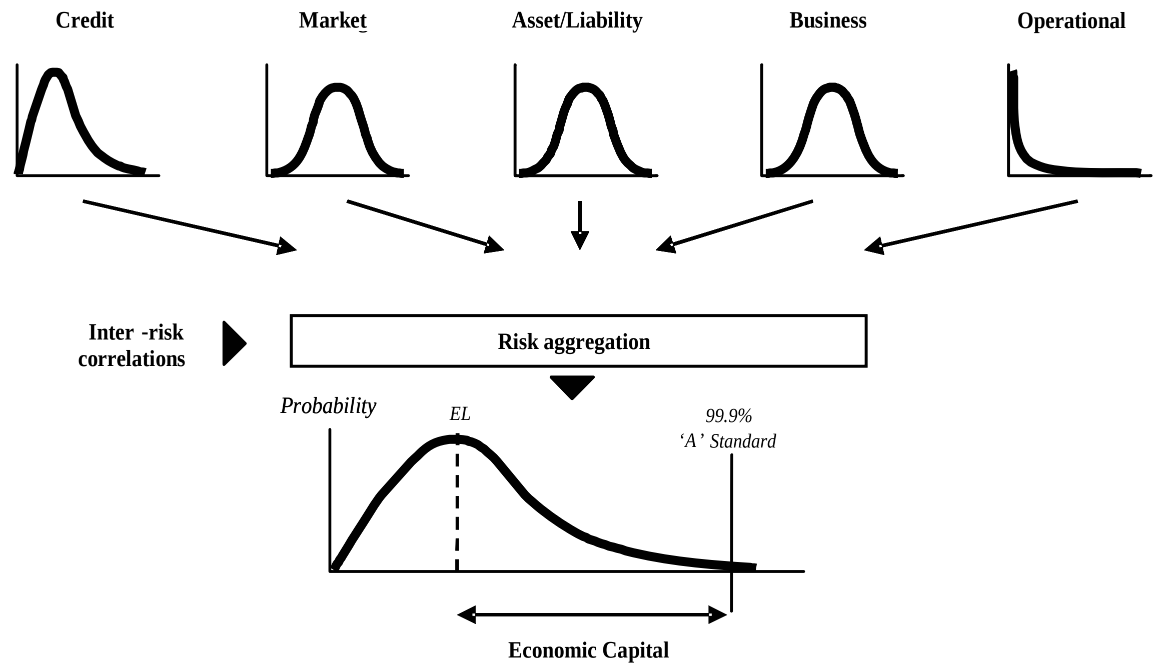

Figure 1: Standalone (marginal) and total (joint) risk distributions and economic capital for five principal risk types in banking.

The confidence interval for economic capital is usually set equivalent to the default rate associated with a bank's target debt rating or solvency standard. Assume, for example, that a bank's target debt rating is A-, and that the annual default rate for A- rated bonds is 0.1% or 10 basis points (bp).[5] In this case, the bank would set the ruler for economic capital to be the amount of annual earnings volatility at the 99.9% confidence level, on the theory that this would determine the amount of capital the bank needs to remain solvent in all but 10 bp of possible loss scenarios – equivalent to the default risk of an A- rated bond.

While there is an internal logic for measuring risk at the same confidence interval as the bank's solvency standard, doing so implies an ability to quantify extreme events far out in the

[5] For no reason other than expediency, we shall be using S&P nomenclature. For a discussion of estimating default rates by credit rating see Section 3.1.

tail. To the extent that knowledge means being able to measure risks in terms of economic capital, then the threshold for K is set very high.

2.2. Taxonomy of Bank Risks

As risk management techniques have progressed, economic capital models have been extended to new classes of risk, providing greater resolution on the composition of total earnings volatility (Allen, Boudoukh, and Saunders 2004). These developments are reflected in the evolution of bank capital regulation under the Basel framework. In 1988, when the original Basel Capital Accord (Basel I) was adopted, bank risk management was overwhelmingly focused on credit risk (BCBS 1988).[6] Basel I based regulatory capital requirements solely on the size of a bank's credit assets, with varying risk weights intended to reflect (crude) differences in the levels of credit risk. In 1996, the Market Risk Amendment to Basel I (BCBS 1996) subjected the price risk of trading positions to an explicit capital charge, and helped institutionalize value-at-risk measures for market risk within trading books. More recently, Basel II has singled out "operational risk" – defined to include losses from internal failures and external events – as a specific category of non-financial risk and is imposing a new capital charge to cover losses associated with operational risk.

[6] At the time the Basel I Accord was adopted, the risk management structure of a typical large bank could be described as consisting of a Credit Department that made loan approval decisions, reporting to a Chief Credit Officer who was responsible for the bank's credit risk performance. Risk disclosure was limited to information about non-performing loans and charge-offs, with no information disclosed about trading risks, asset/liability risks, and non-financial risks. With a few notable exceptions (such as Bankers Trust), banks had yet to build up broader risk management infrastructures or appoint Chief Risk Officers or disclose information about non-credit risks (Holton 2003, ch. 1).

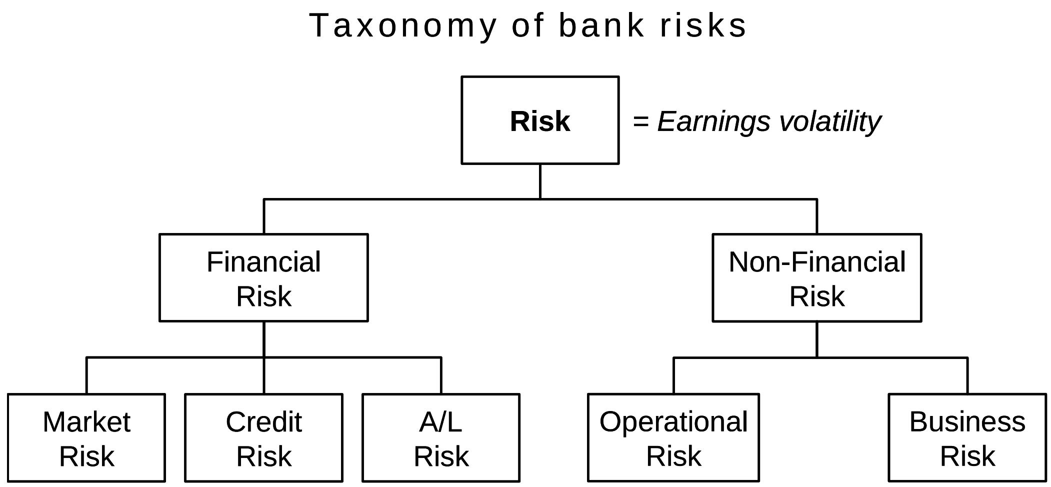

Figure 2: Taxonomy of bank risks.

Current practice among leading financial institutions is to break down earnings volatility into five main sources of risk. This breakdown, illustrated in Figure 2, includes:

(i) market risk, or the earnings impact associated with adverse price movements in the bank's principal trading positions;

(ii) credit risk, or the potential for losses due to the failure to pay of credit counterparties;

(iii) structural asset/liability risk, or the earnings impact from shifts in interest rates on the bank's asset and liability positions;

(iv) operational risk, or (BCBS 2005, §644) "the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events"; and

(v) business risk, or the potential for losses from residual sources of non-financial earnings volatility.

The first three categories are sources of financial risk that are a direct result of a bank's role as financial intermediary or investor. Since the assumption and transfer of financial risk are, in many respects, the defining features of a financial institution, these risks can be expected to predominate in banking. The latter two categories refer to risks that are non-financial in nature, and common to all firms. Business risk, in particular, is a broad catch-all that includes all sources of non-financial risk not directly attributable to internal failures or external events. This category covers a host of sins, ranging from a drop in demand, a cost spike, technological obsolescence, regulatory change, price wars, and failed strategies, and can be expected to be the dominant risk faced by non-financial firms.[7]

2.3. Framework for *K, u*, and *U*

Given the taxonomy of bank risk, we can describe the known, the unknown, and the unknowable from the perspective of a practitioner. We posit that K, u, and U vary according to two main factors. The first factor is *quantification*: K increases, and u and U decrease, as the ability to quantify risk increases. This relationship is axiomatic – it follows directly from our definition of K, u, and U – but it is important to recognize that the ability to quantify risk differs systematically by risk class.

The second factor is *granularity*: K increases, and u and U decrease, as the ability to measure risk at lower levels of aggregation increases. The granularity dimension reflects systematic differences in the ability to measure and manage risks at multiple levels in the organization. The more granular the understanding of risk, the better one is able to identify it, measure it, and control it. In market risk, for example, the marginal impact of individual trades on a bank's overall market position can be measured, possibly even in real-time, with a fairly high degree of accuracy. Risk managers can therefore manage the risks of individual trades, as well as the cumulative risk in a bank's trading businesses, through dynamic VaR limits. In business risk, by contrast, some risks, such as reputation risks, may only manifest themselves at

[7] To be sure, some business risks can be measured somewhat granularly, albeit with low precision. For example, bank branch managers may have detailed knowledge of local business and customer flow.

the firm-wide level, and may not be capable of being disaggregated to lower levels. The inability to disaggregate such risks makes them more difficult to control at the source.

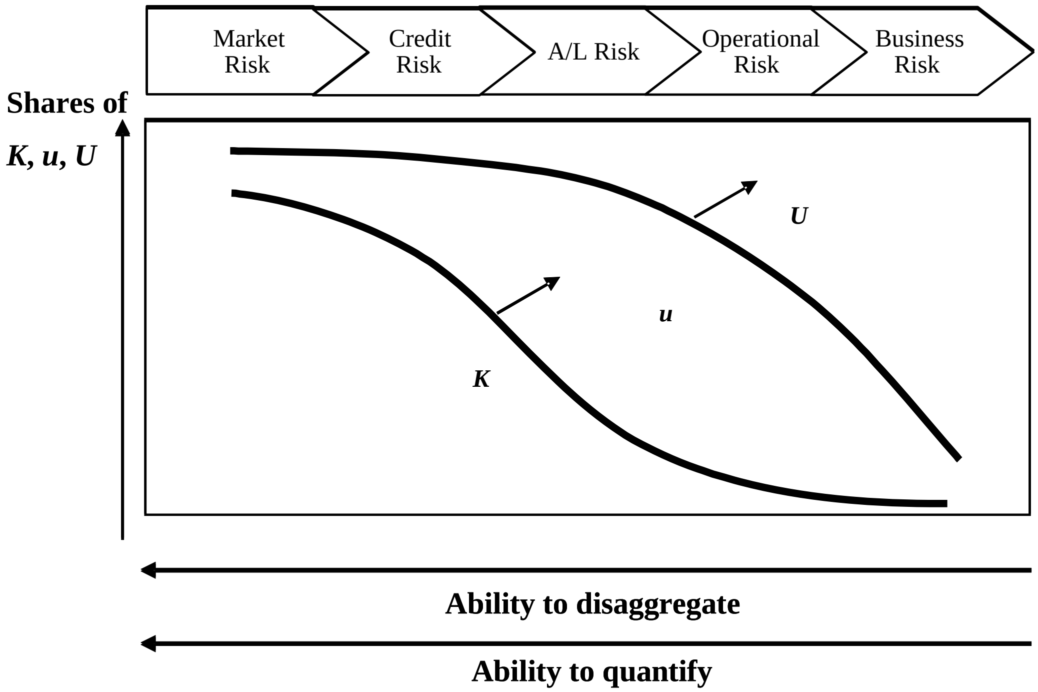

Figure 3: Framework for *K*, *u* and *U* for bank risks. *K*, *u* and *U* shares are represented vertically. Over time the shares for each bank risk type will likely move outward, as illustrated by the arrows.

Based on these factors, we propose a framework for positioning the sources of risk in banking within the *K*, *u*, and *U* space. As illustrated in Figure 3, the five main sources of bank risks can be ordered in terms of their ability to be quantified and disaggregated. We rank the risks in this framework, from the most quantifiable and granular, and hence most "known," to the least. Our framework also has a time dimension to it: the current ordering of risks, and contours of the *K*, *u*, and *U* curves, reflect the existing state of contemporary practice. Over time, the boundaries of the known can be expected to be pushed out, as risks are more finely classified, additional data is collected, and new models are developed.

The rationale for the current positioning of bank risks within the framework is as follows:

2.3.1. Market Risk

Market risk is the most readily quantifiable and granular of the major classes of bank risk. Market risk models date back to the late 1980s, when VaR was first defined as a concept for measuring the risks of trading positions (Holton 2003, ch. 1). By the mid-1990s, when the Market Risk Amendment to the Basel Accord was enacted, VaR models had become widely commercially available. The adoption of VaR models for market risk is now nearly universal among banks active in market making and proprietary trading, with VaR calculated at least daily on virtually all trading positions. And while there are differences in calculation approach – e.g., parametric VaR versus historical simulation – the underlying methodologies are highly standardized across the industry (Jorion 2001, Allen, Boudoukh and Saunders 2004)

The early development of VaR models reflects the rich data environment for market risk. Market risk factors are typically observed at high frequency, at least daily, and for the major currencies, interest rates, and equity indices, ultra-high frequency observations (many trades per minute) are available (Andersen, Bollerslev, Diebold, Labys 2003).

In terms of granularity, market risk VaR can be determined at successive levels of aggregation, from the consolidated firm-wide trading book to individual trader positions, to the risk impact (positive or negative) of a marginal trade on the portfolio. Indeed, trading room systems technology allows individual traders to see the VaR impact of individual trades in real-time.

Not surprisingly, given the state of market risk measurement, the regulatory capital treatment for market risk is more advanced than for other risk types. Table 1 summarizes the regulatory capital treatment under current Basel I rules and proposed Basel II rules for market risk and the other main risk categories. Market risk is the only risk type under existing Basel I rules for which firms are allowed to use their own internal VaR models (with a regulatory-defined scalar) to calculate the level of regulatory capital. Since market risk is modeled daily and measurable at even higher frequency, it is possible to backtest market risk VaR calculations and conduct forecast evaluations against actual results in a statistically meaningful fashion (Diebold, Gunther and Tay 1998, Lopez and Walter 2001).

	Basel I capital charge	**Basis for Basel I capital**	**Basel II capital charge**	**Basis for Basel II Capital**
Market Risk	Yes	Internal VaR models	Yes	Internal VaR models
Credit Risk	Yes	Crude regulatory weights	Yes	Internal ratings models
A/L Risk	No	–	No	Pillar II EVE test
Operational Risk	No	–	Yes	Internal loss models
Business Risk	No	–	No	–

Table 1: Basel regulatory capital treatment of bank risk sources.

Although we consider market risk to be the most "known" of the bank risks, our knowledge is far from perfect. Illiquid instruments, which "trade by appointment," may have daily VaRs calculated for them, but the underlying volatilities may not be very meaningful. More liquid instruments, such as currencies with managed exchange rates, are subject to regime change, as evidenced by the break-up of the European Exchange Rate Mechanism in September 1992. Even the best models sometimes fail to capture complex correlations – witness the collapse of LTCM in the fall of 1998 (Jorion 2000). For this reason, we regard a portion of the space in market risk as unknown and unknowable.

Abstracting from such structural changes, there are limits to the accuracy of market risk models. Marshall and Siegel (1996) conducted a narrow experiment focusing on commercial

VaR models. They supplied the same portfolio to eleven different vendors and found 95% one-day ahead VaR estimates to vary across vendors between 1% for simple FX forwards up to 28% for more complex interest rate options. Pritsker (1997) looked at variation in accuracy and computational time across six different VaR approaches for nonlinear instruments (in his case, FX options) and found a wide range in computational time (unsurprising) and accuracy (surprising). If such a broad range of outcomes is seen with relatively easy to measure market risk, that range is likely to be much wider for the other risk types.

2.3.2. Credit Risk

Credit risk measurement has progressed at a rapid pace since Basel I was adopted in 1988, although there is still a significant drop in the ability to quantify credit risk relative to market risk. At the transaction level, the use of credit rating models is now widespread for measuring expected loss, based on estimates of the probability of default (PD), loss given default (LGD), and exposure at default (EAD) of individual exposures. At the portfolio level, credit portfolio models such as KMV's Portfolio Manager calculate unexpected loss and economic capital, based on structural models of credit risk correlations. The broad framework for measuring credit risk at both the transaction and portfolio levels is standardized across the industry, albeit the internal models and parameters used by individual banks are highly customized (Crouhy, Galai and Mark 2001).

The transaction-level attributes of credit risk indicate that credit risk measurement is highly granular, in principle down to the level of individual loans. This is the level at which credit risk is priced and managed, and a wide range of quantitative applications – including pricing tools, RAROC (Risk Adjusted Return on Capital) measures, and hedging models – support decision-making at this level.

Significantly, Basel II adopts many of the latest credit risk measurement methodologies for setting capital requirements for credit risk. Under the Internal Ratings Based (IRB) approach, banks will be allowed to use internal rating models to determine the transaction level risk attributes of credit exposures (BCBS 2001b). However, because there is a broad range in the correlation assumptions of credit portfolio models used by the industry (BCBS 1999), Basel II requires the mapping of transaction-level risk measures to capital to be based on a regulatory formula employing a universal correlation assumption (BCBS 2005, §272).[8] The regulatory mapping limits the ability to isolate marginal risks of individual loans so as to differentiate economic capital levels based on varying degrees of portfolio diversification.

As with market risk, the state of knowledge within credit risk varies by asset class. More is known about relatively liquid credit classes, including (in the U.S.) corporate bonds, mortgages, credit cards, other consumer receivables, and loans to publicly-rated, large corporates, and less is known about illiquid credit classes, such as loans to small businesses, commercial real estate, and middle-market companies (Treacy and Carey 2000).

Even in the more liquid asset classes, credit risk quantification can only go so far. Default is a rare event, and sparse data sets – unlike the ultra-high frequency observations in market risk – limit the accuracy of measurement at both the transaction (PD, LGD, EAD) and portfolio (UL, economic capital) levels. Moreover, since credit default rates vary over the business cycle, the calibration and validation of credit risk measures pose unique challenges. This is evident in the recent Quantitative Impact Study (QIS 4) undertaken by regulators in the U.S. of anticipated changes in capital levels under Basel II. Both the level and dispersion of the

[8] Basel II has five supervisory portfolios, each with its own somewhat different risk weight function which differ, primarily, in their correlations.

QIS 4 results across banks somewhat surprised the regulators, and is one of the factors that led them to postpone (yet again) the implementation date for Basel II from 2008 to 2009.[9]

At the transaction level, Carey and Hrycay (2001) find bias in credit scoring and mapping models used for determining PD. They also find bias due to ratings instability, as well as evidence of regime shifts and cyclical instability. PD estimates also exhibit a wide range. For example, using 25th and 75th percentile estimates for a given PD rating, they compute a range of implied Basel II style capital estimates for a typical portfolio. Going from the 25th to 75th percentile in PD estimates translates to a more than doubling the level of implied capital.

At the portfolio level, Koyluoglu, Bangia and Garside (2000) compare three commercial models, CreditMetrics, CreditRisk+ and KMV's Portfolio Manager, and find that, similar to the market risk studies (e.g. Hendricks 1996), the choice of tail probability or VaR level matters. Differences across models were modest at the 99% VaR level (max to min difference about 40%), but were almost two to one at the 99.9% VaR level.

Overall, the two-to-one range in results reported by Carey and Hrycay at the transaction level and by Koylouglu, Bangia, and Garside at the portfolio level, are consistent with the view that credit risk is less easily quantified than market risk.

The research in credit risk measurement also suggests that credit risk is subject to more unknowns than market risk. Structural shifts in default risk, recovery levels, utilization rates, and credit correlations can all have a major impact on credit quantification. Credit risk is also subject to unknowable regime change – e.g., a change in bankruptcy laws in the U.S. For example, Gross and Souleles (2002), in looking at the impact of bankruptcy regulation on consumer debt

[9] See remarks by Governor Susan Schmidt Bies before the Institute of International Bankers, Washington, D.C. September 26, 2005; available at http://www.federalreserve.gov/boarddocs/speeches/2005/20050926/default.htm.

in the U.S., find that as bankruptcy costs decline, default likelihoods increase, often substantially. See also Domowitz and Sartain (1999).

2.3.3. Structural Asset/Liability Risk

Structural asset/liability risk is related to market risk, although the measurement problem is far more challenging. While the dominant risk factor in asset/liability risk is movements in interest rates – and there is a long tradition among both financial economists and practitioners in modeling interest rate paths – this is not where the principal difficulty lies. The challenge comes from the need to characterize indeterminate cash flows on both the asset and liability side; from the valuation of embedded options and hedges in a bank's investment portfolio; from the long holding period assumed for a bank's structural balance sheet; and, perhaps most importantly, from the lack of convergence on a measurement standard (Bessis 1998, Saunders 2000).

With regard to cash flow characterization, a bank's sensitivity to changes in interest rates is dependent on the cash flow mismatches across all assets and liabilities. Determining the cash flow mismatches, in turn, requires estimating the duration of indeterminate maturity liabilities – such as "core" demand deposits or cash management accounts – whose effective maturities may be much longer than stated contractual maturities. In addition, fixed assets, tax obligations, and leases all have cash flow characteristics that are not certain, and assumptions need to be made about their maturity characteristics. The approaches to estimating duration for indeterminate maturity cash flows blend art and science, with many banks still reverting to rules of thumb (Mays 1996).[10]

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[10] The impact of changes in duration assumptions can be significant: for a $100 bn bank funded 25% with core deposits, changing the effective maturity assumption on core deposits from 3 years to 5 years would have a duration impact of 0.5 years on the bank's overall gap position. This implies a $500 MM increase in the bank's economic value of equity under a 100 bp interest rate shock.

Investment in securities with interest rate optionality – especially mortgage backed securities with prepayment and extension risks – also complicates risk measurement. The valuation of these embedded options and related hedges is far from an exact science – as reflected in the recent major accounting restatements of both Freddie Mac and Fannie Mae.

At the same time, unlike with trading positions, the holding period for a bank's structural asset/liability position is assumed to be a long time horizon, typically one-year. Short-term volatility in interest rates, however, can lead to dramatic changes in a bank's asset/liability risk. The long holding period makes the impact of dynamic management policies, such as stop-loss limits, more difficult to anticipate.

Nevertheless, at least since the U.S. S&L crisis, structural asset/liability risk has been actively monitored in most major banks. Yet unlike market or credit risk, there is no standardized approach for asset/liability risk measurement. In fact, practitioners do not even agree on whether the appropriate measure is an earnings approach based on Net Interest Revenue volatility, or a value approach based on changes in the Economic Value of Equity (EVE) [defined as the present value of assets minus liabilities (Koch and MacDonald 2000, ch. 9 FRBSL 2004)]. The measurement debate is partly driven by the arcane accounting treatment of interest earnings from a bank's investment portfolio, with some assets (but not necessarily corresponding liabilities) receiving mark-to-market treatment, while other assets (those deemed to be "available for sale" or "held to maturity") are recognized on an accruals basis.[11] Lack of consensus on how to measure asset/liability risk was reported to be a major reason why interest

[11] Under U.S. GAAP, the mark-to-market changes in investment portfolio assets that are "available for sale" or "held to maturity" do not hit a bank's reported net income, but are disclosed in a footnote to the financial statements. At the same time, the MTM changes in the available for sale portfolio reduce a bank's tangible common equity ratio, but the MTM changes in the held to maturity portfolio do not. The hodgepodge of accounting treatment has created genuine confusion over what the relevant unit of "risk" is in Treasury portfolios and how it should be measured.

rate risk outside the trading book was not subjected to an explicit (Pillar 1) capital charge under Basel II but is covered under Pillar 2 instead (BCBS 2005, §762).

Given the lack of standardization, it is not surprising that there is a wide range of sophistication in asset/liability risk measurement. Simplistic approaches include calculating the impact of fixed rate shocks – such as a 100 or 200 bp parallel shift in yield curves – on the bank's EVE and net interest revenues. Basel II suggests such a simple 200 bp parallel shift test as a means of identifying banks that are outliers in terms of asset/liability risk. More sophisticated approaches subject the balance sheet to full simulation of interest rate movements, and calibrate outcomes based on probabilistically-weighted scenarios (including tail-risk scenarios) (Bessis 1998).

In terms of granularity, funds transfer pricing, common in most banks, allows the value of assets and liabilities to be disaggregated (based on behavioral assumptions) to pools of deposits and transactions. In principle, though, A/L risk is a high-level risk that is usually measured and managed at the level of the consolidated balance sheet.

2.3.4. Operational Risk

Operational risk is the newest risk class to emerge as a discrete category. Prior to the early consultative papers for Basel II, there was no agreement on what the definition of operational risk was, let alone how to measure it. Basel II established a standardized definition and classification scheme for operational risk – subdividing internal and external events into seven recognized categories, limiting operational risks to the "direct" consequences of operational losses, and excluding indirect consequences such as reputation effects from the definition. Going forward, Basel II requires that banks seeking to adopt the Advanced Measurement Approach for operational risk (the only option available for U.S. banks) develop internal economic capital models to estimate a bank's exposure to operational losses at the 99.9% level over a one-year horizon (BCBS 2005, §655-659). Prior to the Basel II pronouncements, operational risk was often included together with other non-financial risks as "operating risk," and measured in economic capital frameworks, if at all, through analogs and benchmarks such as revenue and expense ratios (Uyemura and van Deventer 1992, Netter and Poulson 2003).

Basel II has catalyzed a major industry effort to model and measure operational risks. The challenge in operational risk measurement, however, is that operational losses appear to be extremely fat-tailed (De Fontnouvelle, Jesus-Rueff, Jordan and Rosengren 2006, Rosenberg and Schuermann 2006). The losses that are most relevant for measuring economic capital are, by definition, low frequency, high severity events that are difficult to observe within any one firm. For this reason, Basel II requires that banks incorporate information from external data and extreme loss scenarios in their operational loss models. Banks have experimented with a number of different quantitative techniques to fit the tails of operational loss distributions, including techniques from extreme value theory, EVT (Netter and Poulson 2003, Allen, Boudoukh and Saunders 2004).

Despite the recent progress, it is fair to say that operational risk measurement is still at a relatively early state of development. A standard approach for quantifying operational risk has yet to emerge. And small changes in parameter estimation can have a dramatic impact on results at the 99.9% level. For example, de Fontnouvelle, Jordan and Rosengren (2006) apply EVT techniques to estimate the operational risk loss distributions for six banks, based on internally reported data. The resulting estimates are not very precise. In a comment on the de Fontnouvelle, Jordan and Rosengren (2006) paper, Kuritzkes (2006) shows that differences in the shape parameter of the generalized Pareto distributions estimated for the six banks were consistent with a ten to one range in resulting economic capital.

Equally, because of the focus on extreme tail events, operational risks are difficult to break down to lower levels of aggregation. The risks that can be observed within individual business units tend to be high-frequency, low severity risks – not the low frequency, high severity risks that are relevant for economic capital. Tail risks – for example, legal liability risk for accounting mis-statements or securities class action law suits – often need to be imputed from external data sources and may only be meaningful at the level of the firm.

Consistent with the immature state of operational risk measurement, the world of the unknown in operational risk is commensurately larger than for market, credit, or A/L risks. Arguably, operational risk contains risks that are recognized today that were previously unknowable. An example referred to above was the World Trade Center attack on 9/11/2001, the direct consequences of which are an "external event" included within the Basel II definition of operational loss. Kuritzkes and Scott (2005) note the general category of legal risk as being subject to ex post judicial and regulatory interpretations, some of which may not be foreseeable ex ante. Examples of such risks could include the vulnerability of Swiss banks to holocaust claims in the mid-1990s, four or five decades after the accounts of holocaust victims were mishandled, as well as more recent rulings and regulatory decisions in the aftermath of the Enron and WorldCom scandals holding banks to be vicariously liable for customer fraud. Brown, Hillegeist and Lo (2005) show how this type of ex ante legal risk influences management behavior and earnings forecasts.

2.3.5. Business Risk

Business risk is the last frontier of risk classification and measurement. As with operational risk before Basel II, there is no standard definition of business risk, which is sometimes also referred to as "strategic" risk (Slywotzky and Drzik 2005). Within the taxonomy above, business risk is best understood by reference to what it is not: it is residual earnings volatility that is *not* caused by any of the other defined categories, including market, credit, A/L, or operational risks.

Given the catch-all nature of business risk, it is difficult to isolate the independent drivers of residual earnings volatility. Conceptually, business risk reflects the fact that a firm's revenues may be volatile while its costs are somewhat rigid, even after the effects of market, credit, asset/liability, and operational risks have been stripped out. The resulting profit margin reflects the degree to which a firm is able to manage costs relative to revenues and avoid an operating loss – the basic risk that all firms face and which explains why non-financial firms cannot operate on infinite leverage.

Nevertheless, many banks do not include an explicit measure of business risk within their economic capital frameworks. For those banks that do, business risk is measured through one of a few alternative approaches: the simplest approach is to infer business risk capital requirements from the capitalization levels of non-financial firms that are engaged in similar activities (e.g. processing, consulting, IT services). Another approach is to strip out financial and operational risks from publicly-reported data on bank earnings and construct a proxy measure of business risk volatility for a sample of peer banks. A third approach is to develop an explicit model of residual revenue volatility and cost rigidity at the business line level. None of the approaches are based on causal factors of business risk, and little progress has been made in systematically identifying the individual sources of business risk volatility (Slywotzky and Drzik 2005).

In terms of granularity, business risk is easiest to observe at the bankwide level. Of all the risk types, it is the one we are the least able to break down to lower levels of aggregation. This is not to say that business risk is not "managed" but simply that it is hard to manage in a granular fashion. Banks, like the Basel II regulators, have tended to ignore the impact of business risk, or seem to think of it as indistinguishable from "strategy."

2.4. Putting the Pieces Together

Referring again to Figure 3, our positioning of bank risks in the *K*, *u*, *U* space can be summarized in a few propositions:

1) Our knowledge of bank risk increases as our ability to quantify risk increases.
2) Our knowledge of bank risk increases as our ability to disaggregate risk to more granular levels increases.
3) Our knowledge of bank risks shifts over time, as new risks become discretely classified and subject to measurement with increasing granularity

Based on these propositions, the evidence from market practice suggests that:

4) Our current knowledge of market risk > credit risk > structural asset/liability risk > operational risk > business risk.

Although we know more about the ordering of risks than the contours of the *K*, *u*, and *U* curves within the risk space, we reason that:

5) The "known" curve falls off steeply between financial and non-financial risks, as market, credit, and structural asset/liability risks are much easier to quantify and disaggregate than operational or business risk; and
6) The *U* curve also rises steeply for operational and business risk, given the diffuse nature of these risks and the lack of historical focus on their underlying causes.

3. Empirical Analysis

In this section we analyze the earnings volatility of a large sample of U.S. bank holding companies (banks) using publicly available regulatory reporting data to answer two questions: 1) how much bank risk is there in total (in the U.S., at least)? 2) What is the relative contribution to overall risk from each of the five sources of risk identified in our taxonomy? By quantifying earnings volatility systematically, we hope to shed light on the dimensions of *K*, *u* and *U* in the bank risk space.

Our sample range is 1986Q2 though 2005Q1 for quarterly analysis and 1986 to 2004 for annual analysis using Y-9C regulatory reports. The sample period begins in 1986Q2 because prior to that, trading income, needed to parse out market risk, was not reported separately. All banks with at least $1bn in total assets at the beginning of each year are included for a total sample of 22,770 bank-quarters.[12] While our sample period contains only two recessions, and mild ones at that, it does include a period of significantly higher than average bank failures, 1988-1991, but not the severe stress encountered in the Great Depression of the 1930s.[13] We also extend the annual analysis for overall risk back to 1981 as a robustness check. The extended annual sample includes the more pronounced 1982 recession.

3.1. How Much Total Risk?

Given that practitioners and others define risk in terms of earnings volatility (Rajan 2005), we look to actual variations in bank's reported net income to determine how much bank risk is there in aggregate.

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[12] Total assets, reported in nominal dollars, were deflated using the GDP deflator to 2005Q1 dollars. This would err towards including more rather than fewer banks. Note that we did not account for mergers and acquisitions.

To allow direct comparison across banks, earnings need to be converted into a return-based measure. An obvious approach for doing this would be to divide (pre-tax) net income by total assets to yield a return on assets (ROA) measure. This method, however, treats all asset types the same: a treasury bond would be the same as a loan to a small, new firm. Regulatory reports provide risk-weighted assets (RWA) based on the Basel I risk weights. Although crude, and certainly much cruder than under a Basel II style risk weighting, RWA is nevertheless preferable to unweighted (total) assets as it makes at least some adjustment for the risk of the underlying asset. Unfortunately Basel I RWA has only been available since 1996. In an attempt to adjust total assets from the beginning of our sample period we take a simple approach and examine the ratio of RWA to total assets for the available sample period for the industry as a whole and back-fit to the beginning of the sample.

The resulting ratio of net income to RWA, which we call return on risk weighted assets (RORWA), determines our measure of earnings.[14] The average quarterly RORWA in our sample is 0.34%, or 1.35% on an annualized basis. As risk, and hence capital, is concerned with deviations from expected returns, for what follows we compute deviations in RORWA by subtracting, from each period's observation, the average RORWA over the sample period for each bank – neutralizing for bank holding company (or bank) effects. To be precise, let $Y_{i,t}$ be the net income for bank i in period t, and let $\mathrm{RWA}_{i,t}$ be the corresponding level of risk-weighted assets. We then define RORWA for the i^{th} bank in period t as

$$r_{i,t} = \left(\frac{Y_{i,t}}{\mathrm{RWA}_{i,t}} \right), \tag{1}$$

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[13] Carey (2002) using a resampling based approach does try to mimic this "Great Depression" scenario.

[14] Although Basel I style risk weighted assets do capture some off-balance sheet exposure, the picture is not complete. But however incomplete, so long as the proportion captured has stayed relatively constant, our back-

and mean-adjusted RORWA as

$$\tilde{r}_{i,t} = \left(\frac{Y_{i,t}}{\text{RWA}_{i,t}} \right) - \left(\frac{1}{T_i} \sum_{t=1}^{T_i} r_{i,t} \right), \tag{2}$$

where bank *i* is observed for T_i periods. For simplicity in what follows we shall refer to Eq. (2) as RORWA (i.e. always the mean-adjusted return). The quarterly standard deviation or volatility across 22,770 (quarterly) RORWAs is 0.40%, or 0.80% on an annualized basis.[15]

Under the Basel framework (both Basel I and Basel II), regulatory capital requirements are also expressed in terms of RWA, with banks being required to hold sufficient capital *C* such that

$$\frac{C_{i,t}}{\text{RWA}_{i,t}} \geq C_{\min} > 0 \,, \tag{3}$$

for some threshold C_{min}. Typically C_{min} = 0.08.[16] Given that annualized volatility of RORWA is 0.80%, regulatory capital levels, it turns out, are sufficient to enable banks to withstand a 10σ annual event in RORWA. If we assume that the RORWA returns are normally distributed, the likelihood of such an event is infinitesimally small: less than once in 1,000 trillion years. Should we feel safe?

The answer is not nearly as safe as assumptions of normality would lead one to believe. Figure 4 shows the distributions of RORWA calculated over quarterly and annual frequencies. It

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casting method would capture a similar proportion of off-balance sheet exposures. Earnings from those exposures, whether positive or negative, are captured in the numerator of our RORWA metric.

15 A potential disadvantage with this approach of subtracting the bank mean return is that a bank with, say, an average return of 20% which has a "bad" return for one period of 5% would have a deviation of -15%. This would be observationally equivalent for a bank with a mean of 5% and a bad one-period return of -10%. Naturally we would care differently about the latter than the former case. To check we repeated the entire analysis without deviation in means and found that the tails of the return distribution to be somewhat more extreme even though the mean, of course, was higher (positive instead of zero) suggesting that the former example is indeed pathological and the latter typical.

16 The actual capital requirements are, of course, somewhat more complex as they involve differentiated types of capital (Tier 1 vs. Tier 2). We use the 8% threshold for convenience and to allow for easier comparison to other

is apparent that each of these distributions is very fat-tailed, with a kurtosis of 123 for the quarterly and 40 for the annual data; it is 3 for a normal distribution. Under temporal aggregation we would expect the lower frequency data to be closer to normality, as is indeed the case here. Each distribution is also somewhat negatively skewed, with a coefficient of skewness of -1.1 for the quarterly and -2.6 for the annual returns.

There is enough data to allow for nonparametric analysis of the tails, meaning we can estimate tail quantiles directly from the empirical distribution, though for small quantiles in the far tails the estimates are likely to be noisy. Because bank earnings are subject to common effects, other approaches such as EVT may not be suitable as they require the data to be independently distributed (Diebold, Schuermann and Stroughair 1998).

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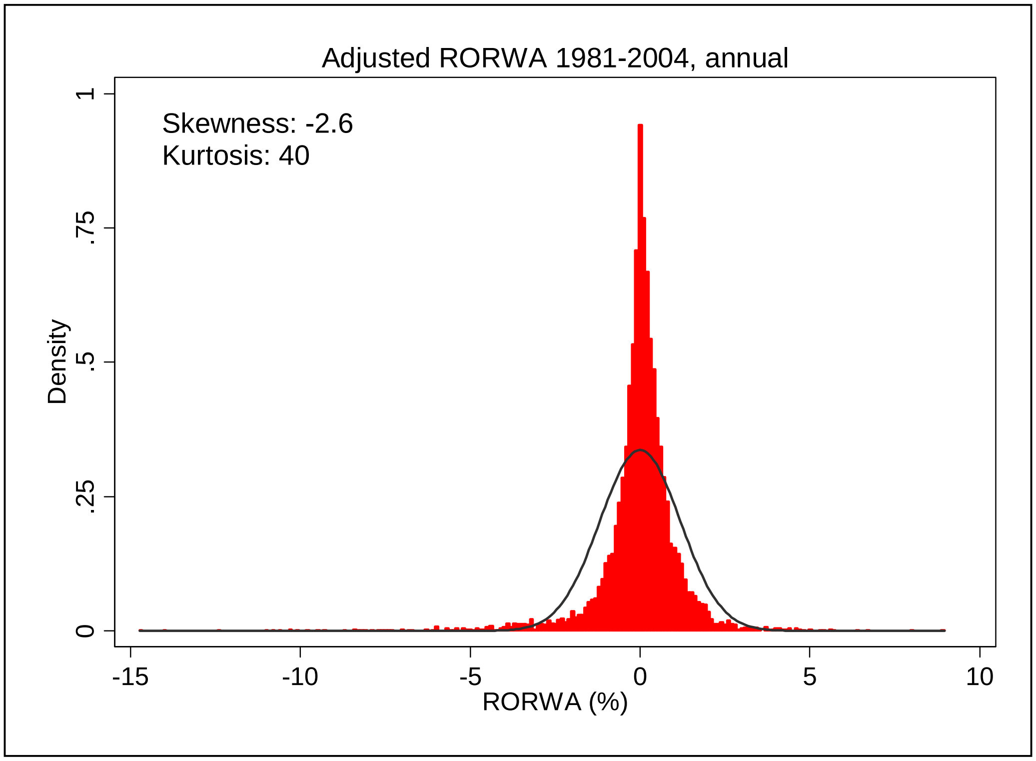
studies in the literature where a simple 8% cutoff is typical. At times we also make reference to a 6% Tier 1 threshold. Of course it is straight forward to use different thresholds.



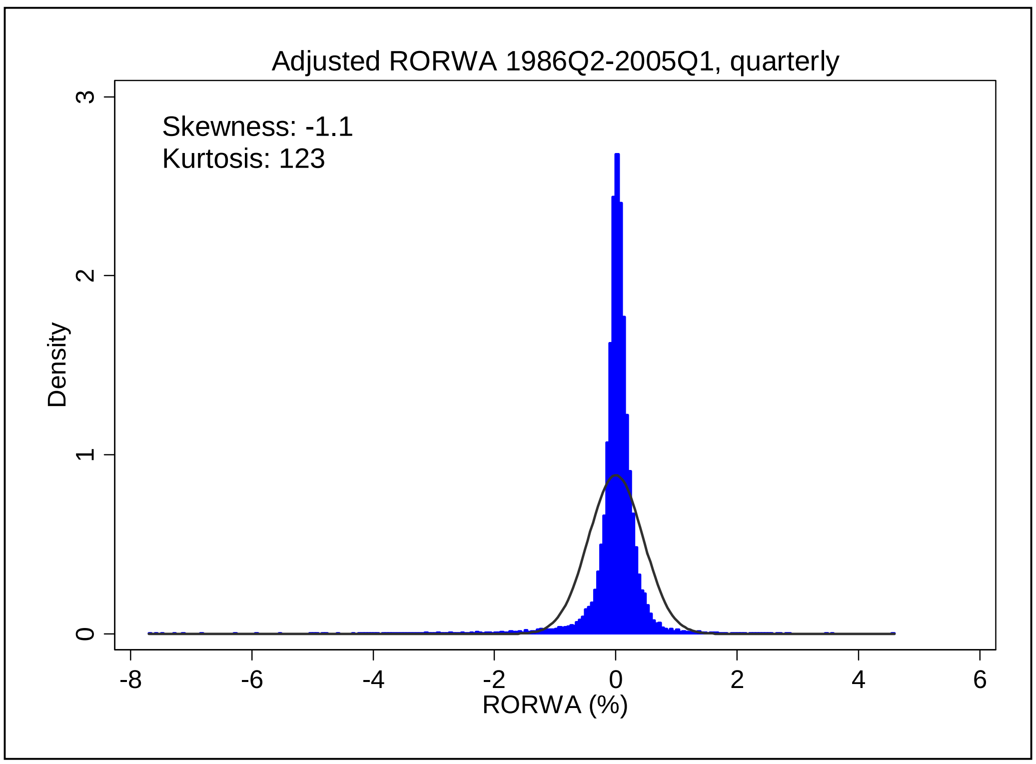


Figure 4: Histograms of quarterly and annual RORWA, adjusted for bank means. Each chart has superimposed the normal density with the same mean (0) and standard deviation as the data.

Zeroing in on the tail, Table 2 reports empirical percentiles for the left tail of the quarterly RORWA distribution. For example, the 0.1^{st} percentile (or 99.9% tail) in the data is a quarterly RORWA of -4.85%, and there are 23 observations that are "worse" (i.e. more negative). All of those tail observations occurred between 1986 and 1992, mostly incurred by Texas and New England banks. Based on the empirical record, if banks hold at least 8% capital, they would be unable to withstand an adverse RORWA event in about two quarters out of every 10,000. These events happen considerably more often than the 1 in 1,000 trillion implied by a normal distribution. Indeed a -8% quarterly RORWA is around the 0.02^{nd} percentile, or the 99.98% tail; using a 6% threshold, the percentile is the 0.06^{th}, or the 99.94% tail. To the extent that there have been significant changes, both in the regulatory arena (e.g. FDICIA in 1991) and industry (e.g. the widespread adoption of risk management tools and techniques since the mid-1990's), we may be less likely to see such extremes going forward. We examine this issue in Section 3.3 by splitting the sample in 1993.

Left Tail of Earnings Distribution/VaR (%)

	0.01 **99.99**	**0.03** **99.97**	**0.05** **99.95**	**0.1** **99.9**	**0.5** **99.5**	**1** **99**
RORWA (%)	-9.69	-7.69	-7.14	-4.85	-2.67	-1.75
# of observations beyond percentile	3	7	12	23	114	228

Table 2: Left tail percentiles for quarterly return on risk weighted assets (RORWA). 22,770 bank quarters, 1986Q2 - 2005Q1. All returns are deviations from bank mean. Data source: Y-9C regulatory reports.

The probability of a loss exceeding 8% can be interpreted through the lens of economic capital as the implied solvency standard of the Basel capital requirements. To translate the solvency standard into familiar terms, we map the bank loss probabilities to empirical default frequencies of rated corporate bonds. Although different approaches have been applied for estimating the PDs for corporate bond ratings, the most common approach – and the one used by the rating agencies themselves – is the frequentist or cohort approach, which divides the number of defaults from a given rating over the number of rated firms in the quarter (year).[17] We apply the cohort approach to estimate annual default probabilities for S&P ratings based on rating histories from 1981 – 2004. The PDs turn out to have roughly a log-linear relation across credit ratings, meaning that PDs increase exponentially as one descends the rating spectrum; see Figure 5. If we assume that this log-linear relationship holds across the entire spectrum, we can impute a PD value for the investment grades, where default observations are scarce. The resulting annual and implied quarterly PDs by rating are presented in Table 3, shown in basis points.

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[17] In the cohort approach ratings migrations within the quarter (year) are ignored. An alternative duration based approach (Lando and Skødeberg 2002) is able to account for these movements by estimating migration, and hence default, intensities, resulting in a non-zero PD estimate for a rating even if no default from that rating has been observed, as is the case for the AAA rating, for instance. This method requires the rather strict assumption that ratings follow a Markov process, and several studies have documented non-Markovian behavior in credit ratings (Altman and Kao 1992, Nickell, Perraudin and Varotto 2000). Hanson and Schuermann (2006) show that neither method produces precise PD estimates, and that observed default rates are indeed inconsistent with a Markov model.

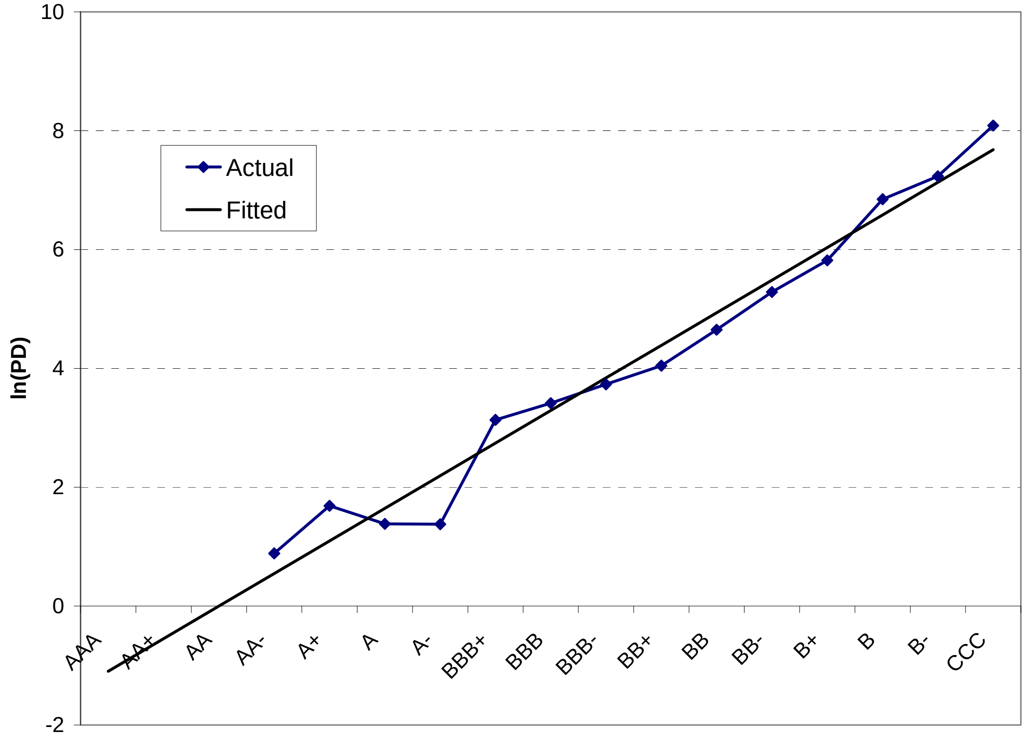

Figure 5: Actual and fitted annual PDs, in logs (i.e. PDs are assumed to be log-linear across the rating spectrum). Actual PDs are estimated using the cohort approach with S&P rating histories for all corporates from 1981-2004. No actual defaults for ratings AA and higher were observed in this sample period.

With these default probabilities, it is straightforward to map the left tail percentiles in Table 2 to an implied credit rating. Recall that a bank with 8% (6%) capital would be able to withstand an adverse quarterly RORWA with 99.98% (99.94%) confidence -- or a default probability of 2bp (6bp) per quarter. This solvency standard corresponds to a low investment grade credit rating of around A- (BBB+); see Table 3.

Rating	Annual PD (smoothed)	Implied quarterly PD[18]
AAA	0.3	0.075
AA+	0.6	0.15
AA	1.0	0.25
AA-	1.7	0.425
A+	3.0	0.75
A	5.0	1.25
A-	9.0	2.25
BBB+	23	5.75
BBB	30	7.50
BBB-	42	10.50
BB+	57	14.25
BB	105	26.25
BB-	197	49.25
B+	337	84.25
B	943	235.75
B-	1,385	346.25
CCC	3,254	813.50

Table 3: Smoothed annual and quarterly PDs by rating using S&P rating histories for all corporates from 1981-2004, in basis points. The dashed line separates investment grades (above) from speculative grades (below).

The typical horizon to which economic capital is set is one year, so we proceed to check the quarterly results against annual earnings using year-end data from 1986 to 2004 resulting in 5,841 bank-years. Quarterly data allows us to better explore the far tails, but we may still compare the two frequencies so long as the calibration is to a common standard, namely a default likelihood or an implied credit rating, albeit frequency consistent.

[18] In the presence of non-Markov behavior, quarterly PDs are not simply equal to ¼ of annual PDs. However, the differences are quite minor, and we use these estimates as guidelines for mapping our empirical analysis into implied credit ratings.

Left Tail of Earnings Distribution/VaR (%)				
	0.05 / 99.95	**0.1 / 99.9**	**0.5 / 99.5**	**1 / 99**
Implied rating: quarterly, annual	BBB+, A	BBB-, A-	BB-, BB+	B+/B, BB
Quarterly (1986Q2 - 2005Q1)	-7.14	-4.85	-2.67	-1.75
Annual (1986 – 2004)	-10.27	-9.81	-5.95	-4.12
Annual (1981 – 2004)	-14.74	-10.81	-6.00	-4.38

Table 4: Implied credit rating for left tail percentiles for quarterly and annual return on risk weighted assets (RORWA), in percent. Implied credit ratings are presented in Table 3. Quarterly data is 1986Q2 - 2005Q1 for a total of 22,770 bank-quarters, first annual data is 1986 – 2004 for a total of 5,841 bank-years, chosen to match the quarterly sample period, and second annual data is 1981 – 2004 for a total of 7,396 bank-years. All returns are deviations from bank mean. Data source: Y-9C regulatory reports.

In Table 4 we present RORWA, in percent, of total earnings measured at quarterly and annual frequencies at varying quantiles (the quarterly returns are from Table 2).[19] The results can be thought of as a Value-at-Risk: for example, looking at the 0.1st percentile, quarterly returns worse than -4.85% and annual returns worse than -9.81% have been seen for 0.1% of bank-quarters/years. These percentiles (VaRs) can also be mapped to their corresponding quarterly and annual default rates using Table 3. For example, what rating corresponds to an annual (quarterly) default rate of 10bp (i.e. a 99.9% VaR)? The implied annual rating closest to 10bp is A-, and the implied quarterly rating closest to 10bp is BBB-. Therefore a bank with 4.85% capital (relative to RWA) would be protected against quarterly earnings volatility at the BBB- level. Note that the same amount of capital would only protect the bank against annual earnings volatility at roughly the 1st percentile, equivalent to a BB rating.

[19] There is not enough data to allow us to explore the annual results beyond the 5 b.p. tail.

More relevant from a regulatory capital perspective is the solvency standard associated with an 8% (6%) capital cushion. Using the longer sample, a -8% (-6%) annual RORWA event is associated with a tail probability of 0.28% (0.49%), which corresponds to a BBB (BBB-) rating – or two (one) rating notches lower than the implied A- quarterly rating reported above. It is interesting to note that the implied annual solvency standard is somewhat less conservative than the 99.9% annual confidence interval used in Basel II for measuring credit, market, and operational risks. Given estimation and model errors, however, the two confidence intervals (99.9% vs. 99.72%**)** could be interpreted as being reasonably close.

These results are consistent with Carey (2002) who uses resampling techniques on a representative corporate loan portfolio to assess the amount of economic capital needed under various economic conditions. In particular, based on the experience of 1989-91, a moderate stress scenario, Carey finds that the loss rate over a two year horizon at the 99.5% (99.9%), is 7.63% (8.80%) respectively (Carey 2002, Table 3), versus our one year loss estimates of 6.00% (10.81%) (Carey 2002, Table 2). Our results are also consistent with Lucas, Klaassen, Spreij and Straetmans (2001) who report one-year likelihoods of exceeding 8% capital ranging from 1bp to 100bp (i.e. 99.99% to 99% VaR), depending on assumptions about average credit quality of the portfolio and the distribution of the underlying risk factor. Note, however, that both of these studies examine credit risk only, while our results attempt to encompass all risk types. Indeed we show in the next section that credit risk makes up just under half of the total risk pie.[20]

[20] Note also that one cannot, however, simply divide our total risk numbers by two as there is inter-risk diversification to contend with. We show in Section 3.2 that the difference between the whole and the sum of the parts is about one-third.

3.2. Relative Risk Contributions

Having answered the first question – how much risk is there in total – we are ready to address the second: what is the relative contribution from each of the five major risk types of the risk taxonomy outlined in Section 2.2? Since by definition the different sources of risk in our taxonomy manifest themselves as earnings volatility, we seek to isolate the impact of each of the individual risk sources on RORWA. Using disaggregate data from the Y-9C regulatory reports, we outline a simple approach to measuring how each risk type affects bank reported net income – the numerator of RORWA. This approach will allow us to understand the relative size of the components of RORWA volatility, and will also highlight the difference between the whole and the sum of the parts. That difference can be thought of as the diversification benefit across the different risk types.

We start from the identity that bank pre-tax net income (i.e., earnings) can be expressed as:

pre-tax net income	= Net interest income (interest income less interest expenses)
	+ net gains (losses) from securities
	+ income (loss) from trading
	– provisions
	+ other income (service charges, fiduciary, fees and other income)
	– non-interest expenses
	+ net extraordinary items.

We may then think about mapping these income statement items to risk types in the following fashion:

Net income =	Trading income	→	Market Risk
-	Provisions	→	Credit Risk
+	NII + Securities gains	→	A/L Risk
	Financial income	→	Financial Risk
	Other income	→	40% Operational Risk
+	NIE + Extraordinary items		60% Business Risk
	Non-financial income	→	Non-financial Risk

Figure 6: Measuring financial and non-financial risks using line items from bank regulatory reports (Y-9C). NII is net interest income; NIE is non interest expenses.

As shown in Figure 6, these line items can be grouped into financial and non-financial sources of net income, and then mapped to individual risk categories. The parsing of total non-financial risk into its two components, operational and business risk, is taken up below.

The mapping of income items to risk types is better for some of the risk categories than for others, but overall the scheme seems to provide a reasonable basis for decomposing earnings volatility into risk sources. The cleanest alignment is between market risk and trading income. Market risk is synonymous with volatility in the trading P&L, while trading income reflects the P&L results of the bank's market making and proprietary position taking activities.[21] For credit risk, we take provisions as the relevant measure (as opposed to net charge-offs) because provisions are what enter the calculation of net income. Put another way, variation in provision

[21] While all banks are subject to minimum capital standards due to credit risk, only banks with a *significant* market risk exposure are required to calculate a risk-based capital ratio that takes into account market risk in addition to credit risk. U.S. regulators deem market risk exposure to be significant if the gross sum of trading assets and liabilities on the bank's balance sheet exceeds 10% of total assets or $1 billion (USGAO, 1998, p. 121). As reported in Hirtle (2003; Table 1), at the end of 2001 there were only 19 bank holding companies (BHCs) that were

levels is what causes volatility in reported earnings and hence RORWA. Provisions, nonetheless, are an imperfect measure of credit risk. Two main disadvantages of using provisions as a proxy for credit risk are timing and loss smoothing. Typically, provisions are made in anticipation of accounting losses and are concurrent with or even lag economic losses. This forecasting element may allow banks to smooth earnings (although this is severely frowned on by FASB regulation and the SEC) and so could lead us to underestimate the contribution of credit risk to overall risk. A separate robustness check using net charge-offs instead of provisions shows that the two results are quite close, and the choice between provision and charge-offs appears to make little difference to our analysis.

Structural asset/liability risk is, in a sense, residual financial earnings volatility once trading gains (losses) and provisions have been stripped out. This is measured by Net Interest Income (NII) plus gains (losses) on securities. Variations in NII (excluding credit provisions) are due to either volume effects (which are captured by scaling NII by risk weighted assets) or to changes in the term structure and spread levels of interest rates – the basic definition of asset/liability risk. Further, principal gains/losses on securities held in the bank's investment portfolio (as opposed to the trading book, which is considered market risk) are also caused by changes in rates or spread levels, and so should be included as an additional source of asset/liability related earnings volatility.

Finally, total non-financial risk represents residual earnings volatility not attributable to market risk, credit risk, or structural asset/liability risk. This is given by the remaining income items: all other income (services charges, fiduciary fees, and other income), less non-interest expenses (NIE), plus net extraordinary income. Note that inclusion of all operating expenses in

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subject to market risk capital standards. Nonetheless many of the larger banks still engage in some trading related this category is consistent with the notion that business risk captures variations in margins due to fixed (or rigid) expenses. While total non-financial risk includes both operational risk and business risk, the line items in bank income reporting do not allow the impact of these two risks to be segregated. Instead, we turn to other empirical research on operational risk (imperfect as it is) to fix the proportion of non-financial risk that appears to be due to operational losses.

As noted above, these mappings are hardly perfect. For instance, interest income volatility could increase by lending to riskier borrowers, thus mixing credit risk with our measure of structural interest rate risk. Similarly, fees on loan commitments mix credit risk with non-financial risk. Nonetheless, we believe that these counter-examples are relatively atypical and that our simple approach provides a reasonable approximation to risk type attribution.

In each case the dollar values are divided by our estimated risk weighted assets, RWA, to arrive at a risk specific "return." As in the RORWA analysis, we look at deviations in the return measures from bank-specific averages. While the overall focus is on large negative outcomes, for credit risk we look at the right tail, namely unusually large provisions, as being adverse.

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activity, and indeed almost half of the banks in our sample reported non-zero trading income.

Left Tail of Earnings Distribution/VaR (%)

Risk Type	**0.01 99.99**	**0.03 99.97**	**0.05 99.95**	**0.1 99.9**	**0.5 99.5**	**1 99**
Market (trading)	-0.93 (5)	-0.71 (5)	-0.57 (5)	-0.43 (6)	-0.16 (4)	-0.11 (4)
Structural A/L	-4.62 (25)	-2.41 (17)	-2.01 (19)	-1.36 (18)	-0.80 (20)	-0.61 (22)
Credit[22]	8.06 (44)	6.79 (48)	4.74 (46)	3.57 (47)	1.89 (47)	1.21 (44)
Total non-financial[23]	-4.71 (26)	-4.17 (30)	-3.00 (29)	-2.30 (30)	-1.17 (29)	-0.83 (30)
Operational	(11)	(12)	(12)	(12)	(12)	(12)
Business	(15)	(18)	(17)	(18)	(17)	(18)
Sum of risks	-18.32	-14.07	-10.32	-7.67	-4.03	-2.77
Total risk	-9.69	-7.69	-7.14	-4.85	-2.67	-1.75
Diversification benefit	47	45	31	37	34	37

Table 5: Allocation by risk type for the left tail of the earnings distribution, measured in return on risk weighted assets (RORWA). Note that for credit risk, proxied by provisions, that a larger (positive) value corresponds to a worse outcome. Diversification benefit is the difference between the sum of the risks (tail components) and the total (reported in Table 2 above). All values in percent, 22,770 bank quarters, 1986Q2 - 2005Q1, net of bank mean.

Table 5 shows empirical results for our earnings volatility measures (following Eq. (2) expressed as a percentage of RWA) for each of the risk categories at different tail quantiles. The numbers in parentheses correspond to the percentage contribution to total risk, measured as the sum of the parts across the risk sources at each quantile. The last row shows the percentage difference between the sum of the parts and overall net earnings volatility from Table 2, which can be interpreted as the inter-risk diversification benefit. To take one quantile, e.g. the 0.1% tail, the single largest source of earnings volatility is credit risk, worth 3.57% of RWA corresponding to 47% of the total, and the smallest risk is market risk, worth -0.43% of RWA

[22] Note that large positive provisions correspond to large credit risk realizations.
[23] We split total non-financial risk into operational and business risk using a 60%/40% allocation following Kuritzkes (2002).

corresponding to just 6% of the total. (Note that for credit risk, proxied by provisions, a larger (positive) value corresponds to a worse outcome.) The sum of the individual risks at the 0.1% tail (99.9% VaR) is -7.67%, and this far exceeds the 0.1% tail of total RORWA which is -4.85% from Table 2. The difference arises from diversification across risks. In other words, if all of the risk types were perfectly correlated in the tails, then a 0.1% event in one risk type would correspond perfectly to the 0.1% event in all other risks. Clearly this is not the case, and the degree of diversification at this quantile is 37%.

Several things are striking about the results. First, the relative contribution is remarkably stable across quantiles, so that our conclusions about which risks matter the most are not sensitive to the choice of tail quantile or confidence interval. For instance, credit risk, the dominant risk type, makes up just under half the total: between 44% and 48%, across the tail quantiles from 1.0% to 0.01%. Market risk in the trading book is by far the smallest source of risk, from 4% to 6% of the total. These results are consistent with industry benchmarks as reported in Kuritzkes, Schuermann and Weiner (2003) and other studies such as Hirtle (2003) and Rosenberg and Schuermann (2006), though arrived at using rather different methods.

Second, risk types that have to date not been subject to a regulatory capital charge, namely structural asset/liability risk and non-financial risk, make up about half of the total risk. As noted above, non-financial risk contains operational risk, which will be subject to a capital charge under Basel II, and business risk, which will not be. While there is limited evidence for the appropriate weighting between these two risk types (reflecting the primitive state of quantification of non-financial risks), Kuritzkes (2002) argues for slightly more than half to business and somewhat less for operational, which would imply that the latter contributes around 12-14% of the total. A 12% allocation to operational risk is also broadly in line with Basel II's suggested calibration for operational risk, as well as with Allen and Bali (2007), and De

Fontnouvelle, DeJesus-Rueff, Jordan, and Rosengren (2006). On this basis, we adopt 12% as a measure of operational risk contribution, and classify residual non-financial risk as business risk.

Structural asset/liability risk, which under Basel II is subject to regulatory capital under Pillar 2 (but is not part of the minimum capital requirement under Pillar 1), makes up about one-fifth of total risk. This too is consistent with industry benchmarks reported in Kuritzkes, Schuermann and Weiner (2003).

Finally, the difference between total risk and the sum of the parts is between 31% and 47%, very much in line with results obtained by Rosenberg and Schuermann (2006), who report a diversification benefit of 45% across market (trading only), credit and operational risk, using a completely different approach based on copulas, although somewhat higher than results reported by Dimakos and Aas (2004), who report a 20% benefit for the same three risk types.

Risk diversification is obtained if the components which make up the sum are imperfectly correlated. While we would expect events that drive large market losses, e.g. unfavorable movements in interest rates or equity prices, also to influence A/L risk and perhaps even credit risk, we would not expect those losses to march in lock-step. Estimates of this kind of dependence can be captured through the correlation of the quantiles or rank correlations, and below in Table 6 we present the median Spearman's rank correlations between the earnings components and of the components with total (pre-tax) earnings across 888 banks. For each bank we computed the set of rank correlations across time, and the table entries represent the median across those banks, the idea being that this is the correlation profile of a typical bank in our sample.

	Total pre-tax earnings	NII + net sec.	Trading income	Provisions	Other income
Total pre-tax earnings	1.000				
NII + net sec.	0.500	1.000			
Trading income	0.023	0.027	1.000		
Provisions	-0.386	0.123	0.049	1.000	
Other income	0.389	-0.481	-0.082	-0.143	1.000

Table 6: Median Spearman's rank correlations of total (pre-tax) earnings and the four major components across 888 banks. Based on quarterly return on risk weighted assets (RORWA). 22,770 bank quarters, 1986Q2 - 2005Q1. All returns are deviations from bank mean. NII + net sec is net interest income plus net gains on securities, a proxy for ALM risk; trading income is a proxy for market risk; provisions is a proxy for credit risk; other income is all other income plus net extraordinary items less non-interest expenses and is a proxy for total non-financial risk.

It is apparent that many of the correlations are small and several are negative. Going down the first column, the correlation of total pre-tax earnings with the components, net interest income plus net gains on securities, our proxy for asset/liability risk, is correlated a modest 0.500 with total earnings; trading income, the market risk proxy, is only weakly correlated at 0.023; while the correlation with provisions, the credit risk proxy, is of the same size as asset/liability risk at -0.386 and has the expected sign – earnings decline when provisions increase. Similarly, earnings increase when other income, the proxy for total non-financial risk, increases (correlation is 0.389).

The correlations between the earnings components, which may be thought of as proxies for inter-risk correlations, show the source of some inter-risk diversification. For instance, other income (non-financial risk) appears to act as a hedge against asset/liability risk: their correlation is -0.481.

There is no guarantee that the correlations reported in Table 6, which are estimated over the entire sample, are necessarily reflective of the tails. Tail dependence is notoriously difficult to estimate with any accuracy (Poon, Rockinger, and Tawn 2004). Prudential risk management suggests that implied hedges across different categories of income may not hold during times of market turmoil.[24]

3.3. Robustness Checks

In this section we conduct a series of robustness checks along two important dimensions: bank size and sample period. First, it is possible that the tails of the RORWA distribution may be dominated by small banks, and thus drawing inferences from the full sample about large banks may not be appropriate. Moreover, large banks may have a different business mix than smaller banks, implying a different risk type allocation. We check for large bank effects by repeating our analysis only for banks with more than $10bn in assets (2005Q1 dollars). Since this reduces the sample by more than 75%, we restrict the large bank analysis to quarterly data.

Second, our full sample period extends from 1981 through 2004 (1986Q1 through 2005Q2 for the quarterly analysis), but the latter half of the period has been much more benign for banks than the first half. The early period was marked by two recessions, serious emerging market debt and real estate lending problems, and the New England and Texas banking crises, culminating in the highest rate of U.S. bank failures since the Great Depression in 1991. Since then, bank failure rates have dropped significantly, due in part to the improved macroeconomic environment, changes in bank supervision, and the growing use of more powerful risk management techniques. We check for differences in both aggregate risk and risk contribution across the two periods by splitting our sample. Given that new regulation in the form of FDICIA

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[24] See, for instance, Longin and Solnik (2001) who find that correlations increase in bear but not in bull markets.

was enacted at the end of 1991 and the full implementation of the first Basel Accord took effect in 1991-92, we think it is reasonable to extend the first period through the end of 1992, and start the second period at the beginning of 1993. Since the sample size is reduced, we confine our analysis just to the 99.9% (or 10bp) tail.

Left Tail of Earnings Distribution/VaR (%): Robustness Check

	# of obs.	0.05 / 99.95	0.1 / 99.9	0.5 / 99.5	1 / 99
Implied rating: quarterly, annual		BBB+, A	BBB-, A-	BB-, BB+	B+/B, BB
Quarterly (1986Q2 - 2005Q1)	22,770	-7.14	-4.85	-2.67	-1.75
Quarterly, big banks (1986Q2 – 2005Q1)	5,153	-5.95	-3.92	-2.42	-1.72
Quarterly (1986Q2 – 1992Q4)	7,963	-9.43	-7.59	-3.59	-2.79
Quarterly (1993Q1 - 2005Q1)	14,807	-3.25	-2.98	-1.36	-0.92
Annual (1981 – 2004)	7,396	-14.74	-10.81	-6.00	-4.38
Annual (1981 – 1992)	3,680	-16.80	-14.74	-7.89	-5.34
Annual (1993 – 2004)	3,716	-8.32	-4.58	-3.20	-2.31

Table 7: Implied credit rating for left tail percentiles for quarterly and annual return on risk weighted assets (RORWA), in percent, for different sample periods. Big banks are defined as banks with more than $10bn in assets (2005Q1 dollars). Implied credit ratings are presented in Table 3.

The results are presented in Table 7, where the full-sample results are repeated from Table 4 for easier comparison. The first comparison is size: large banks appear to experience fewer extremely adverse RORWA outcomes then do smaller banks. For instance, the 99.9% VaR is -3.92% (quarterly) for large banks but -4.85% for all banks.

The differences are more dramatic across time periods. For instance, 99.9% VaR levels are more than double (-7.59% vs. -2.98%) in the first period than in the more recent period using quarterly data, and triple using annual data (-14.74% vs. -4.58%). While the probability of a -8% RORWA occurring is 0.28% over the whole sample period, it is 0.49% in the first sample period, corresponding to about a BBB- rating, and only 0.05% in the second (A).

Despite the apparent reduction in bank risk since 1993, there is no guarantee, of course, that the experience of the first sub-period will not be repeated. We therefore caution against basing conclusions on the benign record of the recent period. Alas, whether a permanent regime shift has occurred is, at this time, unknown.

Next we investigate whether the risk allocation is sensitive to bank size and sample period using the quarterly data. The results are summarized in Table 8, where the first entry in a given cell uses the total sample and is taken from Table 5 for easy comparison. The second entry is for large banks, and the next two are for the first and second sub-period (1986Q2 – 1992Q4, 1993Q1 - 2005Q1) respectively. Size seems to have a rather small impact on the risk allocation. Large banks seem to have somewhat more market (trading) risk at 7-8% of the total rather than 4-6% for all banks. Their level of asset/liability risk is a little higher, they seem to have a little less credit risk and a bit more non-financial risk. That modest difference in business mix, however, results in a larger diversification benefit ranging from 38% to 55% in contrast to 31% to 37% for all banks.

Left Tail of Earnings Distribution/VaR (%): Robustness Check

Risk Type	0.05 99.95	0.1 99.9	0.5 99.5	1 99
A given cell (using first cell)	1986Q2 – 2005Q1: all banks (5), large banks (7) All banks: 1986Q2 – 1992Q4 (3), 1993Q1 – 2005Q1 (10)			
Market (trading)	5, 7 3, 10	6, 8 3, 9	4, 7 3, 6	4, 7 2, 6
Structural A/L	19, 29 16, 28	18, 20 12, 24	20, 20 13, 31	22, 20 13, 31
Credit	46, 41 54, 24	47, 46 58, 22	47, 43 56, 21	44, 44 60, 22
Total non-financial	29, 22 27, 37	30, 26 27, 42	29, 29 28, 44	30, 29 25, 42
Diversification benefit	31, 55 33, 51	37, 48 32, 42	34, 42 27, 46	37, 38 23, 49

Table 8: Allocation by risk type for the left tail of the earnings distribution, measured in return on risk weighted assets (RORWA). All values in percent. The first entry in a given cell uses the total sample and is taken from Table 5. The second entry is for large banks, and the next two are for the first and second sub-period (1986Q2 – 1992Q4, 1993Q1 - 2005Q1) respectively. Diversification benefit is the difference between the sum of the tail components and the total (reported in Table 7 above).

The choice of sample period has a more pronounced effect on risk allocation. When looking at all banks in our sample, the contribution to total earnings volatility seems to have shifted away from credit risk and towards market, structural A/L and non-financial risk in the recent period. In fact, based on the experience since 1993, credit risk accounts for only about

22% of total earnings volatility – an improbably low calibration relative to Basel II and industry norms.[25] This reinforces the caution against extrapolating solely from the recent record.

3.4. Implications for *K, u*, and *U*

If we accept the rank ordering of risks in terms of the *K*, *u*, *U* framework in Section 2.3, we are now in a position to say something about how much we know and don't know about the different sources of bank risk. Figure 7 reproduces our risk taxonomy, with the percentage contributions from each source, as reported in Table 5 using the whole sample period and all banks. It turns out that we know the most about the least significant source of risk, market risk. We know the least about business risk, which accounts for 18% of total earnings volatility and is thus three times bigger than market risk. More generally, the two risks which practitioners have spent the most time quantifying – market and credit risk – account for only about half of total earnings volatility. The three risks – structural asset/liability risk, operational risk, and business risks – whose measurement approaches are non-standardized and under-developed – account for the other half. The two non-financial risks with the largest amount of unknowns and unknowables account for nearly a third of total risk. And splitting non-financial risk based on prior research and the Basel II calibration suggests that operational risk (12%) is actually a less significant source of earnings volatility than business risk (18%) – the last frontier of risk quantification.

[25] As credit instruments have become more tradable, and credit assets have shifted from the banking to the trading book, credit risk too has shifted. In this way our reported credit risk is likely biased downward.

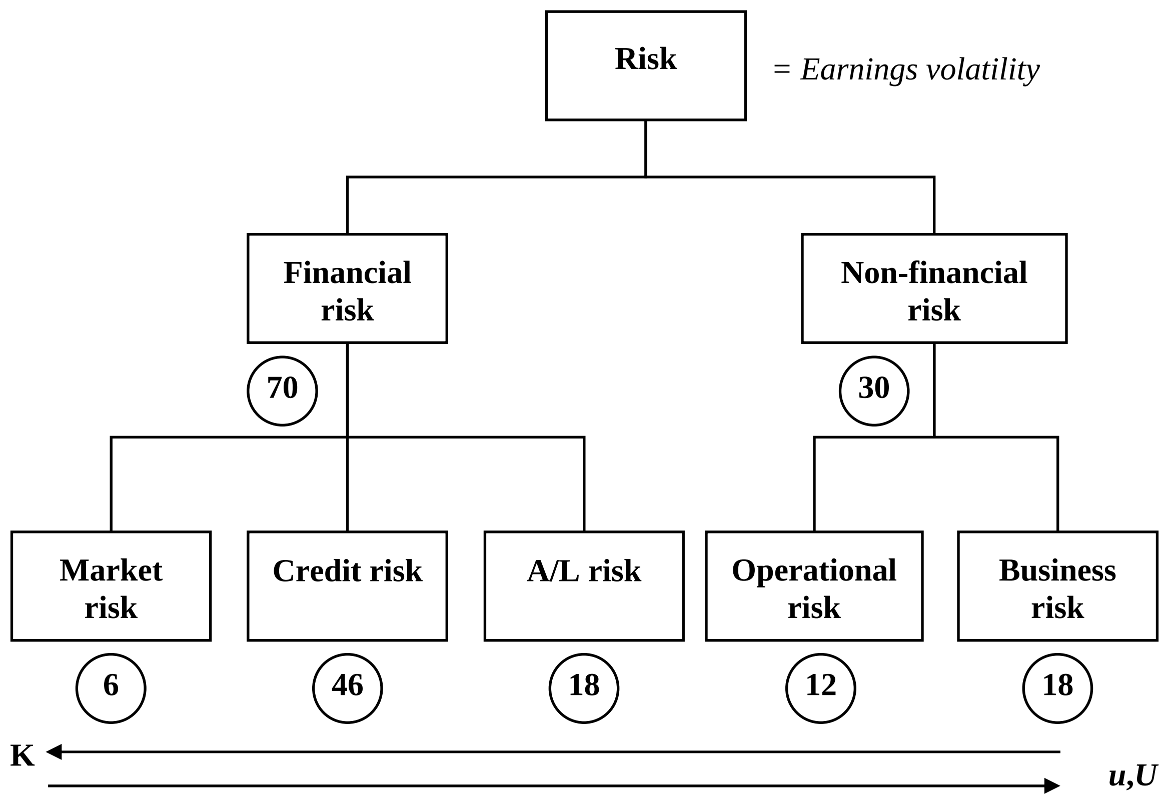

Figure 7: Risk taxonomy revisited, with risk contribution. Numbers in circles are percent risk allocation.

4. Implication for Policy: Private and Public

Our findings on the relative magnitudes of bank risk and their positioning in the *K, u,* and *U* space have implications for policy, both public (supervision and regulation) and private (business strategy). The bigger the source of risk, the more attention it should command from risk managers and regulators. And the more "known" a risk is, the greater our ability to manage it.

The relative contribution of the different sources of bank risk, as reflected in Figure 8, can be seen to justify the attention risk managers and regulators have historically paid to credit risk. Credit risk is the largest source of bank earnings volatility. Although our knowledge of credit risk falls short of market (trading) risk, whose rich data environment enables the most robust economic capital modeling, we have an increasingly strong understanding of credit risk fundamentals. This view is reflected in the proposals to allow (and, for the largest U.S. banks, require) highly granular, transaction-level quantification of credit risk under Basel II. Taken together, the relatively advanced state of knowledge of credit and market risk covers half of the total risk pie.

Looking forward, however, greater returns to risk management can be expected from progress in the three categories of risk that are less well understood. From a policy perspective, Basel II imposes a new Pillar 1 capital charge for operational risk, a relative small source of earnings volatility, while ignoring both asset/liability and business risk, which together account for over one-third of total earnings volatility.[26]

It is perhaps surprising that the regulators chose to tackle operational risk – which, according to our risk positioning is relatively hard to measure and subject to many unknowns – rather than seek to standardize the approach for characterizing and measuring asset/liability risk. Subjecting asset/liability risk to an explicit capital charge would have completed the regulatory capital framework for all of a bank's financial risk taking. Instead, an important source of financial risk is left out of the picture. One need not look too far from banking to understand the significance of risks inherent in structural asset/liability positions – witness the recent financial restatements of Freddie Mac and Fannie Mae, and the public debate over the size of the U.S. mortgage banks' balance sheets. Simply put, if the regulators feel comfortable placing operational risk under Pillar 1, they should feel at least as comfortable doing so with asset/liability risk.

[26] To be sure, interest rate risk is covered under Pillar 2.

At the same time, the recent focus on operational risk management sparked by the inclusion of operational risks within the Basel II framework, should not lead to a false sense of comfort. Operational risk, as defined in Basel II, appears to account for only about 12% of total earnings volatility and less than half of non-financial risk. The more important source of non-financial earnings volatility is business risk, which is still largely unexplored (see Figure 3). It is far from clear, however, whether regulators should seek to impose a mandatory capital charge for this risk source.

The existing risk profile of banks may in part be explained by the state of *K*, *u*, and *U* today. Bank managers may be more comfortable taking market and credit risk because they understand it and feel they can manage it. Or, equally, they may use their knowledge of credit and market risk to carefully control this portion of risk taking so as to keep total earnings volatility within acceptable bounds. As more is learned about the harder to measure risk types, new products will likely evolve to help manage these risks better. This, in turn, may make banks more willing to assume other risks. In this way, there is likely to be an endogenous link between the level of risk knowledge, on the one hand, and banks' business activities and risk profile, on the other.

We have already seen a transformation in bank risk taking as financial innovation, especially in the area of derivatives, has spread. For instance, the development and subsequent spread of credit derivatives and securitizations, such credit default swaps and CDOs, has allowed banks to shed significant amounts of credit risk. Such risk management practices are already bearing fruit: Schuermann (2004) shows that U.S. banks weathered the 2001 recession far better than previous recessions in part due to improved credit risk management techniques. Progress in other parts of the risk space may have a similar influence on bank activities and risk profile.

For both practitioners and policymakers, the message may be to stop looking for keys under the lamppost. The search for improvements in risk management should focus on the sources of risk that are the least “known” and have the greatest impact on earnings volatility.

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