Risk Management Myopia and the Case for Total Exposure Management

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ABSTRACT

The paper addresses critical shortcomings of 'enterprise-wide' risk management mechanisms and suggests a more complete framework as the first step toward remedying those deficiencies. The inadequacy of current approaches is illustrated through analyses of root causes of the Great Recession of 2007 and 2008, which are explored from the standpoint of key failures of what was deemed the state-of-the-art risk management systems. The analysis offers an outline of the developments that eventually precipitated the 2007/2008 financial crisis: Starting with the gradual deregulation of commercial banks (in the U.S), followed by the rise and rapid growth of highly speculative and complex financial derivatives, and the subsequent emergence of credit default swaps – a de facto debt insurance, though structured and positioned to not be subject to insurance-like regulation and mandated reserving discipline; lastly, devastating impact of the wide-scale embrace of an esoteric mathematical formulation – the Gaussian copula function – as the basis of financial risk estimation is also addressed. Casting those developments in the context risk management systems' over-reliance on known, estimable risk exposures, the author proposes a broader and more complete organizational danger abetment framework, Total Exposure Management, encompassing the current disciplines of enterprise risk management, organizational resilience and change management.

Keywords: enterprise risk management; organizational resilience; the Great Recession; credit default swaps

1. INTRODUCTION

At the tail end of 2007, the United States and, to a somewhat lesser degree, the world economy became engulfed in a financial crisis, the likes of which has not been seen since the Great Depression. The Great Recession (Cynamon, Fazzari & Setterfield, 2013; Geisst, 2012) contributed to the loss of trillions of dollars of consumer wealth and a sharp decline in economic activity; even more startlingly, the crisis precipitated failures or near-failures of key financial organizations[1], which were unable

[1] For instance, 140 banks failed in the U.S. in 2009 alone (compared to 25 failure the year before), leaving in their wake more than $34 billion in losses sustained by the Federal Deposit Insurance Corporation. It marked the highest rate of bank failure since the savings and loan crisis of the 1980s and early 1990s, during which time 747 savings and loan associations failed at a combined cost of more than $160 billion.

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to sustain the staggering losses[2] they brought upon themselves. In addition, far-reaching efforts of monetary authorities in the U.S. and abroad, aimed at preventing an outright collapse of the financial system, resulted in substantial fiscal commitments incurred by governments (Cochrane, 2011; Karabegovic & Veldhuis, 2010; Pollin, 2012).

Crises of that magnitude can only happen because of system-wide, structural problems. Looking back, the financial near-catastrophe of 2007 appears to have been a direct consequence of excessive risk taking, itself a product of the gradual deregulation of the financial system. A closer look at the U.S banking industry illustrates that point.

1.1 THE GENESIS OF THE CRISIS

Until the early 1980s, commercial banks were restricted, for the most part, to financial intermediation – deposit taking and lending – to the exclusion of more speculative (i.e., risky) financial activities, such as underwriting of corporate securities (Calomiris, 2000). Furthermore, banks were also geographically constrained – in general, they were not permitted to expand beyond their home states. Under those conditions, the systemic risk – which is the vulnerability of the entire banking system – was relatively low, the assessment of banks' risk exposure fairly straightforward, and the failure of a single bank unlikely to threaten the stability of the entire financial system. At the same time, however, both the growth and the profitability of banks were, according to the proponents of free markets and self-regulation, 'artificially constrained' (Matiland, 1985; Phillips, 1988).

All of that began to change in the early 1980s with the onset of broad deregulation ushered in by the U.S President Reagan's administration. By the mid to late 1980s, essentially all key banking restrictions have been lifted, which freed banks to expand both in terms of geography as well as the scope of operation (see the U.S Banking and Financial Amendments in the Financial Services Competitiveness and Regulatory Relief Act). As evidenced by the rapid growth of financial derivatives, or instruments which derive their value from underlying assets, the banks' risk appetite grew by leaps and bounds. Now largely uninhibited in their pursuit of potentially riskier investment strategies (Demyanyk, Ostergaard & Sorensen, 2007), financial intermediaries embraced ever more speculative and complicated investment vehicles, such as collateralized debt obligations, or CDOs[3]. Some of those vehicles were in fact so complex that their true riskiness was practically indeterminate[4] which, oddly, did not seem to concern the executives investing in them, or the rating agencies evaluating their

[2] A 2010 estimate by the Organization for Economic Cooperation and Development linked $1.23 trillion in banks' losses to the financial crisis of 2007/2008.

[3] Collateralized debt obligations, or CDOs, are a type of structured asset-backed security whose value and payments are derived from a portfolio of underlying fixed-income assets. CDO securities are split into different risk classes, or tranches, whereby senior tranches are considered the safest securities. Interest and principal payments are made in order of seniority, so that junior tranches offer higher coupon payments (and interest rates) or lower prices to compensate for additional default risk. The first CDO was issued in 1987 by the now-defunct Drexel Burnham Lambert Inc.

[4] This is a retrospective conclusion; the Gaussian copula function, discussed later in this section, was at the time thought capable of yielding a reliable, if not deterministic, assessment of the underlying riskiness of investment derivatives.

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investment-worthiness (or, for that matter, regulatory agencies, such as the U.S Securities Exchange Commission).

In the end, the aggressive deregulation of the U.S. financial services industry created an environment where banks had the means, in the form of large deposit pools, and the motives, in the form of potentially high yields, to commit billions of dollars to increasingly more speculative investments. Ultimately, the unchecked demand for exotic (an industry euphemism for 'unintelligible risk') securities infused substantial amounts of systemic risk into the financial system, thus effectively creating a potential for a large scale financial disaster...Yet on paper, trillions of dollars of wealth were created.

The lion's share of the multi-trillion dollars, systemic risk-dressed-as-wealth bonanza was a speculative pyramid, a proverbial house of cards. Its foundation was a combination of housing market-based financial derivatives and the widely held belief in the improbability of a systemic housing price collapse (the belief held by most was that the housing market was primarily driven by regional economic forces, meaning that prices in one region moved independently of other regions' prices). In the end, presumably sophisticated financial intermediaries exposed themselves, their shareholders, and most importantly, those whose assets they managed to unacceptable amounts of risk. For that reason alone, we should view the 2007/2008 financial meltdown as nothing less than one of the farthest-reaching failures of executive risk management of the modern era.

1.2 THE CULPRITS

As tends to be the case with just about any man-made catastrophe, the financial crisis of 2007/2008 led to many revelations and even more accusations. Fingers were pointed at executives of the financial giants teetering on the edge of collapse (e.g., Mardsen, 2010; Santoro & Strauss, 2014), regulatory and rating agencies (e.g., Andenas & Chiu, 2014; Gray & Akseli, 2011), and of course, risk analytical tools that became the staple of financial risk management (Harris, 2014). Undoubtedly, much of the criticism is quite on point and warranted – still, some of the commentaries reflect a lack of deeper understanding of the underlying mechanisms, most notably, those attributing the responsibility for the financial collapse to quantitative risk measurement and management systems. Let us take a closer look.

It is clear that risk management models did not foresee the coming of a catastrophe. That said, the reasons are considerably more complex than what tends to be discussed by media pundits. In the most general sense, the roots of fail we among risk management models' can be traced to multiple factors, perhaps the most visible of which is the normalcy of the patterns embedded in the available data. Simply put, contemplating and event which has not been observed, at least not within a reasonably recent history, is beyond the capabilities of risk assessment tools, or more specifically, mathematical models used to estimate the probability and the severity of adverse events. Stated differently, model-derived projections that comprise the core of risk quantification systems are essentially extrapolations (more or less) of patterns contained in historical data, which effectively define the limits of what a given model can anticipate. It means that if a particular outcome has not occurred within the time horizon covered by the data used in the analysis, the resultant mathematical projections

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will not "foresee" it, which is to say that no numeric chances of that outcome materializing[5] will be generated.

Of course, one can create scenarios that look beyond the available data, but the probabilities associated with such scenarios will lack the requisite empirical rigor, which is usually necessary to establish the credibility of any model-based projections. In other words, without the foundation of hard data, catastrophe-prophesying forecasts are nothing more than speculative guesses, which rarely have behavior-changing impact. And in the case of most risk management models, the available data was simply not indicative of the events that materialized in 2007 and 2008 (Stekler & Talwar, 2013), and if anyone was indeed pursuing speculative doomsday scenarios, that work did not get much attention, at least not among the vast majority of the key decision makers...More on that in the next section.

The relative normalcy of historical trends, however, was only one of the factors that contributed to the inefficacy of risk models. The other major trouble spots were the data analytic methodologies and data analytic assumptions – both of which further 'stacked the cards' against those tools' chances of forecasting the perfect storm of undesirable conditions. An in-depth discussion of those considerations falls outside the scope of this overview, but let it suffice to say that broadly defined statistical analyses (a collection of mathematical techniques for analysis of data) and analytical assumptions were both geared – as it is usually the case – toward forecasting likely, not aberrant outcomes (Banasiewicz, 2014). Stated differently, the inner structure of risk estimation tools has been designed with the goal of identifying events that could occur within a reasonable event and/or time horizon. Focusing on likely rather than aberrant outcomes may be viewed by some as a nearsighted choice, but in fact it is a natural consequence of the scientific method, the philosophical and analytic bedrock of modern science (Diggle & Chetwynd, 2011; Wolf, 1925). The key precepts of the scientific method entail the gathering of observable (i.e., measurable) evidence subject to specific principles of reasoning, which in turn supports the derivation of generalizable knowledge claims; most of what we refer to as empirical knowledge is a product of the broadly defined scientific method. As it relates to the analysis of risk, scientific method-derived outcomes, such as specific risk estimates, are not only more computationally manageable, but are also empirically verifiable – clearly, an important aspect of fostering the believability of numeric estimates. However, it all comes at a cost, which in this case is the aforementioned focus on likely, rather than aberrant outcomes.

Still, the roots of inefficiency in risk assessment tools run deeper than the nature of probabilistic projections. Even the most enlightened knowledge creation processes cannot overcome fundamental data deficiencies or compensate for the lack of data. And

[5] The ideas expressed here touch upon differences separating deterministic algorithms and the Monte Carlo simulation method. The former are often referred to in business as predictive analytics, which most commonly take the form of mathematical functions, where pre-determined inputs are related to an outcome of interest and where a particular set of inputs always produces the same output. The latter rely on repeated computation of random or pseudo-random numbers and are used for modeling phenomenon characterized by significant uncertainty of inputs. The common misconception surrounding the Monte Carlo method is that it can be used to model unknown outcomes, where in fact the (Monte Carlo) method-generated data requires the specification of a probability distribution (from which the data is generated in a random fashion). In other words, Monte Carlo method will not yield worthwhile results without some basic knowledge regarding the phenomenon of interest.

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therein lies the rub: The focal risk projections were based on *proxies*, rather than outcome-specific data, because of the scarcity of direct behavioral data.

That was precisely the case with credit default swaps, or CDSs[6]. In the world of commercial transactions, the actual credit defaults are relatively rare, which means data paucity, which in turn impedes the estimation of (future) default probabilities[7]. At the same time, default swap price data, which tracks third party credit risk insurance (called 'swaps' for reasons discussed later) premium prices, is readily available. Taking a seemingly small leap of faith of assuming that the market prices individual risks correctly, an idea itself inspired by the efficient market hypothesis (Burton & Shah, 2013), CDS price spreads can then be interpreted as risk differentials. Add to that an ingenious application of a long-standing mathematical formula bearing the esoteric name of Gaussian copula function (named after its creator, a prodigal 18th//19th century mathematician C. F. Gauss) and the result is an elegantly simple solution to the previously intractable problem of quantifying default probabilities of bundled securities (Jaworski, Durante & Hardle, 2013). In essence, the application of the Gaussian copula function to CDSs' prices reduced a conceptually complex and computationally messy task of estimating joint default probabilities to a relatively simple measure of bundled risk, expressed in the form of a single correlation estimate.[8] It did not matter how large or diverse the underlying asset pool was – if the overall credit default swap price correlation was low, the bundle of securities was deemed to be low risk. It was indeed a powerfully compelling idea, and essentially every major financial institution, from Wall Street to Main Street, embraced it.

The result was that just about anything that could be packaged into attractive investment pools – consumer mortgages, corporate bonds, bank loans – was indeed packaged, with the resultant market becoming known as collateralized debt obligations, or CDOs mentioned earlier. The wide-spread reliance on – and belief in – the Gaussian copula function-based risk measurement was the engine that propelled the CDO market to a spectacular growth, expanding from about $275 billion in 2000 to more than $4.7 trillion in 2006 – a 17-fold increase in just six or so years. The credit default swap market, which provided default insurance for the CDOs, grew right along with it. Aided by the absence of a natural ceiling on a number of swaps that could be sold against a

[6] A type of financial derivative product, a *credit default swap* is a transaction where the buyer of the swap receives credit protection, while the seller guarantees the credit worthiness of the product. In general, it is a means of transferring the credit exposure of fixed income products between parties.

[7] In order to be projectable and representative, statistically derived estimates require adequately large sample sizes, which translates into adequately high historical default rates (what constitutes adequate sample size is subject to numerous technical considerations which fall beyond the scope of this book, though they are detailed in most basic statistics texts).

[8] In statistics, *copula function* is a general method of formulating multivariate distribution in such a way that variable interdependencies can be captured; the Gaussian function is one of many different types of copula functions. The appeal of this approach stemmed from the fact that by employing simple transformations (which themselves make use of an established methodology, known as the Sklar's theorem) otherwise disparate default rates could be expressed in terms of a uniform distribution, which in turn would make it possible for a bundle of risks to be expressed as a multivariate distribution of marginally random default rates. All of this means that Gaussian copula enabled financial intermediaries to quantify the combined risk of bundles of otherwise dissimilar securities as a single number, the inter-item correlation among component risks. The lower the correlation – the lower the risk, since the correlation measures the degree to which the component securities' credit default prices tend to move, or vary together.

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single borrower, the CDS market grew to enormous proportions – from little more than $900 billion at the tail end of 2001, to its peak of more than $62 trillion at the end of 2007. It is a staggering amount of financial obligations, to say the least – to put it into perspective, the 2008 gross domestic product (GDP) of the United States was about $14.4 trillion; the combined GDP of all countries of the world was about $60.9 trillion.[9] In other words, the peak value of the CDS market was greater than the combined economic output of the entire world! A speculative bubble of truly epic proportions.

And last but not least: Even though, as mentioned above, credit default swaps were essentially a form of insurance, they were not treated as such – i.e., the obligations were not subject to insurance-like regulatory or reserving requirements.[10] Betting on the steadily increasing home values and the improbability of systemic defaults, the underwriters, such as the now-defunct Lehman Brothers and Bear Sterns as well as nearly-defunct AIG, were issuing billions upon billions of IOUs, making hefty profits at the time of issuance, while setting aside precariously little in reserves to cover future obligations…

What does all of that tell us about risk management? For one, it points to the conclusion that the failure to anticipate and manage the exposure of organizations to large scale risks was correlated with – but not caused by – risk estimation tools failing their users. The true cause of the meltdown was the users' failure to take the models for what they were – estimates that were subject to data and methodological limitations.

Those who continue to point to the inadequacy of risk quantification methodologies as the primary culprit of the financial meltdown seem to have lost sight of the obvious – namely, that the goal of mathematical models is to extract meaningful insights out of otherwise prohibitively large amounts of disaggregated data, not to make decisions, per se. In that sense, risk models provide decision makers with information pertinent to the decision at hand, but always subject to data and methodological limitations. The making of the actual decision almost always entails a combination of multiple data-derived projections or estimates and the decision maker's subjective knowledge and experience. All considered, mathematical models always have been – and as far as I can tell – always will be subject to data limitations and computational assumptions, while the decision making process will (hopefully) remain to be a uniquely human endeavor. And so will the responsibility for errors in judgment – hiding behind data support systems' inadequacy amounts to nothing less than a remarkable abdication of decision makers' responsibilities.

1.3 WHAT IF?

In the earlier discussion of the nature of quantitative risk models, I mentioned that if anyone was indeed pursuing speculative doomsday scenarios, that work did not get much attention (among decision makers). This statement touches upon an important consideration, one that I would like to explore further: What if the failed and nearly-

[9] According to the International Monetary Fund's *World Economic Outlook* database, October 2009.
[10] A reserve, from an insurance standpoint, is a sum of money that is set aside to meet some future obligation; its purpose is to make sure that the policy issuer is able to meet its obligations with regard to individual policies. Reserves are classified as liabilities on the company's balance sheet, which is one of the principal reasons the issuers of CDSs avoided classifying their product as insurance.

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failed organizations' risk management models did indeed forecast the very scenario we watched unfold in the latter part of 2007 and beyond? Would enough of the decision makers have believe those forecasts and acted accordingly?

Naturally, it is a lot easier to point out faulty reasoning looking back rather than looking ahead, yet at the same time, singling out the mistakes of the past is an important aspect of learning for the future. However, it is not as simple as just describing the chain of events that precipitated the event of interest or detailing the overt circumstances surrounding it. In general, the majority of economically catastrophic events are circumstantially dissimilar, which means that the uniqueness of each man-made catastrophe may greatly outweigh any cross-event commonalities. Stated differently, studying the root causes of the financial meltdown of 2007/2008 may help relatively little in preventing another crisis from occurring in the future, just as lessons learned from the Great Depression (late 1920s – early 1930s), the Black Friday stock market crash of 1987, the European Sovereign Debt Crisis and other severe economic downturns did little to help forecasters foresee the looming crash. A more instructive approach –at least insofar as economic crisis-like events are concerned – is to evaluate the event of interest in the context of the fundamental nature of human behavior, the key aspects of which capture the more generalizable and enduring qualities likely to shape the future.

In business, as well as a number of other contexts, human behavior is driven primarily by the balance between reward and punishment – the larger the disparity between these two elements, the more the heavier-weighted of the two will influence behavioral outcomes (Dufflo, 2012; Mohr, 1996). That means that, if the upside (i.e., reward) of risk taking is significantly greater than its downside (i.e., punishment), the propensity of individuals to take on greater amount of risk will increase, which in aggregate will lead to the heightening of systemic risk. With that in mind, let us consider the character of (broadly defined) financial intermediation. As it relates to the balance between reward and punishment, financial intermediation is primarily institutional in nature (i.e., the ultimate risk takers are the shareholders of organizations, not the individual decision makers within organizations), but the reward structure favors the individual decision makers over the shareholders as a group (Santoro & Strauss, 2012), as evidenced by Wall Street bonuses awarded to individual decision makers being generally higher than gains realized by Wall Street firms' shareholders (Stewart, 2010). Hence when big bets lead to big losses, it is typically the shareholders who suffer the consequences (as the value of their equity holdings declines) – yet, when big bets lead to big gains, it is the individual decision makers who reap the greatest benefits, typically through large cash bonuses (the share prices of their organizations may not necessarily increase – even if they do, the gains will typically be comparatively modest). In short, there are ample examples where the decision makers' upside of risk taking greatly outweighs its downside. Under those circumstances, risk taking tends to not be a zero sum (where reward and punishment are proportional), but rather a positive sum (where reward is significantly greater than the punishment) game, which manifests itself in a heightened propensity to take risks.

Given the above outlined reasoning, let us go back to the original question: What if the failed and nearly-failed organizations' risk management models did indeed forecast the very scenario we watched unfold in the latter part of 2007 and beyond? Would enough decision makers believe those forecasts and act accordingly?

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In my view not likely, simply because the reasons for dismissing doomsday forecasts (i.e., the potential rewards) were much more enticing than the reasons to accept those forecasts were threatening (i.e., the potential punishment). Stated differently, given the reward—punishment asymmetry, there are good reasons to believe that the majority of institutional investors would have looked past doomsday projections, even if such forecasts were readily available. In a more general sense, we could say that so long as it is possible (at least for some) to engage in high risk—high potential payoff activities with relative impunity (i.e., little-to-no punishment), even clairvoyant risk assessment models will be of little help in averting disasters...

2 RISK MANAGEMENT MYOPIA & THE WAY FORWARD

Let us take the idea of informational adequacy a step further and imagine for a moment that the reward—punishment asymmetry is corrected: Would the current risk management structures provide an acceptable risk measurement and response mechanism, at least for most organizations, most of the time?

Clearly, this is a very broad question and the answer will, to a large degree, vary across industries and organizations. For instance, financial companies are typically quite proficient at managing credit risk because they are in the business of lending money; industrial companies, on the other hand, tend to excel in operational risk management, such as workplace safety, as exemplified by DuPont, long a standard-bearer in workplace safety, tracing its proficiency to the company's heritage as an explosives manufacturer. However, risk type-specific proficiencies usually do not translate into overall risk management excellence for three fundamental reasons: 1. skill, data and methodological differences across different types of threats; 2. different levels of importance implicitly or explicitly assigned to different risks; 3. myopic risk management practices. The implications of the first two contributors are intuitively obvious – the third one, however, requires a more in-depth explanation.

To be carried out effectively, the task of managing risk needs to be approached as a system of interconnected decisions that jointly determine the organization's performance rather than as a series of largely unconnected tasks, which is essentially the idea behind enterprise risk management, or ERM (ISO 31000, 2009; Lam, 2014; Taylor, 2014). However, even the state-of-the-art ERM approaches are ultimately focused on known risks with well-defined mathematical properties (Bromiley, et al., 2014), which renders those approaches ineffective for anticipating and responding to Great Recession-like events. Furthermore, to understand and manage the organization's aggregate risk exposure, one must consider not just individual risks – such as natural disasters, labor disputes, product liability or securities litigation – but must also develop a robust understanding of system-level interdependencies among the individual components of the entire risk management system (Marchetti, 2012), which is not expressly contemplated by leading enterprise risk management frameworks (COSO, 2004; ISO 3100, 2009). In short, to effectively manage the *totality* of threats confronting them, organizations need to look beyond current ERM frameworks that emphasize estimation-friendly known risks.

A word of clarification: I am not suggesting that effective management of risk is contingent on the development of some type of a complex super-model encompassing all aspects of the organization and reducing complex systems to a set of deceitfully

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simple indicators. Quite to the contrary, I believe that such a mindset can lead to over-reliance on poorly understood and, quite possibly, unreliable decision guides, such as the Gaussian copula function discussed earlier. More specifically, risk managers should embrace purposeful and coordinated mining of the available data – and – should use the resultant insights as guides to reducing chances of selecting disadvantageous (to the organization) courses of action. However, rather than blindly depending on complex model-generated predictions of future states, managers would be well-advised to make use of data analytical techniques that 'fit' the quality and reliability of the available data, which could be simple measures of association or tests of difference yielding analytically simpler, but nonetheless more reliable insights. Stated differently, risk management should be approached as an empirical process, or one focused on revealing objectively verifiable causal interdependencies, but the use of the available data needs to reflect data's quality (accuracy, completeness, representativeness, etc.) as well as the projectability of historical trends.

Almost running counter to the aforementioned over-reliance on 'black box' mathematical models is the invariance in the use of the available data across different decision contexts. In some situations, such as credit risk assessment, data is used routinely to support decision making processes, while in other contexts, such as cultural, political or competitive risks, hardly at all. The reasons for that are both tangible (i.e., the availability of data) as well as intangible, the latter captured in the idea of behavioral inertia.

Nearly a century has passed since the pioneering work of F. W. Taylor (considered by many the father of scientific management) and more often than not, management is still viewed (and more importantly, practiced) as art, rather than science. We tend to favor our subjective 'gut feelings' over objective evidence, a phenomenon attributed, by cognitive psychologists and brain researchers alike, to our evolutionary development (Fleagle, 2006; Lawrence, 2011). Obviously, intuition and experience-based decision making worked remarkably well within the confines of grand evolutionary processes – why couldn't it work equally well in business? Indeed, there are times when our instincts can and do work quite well, so long as the economic climate is calm and stable (as was the case through much of the 1990s). However, there are reasons to believe that the future might be considerably less unwavering. Even looking past the myriad social and security related flashpoints, there is emerging evidence suggesting that the economy is growing more turbulent; in fact, some of the leading management strategists now believe that turbulence is not an aberration, but the new face of normal (Kotler & Caslione, 2009). What does this mean for management decision making? The frequency with which many decisions will need to be made will rapidly increase, which means that effective risk management in the 21st century and beyond will have to be considerably more information-intensive. Intuition alone simply will not suffice.

It is not to say, however, that it will become less demanding of human problem solving. Quite to the contrary—the demands on decision makers will increase, most notably in terms of decision lead time and decision making frequency. As suggested earlier, experience and intuition alone, though always of value, will be insufficient if not aided by robust, objective informational infrastructure. Incidentally, business landscape is becoming more and more permeated by database systems and complex data crunching algorithms, a trend which contributes to the growing automation of various

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aspects of operational decision making. Unfortunately, it is a mixture of good and bad. On the plus side, it helps to translate (and thus, utilize) the vast quantities of data available to most organizations into more usable decision-aiding knowledge. Yet (and that is the negative), the resultant knowledge is not always consumed in the most beneficial manner, or not consumed – in the sense of being used in the decision process – at all. Using objectively derived insights as a decision linchpin is slowly gaining grounds, but old habits are, once again, proving themselves to be hard to break...

Lastly, it is important to not lose sight of the fact that the goal of automated information processing is to reduce or altogether eliminate tedious, non-thinking, and non-creative tasks and by doing so, free up time and resources for a more constructive use. The goal is not to replace creative problem solving with 'check-the-box approaches. Yet, that is not always the case in risk management, where there is a tendency to use decision support systems as an excuse not to think, as opposed to a reason to think and look deeper. In a very basic way this type of risk management automation was probably a strong contributor to the financial community's willingness to accept collateralized debt obligations and other convoluted investment instruments with structures so complex that they required Nobel-track scientists to set up, and dozens of pages of contractual documents to describe.

2.1 TOTAL EXPOSURE MANAGEMENT

Historically, business organizations approached management of risk as expense minimization function, aiming to secure the greatest amount of risk protection for the lowest possible cost (Eckles, Hoyt & Miller, 2014; McPhee, 2014). In fact, even the state-of-the-art enterprise risk management (ERM) approaches (COSO, 2004; ISO 31000, 2009) are still primarily focused on risk economics (Marchetti, 2012), striving to optimize the net risk reduction, transfer and mitigation costs. The desirability of risk transfer efficiencies notwithstanding, the attainment of competitively advantageous danger abetment structure demands active management of not only estimation-friendly known risks, but also harder to grasp unknown, or non-estimable threats. Furthermore, it also calls for inclusion of self-imposed organizational transformations, typically aimed at enhancing organizational functioning, efficiency and effectiveness, broadly referred to as change management (Baca, 2005; Franklin, 2014; Green, 2007; Smith, 2015).

Considering that the widely accepted ERM frameworks effectively restrict the definition of 'enterprise-wide' to known risks with well-defined statistical properties (Bromiley et al., 2014), the management of the *totality* of organizational exposures necessitates looking those conceptualizations. That line of reasoning appears to be supported by the emergence and rapid maturing of two additional (to ERM) and distinct, danger abetment focused disciplines: *organizational resilience* (OR) and *change management* (CM). A relatively recent concept, OR builds on the more established (dating back to 1970s) disciplines of business continuity management (Engemann & Henderson, 2012; Sheffi, 2005), disaster risk reduction (Doefel, Chewning & Lai, 2013; Fleming, 2012) and adaptability (Moran, 2014; Strycharczyk & Elvin, 2014); its goal is build and continuously strengthen the organization's ability to absorb and recover from the impact of unknown or non-estimable events. The second of the two new risk abetment focused disciplines, CM, first emerged in 1980s as a consulting practice helping large business organizations with adaption of new programs and technologies

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(Smith, 2015); now more broadly focused and theoretically sound, it is primarily concerned with maximizing the benefits of self-imposed organizational transformations (Franklin, 2014; Green 2007; Raineri, 2011). Given the obvious dangers associated with 'shacking up' of organizations, change management addresses important aspects of managing organizational dangers, not contemplated by traditional risk management practices.

Consider the high level outline of the Total Exposure Management (TEM) framework, graphically depicted in Figure 1. The centerpiece of this conceptualization are organizational assets, ore more specifically, protection of those assets. The three distinct organizational asset protection focused disciplines – risk management, organizational resilience and change management – are shown as rings, each responsible for a different dimension of the *total* organizational asset exposure management: *Risk management*, the outermost ring, shields organizational assets from the impact of known, estimable risks; *organizational resilience* provides a buffer which absorbs unknown / non-estimable threats; lastly, *change management* maximizes the organization's ability to grow its assets by facilitating successful organizational transformations.

Figure 1
Total Exposure Management

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REFERENCES

[1] Andenas, M. and Iris H. Y. Chiu (2014), *Foundations and Future of Financial Regulation: Governance for Responsibility,* Routledge, Abingdon, UK.

[2] Baca, C. (2005), *Project Manager's Spotlight on Change Management*, Harbor Light Press, San Francisco, CA.

[3] Banasiewicz, A. D. (2014), *Risk Profiling of Organizations,* 2nd ed., Erudite Analytics, Boston, MA.

[4] Bromiley, P., M. K. McShane, A. Nair and E. Rustambekov (2014), "Enterprise Risk Management: Review, Critique, and Research Directions", *Long Range Planning,* in press, 1-12.

[5] Burton, E. T. and S. N. Shah (2013), *Behavioral Finance: Understanding the Social, Cognitive, and Economic Debates,* Wiley, Hoboken, NJ.

[6] Calormiris, C. W. (2000), *US Bank Deregulation in Historical Perspective,* Cambridge University Press, New York, NY.

[7] Cochrane, J. (2011), "Understanding Policy in the Great Recession: Some Unpleasant Fiscal Arithmetic", *European Economic Review,* 55(1), 2-30.

[8] Cynamon, B. Z., S. M. Fazzari and M. Setterfield (2013), *After the Great Recession: The Struggle for Economic Recovery and Growth,* Cambridge University Press, Cambridge, UK.

[9] Demyamyk, Y., C. Ostergaard and B. E. Sorensen (2007), "U.S Banking Deregulation, Small Businesses, and Interstate Insurance of Personal Income", *The Journal of Finance,* 62(6), 2763-2801.

[10] Diggle, P. and A. Chetwynd (2011), *Statistics and Scientific Method: An Introduction for Students and Researchers,* Oxford University Press, Oxford, UK.

[11] Doerfel, M. L., L. V. Chewning and C. H. Lai (2013), "The Evolution of Networks and the Resilience of Interorganizational Relationships after Disaster", *Communication Monographs,* 80(4), 533-559.

[12] Duckert, G. H. (2011), *Practical Enterprise Risk Management: A Business Process Approach*, Wiley, Hoboken, NJ.

[13] Dufflo, E. (2012), "Rigorous Evaluation of Human Behavior", *Science,* 336, 1398.

[14] Eckles, D. L., R. E. Hoyt, and S. M. Miller (2014), "Reprint of: The Impact of Enterprise Risk Management on the Marginal Cost of Reducing Risk: Evidence from the Insurance Industry", *Journal of Banking & Finance,* 49, 409-423.

[15] Engemann, K. J. and D. M. Henderson (2012), *Business Continuity and Risk Management: Essentials of Organizational Resilience,* Rothstein, Brookfield, CT.

[16] Fleming, R. S. (2012), "Ensuring Organizational Resilience in Times of Crisis", *Journal of Global Business Issues,* 6(1), 31-34.

[17] Fleagle, J. G. (2006), *The Human Evolution Source Book,* Prentice Hall, Upper Saddle River, NJ.

[18] Franklin, M. (2014), *Agile Change Management: A Practical Framework for Successful Change Planning and Implementation,* Kogan Page, London, UK.

[19] Geisst, C. (2012), "The Great Recession", *Financial History,* 104, 36-38.

[20] Goldman, E. F. (2006), "Strategic Thinking at the Top", *MIT Sloan Management Review,* 48(4), 75-81.

[21] Gray, J. and O. N. Akseli (2011), *Financial Regulation in Crisis? The Role of Law and the Failure of Northern Rock,* Edward Elgar, Cheltenham, UK.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM)

[22] Green, M. (2007), *Change Management Masterclass: A Step by Step Guide to Successful Change Management,* Kogan Page, London, UK.
[23] ISO 31000, International Organization for Standardization (2009), *Risk Management – Principles and Guidelines*, www.iso.org
[24] Jaworski, P., F. Durante and W. K. Hardle (2013), *Copulae in Mathematical and Quantitative Finance: Proceedings of the Workshop Held in Cracow,* Springer, Berlin, Germany.
[25] Harris, M. (2014), *Inside the Crystal Ball: How to Make and Use Forecasts,* Wiley, Hoboken, NJ.
[26] Karabegovic, A. and N. Veldhuis (2010), "The 'Great Recession'?", *Fraser Forum,* May, 12-16.
[27] Kotler, P. and J. A. Caslione (2009), *Chaotics: The Business of Managing and Marketing in the Age of Turbulence,* American Management Association, New York, NY.
[28] Lam, J. (2014), *Enterprise Risk Management: From Incentives to Controls,* 2nd ed., Wiley, Hoboken, NJ.
[29] Lawrence, P. (2011), "What Leaders Need to Know about Human Evolution and Decision Making", *Leader to Leader,* 60, 12-16.
[30] Marchetti, A. M. (2012), *Enterprise Risk Management: Best Practices from Assessment to Ongoing Compliance,* Wiley, Hoboken, NJ.
[31] Mardsen, C. (2010), "Economics, the Financial Crisis and Corporate Responsibility", *Corporate Governance,* 10(4), 360-364.
[32] Matiland, I. (1985), "The Limits of Business Self-Regulation", *California Management Review,* 27(3), 132-147.
[33] McPhee, J. E. (2014), *Mastering Strategic Risk: A Framework for Leading and Transforming Organizations,* Wiley, Hoboken, NJ.
[34] Mohr, L. B. (1996), *The Causes of Human Behavior: Implications for Theory and Method in Social Sciences,* University of Michigan Press, Ann Arbor, MI.
[35] Moran, A. (2014), *Agile Risk Management,* Springer, New York, NY.
[36] Phillips, J. (1988), "The Self-Interest of Self-Regulation", *Freeman,* 38(2), 66-68.
[37] Pollin, R. (2012), "US Government Deficits and Debt amid the Great Recession: What the Evidence Shows", *Cambridge Journal of Economics,* 36(1), 161-187.
[38] Raineri, A. B. (2011), "Change Management Practices: Impact on Perceived Change Results", *Journal of Business Research,* 64(3), 266-272.
[39] Santoro, M. A. and R. J. Strauss (2012), *Wall Street Values, Business Ethics and the Global Financial Crisis,* Cambridge University Press, New York, NY.
[40] Sheffi, Y. (2005), *The Resilient Enterprise: Overcoming Vulnerability for Competitive Advantage,* MIT Press, Cambridge, MA.
[41] Smith, R. (2015), *The Effective Change Manager's Handbook: Essential Guidance to the Change Management Body of Knowledge*, Kogan Page, London, UK.
[42] Stekler, H. O. and R. M. Talwar (2013), "Forecasting the Downturn of the Great Recession", *Business Economics,* 48(2), 113-120.
[43] Stewart, J. (2013), "Common Sense: Looking for Fairness in Wall Street Bonuses", *Wall Street Journal,* Jan. 13, D-2.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM)

[44] Strycharczyk, D. and C. Elvin (2014), *Developing Resilient Organizations: How to Create an Adaptive, High Performance and Engaged Organization,* Kogan Page, Philadelphia, PA.
[45] Taylor, L. (2014), *Practical Enterprise Risk Management: How to Optimize Business Strategies through Managed Risk Taking*, Kogan Page, Philadelphia, PA.
[46] Wolf, A. (1925), *Essentials of Scientific Method*, Macmillan, New York, NY.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM)