

When Is the Root of All Evil not Money? The Impact of Load on Operational Risk at a Commercial Bank

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Abstract

Operational risk is now among the three most significant types of risks in the financial services industry, and its management is mandated by Basel II regulation. This paper studies how bank operational risk event frequency (or error rate) and severity (potential losses) are affected by workload to inform better labor decisions. To achieve this goal, we use a unique operational risk event data set from a commercial bank in China that contains 1,441 operational risk events in two years. We find that workload has a U-shaped impact on operational risk frequency. More specifically, the error rate of operational risk events would decrease first as workload increases and then increase. In addition, we show that workload has an inverted-U shaped impact on bank profit. Based on the causal relationships between workload and operational risk events and profit, respectively, we discuss bank capital allocation impact of changing the staffing level among branches so as to reduce operational risk losses and improve profit. We compare our optimal staffing policy with bank's original policy, and estimate that the new staffing policy would reduce the current number of employees by 7.56%, which would further decrease the number of risk events by 4.51%, cut the total losses by 4.58%, and increase profits by 1.24%.

Key Words: operational risk, workload, frequency, severity, capital allocation, optimal staffing.

1 Introduction

Operational risk (OpRisk) in financial services is defined as *the risk of losses due to failures of internal processes, people or systems, or due to occurrences of unexpected external events* (see the Basel Committee on Banking Supervision (2006)). For example, it includes execution and process management-related risk events, such as data entry errors, accounting errors, failed mandatory reporting, and negligent loss of client assets. OpRisk is one of the three major risks (together with credit risk and market risk) that banks face and have a dire need to minimize, especially after the 2007-2009 global financial crisis, which cost the banking sector trillions of dollars due to poor risk management (Ashby, 2010). For example, according to Barclays 2014 Annual Report¹, OpRisk accounts for 9% of its total risk exposure (around 3,285 million USD), tied with market and liquidity risk (9%), and second only to credit risk (72.4%), while the remainder

¹<http://www.home.barclays/annual-report-2014.html>.

is due to various other risks (e.g., funding, conduct risks). Because of its significance, regulators from all over the world generally require their banks to set aside capital in reserve in order to protect themselves in the OpRisk event. The Basel Committee on Banking Supervision (BCBS) in Basel, Switzerland, whose members include 27 major economies (e.g., the U.S., the U.K., Japan and the BRIC countries), makes recommendations and sets guidelines with regard to minimum capital requirements for risk management (Marrison, 2005). After making recommendations for the credit and the market risks in 1988 (i.e., Basel I), the Basel Committee issued a new set of regulations and guidelines with regard to capital reserves for the OpRisk in 2004, which is referred to as Basel II. Recent regulations (Basel and Sarbanes Oxley) have made operational risk management even more important in the financial industry. Hence, mitigating the OpRisk so as to reduce the capital reserves is a practically significant goal that global banks earnestly strive for.

Furthermore, unlike the credit and the market risks, OpRisk is often perceived by the management as more controllable (Deloitte, 2013) because proper monitoring process can prevent such risk events from happening (Kaplan and Mikes, 2012). However, it is the most difficult type of risk to assess its consequences and causes, since OpRisk is a type of low-frequency high-severity risk, which means only a few data are available (Cruz, 2002). Therefore, there are many opportunities for operations management researchers to improve our understanding about the causes of the OpRisk and make better operational decisions to mitigate such risks in the future. Despite its importance, little empirical Operations Management research has been done probably because the OpRisk data set is typically unavailable for academic research.

In this paper, we study how workload (defined as the total number of transactions handled per employee), an important work environment factor (see Bendoly et al. (2006), and more details will be provided in Section 2), affects the operational risk events frequency (or error rate) and severity (potential loss scale). In particular, we use a unique longitudinal operational risk data set from a Chinese commercial bank that contains 1,441 operational risk events between August 22nd, 2013 and April 30th, 2015. The operational risk events in our data set are all execution and process management-related, with examples provided in Subsection 4.1. Adopting an instrumental variable (IV) approach to account for potential endogeneity issues, we find that workload has a U-shaped relationship with operational risk error rate. More specifically, the error rate of operational risk events would decrease first and then increase as workload increases. Using the detailed description of our risk events data, we find that, under low workload scenario, employees tend to make performance-seeking risks, while under high workload scenario, employees tend to make errors or have quality degradation due to cognitive multitasking. Moreover, we find that the workload has an inverted-U shaped impact on bank profits. When the workload is low, positive effects dominate as more transactions happen, but when the workload is high, negative effects dominate as excessively high workload degrades the employees' performance.

Based on the causal relationships between workload and operational risk events and profit, respectively, we discuss the impact of bank capital allocation by changing staffing level among branches to reduce operational risk losses. We compare our optimal staffing policy with bank's original policy, and estimate that the new staffing policy would reduce the current number of employees by 7.56%, which would further decrease the number of risk events by 4.51%, cut the total losses by 4.58%, and increase profits by 1.24%.

The contributions of this paper are three-fold. First, to the best of our knowledge, our paper provides the

first empirical analysis of the causes of operational risks in the banking industry, while the previous studies tended to model OpRisk as an exogenous probability distribution. In particular, we establish a causal link between workload, an important work environment factor which is determined by management, and the error rate of operational risk events. Second, we revisit the growing area in operations management on the impact of workload on operational performance, and we broaden our understanding about workload and staffing decisions in the financial industry. This area is understudied in the empirical OM literature. Third, our empirical study enables us to explain the variation in OpRisk events, so that we can build a capital allocation model to re-optimize bank staffing levels among branches to improve OpRisk management.

2 Related Literature

Our research contributes to three streams of literature: i) retail banking operations, ii) labor management and iii) OpRisk in financial services, respectively.

The first stream of literature relevant to our work concerns the retail banking operations. Hitt and Frei (2002) explore the difference between electronic and physical distribution channels by studying the case of personal-computer-based (PC) banking. Campbell and Frei (2004) use a unique data set from a financial services firm to study the persistence in customer profitability. Xue et al. (2007) study the effect of customers' banking channel usage on retail banking performance. Campbell and Frei (2010) research the impact of consumers' adoption of online banking channel on their interactions with a major U.S. retail bank. Buell et al. (2016) probe customers' reaction to the increasing service quality competition, and find that for firms to maintain high quality level they need to attract and retain profitable consumers over time. In general, existing literature on retail banking operations focused on channel decisions and customer management; however, no research has been done to study OpRisks and bank operations.

The second stream of relevant work studies optimal labor decisions in service industries. One large stream is labor management in retail, (please see Ton and Huckman (2008) and Kesavan and Mani (2015) for a comprehensive literature review). Staffing is a key managerial decision in this setting because it affects operational performance. For example, Perdikaki et al. (2012) find that increasing staffing level by one standard deviation from the sample mean improves the marginal returns to traffic from \$10.00 to \$11.32 per person. In addition, Chuang et al. (2016) suggest that sufficient staffing critically enables retailers to fully seize the sales opportunities of increasing store traffic. If understaffed, however, stores are estimated to suffer from lost sales by 8.56%, and lower profitability by 7.02%, a result found in an apparel retailer setting (Mani et al., 2015). Beyond estimating the counter-factual effect of staffing decisions, Fisher et al. (2017) implement a new staffing rule and validate the counter-factual estimation in practice. They find that their staffing rule increases revenues by 4.5%, and annual profits by \$8.9 million, adjusting for the additional labor costs. In this study, we additionally show the importance of staffing decisions by analyzing one pathway of how staffing affects operational performance through the workload.

Studying workload and operational risks adds to an increasing number of Operations Management papers that have answered to the call for researching how external factors, such as workload, affect workers' performance (Boudreau et al., 2003). These papers have mostly examined the impact of workload on op-

erational performance in a healthcare setting, but none of these have studied the financial sector, one of the most significant sectors of the economy². For instance, KC and Terwiesch (2009) conduct an empirical analysis of the impact of workload on service time using operational data from patient transport services in cardiothoracic surgery. KC and Terwiesch (2012) find that the occupancy level of a cardiac intensive care unit is negatively correlated with patients' length of stay. In addition, Powell et al. (2012) find that overworked physicians generate less revenue per patient because of a workload-induced reduction in due diligence with regard to paperwork. Kuntz et al. (2014) discover a nonlinear relationship between hospital workload and mortality rates. Berry and Tucker (2016) analyze two years of inpatient data from 203 hospitals in California and find an N-shaped relationship between occupancy and length of stay. Aral et al. (2012) find that multitasking (a proxy for workload) level exhibits diminishing returns to project output in a midsize executive recruiting firms. Tan and Netessine (2014) analyze a large, detailed operational data set from a restaurant chain and show an inverted-U-shaped relationship between the workload and the waiter's service speed and sales output. In this paper, we broaden the studies on workload to the financial services industry, an economically significant industry, and study the impact of workload on operational risks in financial services.

Finally, compared to the extensive literature on market risk and credit risk (e.g., French et al., 1987; Jarrow and Turnbull, 1995; Altman and Saunders, 1997; Dowd, 2007), OpRisk in financial services has generally received little attention in the past. Nevertheless, given its practical significance and new regulations, OpRisk has been receiving growing interest in the academic literature in the recent years, which we contribute to in three ways. First, much of the academic research tended to discuss the modeling, the measurements, and the regulations of OpRisk at the strategic levels, rather than at the operational level, which we study in this paper. For example, Cruz (2002) discusses the background and the definition of operational risk, explains measurement methods, and discusses operational risk management strategies. Chernobai et al. (2007) provide the framework and guidelines regarding operational risk background and measurement models based on Basel regulations. Scharfman (2008) examines the operational risk management framework and measurements with a focus on hedge fund operational risk. None of these studies discuss the operational level decisions that cause operational risks, which is the focus of this paper.

Second, most of the recent papers tend to focus on the statistical modeling of aggregate operational risk loss distributions to estimate the Operational Value at Risk (Ops-VaR) rather than explaining what factors may explain the variation of OpRisk events. For example, Neil et al. (2005) propose a Bayesian Network approach to model both expected and unexpected OpRisk losses. Bocker and Kluppelberg (2005) find a closed-form approximation for Ops-VaR exists when the distribution of OpRisk loss data are heavy-tailed. Unlike these papers, we examine how an important work environmental factor (i.e., workload) affects the frequency and severity of OpRisk events, so that managers can make better decisions to distribute an optimal workload.

Third, recent papers on OpRisk started to focus on the financial applications, but only a handful papers have considered the actual operations management decisions. For example, Leippold and Vanini (2003) propose a theoretical model together with numerical experiments to quantify risk losses for banks through

²<https://www.selectusa.gov/financial-services-industry-united-states>

their value chain. Jarrow (2008) suggests a modeling framework for firm asset pricing with operational risk losses. Within this asset pricing framework, Jarrow et al. (2010) further studied the OpRisk insurance contract. It's noteworthy that these papers tended to neglect the granular level operations decisions (e.g., workforce management), which should significantly affect the OpRisk events in an applied context. Unlike these papers, we examine how an important endogenously determined by management work environmental factor (i.e., workload) affects the frequency and severity of OpRisk events, and we point out that managers can make better decisions to distribute workload optimally. The limited OM literature has recently started to study the causes of OpRisk in non-finance settings. For example, Shah et al. (2017) study the causes of product recalls in the automotive industry. Hora and Klassen (2013) conduct a field experiment to analyze factors that affect firm manager's knowledge acquisition from operational risk losses of other firms. One goal of our paper is to take an initial step in filling the gap between operational risk in financial services and operations management by showing the implications of a fundamental OM decision (i.e., staffing decision) for mitigating OpRisk in financial services.

3 Theory and Hypothesis

Building on the extensive literature about the effect of workload on performance, we propose four main mechanisms for workload to affect OpRisk occurrence. The first two mechanisms will suggest a positive relationship between workload and the frequency of OpRisk events, while the last two will predict a negative relationship. We then develop our main hypothesis, which reconciles these seemingly conflicting mechanisms.

Workload Increases OpRisk (Positive Effect) The first mechanism is cognitive multitasking, which suggests that workers will become less capable of focusing on an individual task when they have to pay attention to an increasing number of tasks because of a limited cognitive capacity (Charron and Koechlin, 2010). In other words, when the cognitive load is high, any additional task will consume a portion of cognitive bandwidth at the cost of other tasks (Schmidt and DeShon, 2007), causing more errors and service quality degradation. A significant amount of empirical literature supports this theory. For example, Powell et al. (2012) find that overloaded physicians become careless about insurance paperwork, which reduces revenue per patient. KC (2013) discovers that when doctors become extremely busy in the emergency room, they need longer time to discharge patients while providing lower quality care. In addition, in a Japanese bank's home loan application-processing line, which is relevant to the setting of this study, Staats and Gino (2012) report that having the workers specialize in one task improves their productivity in a single day because alternating focus among multiple tasks may distract workers' attention in the short term.

Bank employees in our empirical setting also perform multiple cognitive tasks. For example, loan officers usually handle multiple loan requests simultaneously because processing loans takes time while awaiting approvals; financial advisers work with different clients for their investment needs; branch managers oversee all the activities within the branch. When workload increases, bank employees are more and more likely to lose focus on any particular task, causing them to make errors and increase OpRisk of various

severity, which may range from forgetting to make photo copies of required documents to failing to verify the validity of clients' information, to losing important documents/seals or even forgetting to lock the safe.

The second mechanism concerns various workload-induced anti-productive emotions. Excessively high workload may exhaust workers and reduce their physical and cognitive capacities, making them prone to errors (Cakir et al., 1980; Setyawati, 1995). In addition, heavy workload can stress and frustrate workers, who may consequently cut corners and produce low-quality work (Peters and O'Connor, 1980; Oliva and Sterman, 2001; Bendoly, 2011). Moreover, extra workload can confuse and intimidate workers because various tasks may create conflicting goals and exacerbate the difficulty of accomplishing these tasks, which can lead to a lack of commitment and motivation to fulfill them (Donahue et al., 1993; Dalton and Spiller, 2012). Empirically, Kuntz et al. (2014) examine the discharge records and discover that high hospital occupancy increases front-line clinical workers' stress hormones and forces them to ration resources and become more error-prone, thus increasing patient's mortality rate.

As front-line workers in banks, tellers have to perform multiple duties, such as check cashing, depositing, transfer, withdrawals, and issuing cashier's checks and money order. In addition, they need to promote the bank's products, resolve various customer issues, batch and process proof of work, while following all the OpRisk standards. When their workload expands, these tellers may encounter all the aforementioned anti-productive emotions and consequently violate the OpRisk protocols. For example, a tired teller may type the wrong deposit amount into the system or mishandle counterfeit money. In addition, a frustrated teller may become impatient with clients and even violently quarrel with them, damaging the bank's reputation and future business. A confused or intimidated worker may even commit financial fraud.

To sum, workload may increase OpRisk because of cognitive multitasking and various anti-productive emotions. Nevertheless, workload may also reduce OpRisk through the following two mechanisms.

Workload Reduces OpRisk (Negative Effect) The first negative effect mechanism is motivation, which can be strengthened by workload to increase workers' human capacity and thence performance (Deci et al., 1989). Indeed, additional workload can increase arousal regarding the work, which helps workers stay "in the zone" (Bendoly and Prietula, 2008; Bendoly, 2011). Increased workload may also be perceived as exciting and setting challenging goals. Such goals may improve workers' motivation according to the goal-setting theory (Locke, 1968; Latham and Locke, 1979). In addition, extra workload is found in cognitive psychology to trigger the cortex to release hormones that enhance cognitive performance (Lupien et al., 2007). On the other hand, a very light workload may trigger workers to fill the idle time with irrelevant and counter-productive activities, aka "Parkinson's Law" (Parkinson, 1958).

When workload is low at banks (e.g., branch traffic is low), bank employees are more likely to be inclined to engage in counter-productive activities, such as chit-chatting with coworkers, checking their phones, playing with games, and attending their own personal affairs, all of which can distract workers' attention and make OpRisk-related mistakes. On the opposite side, increasing workload can reduce such idle time and stimulate the workers to expend more effort to ensure their work quality and follow the OpRisk protocol.

The second mechanism is economic multitasking (e.g., Holmstrom and Milgrom, 1991), which suggests

that employees may rationalize their effort provision towards different tasks, where they earn their rewards. This theory implies that varying workload may change the risk and return of the tasks, thus prompting workers to reallocate their attention priority. For example, Tan and Netessine (2014) find that restaurant waiters have a strong incentive to increase attention to generating sales from each table at the expense of slower service speed under light workload (measured in terms of the number of tables that a waiter simultaneously handles) because waiters want to maximize their earnings (i.e., tips, which are directly related to sales) from the limited number of tables that they are assigned to, and because the waiting cost of customers is low. Under heavy workload, however, waiters have a different incentive to shift the focus onto faster service speed because the waiting cost becomes high, and because turning tables faster will seat new customers sooner, and these customers generally spend more money per unit of time than incumbent customers.

Bank employees are faced with two possible income-generating “tasks” - legal day-to-day duties and illegal reward-seeking activities. The former task typically includes increasing deposits, account openings, and other financial product sales, and providing quality service, which are tied to bonus and promotion. The latter is exemplified by various malicious activities, such as coercing customers into making a deposit before releasing a loan payment in order to boost deposit performance, stealing and colluding with outsiders for personal gains, all of which violates the OpRisk protocol. When the workload of regular business is low, bank employees may increase their attention to illegal reward-seeking activities because 1) they may feel considerable pressure to compensate for their otherwise low income from slow regular business and 2) they have more idle time (i.e., lower cognitive costs). However, when the workload of regular business is high, the bank employees may curb the illegal reward-seeking activities because 1) they are more likely to reach their performance goals of legal duties to earn the rewards and 2) they have little latitude to undertake an illegal reward-seeking activities³.

Within these two main effects, we argue that the positive effect may dominate when the overall workload is high, while the negative effect may dominate when the overall workload is low. First, under a heavy workload, employees are more likely to reach or exceed their cognitive and physical capacities, which triggers both cognitive multitasking mechanism and anti-productive emotions to take effect. Second, such heavy load on the worker capacity may further diminish the return of the additional motivation which has to be spread thin across an increasing number of tasks. By contrast, under low workload, the gain of the additional motivation is maximized because workers only focus on a limited number of tasks. Third, the low workload setting is especially conducive to economic multitasking because the pressure of income is intensified. For these reasons, we hypothesize that:

There is a U-shaped relationship between workload and OpRisk occurrence. That is, as workload increases, the frequency of OpRisk events will first decrease and then increase, controlling for everything else.

³We assume that the employees will prioritize regular legal duties because illegal activities bear two additional costs - a chance of being caught and punished and moral/ethical costs.

4 Data

Our empirical setting is the 49 branches that belong to one major Chinese commercial retail bank in Jiangsu Province. Jiangsu is one of the largest provinces in China with second highest GDP nationwide⁴. In 2013, the bank implemented a new system to record operational risk events, from which we collected our data. Our data covers time period from January 1st, 2014 to April 30th, 2015, when 1,441 operational risk events in total were observed.

The data consist of three parts – operational risk events, transaction-related information, and branch characteristics. In particular, the operational risk event data include bank branch id, event description (in text format), date of occurrence, and severity level. In addition, the transaction-related information contains monthly total number of transactions (deposits and withdrawals) and sales of asset management products. Finally, the branch characteristics capture the total number of employees, branch address, and its distance to the headquarters.

4.1 Operational Risk Events

The operational risk events in our dataset are all execution and process management-related. Some operational risk events in our dataset cause immediate losses to the bank. For example, "Branch X issued loan contract with an interest rate of 1.23 percent instead of 7.23 percent" (translated from Chinese). However, some events may cause losses only in the long run. One such risk event is recorded as follows, "On August 25th, 2014, Branch X issued Company X RMB 2 million (Note: Chinese currency) loan, and wrote the wrong maturity date as September 1st, 2014 (Error in the date)." Another such event is documented as follows, "On September 10th, 2014, Branch X issued Company X business loans without checking the collateral." In sum, these OpRisk events are related to process conformance (Ton and Huckman, 2008), and will considerably cost banks either in the short or in the long term. All of the events in our dataset were caught and recorded by the audit department of our focal bank, which check the operational processes of each branch every week. Once a risk event was caught, the audit department assigned an operational risk severity score (following the internal risk severity score standard) to each event, which is determined by the potential losses of each event.

4.2 Risk Measures

In this subsection, we define our dependent variables that are related to operational risk losses. We examine two performance measures: the error rate and the average risk severity level per event because they are the two most important performance measures for operational risk losses in practice (Cruz, 2002). In particular, error rate is computed as the total number of risk events divided by the total number of transactions at branch i during month t , namely,

$$Err.rate_{it} = \frac{\text{total number of risk events}_{it}}{\text{total number of transactions}_{it}}. \quad (1)$$

⁴http://www.guancha.cn/economy/2017_01_27_391590.shtml

We call this variable “error rate” because the operational risk events in our dataset are mainly human errors or mistakes. One advantage of using error rate as compared to frequency is that the error rate is scale free relative to the number of transactions. However, later in our robustness check, we conduct Poisson regression on frequency controlling for the number of transactions to further validate our results. We further transform *Err.rate* into its LOGIT form, defined as

$$\text{Logit.err}_{it} = \text{LOGIT}(\text{Err.rate}_{it}) = \log \left(\frac{\text{Err.rate}_{it}}{1 - \text{Err.rate}_{it}} \right), \quad (2)$$

for three reasons (Warton and Hui, 2011). First, the logit scale covers all of the real numbers instead of being limited to a particular range. For example, just as proportion is limited to 0 - 1, the arcsine square root scale is limited to 0 to π . In contrast, the limits of the logit scale are negative infinity and positive infinity. This is particularly important where prediction is needed, as having a bounded scale could give nonsensical results (e.g., more than 100% or less than 0%). Second, the logit scale is more intuitive in that it is the log-odds. This is particularly useful in interpreting slopes from a logistic regression, in which the logit transformation is central. Third, the logit scale correctly models the relationship between the mean and variance in binomial data, where variance is $p(1-p)/n$.

The second dependent variable is *Severity_{it}*, which is calculated as the average severity level of all the events happened at branch *i* during month *t*. The severity level is defined by the central bank of China to reflect the potential losses of each event. It is measured on a scale from 0 to 30, with the higher value indicating a more severe risk. Based on our discussion with the bank, one severity point is associated with approximately 100,000 RMB in potential losses (around 15,000 USD), and we will use this dollar value in our Section 6. Although it is almost impossible to objectively quantify all the losses, the severity level serves as an approximation of actual loss severity because it is measured based on historical event losses.

4.3 Independent Variables

The main independent variable that we study is the workload denoted by *Load_{it}*, which is the average number of transactions that an employee handles at branch *i* during month *t*. We also use an alternative definition of workload to reflect the utilization of the branch in our robustness check section. We further take the square of *Load_{it}* and call it *Loadsq_{it}* to test our hypothesis about the non-linear effect of workload. We standardize these variables by first subtracting their means and then dividing them by the standard deviations, so that the variables are between zero and one.

There is not much guidance in the literature on which controls to use in a study like ours since we are the first to study empirically causes of operational risks in banks. Nevertheless, in addition to the workload measure, we propose the following three types of control variables. First, we account for risk monitoring level. Existing finance literature on bank information production has shown that geographical distance affects bank’s soft information production (J. C. Stein, 2002; Petersen and Rajan, 2002; Agarwal and Hauswald, 2010). We expect the branches that are closer to the bank headquarters to have higher level of monitoring because the headquarters would have better information about branches nearby. Accordingly, we introduce the *Distance_i* variable measured as the distance between the branch and the bank headquarters

as a proxy for monitoring level.

Second, we attempt to control for the difficulty level of the work, which should be correlated with operational risk events because difficult tasks require more cognitive capacity and may be more prone to errors. After meeting with bank managers, we chose to use the sales of financial products, $Mgmtsale_{it}$, as an approximation of task difficulty levels because selling financial products involves comprehensive knowledge and effective communication so as to convince a client.

The third control variable is the “quality” of the branch manager, which should affect company performance including OpRisk control (Core et al., 1999; Huson et al., 2004). Manager quality is typically hard to directly measure. Following the finance and management literature, which used a similar proxy (Hambrick and Mason, 1984; Bhagat et al., 2010), we use the base salary of a branch manager, denoted as $Salary_{it}$, as the manager quality control because the base salary reflects the manager’s industry experience, previous salary, previous position in the company, and other unobserved factors related to past performance. Note that we only use the base salary rather than the total salary of a manager because inclusion of the bonus, which is affected by the operational risk events during the same month, would cause a reverse causality.

Finally, we include a categorical variable (i.e., $Trend_t$) of the 16 months in our dataset to control for the trend and other longitudinal factors.

Table 2 presents the summary statistics of our key variables based on 776 observations (N=776) at a monthly level. Besides the above mentioned variables, we present the summary statistics of the variable $Profit_{it}$, the total profit of branch i at time t , which we will use in our later discussion on capital allocation. On average, each employee at each bank branch handles 1,678 transactions every month, which is equivalent to 56 transactions per day and 5.6 transactions per hour (assuming 10 working hours per day). The risk frequency per month is 1.692 which is consistent with the low frequency property of operational risk (Cruz, 2002). The risk severity level on average is 3.565, which, based on the standard of our focal bank, is equivalent to 356,500 RMB (53,475 USD) in potential losses per risk event. Moreover, the variation of risk severity level is quite large with the standard deviation being 11.2 and the maximum being 94. Notably, certain risk events can cause significant amount of losses, with the maximum in our dataset of 1.41 million USD (94 severity score).

Furthermore, Table 3 presents the correlation coefficients of our variables. We can see that the correlation coefficients among the independent variables are quite low, which alleviates the concern of multicollinearity issues in our estimation.

5 Estimation and Results

We now estimate two panel data models to study the impact of workload on operational risk error rate and severity. Section 5.1 and 5.2 discuss the details of random effects model and fixed effects model, respectively; Section 5.3 presents our identification strategy with instrumental variables (IVs); Section 5.4 shows our empirical results with IV estimation; Section 5.5 summarizes robustness checks of our main results with alternative workload measure and model specification.

5.1 Panel Data Analysis

We specify the random-effects model as follows:

$$\text{Logit.err}_{it} = \alpha + \alpha_1 \text{Load}_{it} + \alpha_2 \text{Loadsq}_{it} + \alpha_3 \text{Control}_{it} + \varepsilon_i^f + u_{it}^f, \quad (3)$$

$$\text{Severity}_{it} = \beta + \beta_1 \text{Load}_{it} + \beta_2 \text{Loadsq}_{it} + \beta_3 \text{Control}_{it} + \varepsilon_i^s + u_{it}^s, \quad (4)$$

where Control_{it} includes Salary_{it} , Mgmtsale_{it} , Distance_i , and Trend_t . In addition, ε_i^f (ε_i^s) and u_{it}^f (u_{it}^s) should satisfy the assumptions of the random effects model (we use ε_i^f and u_{it}^f as an example):

$$\begin{aligned} \varepsilon_i^f &\sim N(0, \sigma_\varepsilon^{f2}), \quad E(\varepsilon_i^f \varepsilon_j^f) = 0 \text{ for } i \neq j, \\ u_{it}^f &\sim N(0, \sigma_u^{f2}), \quad E(u_{it}^f u_{is}^f) = E(u_{it}^f u_{it}^f) = E(u_{it}^f u_{jt}^f) = 0 \text{ for } i \neq j, t \neq s, \\ &E(\varepsilon_i^f u_{it}^f) = 0. \end{aligned}$$

We show our regression results in Table 4. First, column ‘‘RE I’’ in Table 4 shows the estimation result for our model 3 excluding the quadratic term. The result seems to suggest that, as *Load* increases, $\text{LOGIT}(\text{Err.rate})$ decreases, with a negative coefficient -0.326 (at a significance level of 0.1%). Next, column ‘‘RE II’’ in Table 4 shows the estimation results for our model 3 with the quadratic workload term. In Table 4 column ‘‘RE II’’, we find that the coefficient of *Load* is -0.911 and *Loadsq* is positive 0.913 (both at a significance level of 0.1%), which support our hypothesis that states that error rate first decreases in workload and then increases. Interpreting the coefficients, the critical point is equal to $0.911/(2 \times 0.913) \approx 0.5$. Moreover, the manager’s salary has a negative correlation with the error rate with a coefficient -0.185 at a 5% significance level. As we stated in Section 4.3, we use the manager’s salary as a proxy of his/her quality, our estimation results suggest that the manager’s quality has a negative relationship with the error rate, which is expected. We conducted similar analysis for the severity variable, but we did not find statistically significant results for either the linear or the quadratic terms. We omit these results for space considerations. Finally, we find that the quadratic model has a higher R^2 (0.4272 v.s. 0.3856) than the linear model, suggesting that the quadratic model provides a better goodness-of-fit.

We now proceed with the fixed-effects model that captures constant branch-level unobserved heterogeneity. Columns ‘‘FE I’’ and ‘‘FE II’’ of Table 4 in our Appendix show the estimation results. We find results that are consistent with the random effects models. First, $\text{LOGIT}(\text{Err.rate})$ decreases in *Load* in linear model with a negative coefficient -0.164 (at a significance level of 5%). In addition, $\text{LOGIT}(\text{Err.rate})$ first decreases in workload and then increases, with the coefficient of *Load* being -0.428 and *Loadsq* being 0.523 (both at a significance level of 5%). The coefficients suggest that the critical point is close to $0.523/(2 \times 0.428) \approx 0.61$. Furthermore, the impact of workload on risk severity turns out to be not statistically significant in both linear and nonlinear models. Finally, the quadratic specification of the error rate model again yields a better goodness-of-fit ($R^2 = 0.312$) than the linear model ($R^2 = 0.309$), which lends further support for our inverted-U shaped hypothesis.

Between the two panel data models, we elect to use the random-effects model as the primary evidence for the following reasons. First, we conduct the Hausman test (Hausman (1978)), whose null hypothesis

(alternative hypothesis) considers the random-effects (fixed-effects) model specification as an efficient specification of the individual effects. The p -value turns out to be 0.332, which suggest that we fail to reject our null hypothesis at 0.05 level. Second, we find the random-effects model results generally have higher R^2 values than the fixed-effects model results, which indicates that the random-effects model should provide a better goodness-of-fit than the fixed-effects model.

5.2 Identification with Instrumental Variables

Although our panel data models control for both observed and unobserved heterogeneity at the branch level, the models may be prone to some endogeneity issues. For instance, one potential omitted variable could be the branch manager's effort level of engaging in risk management, which should be negatively correlated with the frequency and the severity of OpRisks. In addition, the risk management effort level should be negatively correlated with workload because the manager may be too busy with their actual transactions to manage OpRisks. Hence, we may potentially underestimate the true impact of workload on risk frequency and severity.

To alleviate the endogeneity issue mentioned above, we use instrumental variable (IV) approach, which is widely used to address such endogeneity issues (Kennedy, 2003). The choice of a good instrumental variable should meet two conditions, namely relevance and exclusion (Wooldridge, 2010). The relevance condition requires the IV to be correlated with the endogenous variable, while the exclusion condition requires the IV to be uncorrelated with the error term. In essence, the IV should only be correlated with the dependent variable through the endogenous variable. In our estimation, we use two types of IVs. The first is the local weather variable, namely the monthly average temperature near the branch location (Cachon et al., 2013). In particular, we use the publicly available temperature data⁵ to compute the monthly average temperature of the district where each of the 50 branches is located. On the one hand, the weather variable should be correlated with the workload because customers may refrain from visiting branches and instead use online banking or call centers in extremely low or high temperatures. On the other hand, the weather variable should not affect the risk frequency and severity variables other than through workload because bank workers work in air-conditioned rooms, whose temperature conditions are unaffected by the weather and there are rather strict rules regarding showing up for work independent of the weather.

The second type of IV is the lagged values of the endogenous independent variables, namely the lagged *Load* and *Loadsq*. Following Bloom and Van Reenen (2007), Siebert and Zubanov (2010), and Tan and Netessine (2014), we compute *Lag_load* and *Lag_loadsq* as instruments for the workload of the current month, which are the *Load* and *Loadsq* of the same branch, but one month before. We expect that these lagged values of the endogenous variables should not determine the unobserved factors for risk frequency and severity during the current month but they should be correlated with the current month workload because forecasting for staffing purposes is done one month in advance. Admittedly, the lagged workload may not be ideal instruments because of possible common demand shocks that are correlated over time. However, these common shocks are basically systemic trends (Villas-Boas and Winer, 1999), which are already controlled

⁵https://www.worldweatheronline.com/lang/en-us/v2/historical-weather.aspx?locid=455878&root_id=382895&wc=local_weather&map=~/rugao-weather-history/jiangsu/cn.aspx

for with the monthly dummies. Hence, such a concern about the common shocks should be alleviated.

5.3 IV Estimation Results

We used two-stage least square procedure to re-estimate our random-effects and fixed-effects models with the three IVs and show our estimation results in Table 4. Table 4 Column “RE I (IV)” shows the IV estimation results for our model 3 without the nonlinear term. As the endogeneity issue is corrected by the instruments, the estimated coefficient increases to -0.281 (at a significance level of 0.1%). Next, columns “RE II (IV)” shows the IV estimation results for model 3 with the nonlinear term. We find that the coefficient of *Loadsq* is still positive (coefficient = 0.902 significant at 0.1% level). In addition, the linear term is significant and equal to -0.935 , which implies that the critical point is approximately 0.518 ($-\alpha_1/2\alpha_2$). Comparing the values of R^2 in the linear and nonlinear models, we again find that nonlinear model has a better goodness-of-fit than the linear model ($R^2 = 0.4286$ v.s. 0.3871), which further supports our hypothesis about the U-shaped relationship between workload and the error rate. In addition to the workload impact, we can see that branches where managers have higher salary are negatively associated with $LOGIT(Err.rate)$, which is consistent with our expectation. Higher base salary is correlated with better professional experience of a branch manager, so we would expect that more experienced managers can better control operational risk events. The coefficients of the other two control variables, *Distance* and *Mgmtsale* are not statistically significant.

Again, we did similar analysis for the severity variable, but workload turns out to have no statistically significant impact on risk severity, probably because exogenous external factors of the risk severity (losses), such as market conditions (e.g., interest rate, stock prices) and the value of the transaction, may outweigh endogenous factors, such as worker performance (a more detailed explanation is discussed in Subsection 5.4).

In addition to the RE results, we also show the IV estimation results of the FE model in Tables 4. The main results of workload measures are consistent with the RE models. However, for the FE model, we do not observe statistically significant correlation between managers’ salary and $LOGIT(Err.rate)$. Finally, in order to support our three instrumental variables from a statistical perspective, we first conduct the first-stage regression with RE specification with respect to *Load* and *Loadsq*, and show the results in Table 7. All the three instrumental variables, namely *Lag_load*, *Lag_loadsq* and *Temp* are statistically significant and have the expected signs. In particular, the one month lagged workload is positively correlated with workload in the current month with a coefficient of 0.53. The quadratic term of the last week is also positively correlated with the quadratic term of the current week with a coefficient of 0.447. Finally, the higher the temperature, the higher both *Load* and *Loadsq*, suggesting that under cold weather people tend not to visit bank branches as frequently as under warm weather. We also check the *F*-Statistics (Staiger and Stock, 1997) for the joint significance of the first-stage estimations, and find that they are both over 10, suggesting that our instrumental variables combination is not weak and should satisfy the relevance condition. Finally, for the exclusion restriction condition, we conduct Sargan overidentification (Sargan and Desai, 1988). The *p*-value turns out to be over 0.6, so we fail to reject the null hypothesis that the error terms of the structural models are uncorrelated with the instrumental variables.

5.4 Workload Impact Discussion

Based on the discussion above, so far we find two major results. First, workload has a U-shaped impact on error rate; and second, workload has no statistically significant impact on risk severity. To further understand the estimation results with our proposed workload mechanism, we check the detailed text description of operational risk events in our dataset under two extreme scenarios: extremely high workload environment and extremely low workload environment. We define the extremely high workload environment as top 10% highest workload observations. In this scenario, we find that each employee handles between 21 to 48 transactions per day, and in total there are 29 risk events. Similarly, in the 10% lowest workload observations, each employee handles around 0.5 to 1.5 transactions per day, and there are 11 risk events in total. Table 10 in our Appendix shows the detailed description of the 29 risk events under high workload scenario, while Table 11 presents the 11 risk events under low workload scenario. In Table 10, we can see that under high workload, employees tend to make errors or have quality degradation due to cognitive multitasking. For example, the risk event “Issued 3 million RMB business loan with maturity date as the next day” or “Issues 1 million business loan without the loan usage/interest rate” are such errors. In general, there is a variety of risk events in this table, but most of them seem to be simple mistakes, which neither enhance the performance of employees nor do they appear malicious. By contrast, under low workload (Table 11), employees tend to make performance-seeking risks. For instance, the risk event “Client manager issued 5 million loan without the branch manager’s signature” shows that the client manager used discretion without proper approval to issue the loan to the customer, probably in an attempt to reach certain performance target. In fact, all risk events here are related to issuing loans inappropriately, and issuing more loans is both a major component of employees’ incentives and, at the same time, loans can be issued maliciously (e.g., to relatives). In general, our extreme scenario analysis here is consistent with our proposed mechanisms.

Next, we try to understand why workload has no statistically significant impact on risk severity. From the text description of the risk events, we find the severity level for most risk events depends more on the financial aspect of risk events than on the operational aspect. For example, one such risk is described as follows, “Issued collateral-based loan but did not collect collateral” has a severity score of 6. This severity score is mainly determined by the credit rating of the borrower, a given financial characteristics uncontrollable by the bank employees or by operational characteristics. Another example, “Issued 500,000 loan with 0 interest rate” has a severity score of 5. Again, the severity score 5 here is mainly determined by the current interest rate, which workload of employees would have limited impact on.

5.5 Robustness Checks

In this subsection, we discuss several robustness checks for the impact of workload. First, we consider an alternative definition of workload, which is operationalized as

$$Load2_{it} = \frac{Tran.num_{it}}{Tran.cap_{it}}, \quad (5)$$

where the transaction capacity $Tran.cap_{it}$ is defined as the 95% of the maximum monthly number of transactions (a similar measure is used in Jaeker and Tucker (2016)). We then define the quadratic term $Load2sq$

and use it and *Load2* to replace *Loadsq* and *Load* in RE specification, controlling for the number of employees. The results are shown in first 4 columns of Table 5. As can be seen, the coefficients of the quadratic terms are significant and positive, supporting the U-shaped relationship between workload and error rate. Interpreting the IV results, the critical point is equal to $0.473 (-1.401/(2 \times 1.481))$. We checked once again that the workload has no impact on the risk severity level and we omit these results for space considerations. We further conduct robustness checks with the alternative model specification, Poisson regression. Poisson regression is appropriate here for two reasons: i) our dependent variables (both risk frequency and severity) are count data; ii) most OpRisk measurement models use compound Poisson process to capture the convolution of risk frequency and severity (Cruz, 2002). We show consistent estimation results in last 4 columns of Table 5. Poisson regression also suggests a U-shape impact of workload on error rate, but it again shows no impact of workload on risk severity (results are omitted).

Finally, we adopt alternative approaches to test the U-shaped relationship hypothesis. We first consider a spline regression of workload on error rate. Spline regression can be viewed as an extension of the linear models that are used to characterize the specific nonlinear relationship. It has an advantage of being a non-parametric approach as it does not impose a specific (e.g., quadratic) functional form on the data (Friedman, 1991). Table 8 shows the spline regression results. As can be seen, the coefficient of workload for the piecewise linear function when workload is low is negative starting from -17.419 at a 5% significance level, and it increases to positive with a value of 5.866 at a 5% significance level. This finding is consistent with a U-shape hypothesis. Furthermore, we conduct two-line test and Lind test. The two-line test is used to test the U-shape relationship between x (independent variable) and y (dependent variable) with two separate lines that characterize the low and high value of x separately. Following Simonsohn (2016), we conduct a two-line test. We have the p -value of 0.011 for the left line and 0.0276 for the right line, which suggests the statistical significance of a U-shape. The Lind-test is another method to test the U-shape relationship, which characterizes both necessary and sufficient conditions for such relationship. Following Lind and Mehlum (2010), we conduct the Lind test to validate the quadratic specification, and we have a p -value of 0.025 of the test which rejects the null hypothesis of monotone or inverse U-shape, see Table 9.

6 Discussion on Optimal Staffing Level

Our empirical results suggest a U-shape relationship between workload and error rate. This finding can help banks make better capital allocation decisions on the optimal staffing level among retail branches so as to reduce operational risk losses and improve profit. However, we also need to understand the impact of workload on branch profit. In this section, we first try to understand which factors affect the branch profit, and then we propose a capital allocation model to help make the optimal staffing decision.

6.1 Profit Model

Traditional retail bank staffing decisions at the bank branch level have the goal of maximizing profits, which are also tracked at the branch level. Therefore, in order to understand bank staffing and capital allocation policies, it is important to first understand how staffing decisions affect bank profit. The staffing decision in

our study plays a vital role in determining the workload. Therefore, we estimate the following fixed-effects and random-effects models to explain branch profitability:

$$Profit_{it} = \alpha_i + \alpha_1 Load_{it} + \alpha_2 Load_{it}^2 + \alpha_3 Control_{it}^{fe} + u_{it}, \quad (6)$$

$$Profit_{it} = \beta + \beta_1 Load_{it} + \beta_2 Load_{it}^2 + \beta_3 Control_{it}^{re} + \varepsilon_i + u_{it}. \quad (7)$$

In the fixed effects model (Model 6), $Control_{it}^{fe}$ includes $Transaction_{it}$, $Mgmtsale_{it}$, and monthly dummy variables, and in the random effects model (Model 7), $Control_{it}^{re}$ additionally includes $Distance_i$. We show our regression results in Table 6. In columns “RE I” and “RE II” of Table 6, the coefficients of workload are insignificant, and likewise in columns “FE I” and “FE II” they are insignificant. However, endogeneity issues might exist again here in the profit model.

First, one potential omitted variable might be the level of how aggressive the branch manager is towards performance (profit), which should be positively correlated with workload as well as with profit. Second, workload might increase profit, but on the other hand high profit might also increase workload, which would lead to simultaneity bias. Therefore, to deal with the endogeneous issues here, we use the same set of IVs in our profit function, namely lagged workload and workload square and weather variable, for the same reasons as we mentioned in Section 5.2. We show our estimation results with IVs in column “RE I (IV)” and “RE II (IV)” of Table 6. From Table 6 column “RE II (IV)”, we find that the coefficient of $Load$ is 0.368 and $Loadsq$ is positive -1.057 (both at a significance level of 0.1%), which suggests an inverted U-shaped relationship between workload and profit. More specifically, profit first increases in workload and then decreases. We, here again, conducted Sargan test of overidentification, and we find that the p -value is over 0.4. Hence, together with the first-stage regression results in Table 7, we conclude that our IVs are again valid for this estimation.

We conducted a similar analysis for the fixed effects model and show our results in Table 6, columns “FE I (IV)” and “FE II (IV)”. The results are consistent with the random effects model. To compare the two model specifications, we again conducted the Hausman test (Hausman, 1978). Our null hypothesis considers the RE specification to be an efficient specification of the individual effects. We then compare the results with alternative hypothesis which assumes fixed-effects model, and our Hausman test shows a P -value of 0.016 which means we can reject our null hypothesis. Therefore, fixed-effects model is more appropriate here to capture our profit specification. With this estimation result, we then proceed with capital allocation model.

6.2 Capital Allocation Model

For the banks to decide on the capital allocation to offset the operational risk losses, they need to first estimate the potential losses. As mandated by regulation, a bank typically uses a frequency distribution to project the total number of loss events in given time period, and a severity distribution to represent the potential loss amount of each risk event (Frachot et al., 2001; Guegan and Hassani, 2013a,b). The industry practice is to further assume that the frequency and severity distributions are independent. The total loss is then computed by the convolution of these two distributions using a compound Poisson model. In our case,

the total operational risk losses L_{it} of branch i in month t could be written as

$$L_{it} = \sum_{n=1}^{N_{it}} X_{itn}, \quad \text{for } t = 1, \dots, 16, \quad i = 1, \dots, 49, \quad (8)$$

where X_{itn} is the severity of each risk event at each of the 16 branches in each of the 49 months, and N_{it} is the monthly frequency of the risk events. The monthly risk frequency is found to be affected by workload (a division of the number of transaction by the staffing level) through a U-shaped relationship. In other words, keeping the transaction number constant, optimally changing the staffing levels at each branch, denoted as $S = \{S_1, \dots, S_{49}\}$, affects the risk frequency as follows:

$$\text{LOGIT}(\text{Err.rate}_{it}(S)) = \alpha + \alpha_1 \text{Load}_{it}(S) + \alpha_2 \text{Loadsq}_{it}(S) + \alpha_3 \text{Control}_{it} + \varepsilon_i + u_{it},$$

or equivalently,

$$\text{Err.rate}_{it}(S) = \frac{\exp(\alpha + \alpha_1 \text{Load}_{it}(S) + \alpha_2 \text{Loadsq}_{it}(S) + \alpha_3 \text{Control}_{it} + \varepsilon_i)}{1 + \exp(\alpha + \alpha_1 \text{Load}_{it}(S) + \alpha_2 \text{Loadsq}_{it}(S) + \alpha_3 \text{Control}_{it} + \varepsilon_i)}.$$

Given that

$$N_{it}(S) = \text{Tran}_{it} \cdot \text{Err.rate}_{it}(S),$$

we can obtain the Poisson arrival rate of operational risk events.

After computing the frequency rate, we use the actual severity scores in our data set to estimate the corresponding potential loss X_{itn} . Specifically, according to our conversation with the bank managers, one severity point here is associated with approximately 100,000 RMB (approximately 15,000 USD). Therefore, the potential operational risk losses can be approximated with $100k \times \text{Severity}_{itn}$ RMB. With both X_{itn} and $N_{it}(S)$ defined, the total loss for all the branches over time is

$$L(S) = \sum_{i=1}^M \sum_{t=1}^T \sum_{n=1}^{N_{it}(S_i)} X_{itn}.$$

Since X_{itn} are assumed to be i.i.d, the expected total loss should be

$$E[L(S)] = \sum_{i=1}^M \sum_{t=1}^T N_{it}(S_i) E[X_{it}].$$

Besides capital allocation for OpRisks, we also consider the labor costs in our cost function. From the public income data for retail bank employees in China⁶ and after confirming with bank managers, we use a constant $C = 100,000$ RMB (approximately 15,000 USD) as a proxy for the average annual income of employees, so the annual labor cost is equal to $C \sum_{i=1}^M S_i$. Now we consider the following optimization

⁶http://finance.sina.com.cn/money/bank/bank_hydt/20140401/070918674850.shtml

problem,

$$\max_{S=\{S_1, \dots, S_M\}} \sum_{i=1}^M \sum_{t=1}^T Profit_{it}(S) - \{E[L(S)] + C \sum_{i=1}^M S_i\}. \quad (9)$$

Note that $Profit_{it}(S)$ is the monthly profit function from Section 6.1 which is also determined by the staffing level S . Finally, we use the Gradient Descent algorithm in an integer programming problem to maximize the operational risk adjusted profit, which yields the optimal integer staffing level S^* .

6.3 The Optimal Staffing

We now show the comparison between the optimal staffing level and the original staffing level in Figure 1. As can be seen, by relocating the employees among the branches, our new staffing policy staffs in total 624 employees, 51 (7.5%) lower than the current staffing level (675 employees). Moreover, given that the monthly average number of transactions in all the branches is $15,850 \times 49$, we find that the optimal workload is approximately 41.5 ($15,850 \times 49 / (624 \times 30)$) transactions per day per person as compared to the original 38 transactions per day per person.

We next show the comparison of the risk events frequency in Figure 2. We find that our new staffing policy should reduce the total number of risk events in most of the branches, from 1,441 events in total to 1,375 events in total, a 4.58% decrease. Moreover, we find that the number of risk events spreads more evenly among the branches than before, likely due to the elimination of scenarios with extreme workloads. Combining the results in Figure 1 and 2, we show that banks may reduce operational risk events without even hiring additional people.

Furthermore, we compare the expected losses in Figure 3, and find that the new staffing policy may reduce the operational risk loss amount from 483.35 million to 461.57 million, a 4.51% reduction. In addition, unlike under the current staffing policy, several branches (e.g., branch 19) no longer experience extreme losses under the new staffing policy.

Finally, we compare the OpRisk adjusted profits in Figure 4. The new staffing policy may increase the risk-adjusted profit from 2,967.41 million to 3,004.15 million, a 1.24% improvement, which is practically significant given the 10-year annualized return in money market between 2004 and 2013 was about 1.7%⁷.

7 Conclusion

In this paper, we use a detailed operational risk data set gathered from a commercial bank to study the effects of workload on operational risks in terms of error rate and severity. We adopt an IV estimation strategy to address potential endogeneity issues. We find a U-shaped relationship between workload and error rate. That is, when the overall workload is low, increasing workload will reduce the error rate; however, when the overall workload is high, increasing workload increases the error rate. To explain the mechanism of such empirical finding, we discover that under the low workload scenario employees tend to take performance-enhancing risks as workload increases. By contrast, under the high workload scenario, as workload further increases, employees tend to make more errors or have quality degradation due to cognitive multitasking.

⁷<https://www.forbes.com/sites/advisor/2014/04/24/why-the-average-investors-investment-return-is-so-low/#71d11a2e111a>

Although we find an U-shaped relationship between workload and error rate, we do not observe statistically significant impact of workload on risk severity because the importance of exogenous external factors of the risk severity (losses), such as market conditions (e.g., interest rate, stock prices) and the value of the transaction, seem to outweigh the impact of endogenous factors, such as worker performance.

We find that bank's current staffing decisions create avoidable operational risk events because of imbalanced workload among branches. To generate an alternative staffing policy, we solve an OpRisk-adjusted profit maximization problem. In particular, we first estimate a profit function in terms of workload, controlling for everything else. Then we combine this profit function with an OpRisk loss function, approximated by a compound Poisson model, together with the labor costs, and we maximize the risk-adjusted objective function. The new staffing policy would reduce the staffing level by 7.56%, which should reduce the OpRisk error rate by 4.51% , and the total OpRisk losses by 4.58%, while increasing the OpRisk-adjusted profit by 1.24%.

Our study makes the following contribution to the literature. To the best of our knowledge, our paper is the first empirical work that analyzes the causes of operational risk from an OM perspective in the banking industry, while the previous studies tended to model OpRisk as an exogenous probability distribution. In particular, we establish a causal link between workload, an important work environment factor, and the error rate of operational risk events. Second, we revisit the growing area in operations management - the impact of workload on operational performance - and broaden our understanding about the importance of the workload and staffing decisions in the financial industry, which is understudied in the empirical OM literature. Third, our empirical study enables us to explain the variation in OpRisk events, so that we can build a capital allocation model to re-optimize bank staffing levels among branches and improve OpRisk management.

Finally, it is important to understand the limitations of our work and establish future research directions. First, although our dataset is very unique with respect to the operational risk events collection, we only cover the category of data entry errors, accounting errors, failed mandatory reporting and negligent loss of client assets. Clearly, there are still other types of operational risk events that we did not study in this paper. An interesting future research direction could be in conducting field experiments to study the internal fraud or external fraud events and explore incentive issues. Second, our data do not specify the complexity of the transactions which may also affect the workload. Future research with more granular level data can study how the complexity of transactions would affect workload and thus operational risks. Third, our work focuses on the workload and operational risk events in the physical branches. Given the growing adoption of online and mobile banking, it is worth examining online, or mobile banking channels would affect OpRisk.

Appendix A: Tables

Table 1: Gross Losses by Event Type–Reported to ORX over the Period 2008-2012.

Risk Event Type	Total (Million)	% of Total
Internal Fraud	3,142	2.57%
External Fraud	12,322	10.06%
Employment Practices & Workplace Safety	2,844	2.32%
Clients, Products, & Business Practices	77,505	63.28%
Disaster Recovery & Public Safety	504	0.41%
Technology & Infrastructure Failures	2,236	1.83%
Execution, Delivery & Process Management	23,921	19.53%

Table 2: Summary statistics (monthly).

Variable	Definition	Mean	Sd.	Min	Max
Mgmtsale	Sales of financial products in 10,000 RMB	133.7	167.4	0.000	1,637
Tran.num	Number of transactions each branch in 1,000	15.85	1.850	14.00	43.50
Num.empl	Number of employees in each branch	10.16	2.790	6.000	19.00
Salary	Annual salary of manager 10,000 RMB	20.56	3.850	13.73	33.16
Distance	Distance to the headquarter in km	21.38	12.58	1.000	47.00
Load	Tran.num / Num.empl	1,678	1,145	777.8	71,600
Err.num	Number of risk events	1.692	4.780	0.000	26.00
Severity	Average event severity level	3.565	11.20	0.000	94.00
Err.rate	Err.num / Tran.num in 100%	0.008	0.036	0.000	0.552
Logit.err	$\log(\text{Err.rate} / (1-\text{Err.rate}))$	-9.243	1.179	-11.45	-5.529
Profit	Monthly branch profit in million RMB	3.785	4.412	1.061	26.45

Table 3: Correlation Matrix of Variables

	Logit.err	Severity	Distance	Mgmtsale	Salary	Load
Logit.err	1.000					
Severity	0.715*	1.000				
Distance	0.055	0.084*	1.000			
Mgmtsale	-0.163*	-0.108*	-0.059*	1.000		
Salary	-0.312*	-0.038	-0.078*	0.054*	1.000	
Load	-0.244*	0.063	-0.097*	0.107*	0.060*	1.000

* Significant at the 0.01 level.

Table 4: Impact of Workload on LOGIT(Error)

	RE I	RE II	RE I (IV)	RE II (IV)	FE I	FE II	FE I (IV)	FE II (IV)
Load	-0.326*** (0.061)	-0.911*** (0.173)	-0.281*** (0.070)	-0.935*** (0.195)	-0.164* (0.076)	-0.428* (0.198)	-0.173* (0.083)	-0.415* (0.192)
Loadsq		0.913*** (0.211)		0.902*** (0.216)		0.523* (0.249)		0.574* (0.261)
Distance	-0.043 (0.070)	0.053 (0.070)	-0.043 (0.077)	0.061 (0.069)				
Mgmtsale	-0.029 (0.058)	-0.035 (0.057)	-0.027 (0.053)	-0.034 (0.054)	0.097 (0.101)	0.077 (0.084)	0.089 (0.093)	0.081 (0.112)
Mgmnsalary	-0.302*** (0.062)	-0.185* (0.071)	-0.303*** (0.070)	-0.188* (0.072)	0.467 (0.876)	0.579 (0.621)	0.521 (0.846)	0.388 (0.649)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	776	776	727	727	776	776	727	727
<i>R</i> ²	0.386	0.427	0.387	0.429	0.312	0.326	0.314	0.328
Prob>Chi-sq	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Robustness Checks

	RE I	RE II	RE I (IV)	RE II (IV)	RE I (Poisson)	FE I (Poisson)	RE II (Poisson)	FE II (Poisson)
Load2	-0.221** (0.072)	-1.330*** (0.281)	-0.207** (0.073)	-1.401*** (0.325)				
Load2sq		1.388*** (0.346)		1.481*** (0.388)				
Load					-0.124*** (0.035)	-0.183*** (0.053)	-0.436*** (0.094)	-0.523* (0.205)
Loadsq							0.352* (0.149)	0.445* (0.212)
Distance	0.016 (0.067)	0.062 (0.066)	0.019 (0.067)	0.066 (0.066)	0.224*** (0.062)		0.193*** (0.061)	
Num.empl	-0.263*** (0.077)	-0.088 (0.088)	-0.271*** (0.078)	-0.076 (0.093)				
Mgmtsale	0.070 (0.058)	0.052 (0.058)	0.072 (0.059)	0.050 (0.058)	0.069* (0.030)	0.046 (0.040)	0.077** (0.025)	0.057 (0.040)
Mgmnsalary	-0.155* (0.068)	-0.045 (0.081)	-0.150 (0.079)	-0.035 (0.082)	0.024 (0.067)	1.022** (0.321)	-0.038 (0.069)	0.913** (0.304)
Trend	Yes	Yes						
<i>N</i>	776	776	727	727	776	776	776	776
<i>R</i> ²	0.403	0.442	0.403	0.442	0.370	0.376	0.398	0.401
Prob>Chi-sq	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Profit Models

	RE I	RE II	RE I (IV)	RE II (IV)	FE I	FE II	FE I (IV)	FE II (IV)
Load	-0.029 (0.021)	0.059 (0.078)	0.219** (0.070)	0.368*** (0.087)	-0.047 (0.119)	-0.024 (0.075)	0.222*** (0.072)	0.871*** (0.084)
Loadsq		-0.082 (0.070)		-1.057*** (0.188)		-0.021 (0.067)		-1.070*** (0.212)
Distance	-0.620*** (0.072)	-0.618*** (0.072)	-0.575*** (0.071)	-0.529*** (0.077)				
Mgmtsale	0.275*** (0.028)	0.272*** (0.028)	0.231*** (0.033)	0.160*** (0.056)	0.342*** (0.026)	0.341*** (0.027)	0.319*** (0.032)	0.357*** (0.055)
Transactions	0.267 (0.188)	0.356 (0.332)	0.193 (0.114)	0.324 (0.299)	0.476 (0.512)	0.522 (0.494)	0.385 (0.332)	0.441 (0.379)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	776	776	727	727	776	776	727	727
R ²	0.136	0.141	0.177	0.180	0.299	0.298	0.308	0.312
Prob>Chi-sq	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: First-stage regression of Load and Loadsq.

	Load	Loadsq
Lag_load	0.530*** (0.032)	-0.530*** (0.035)
Lag_loadsq	-0.451*** (0.031)	0.447*** (0.034)
Temperature	0.627*** (0.103)	0.652*** (0.110)
Distance	0.016 (0.013)	-0.020 (0.014)
Mgmtsale	-0.051*** (0.013)	0.059*** (0.014)
Mgmnsalary	0.062*** (0.014)	-0.070*** (0.014)
Trend	Yes	Yes
N	727	727
R ²	0.519	0.516
Prob>Chi-sq	<0.001	<0.001

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Spline Regression with Ten Equal Intervals

	Coefficient
0%-10%	-17.419* (8.292)
10%-20%	-15.994* (7.244)
20%-30%	-12.678* (5.887)
30%-40%	-9.194* (4.257)
40%-50%	-5.194* (2.427)
50%-60%	-2.187* (1.013)
60%-70%	-0.187* (0.085)
70%-80%	1.482* (0.666)
80%-90%	5.866* (2.566)
90%-100%	9.408 (10.038)
Distance	0.016 (0.075)
Mgmtsale	-0.046 (0.062)
Salary	-0.139* (0.063)
Trend	Yes
N	776
R ²	0.463
Prob>Chi-sq	<0.0001

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Lind and Mehlum U-shape test on Logit error and Workload

	Lower bound	Upper bound
Interval	-0.542	16.426
Slope	-0.000	0.002
t-value	-2.024	1.963
P > t	0.022	0.025

Specification $f(x) = x^2$ Extreme point: .584

Overall test of presence of a U shape: t-value = 1.96, P > |t| = .025

Note: H1: U shape vs. H0: Monotone or Inverse U shape

Table 10: Operational Risk Events under High Workload

1	Issued 3 million RMB business loan with maturity date as the next day.
2	Issued collateral based loan but did not collect collateral.
3	Issued RMB 500,000 loan with 0 interest rate.
4	Issued RMB 800,000 loan with maturity date as 02/2013.
5	Opened new client account without collecting client information into the system.
6	Did not record the withdrawal client ID number.
7	Client manager issued a business loan of 100,000 RMB to a company with an expired license.
8	Deposit without currency tag.
9	Issued 500,000 RMB business loan on 12/2014 with maturity date as 12/2013.
10	Issued 1 million business loan without an interest rate.
11	Opened new account with wrong client name.
12	Issued 100,000 personal loan to a client with credit card delinquency of 43,817.65.
13	Issued 1 million business loan without borrower's name.
14	Issued 1 million business loan without the loan usage.
15	XXX did not log out computer system after the transaction is done.
16	XXX did not lock the safe of the client.
17	Opened the ATM machine without locking it.
18	Issued 500,000 business loan with different interest rates in the system and on paper.
19	Total withdrawal amount is different between the central system and client manager's system.
20	Typed the wrong deposit date.
21	Large amount cash withdrawal without client signature.
22	Opened asset management account without validating client ID.
23	Did not double check the capital in reserve of the branch at the beginning of the day.
24	Loan issuance with different company license numbers in the system and on paper.
25	Asset management transaction without the specification of commission fee.
26	Did not double check the collateral at the end of the season.
27	XXX did not log off computer system when leaving back home.
28	A deposited account without client ID.
29	Issued 1 million business loan with maturity date as the previous month.

Table 11: Operational Risk Events under Low Workload

1	Client manager issued 5 million loan without the branch manager's signature.
2	Issued business loan 1 million to a firm manager without checking his personal debt status.
3	Issued business loan 2 million to a firm without checking the company operations and profits.
4	Issued personal loan to client with age exceeds the allowance limit.
5	Issued 2 million business loan without checking the owner's credit score.
6	Issued 1 million business loan to client with existing business loans but without explanation.
7	Issued 200,000 personal loan without credit check.
8	Issued 1 million business loan to client with default history but without explanation.
9	Issued 1 million business loan to a client who changed the name of guarantor several times.
10	Issued 2 million business loan without validating the purpose of loan.
11	Issued 1 million business loan with wrong interest rate calculation (lower than actual rate).

Appendix B: Figures

Figure 1: Comparison between staffing levels.

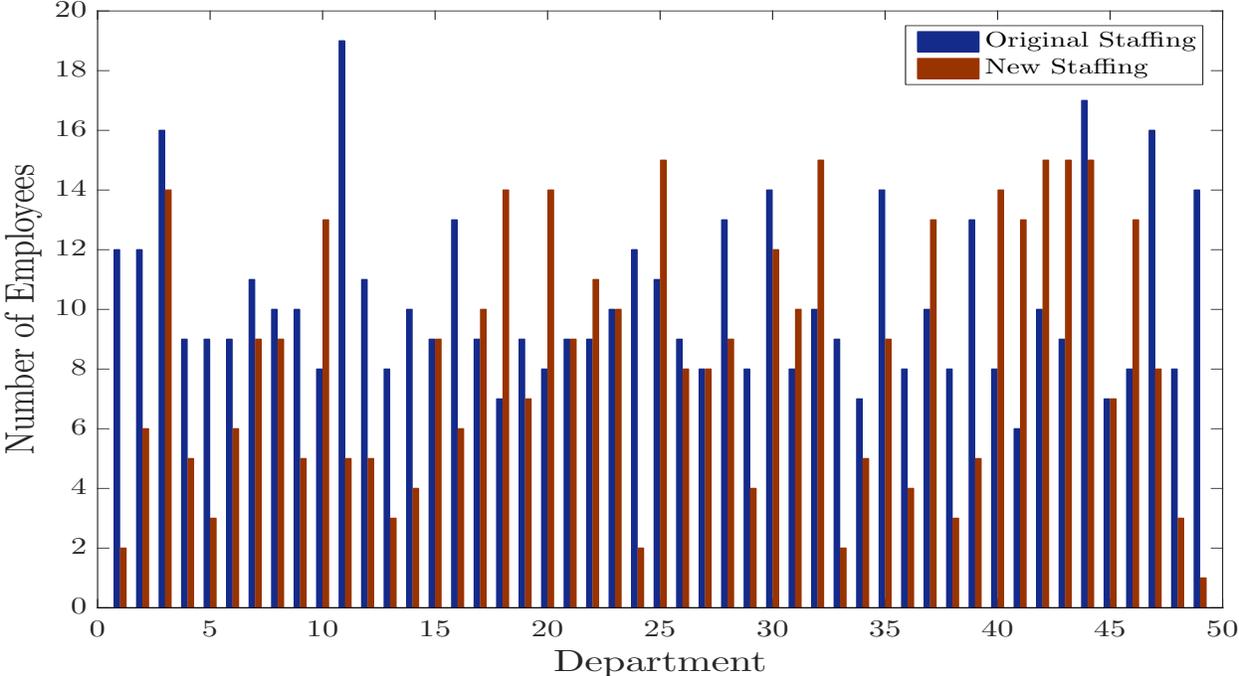


Figure 2: Comparison between risk events frequency (16 months).

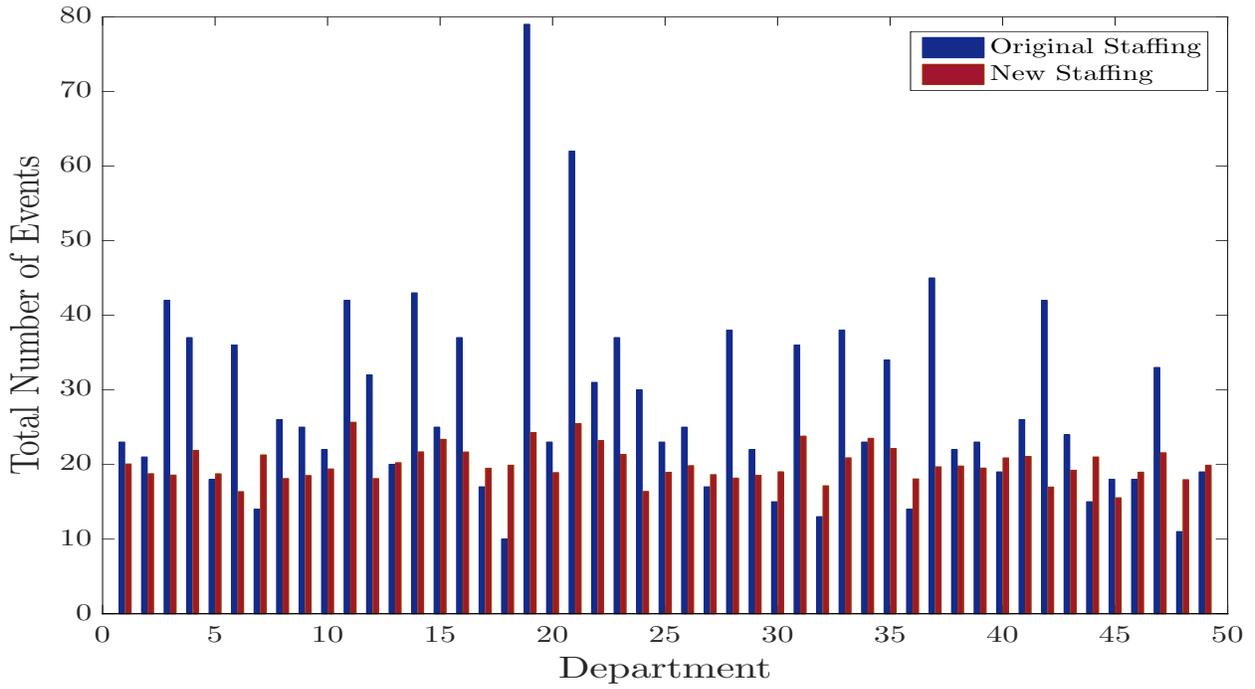


Figure 3: Comparison between expected losses (16 months).

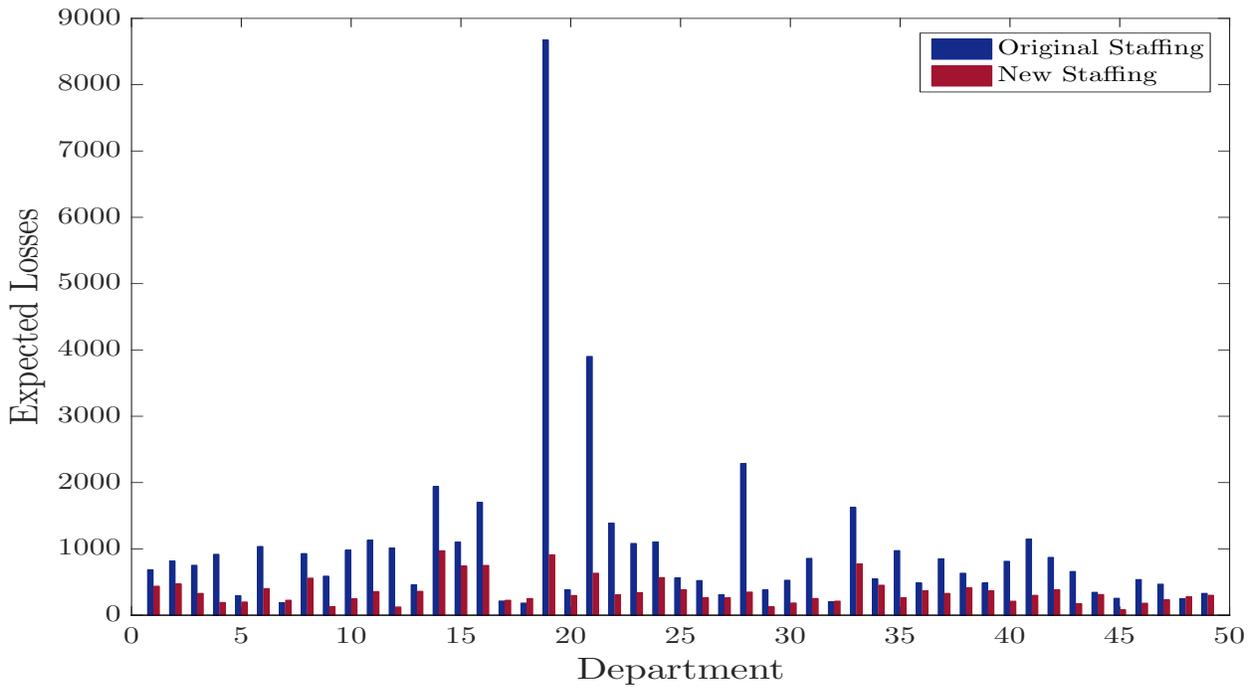
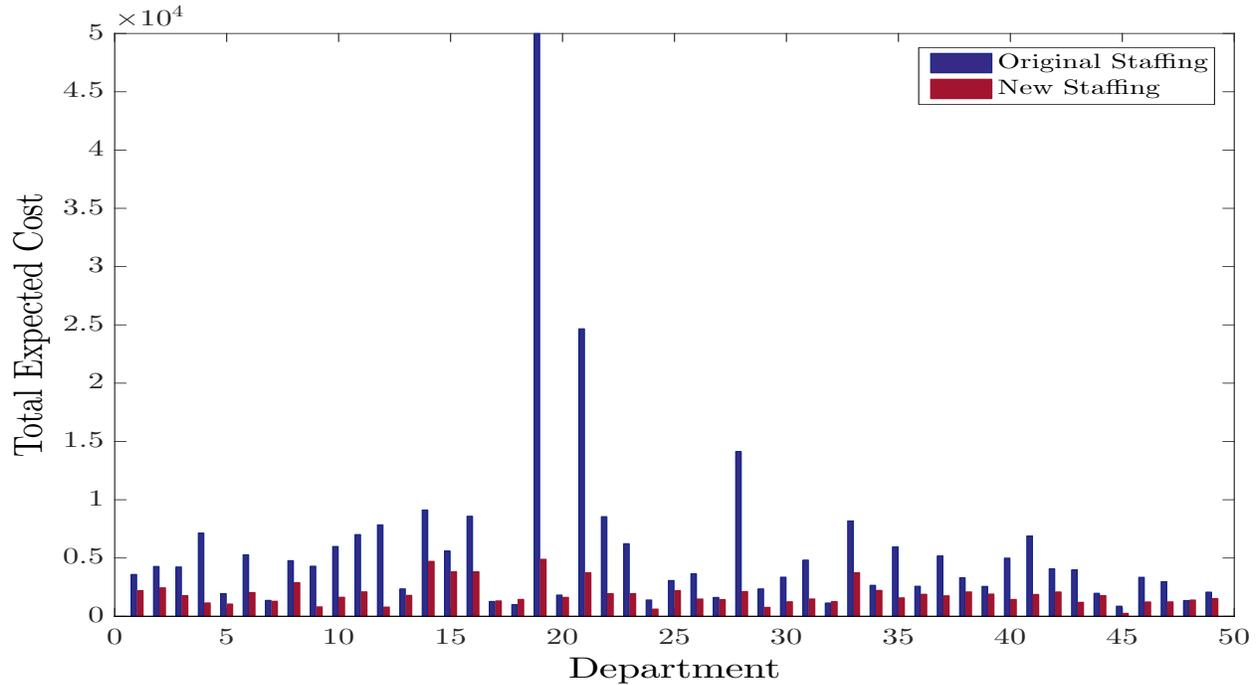


Figure 4: Comparison between expected loss-adjusted profits (16 months).



References

- Agarwal, S., R. Hauswald. 2010. Distance and private information in lending. *The Review of Financial Studies* **23**(7) 2757–2788.
- Altman, E. I., A. Saunders. 1997. Credit risk measurement: Developments over the last 20 years. *Journal of Banking & Finance* **21**(11) 1721–1742.
- Aral, S., E. Brynjolfsson, M. Van Alstyne. 2012. Information, technology, and information worker productivity. *Information Systems Research* **23**(3-part-2) 849–867.
- Ashby, S. 2010. The 2007-2009 financial crisis: learning the risk management lessons. *Financial Services Research Forum, Nottingham*.
- Basel Committee on Banking Supervision. 2006. The first pillar-minimum capital requirements. BIS consultative document.
- Bendoly, E. 2011. Linking task conditions to physiology and judgment errors in RM systems. *Production and Operations Management* **20**(6) 860–876.
- Bendoly, E., K. Donohue, K.L. Schultz. 2006. Behavior in operations management: Assessing recent findings and revisiting old assumptions. *Journal of Operations Management* **24**(6) 737–752.
- Bendoly, E., M. Prietula. 2008. In the ‘Zone’: The role of evolving skill and transitional workload on motivation and realized performance in operational tasks. *International Journal of Operations & Production Management* **28**(12) 1130–1152.

- Berry, J. J., A. Tucker. 2016. Past the point of speeding up: The negative effects of workload saturation on efficiency and patient severity. *Management Science* **63**(4) 1042–1062.
- Bhagat, S., B. J. Bolton, A. Subramanian. 2010. Ceo education, ceo turnover, and firm performance. *Available at SSRN: <https://ssrn.com/abstract=1670219>* .
- Bloom, N., J. Van Reenen. 2007. Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics* **122**(4) 1351–1408.
- Bocker, K., C. Kluppelberg. 2005. Operational VaR: a closed-form approximation. *RISK-LONDON-RISK MAGAZINE LIMITED* **18**(12) 90.
- Boudreau, J. W., W. Hopp, J. O. McClain, L. J. Thomas. 2003. On the interface between operations and human resources management. *Manufacturing and Services Operations Management* **5**(3) 179–202.
- Buell, R. W., D. Campbell, F. X. Frei. 2016. How do customers respond to increased service quality competition? *Manufacturing & Service Operations Management* **18**(4) 585–607.
- Cachon, G., S. Gallino, M. Olivares. 2013. Does adding inventory increase sales? evidence of a scarcity effect in us automobile dealerships. *Working Paper* .
- Cakir, A., DJ Hart, TFM Stewart. 1980. *Visual display terminals: A manual covering ergonomics, workplace design, health and safety, task organization*. Wiley.
- Campbell, D., F. Frei. 2004. The persistence of customer profitability: Empirical evidence and implications from a financial services firm. *Journal of Service Research* **7**(2) 107–123.
- Campbell, D., F. Frei. 2010. Cost structure, customer profitability, and retention implications of self-service distribution channels: Evidence from customer behavior in an online banking channel. *Management Science* **56**(1) 4–24.
- Charron, S., E. Koechlin. 2010. Divided representation of concurrent goals in the human frontal lobes. *Science* **328**(5976) 360–363.
- Chernobai, A. S., S. T. Rachev, F. J. Fabozzi. 2007. *Operational Risk: A Guide to Basel II Capital Requirements, Models, and Analysis*. John Wiley and Sons, New York.
- Chuang, H. H., R. Oliva, O. Perdikaki. 2016. Traffic-based labor planning in retail stores. *Production and Operations Management* **25**(1) 96–113.
- Core, J. E., R. W. Holthausen, D. F. Larcker. 1999. Corporate governance, chief executive officer compensation, and firm performance. *Journal of financial economics* **51**(3) 371–406.
- Cruz, M. G. 2002. *Modeling, Measuring and Hedging Operational Risk*. John Wiley and Sons, New York.
- Dalton, A. N., S. A. Spiller. 2012. Too much of a good thing: The benefits of implementation intentions depend on the number of goals. *Journal of Consumer Research* **39**(3) 600–614.
- Deci, E.L., J.P. Connell, R.M. Ryan. 1989. Self-determination in a work organization. *Journal of Applied Psychology* **74**(4) 580.
- Deloitte. 2013. Directors, CFOs Share Views on Risk, but Diverge on Time Spent. URL <http://deloitte.wsj.com/riskandcompliance/2013/04/16/>.

- Donahue, E.M., R.W. Robins, B.W. Roberts, O.P. John. 1993. The divided self: Concurrent and longitudinal effects of psychological adjustment and social roles on self-concept differentiation. *Journal of Personality and Social Psychology* **64**(5) 834–846.
- Dowd, K. 2007. *Measuring market risk*. John Wiley & Sons.
- Fisher, M., S. Gallino, S. Netessine. 2017. Setting retail staffing levels: A methodology validated with implementation. *Working paper* .
- Frachot, A., P. Georges, T. Roncalli. 2001. Loss distribution approach for operational risk .
- French, K. R., W. G. Schwert, R. F. Stambaugh. 1987. Expected stock returns and volatility. *Journal of financial Economics* **19**(1) 3–29.
- Friedman, J. H. 1991. Multivariate adaptive regression splines. *The Annals of Statistics* 1–67.
- Guegan, D., B. K. Hassani. 2013a. Operational risk: A basel ii++ step before basel iii. *Journal of Risk Management in Financial Institutions* **6**(1) 37–53.
- Guegan, D., B. K. Hassani. 2013b. Using a time series approach to correct serial correlation in operational risk capital calculation. *The Journal of Operational Risk* **8**(3) 31.
- Hambrick, D. C., P. A. Mason. 1984. Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review* **9**(2) 193–206.
- Hausman, J. A. 1978. Specification tests in econometrics. *Econometrica* 1251–1271.
- Hitt, L. M., F. X. Frei. 2002. Do better customers utilize electronic distribution channels? the case of pc banking. *Management Science* **48**(6) 732–748.
- Holmstrom, B., P. Milgrom. 1991. Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, & Organization* **7** 24–52.
- Hora, M., R. D. Klassen. 2013. Learning from others' misfortune: factors influencing knowledge acquisition to reduce operational risk. *Journal of Operations Management* **31**(1) 52–61.
- Huson, M. R., P. H. Malatesta, R. Parrino. 2004. Managerial succession and firm performance. *Journal of Financial Economics* **74**(2) 237–275.
- J. C. Stein, Jeremy C. 2002. Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance* **57**(5) 1891–1921.
- Jaeker, J. B., A. L. Tucker. 2016. Past the point of speeding up: The negative effects of workload saturation on efficiency and patient severity. *Management Science* **63**(4) 1042–1062.
- Jarrow, R. A. 2008. Operational risk. *Journal of Banking and Finance* **32**(5) 870–879.
- Jarrow, R. A., J. Oxman, Y. Yildirim. 2010. The cost of operational risk loss insurance. *Review of Derivatives Research* **13**(3) 273–295.
- Jarrow, R. A., S. M. Turnbull. 1995. Pricing derivatives on financial securities subject to credit risk. *The journal of finance* **50**(1) 53–85.
- Kaplan, R. S., A. Mikes. 2012. Managing risks: a new framework. *Harvard Business Review* **90**(6).

- KC, D. S. 2013. Does multitasking improve performance? Evidence from the emergency department. *Manufacturing & Service Operations Management* **16**(2) 168–183.
- KC, D. S., C. Terwiesch. 2009. Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science* **55**(9) 1486–1498.
- KC, D. S., C. Terwiesch. 2012. An econometric analysis of patient flows in the cardiac intensive care unit. *Manufacturing and Services Operations Management* **14**(1) 50–65.
- Kennedy, P. 2003. *A Guide to Econometrics*. MIT Press, Cambridge, MA.
- Kesavan, S., V. Mani. 2015. An overview of industry practice and empirical research in retail workforce management. *Retail Supply Chain Management*. Springer, 113–145.
- Kuntz, L., R. Mennicken, S. Scholtes. 2014. Stress on the ward: Evidence of safety tipping points in hospitals. *Management Science* **64**(1) 754–771.
- Latham, G.P., E.A. Locke. 1979. Goal setting: A motivational technique that works. *Organizational Dynamics* **8**(2) 68–80.
- Leippold, M., P. Vanini. 2003. The quantification of operational risk. Available at SSRN 481742.
- Lind, T., H. Mehlum. 2010. With or without U? the Appropriate Test for a U-Shaped Relationship. *Oxford Bulletin of Economics and Statistics* **72**(1) 109–118.
- Locke, E.A. 1968. Toward a theory of task motivation and incentives. *Organizational Behavior and Human Performance* **3**(2) 157–189.
- Lupien, S.J., F. Maheu, M. Tu, A. Fiocco, T.E. Schramek. 2007. The effects of stress and stress hormones on human cognition: Implications for the field of brain and cognition. *Brain and Cognition* **65**(3) 209–237.
- Mani, V., S. Kesavan, J. M. Swaminathan. 2015. Estimating the impact of understaffing on sales and profitability in retail stores. *Production and Operations Management* **24**(2) 201–218.
- Marrison, C. 2005. The fundamentals of risk measurement. *The Mathematical Intelligencer* **27**(2) 83–83.
- Neil, M., N. Fenton, M. Tailor. 2005. Using bayesian networks to model expected and unexpected operational losses. *Risk Analysis* **25**(4) 963–972.
- Oliva, R., J.D. Sterman. 2001. Cutting corners and working overtime: Quality erosion in the service industry. *Management Science* **47**(7) 894–914.
- Parkinson, C. 1958. Parkinsons Law: The pursuit of progress.
- Perdikaki, O., S. Kesavan, J. M. Swaminathan. 2012. Effect of traffic on sales and conversion rates of retail stores. *Manufacturing & Service Operations Management* **14**(1) 145–162.
- Peters, L.H., E.J. O'Connor. 1980. Situational constraints and work outcomes: The influences of a frequently overlooked construct. *Academy of Management Review* **5**(3) 391–397.
- Petersen, M. A., R. G. Rajan. 2002. Does distance still matter? the information revolution in small business lending. *The Journal of Finance* **57**(6) 2533–2570.

- Powell, A., S. Savin, N. Savva. 2012. Physician workload and hospital reimbursement: Overworked physicians generate less revenue per patient. *Manufacturing and Services Operations Management* **14**(4) 512–528.
- Sargan, D., M. Desai. 1988. *Lectures on Advanced Econometric Theory*. Blackwell.
- Scharfman, J. A. 2008. *Hedge Fund Operational Due Diligence: Understanding the Risks*. John Wiley and Sons, New York.
- Schmidt, A. M., R. P. DeShon. 2007. What to do? the effects of discrepancies, incentives, and time on dynamic goal prioritization. *Journal of Applied Psychology* **92**(4) 928.
- Setyawati, L. 1995. Relation between feelings of fatigue, reaction time and work productivity. *Journal of Human Ergology* **24**(1) 129–135.
- Shah, R., G. P. Ball, S. Netessine. 2017. Plant operations and product recalls in the automotive industry: An empirical investigation. *Management Science* **63**(8) 2439–2459.
- Siebert, W. S., N. Zubanov. 2010. Management economics in a large retail company. *Management Science* **56**(8) 1398–1414.
- Simonsohn, U. 2016. Two-lines: The first valid test of ushaped relationships. *Working Paper* .
- Staats, B. R., F. Gino. 2012. Specialization and variety in repetitive tasks: Evidence from a Japanese bank. *Management Science* **58**(6) 1141–1159.
- Staiger, D., JH. Stock. 1997. Instrumental variables regression with weak instruments. *Econometrica* **65**(3) 557–586.
- Tan, T. F., S. Netessine. 2014. When does the devil make work? An empirical study of the impact of workload on worker productivity. *Management Science* **60**(6) 1574–1593.
- Ton, Z., R. S. Huckman. 2008. Managing the impact of employee turnover on performance: The role of process conformance. *Organization Science* **19**(1) 56–68.
- Villas-Boas, J. M., R. S. Winer. 1999. Endogeneity in brand choice models. *Management Science* **45**(10) 1324–1338.
- Warton, D., F. Hui. 2011. The arcsine is asinine: the analysis of proportions in ecology. *Ecology* **92**(1) 3 – 10.
- Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*. MIT press.
- Xue, M., L. M. Hitt, P. T. Harker. 2007. Customer efficiency, channel usage and firm performance in retail banking. *Manufacturing and Services Operations Management* **9**(4) 535–558.