The Impact of Workload on Operational Risk: Evidence from a Commercial Bank

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Abstract

Operational risk has been among the three most significant types of risks in the financial services industry, and its management is mandated by Basel II regulations. To inform better labor decisions, this paper studies how workload affects banks' operational risk event occurrence. To achieve this goal, we use a unique data set from a commercial bank in China that contains 1,441 operational risk events over 16 months. We find that workload has a U-shaped impact on operational risk error rate. More specifically, the error rate of operational risk events decreases first, as workload increases, and then increases. Furthermore, when workload is low, employees tend to make performance-seeking risks; however, when workload is high, employees tend to exhibit quality degradation due to cognitive multitasking. Based on the causal relationship between workload and operational risk events from the empirical analysis, we discuss staffing policies among branches aimed at reducing operational risk losses. We find that employing a flexible staffing rule can significantly reduce the number of operational risk events by 3.2% to 10% under different scenarios. In addition, this significant performance improvement can be achieved by adding even a little bit of flexibility to the process by allowing employees to either switch their business lines in the same branch or switch branches within the same business lines on a quarterly basis.

Keywords: operational risk, workload, performance-seeking risks, quality degradation, optimal staffing.

1 Introduction

Operational risk 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 instance, 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. Operational risk 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 2008 global financial crisis, which cost the banking sector trillions of dollars due to poor risk management (Ashby, 2010). According to Barclays 2014 Annual Report,[1] operational risk 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 is due to various other risks (e.g., funding, conduct risks). Because of its significance, regulators throughout the world generally require their banks to set aside capital in reserve in order to protect themselves from operational risk events. The Basel Committee on Banking Supervision (BCBS) in Basel, Switzerland, whose members include 27 major economies (e.g., the U.S., the UK, 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 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 operational risk in 2004, which is referred to as Basel II. Recent regulations (Sarbanes-Oxley Act, 2002, and Basel, 2012) have made operational risk management even more important in the financial industry. Hence, mitigating operational risk to reduce the necessary capital reserves is a practically significant goal that global banks earnestly strive for.

Furthermore, unlike credit and market risks, operational risk is often perceived by management as more controllable (Deloitte, 2013) because proper monitoring processes can prevent such risk events from happening (Kaplan and Mikes, 2012). However, in practice, the compliance system alone does not guarantee

[1] http://www.home.barclays/annual-report-2014.html.

that operational risk events can be averted. Companies are often advised to promote a corporate culture that enables prudent decision-making processes that reduce the opportunity for operational risk (Healy and Serafeim, 2019). Therefore, many opportunities exist for operations management researchers to improve our understanding of the causes of the operational risk in financial services and make better operational decisions to mitigate such risks in the future. Nevertheless, despite such opportunities, little empirical operations management research has been conducted in this area, probably because the operational risk data of financial service companies are rarely available for academic research.

In this paper, we collect novel operational risk data from a Chinese commercial bank to study how workload (defined as the total number of transactions handled per employee per hour), an important work environment factor (see Bendoly et al. (2006) and more details will be provided in the Related Literature section) affects the operational risk error rate (the number of risk events normalized by transactions). Furthermore, we examine different mechanisms through which workload affects operational risk events. Our data set contains 1,441 operational risk events from January 1, 2014, to April 30, 2015. Adopting a control function approach with instrumental variables 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 decreases first and then increases as workload increases. Using the detailed categories of our risk events data, we further find that, under a low workload scenario, employees tend to take performance-seeking risks, while under a high workload scenario, employees tend to make errors or exhibit quality degradation due to cognitive multitasking.

Based on the causal relationship between workload and operational risk events established by empirical analysis, we discuss staffing rules among branches to reduce operational risk losses. We find that employing a flexible staffing rule can significantly reduce operational risk losses by 3.2% to 10% under different scenarios. In addition, a significant performance improvement can be achieved by adding even a little bit of flexibility to the process by allowing employees to either switch their business lines in the same branch or switch branches within the same business lines on a quarterly basis.

The contributions of this paper are threefold. First, to the best of our knowledge, our paper provides the first empirical analysis of one of the causes of operational risks in the banking industry, while previous studies have tended to model operational risk as an event with exogenous probability distribution. In particular, we establish a causal link between workload, an important work environment factor that can be controlled by staffing decisions, and the error rate of operational risk events (officially defined by Basel II). Second, we revisit the growing research area in operations management dedicated to the impact of workload on operational performance, and we broaden our understanding of workload and staffing decisions in the financial industry. We particularly examine the mechanisms through which workload affects operational risk events. Third, our empirical study enables us to explain the variation in operational risk events so that we can build a capital-allocation model to re-optimize bank staffing levels among branches to improve operational risk management. Our paper therefore provides a novel consideration for the labor optimization literature: staffing to avert operational risk events.

2 Related Literature

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

The first stream of literature relevant to our work concerns retail banking operations. Prior work in this stream has looked into customer-channel adoption decisions. 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 of 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 customers' adoption of online banking channels on their interactions with a major U.S. retail bank. More recent work in retail banking operations has studied service quality issues. Buell et al. (2016) probe customer reactions to increasing service quality competition, and find that for firms to maintain high quality levels, they need to attract and retain profitable customers over time. In general, existing literature on retail banking operations has focused on channel decisions and customer management; however, limited work has been conducted to specifically study and mitigate operational risk using optimal staffing.

The second stream of relevant work studies optimal labor decisions in service industries. One large stream focuses on labor management in retail (see Ton and Huckman, 2008, and Kesavan and Mani, 2015, for comprehensive literature reviews). Staffing is a key managerial decision in this setting because it affects operational performance (e.g, Perdikaki et al., 2012; Chuang et al., 2016; Mani et al., 2015; Fisher et al., Forthcoming 2020). Staffing also adjusts workload, which research shows can affect operational performance in healthcare (e.g., KC and Terwiesch, 2009; KC and Terwiesch, 2012; Powell et al., 2012; Kuntz et al., 2014; Berry and Tucker, 2016). Moving away from the healthcare industry, Aral et al. (2012) find that multitasking (a proxy for workload) level exhibits diminishing returns in projecting output in a mid-size executive recruiting firm. Tan and Netessine (2014) analyze an operational data set from a restaurant chain and show an inverted-U-shaped relationship between the workload and the waitstaff's service speed and sales output. However, there is no work studying the effect of workload in the banking industry, which is one of the most significant industries in the economy.[2] We use a novel data set to study this question in this paper. Previously, Oliva and Sterman (2001) examine the impact of work pressure on service quality erosion for a lending service center in a major bank in the UK. However, work pressure in their study is different from workload in our setting and the quality erosion in their work is not directly related to operational risk studied in our paper.

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), operational risk in financial services has generally received little attention. Nevertheless, given its practical significance and new regulations, operational risk has been receiving growing interest in the academic literature in recent years. We contribute to this burgeoning literature in three ways.

[2]https://www.selectusa.gov/financial-services-industry-united-states

First, much of the academic research has tended to discuss the modeling, measurement, and regulation of operational risk at the strategic level 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 a 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, however, discuss the operational-level decisions that result in operational risk in the financial services industry, which is the focus of this paper.

Second, most 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 identifying the factors that may explain the variation of operational risk events. For example, Neil et al. (2005) propose a Bayesian network approach to model both expected and unexpected operational risk losses. Bocker and Kluppelberg (2005) find that a closed-form approximation for Ops-VaR exists when the distribution of operational risk loss data is heavy-tailed. Unlike these studies, we examine how an important work-environmental factor (i.e., workload) affects the error rate of operational risk events, so that managers can make better decisions to distribute workload optimally.

Third, recent papers on operational risk have started to focus on the financial applications, but only a handful of papers have considered 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 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 operational risk insurance contract. It is noteworthy that these studies tended to neglect granular-level operations decisions (e.g., workforce management), which should significantly affect operational risk events in an applied context. Unlike these studies, we examine how an important factor that is endogenously determined by the management work environment (i.e., workload) affects the error rate of operational risk 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 operational risk 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 the operational risk losses of other firms. One goal of our paper is to take an initial step toward 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 operational risk in financial services.

3 Context and Hypothesis Development

3.1 Retail Banking Branch

Before developing our theoretical hypotheses, we explain the specific context of our data. The mother bank of the branches under study is one of the city commercial banks in China, which belongs to the third most significant group in Chinese banking market (KPMG, 2007). Many of these city commercial banks were founded based on urban credit cooperatives. The branch in our study is the lowest-level branch in the Chinese commercial bank system, comparable to a credit union branch in the United States. It handles only basic personal and business banking, which mainly includes deposit and savings services, processing loans, and selling wealth-management products, such as mutual funds and bonds. It generally employs two types of workers: tellers and a manager. There are new, junior, and senior tellers in the branch, none of which are considered to be middle-tier employees between the manager and the front-line employees.

All the tellers conduct front-line work. During the shift, they sit behind a glass window and directly serve the customers. They press a button to call the next customer in line. They first verify the customer's identity, and then process the service request. Depositing and withdrawing money are the most common personal banking services in China. Other services include issuing cashier's checks, transferring funds, selling wealth-management products, and processing personal loans. At the end of their shift, the tellers need to balance the accounts and secure all the stamps and blank checks. The branch manager manages branch performance, including both revenues and risks. One of the important decisions the manager makes is the staffing decision (i.e., the number of employees needed for each line of business at the branch). He or she generally makes the staffing decision one calendar quarter in advance and keeps it unchanged.

All the branch employees receive income that is comprised of three parts–base salary, performance-based bonus, and commissions. The base salary and the bonus are the largest parts (around 90%) of the total income, and are typically the same across the same level (i.e., new, junior, senior) of employees. A bonus will be reduced if an employee makes mistakes, such as by committing operational risk violations, and the amount of the reduction depends on how serious the mistake is. The commission is proportional to the number and amount of transactions and the wealth-management products that the employee processes. The commission rate typically ranges between 0.5% and 2% of the total transaction revenue, depending on the line of business.

3.2 Operational Risk Events

Now that we have described the employees in our setting, let us define the operational risk events within it. Basel II defines (see Bank for International Settlements, 2011) seven categories of operational risk events, which include the following.

(1) Internal Fraud: misappropriation of assets, tax evasion, intentional mismarking of positions, bribery.

(2) External Fraud: theft of information, hacking damage, third-party theft and forgery.

(3) Employment Practices & Workplace Safety: discrimination, workers compensation, employee health and safety.

(4) Clients, Products, & Business Practices: market manipulation, antitrust, improper trade (aggressive sales), product defects, fiduciary breaches, account churning.

(5) Damage to Physical Assets: natural disasters, terrorism, vandalism.

(6) Business Disruption & System Failures: utility disruptions, software failures, hardware failures.

(7) Execution, Delivery, & Process Management: data-entry errors, accounting errors, failed mandatory

reporting, negligent loss of client assets.

Table 9 in Appendix A further provides the detailed gross losses for all these categories. According to the Basel II definitions, our focal bank has labeled the 1,441 risk events caught in our data set as one of four types: (i) data-entry errors, (ii) failed mandatory reporting, (iii) operation failure, and (iv) aggressive sales. Here, types (i), (ii), and (iii) belong to Execution, Delivery, & Process Management (ED&PM), which corresponds to losses arising from an unintentional or negligent failure to meet a professional obligation. On the other hand, those of type (iv) belong to Clients, Products, & Business Practices (CP&BP), which corresponds to intentional improper trade due to performance-seeking behaviors. Our focal bank did not experience all seven categories of operational risk events in our study period. In addition to the four labels provided by the bank, we also conduct text-mining analysis of risk events, described in Appendix B. We further categorize our risk events into ten types through text mining and conduct robustness check with alternative specification of risk types in our fixed-effects model in Section 5.4.3.

Some operational risk events in our data set 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." However, some events may cause losses only in the long run. One such risk event is recorded as follows: "On August 25, 2014, Branch X issued Company X RMB 2 million (note: Chinese currency) loan and wrote the wrong maturity date as September 1, 2014 (error in the date)." Another such event is documented as follows: "On September 10, 2014, Branch X issued Company X business loans without checking the collateral." Admittedly, some of these events may not cause actual losses if they are caught and corrected in time. Nevertheless, they might still have been potentially harmful had they not been corrected. In sum, these operational risk events are related to process conformance (Ton and Huckman, 2008) and will cost the bank considerably either in the short or in the long term. All of the events in our data set were caught and recorded by the audit department of our focal bank, which checks the operational processes of each branch every week (more details about the auditing process is provided in the subsection below). None of the events were self-reported by the branches. Once a risk event is caught, the audit department assesses the potential loss of the event. It then follows the standards prescribed by the Basel Committee on Banking Supervision (2011) and the People's Bank of China to assign an operational risk severity level to reflect the potential loss. The severity level is similar to a scorecard system (see UFJ Holdings, 2003; Society of Actuaries, 2010). The level ranges from 0 to 100 to reflect the potential losses of each event, with the higher value indicating a more severe risk. 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 the rules from both Basel regulations and the People's Bank of China (the regulator).

3.3 Hypothesis Development

Combining the institutional knowledge of the banking setting and the extensive literature dedicated to the effect of workload on performance, we propose four main mechanisms through which workload could affect operational risk occurrence. The first two mechanisms suggest a negative relationship between workload and the error rate of operational risk events, while the second two predict a positive relationship. We argue that the inhibition effect dominates under low workload conditions, and that the promotion effect dominates under high workload conditions. This argument reconciles these seemingly conflicting mechanisms, and leads to our main hypothesis.

Workload Reduces Operational Risk (Inhibition Effect). The first inhibition effect mechanism is motivation, which can be strengthened via 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 goal-setting theory (Locke, 1968; Latham and Locke, 1979). In addition, research in cognitive psychology has found that extra workload triggers 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).

In our setting, 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 games, and attending to their own personal affairs, all of which can distract workers' attention and result in operational risk-related mistakes. For example, absentminded workers may fail to carefully verify all the required documents/information, such as credit history, for a loan service. On the opposite side, increasing workload can reduce such idle time and stimulate workers to expend more effort to ensure their work quality and accurately follow the operational risk protocols.

The second inhibition effect mechanism is economic multitasking (e.g., Holmstrom and Milgrom, 1991), which is based on the premise that employees may rationalize their effort provision toward different tasks to maximize 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 a 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 to which they are assigned, and because the waiting cost of customers is low. Under heavy workload conditions, however, waiters have a different incentive to shift the focus to faster service speed because the waiting cost becomes high and because turning over tables faster will seat new customers sooner, and these customers generally spend more money per unit of time than incumbent customers. Sasser and Klug (1972) find a similar behavior in restaurant chefs. Economic multitasking may even trigger workers to commit misconduct. Chen and Sandino (2012) find that employees are inclined to steal when they perceive that they are paid unfairly relative to their co-workers. Dimmock et al. (2018) also find that investment managers are more likely to commit financial misconduct when the monetary incentive is higher and level of monitoring is lower.

Bank employees in our setting are faced with two possible income-generating "tasks"—regular day-to-day duties and alternative reward-enhancing activities. The former tasks typically include accurately and efficiently processing various customer service requests, which are tied to bonuses, commissions and promotions. The latter are exemplified by various malicious activities, such as coercing customers into making a deposit before releasing a loan payment in order to boost deposit performance, aggressively selling financial products, or even committing fraud.[3] Employees engage in these activities because they may be pressured by aggressive performance targets linked to bonuses and promotions. All of these activities may boost income in the short run, but they violate the operational risk protocols. When the workload of regular business increases, the bank employees may start to curb these alternative performance-seeking activities and more diligently follow protocols because 1) they are more likely to reach performance goals connected with their regular duties to earn rewards (i.e., they are less pressured by aggressive performance targets), 2) they have little latitude to undertake such performance-seeking activities, and 3) violation of operational risk protocols may be caught and penalized.[4]

We argue that the inhibiting effect of workload dominates when the overall workload is low. First, idle time is more likely to happen under low workload conditions, triggering the motivation mechanism. Second, workers have extra incentives to neglect operational risk protocols to pursue alternative award-enhancing activities when regular business workload is low (i.e., economic multitasking). Hence, we expect to observe that increasing workload reduces the number of operational risk events, especially those award-enhancing ones (i.e., CP&BP-type events), when the overall workload is low. However, when the overall workload is high, a further increase in workload may increase operational risk events, as we discuss below.

Workload Increases Operational Risk (Promotion Effect). The first promotion effect mechanism is cognitive multitasking, which is based on the premise that workers become less capable of focusing on an individual task when they have to pay attention to an increased number of tasks because of limited cognitive capacity (Charron and Koechlin, 2010). In other words, when the cognitive load is high, any additional

[3] Activities such as coercing customers into making a deposit before releasing a loan payment in order to boost deposit performance, as well as aggressively selling financial products, were observed in our data set. We did not observe cases of fraud in our data. Nevertheless, fraud boosts short-term income and violates risk protocols. Therefore, we listed it as an example of potential alternative reward-enhancing activities, even though it was not observed at our bank.

[4] We assume that employees will prioritize regular legal duties because illegal activities bear two additional costs—a chance of being caught and punished and moral/ethical costs.

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 body of empirical literature supports this theory. For example, Powell et al. (2012) find that overloaded physicians become careless about insurance paperwork, which reduces their revenue per patient. KC (2013) finds that when doctors become extremely busy in the emergency room, they take longer 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 their 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, tellers usually handle multiple loan requests simultaneously because processing loans takes time while awaiting approvals. When workload increases, employees are more and more likely to lose focus on any particular task, causing them to increase operational risk by making errors of varying severity, which may range from forgetting to make photocopies 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, a 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). Using an empirical approach, Kuntz et al. (2014) examine discharge records and argue that high hospital occupancy forces front-line clinical workers to ration resources and become more error-prone, thus increasing patient mortality rates. They hypothesize that high occupancy may increase workers' stress hormones, even though they neither directly observe nor measure the hormones.

As front-line workers in banks, tellers have to perform multiple duties, such as deposits, transfers, withdrawals, and issuing cashier's checks and money orders. In addition, they need to promote the bank's products, resolve various customer issues, batch and process proof of work, while following all the operational risk standards. When their workload expands, these tellers may encounter all the aforementioned anti-productive emotions and consequently violate the operational risk 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.[5] Workers may even commit financial fraud because they are confused or intimidated by the exacerbated difficulty of accomplishing various tasks.

We posit that when the overall workload is high, further increasing the workload may increase operational risks, especially those that are execution-related or corner-cutting errors (i.e., ED&PM-type events). Under a heavy workload, employees are more likely to reach or exceed their cognitive and physical capacities, which triggers both the cognitive multitasking mechanism and anti-productive emotions.

To sum up, we formally hypothesize the following: There is a U-shaped relationship between workload and operational risk occurrence. That is, as workload increases, the error rate of operational risk events first decreases and then increases, controlling for all other factors.

4 Data

Our empirical setting is based on 49 branches that belong to one of the Chinese city commercial banks in Jiangsu Province. Jiangsu is one of the largest provinces in China, with the second-highest GDP nationwide.[6] In 2013, the bank implemented a new system to record operational risk events, from which we collected our data. Our data covers the time period from January 1, 2014, to April 30, 2015, when 1,441

[5] "Violently quarreling with clients" is indeed an operational risk event considered by our focal bank. It belongs to ED&PM because it deviates from conducting the service delivery process in a friendly and professional manner.

[6] http://www.guancha.cn/economy/2017_01_27_391590.shtml

operational risk events in total were observed.

The data consist of four parts—operational risk events, transaction-related information, branch characteristics, and employee demographics. In particular, the operational risk event data include the bank branch ID, event description (in text format), date of occurrence, and severity level. In addition, the transaction-related information contains the transaction date, type, and size. There are five general types of transactions in our data set, namely, deposit/withdrawal for individual client, credit/loan for individual client, sales of wealth management products for individual client, deposit/withdrawal for business client (firm), and credit/loan for business client (firm). The branch characteristics capture the total number of employees, branch address, and its distance to the headquarters. The employee demographic information includes education, industry working experience, and the line of business (associated with the transaction type) in the branch.

4.1 Risk Measures

In this subsection, we define our operational risk performance measure, the error rate, because it is one of the 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 handled by employee i at branch j in month t, namely,

$$ErrorRate_{ijt} = \frac{\text{total number of risk events}_{ijt}}{\text{total number of transactions}_{ijt}}. \tag{1}$$

One advantage of using error rate as compared to frequency (the number count of event occurrences) is that the error rate is scale-free relative to the number of transactions. Later, we conduct zero-inflated Poisson regression on frequency, controlling for the number of transactions as a robustness check to further validate our results.

4.2 Independent Variables

We operationalize our workload variable $Load_{ijt}$ as the number of transactions handled by employee i at branch j during month t divided by the number of hours worked during the same month. We also use an alternative definition of workload to reflect the utilization of the employee capacity in our robustness check section. Following previous literature (see Tan and Netessine, 2014; Macchiavello and Morjaria, 2015) on using linear and quadratic terms to study inverted-U or U-shaped relationships, we further include the square of $Load_{ijt}$ (i.e., $Load_{ijt}^2$) to test our hypothesis about the non-linear effect of workload. For interpretation purposes, we standardize these variables by first subtracting their means and then dividing them by the standard deviations. To reduce the concern regarding multicollinearity, we show the correlations before and after the mean-centering. Before the mean-centering, the correlation coefficient between the linear and non-linear terms is 0.156. After the mean-centering, the correlation coefficient is 0.102. Therefore, we do not think our findings will suffer from multicollinearity.

There is not much guidance in the literature on which controls to use in a study like ours since we are the first to empirically study the causes of operational risks in banks. Nevertheless, we propose the following four types of control variables.

1. We account for the learning effects, and introduce the variable of cumulative workload. Following Lapré and Nembhard (2011) and Clark et al. (2013), the cumulative workload is computed as the total number of transactions for the employee from the beginning of our observation period until the month under study.

2. We control for the number of hours worked by an employee in a month to account for employees taking some days off or working part-time during the month.

3. We adjust for the risk event types to ensure that the varying operational risk error rates are not caused by the differences in the "complexity" of event cases. In particular, we compute the percentages of the focal risk type among all risk types in a month, i.e., (i) data-entry errors, (ii) failed mandatory

reporting, (iii) operation failure, and (iv) aggressive sales. We later change these four risk types into the ten labels derived via text mining as a robustness check.

4. We introduce categorical variables of employee's line of business to control for the idiosyncratic factors of operational risks in different types of transactions. These include deposit/withdrawal for individual client, credit/loan for individual client, sales of wealth-management products for individual client, deposit/withdrawal for business client (firm), and credit/loan for business client (firm).

Besides these time-varying controls, we also add employee, branch, and month-year fixed effects to our main estimation. The employee fixed effects isolate employees' idiosyncratic tendency to violate operational risk rules, as they may switch lines of business or even branches from month to month. The branch fixed effects control for branch-level heterogeneity (e.g., branch risk monitoring level and branch manager effort level). Finally, month-year fixed effects adjust for all temporal effects, such as seasonality or trend.

Table 1 presents the summary statistics of our key variables and some additional institutional knowledge about our focal bank, based on 9,954 observations (N = 9,954) of 675 employees in 49 branches at a monthly level. Our data set is an unbalanced panel because some employees joined the bank after January 1, 2014, and some employees left before April 30, 2015. On average, one employee at each bank branch handles 4.748 transactions per hour. The error rate per employee every month is 0.010%, which is consistent with the low occurrence feature of operational risk (Cruz, 2002). An employee works for approximately 234.8 hours a month, and has experience with 8,024 transactions, on average. In addition, each branch hires 13.77 employees, who jointly process 15,850 transactions per month. Finally, operational risk events related to data-entry, reporting, operations, and sales constitute 26.42%, 30.63%, 28.36%, and 14.59% of total operational risk events, respectively.

Table 1: Summary Statistics (Monthly)

Variable	Definition	Mean	SD	Min	Max
Error rate (%)	Total number of risk events over the total number of transactions	0.010	0.002	0.000	0.036
Load	Number of transactions handled per employee per hour	4.748	1.471	0.317	25.34
Work_hour	Number of hours worked by an employee in a month	234.8	43.31	75.50	302.0
Cum_load	Total number of transactions per employee until the month under study in 1,000s	8.024	0.974	0.000	30.15
Tran.num	Number of transactions in each branch in 1,000s	15.85	1.850	14.00	43.50
Num.empl	Number of employees in each branch	13.77	2.790	6.000	19.00
Data-entry (%)	Percentage of data-entry errors	26.42	25.43	0.000	100.0
Reporting (%)	Percentage of failed mandatory reporting errors	30.63	28.94	0.000	100.0
Operation (%)	Percentage of operation failure events	28.36	29.52	0.000	100.0
Sales (%)	Percentage of aggressive sales events	14.59	20.47	0.000	100.0

5 Estimation and Results

In this section, we discuss our model and the estimation results. Section 5.1 presents the details of the identification strategy. Section 5.2 describes our main empirical results. Section 5.3 discusses the mechanisms behind our main results through subset analyses; Section 5.4 shows the robustness checks of our main results with an alternative workload measure and model specification.

5.1 Model and Identification

In our study, we choose to aggregate the panel data at the employee-month level instead of analyzing transaction-level or daily-level data. Either transaction or daily-level analysis is difficult in our setting because operational risk events occur very infrequently (only approximately two events per month out of an average of 15,850 transactions at a branch, see Table 1). The commonly used regression models for binary outcomes (e.g., probit and logistic regressions) are ineffective in the presence of rare events data because the model may not converge given the sparse outcome variable. Even if the model converges, the estimated coefficients might be biased (Greenland et al., 2016). Therefore, we aggregate the data at the monthly level instead of the transaction or daily level. Furthermore, we analyze employee-level data because one and only one employee is responsible for one operational risk event. The employee-level analysis controls for individual ability and line of business heterogeneity.

We start with the following fixed-effects model for the error rate of employee i at branch j in month t:

$$ErrorRate_{ijt} = \beta_0 + \beta_1 Load_{ijt} + \beta_2 Load_{ijt}^2 + \boldsymbol{\beta X}_{ijt} + \kappa_i + \phi_j + \omega_t + u_{ijt}. \tag{2}$$

The vector $\boldsymbol{X}_{ijt}$ contains a list of covariates including cumulative workload, monthly hours worked, the percentage measure of the four risk types, and categorical variables for lines of business (see description of these controls in Subsection 4.2). We also control for the employee, branch, and month-year fixed effects (κ_i, ϕ_j, and ω_t). Although our fixed-effects models control for both observed and unobserved heterogeneity at the individual level, the models may still be prone to endogeneity. For instance, one potential omitted variable could be the employee's effort level in engaging in risk management, which should be negatively correlated with the error rate. In addition, the risk-management effort level should be negatively correlated with workload because the employee may be too busy handling transactions to manage operational risk. Hence, we may potentially underestimate the true impact of workload on error rate.

To alleviate the endogeneity issue mentioned above, we use the instrumental variable (IV) approach, which is widely used to address such endogeneity issues (Kennedy, 2003). The choice of a good IV should meet two conditions, namely, relevance and exclusion restriction (Wooldridge, 2010). The relevance condition requires the IV to be correlated with the endogenous variable, while the exclusion restriction 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 IV is the number of visits to the branch's web portal (*E-visit*). *E-visit* varies by branch since customers need specific branches to grant access to online banking accounts in China. During our observation period, the online channel only offered basic deposit and withdrawal functions. Customers were only able to obtain services such as credit applications and sales of asset management products in the physical branches. In other words, the online channel did not serve as a sales channel for the bank. We believe the online channel does not directly affect the offline operational risk events because the branch employees do not handle online business. For instance, the online visit variable should not be correlated with the individual employee's risk-management effort level offline since an online visit does not relate to branch risk-management actions. Therefore, this variable should satisfy the exclusion restriction condition. Furthermore, the website traffic and the physical store traffic can be correlated because of common demand shock. For example, some online transactions may require in-store verification or processing. When the online customer arrives at the branch to finish the online business, he or she may conduct some additional business, such as withdrawing money. We also observe that the coefficient of *E-visit* is positive and significant (0.412) in the first-stage regression (see Table 10), supporting this mechanism. In addition, we compute the Cragg-Donald Wald F statistics, and the values are 15.4 and 14.7 (both are greater than 10), which verifies that this IV is not weak. The month and branch fixed effects do not fully mediate this common demand shock because we did not include the interaction terms of branch and month fixed effects. Thus, the web visit variable should satisfy the relevance condition.

Because *E-visit* does not vary by employee in the same branch, we therefore supplement this IV with Hausman-type IVs (see Hausman, 1996). In our case, it is the average workload of all other employees in the *same* business line of the *same* branch during the *same* month. We include its square term as an extra IV because $Load_{ijt}^2$ is also endogenous. The Hausman-type IVs should satisfy the exclusion restriction condition because the focal worker is fully responsible for the error captured. The cross-trained workers are fully authorized and solely responsible to perform their assigned transactions. They sit at their designated counters and use individual equipment, such as computers, printers, and seals. They use their integrated circuit (IC) card to access the system, so that their individual transactions can all be identified and traced. For the individual work that they perform, they receive rewards and also face penalties. For example, they earn commission proportional to the number and amount of transactions and the wealth-management products that they processes. However, if they cannot reach an account settlement at the end of the business day, they have to pay the difference with their own money. Their bonus is also reduced if they make mistakes. Hence, the common resource usage is limited, and the transaction performed is highly individualized in our setting. In other words, other workers' workload would not affect the focal worker's error. It is not a teamwork scenario.

Admittedly, all the workers would access the same remote/background verification system (i.e., a common resource), which is susceptible to a collapse or a glitch. Nevertheless, this type of system failure would not be counted against the individual employee. Besides, if the system glitch slows down the transaction progress, it would directly affect our independent variable (workload measure), thus keeping the exclusion restriction condition intact. We would also like to add that we have accounted for various other sources of spillovers in our analysis. For example, employees may share knowledge and create a spillover. We use a cumulative workload variable to control for such knowledge sharing and learning effects. Moreover, the employees work at the same office branch so we include the branch fixed effects.

The Hausman-type IVs should also satisfy the relevance condition. Employees in the same business line of the branch should have workloads that are positively correlated with each other's because they serve the same customer base and are subject to common demand shock. It is also possible that other employees' workloads may affect the focal employee's workload because of peer effects. In fact, we also observe that the coefficients of our Hausman-type IVs have respective positive coefficients of 0.102 and 0.079 (see Table 10) in the first-stage estimation, consistent with this explanation. Computing the Cragg-Donald Wald F statistics, we find the values are 19.7 and 17.1 (both are greater than 10), which suggests that this IV is not weak. Similarly to how we standardize our independent variables, we standardize all three of these IVs for interpretation purposes.

Given that we are testing a non-linear effect hypothesis, we consider a control function approach, which has been shown to be efficient in estimating non-linear causal effects (Guo and Small, 2016). In particular, we estimate the following first- and second-stage equations to examine the effect of workload on error rate, and bootstrap the standard errors based on 1,000 replications. Consider employee i at branch j in month t:

$$Load_{ijt} = \gamma_0 + \gamma_1 E\_visit_{jt} + \gamma_2 Haus\_load_{ijt} + \gamma_3 Haus\_loadsq_{ijt} + \boldsymbol{\gamma X}_{ijt} + \eta_i + \xi_j + \tau_t + \varepsilon_{ijt} \tag{3}$$

$$Load^2_{ijt} = \alpha_0 + \alpha_1 E\_visit_{jt} + \alpha_2 Haus\_load_{ijt} + \alpha_3 Haus\_loadsq_{ijt} + \boldsymbol{\alpha X}_{ijt} + \delta_i + \zeta_j + \theta_t + e_{ijt} \tag{4}$$

$$ErrorRate_{ijt} = \beta_0 + \beta_1 Load_{ijt} + \beta_2 Load^2_{ijt} + \boldsymbol{\beta X}_{ijt} + \kappa_i + \phi_j + \omega_t + \hat{v}_{ijt} + u_{ijt}. \tag{5}$$

In the first-stage equations (3) and (4), we regress the workload (both linear and nonlinear terms) on the instruments (i.e., E_visit, $Haus\_load$, and $Haus\_loadsq$) and baseline covariates (vector $\boldsymbol{X}_{ijt}$), control for the employee, branch, and month-year fixed effects, and get the residuals of the first-stage regressions $\hat{v}_{ijt}$ ($\hat{v}_{ijt} = (\hat{\varepsilon_{ijt}}, \hat{e_{ijt}})$). Note that vector $\boldsymbol{X}_{ijt}$ contains a list of covariates including cumulative workload, monthly hours worked, the percentage measure of the four risk types, and categorical variables of lines of business (see the description of these controls in Subsection 4.2). In the second stage of the control function method, the outcome ($ErrorRate_{ijt}$) is regressed on the workload measures ($Load_{ijt}$, $Load^2_{ijt}$), baseline covariates (vector $\boldsymbol{X}_{ijt}$), and the vector of residuals of the first-stage regression ($\hat{v}_{ijt}$). The residuals of the first-stage regressions account for the unmeasured confounders. We also control for the employee, branch, and month-year fixed effects (κ_i, ϕ_j, and ω_t). In our analyses, we standardize all variables by mean-centering and dividing them by their standard deviations, except for binary variables. We also cluster the standard errors at both the employee level and the branch level (i.e., two-way clustering) to account for the correlation within the same employee over time, as well as the correlation among employees working in the same branch (Baum and Christopher, 2006; Xu et al., 2017). We also conduct two-way clustering at both the branch and month level as a robustness check to control for the heteroskedasticity in errors across months and allow for the correlation of errors within branches (Section 5.4).

5.2 Estimation Results

Table 2 shows our main results. We present the results without using the IVs in Columns 1 and 2, and the results with the IVs in Columns 3 and 4. Moreover, Columns 1 and 3 show the linear specification, while Columns 2 and 4 contain the non-linear specification. The linear coefficients estimated without using the IVs (-0.054 and -0.241) are larger than those estimated with the IVs (-0.104, -0.513), which suggests that the IVs seem to correct the upward omitted variable bias in the expected direction. In addition, we find the coefficients of $Load^2$ are consistently positive and significant (0.196, 0.487). Interpreting the results with the IV, we calculate that the critical point of the quadratic function is approximately 0.527 ($-\beta_1/2\beta_2$) standard

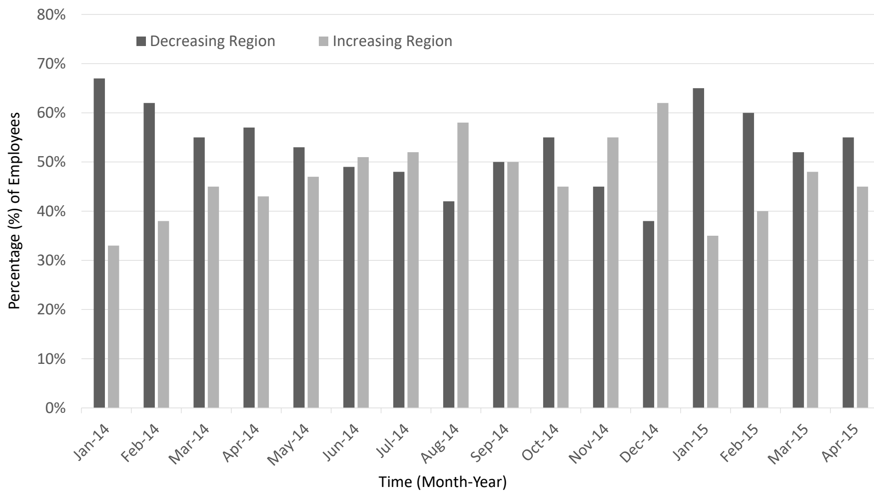

Figure 1: Fractions of Employees Falling below and above the Critical Point of Monthly Workload

deviations above the sample mean. This result supports our hypothesis that predicts an U-shaped relationship between workload and error rate. The critical point 0.527 means the corresponding workload level for the minimum number of errors is approximately 5.5 transactions per worker per hour ($0.527 \times 1.471 + 4.748$). To help interpret this critical point, we further compute the fractions of employees every month who fall below and above the critical point, separately in Figure 1. If, in any particular month, the workload of an employee falls into the decreasing region (below the critical point), then increasing the workload would likely decrease the employee's error rate. In other words, additional workload helps mitigate error rates for this employee. On the other hand, if the workload of an employee falls into the increasing region (above the critical point), then additional workload increases the error rate. In addition, employees seem to be evenly distributed on either side of the critical point (no fraction is below 0.3 or greater than 0.7), which reduces the standard error of forecasting due to sampling.

To clearly illustrate the U-shaped relationship between workload and error occurrence, we plot the predicted number of errors per month by untransformed workload based on our estimation results in Figure 2 below. As the workload increases from 1 to 5.5 transactions per hour (the critical point), the number of errors drops from around 2.2 to almost 0. When the workload further increases from 5.5 to 11, the number of errors increases to around 3.2. Although 5.5 transactions per hour minimizes the number of errors, it does not necessarily suggest that each employee should handle just 5.5 transactions per hour. Note that this critical point does not take into account other important managerial factors, such as store revenues and labor costs.

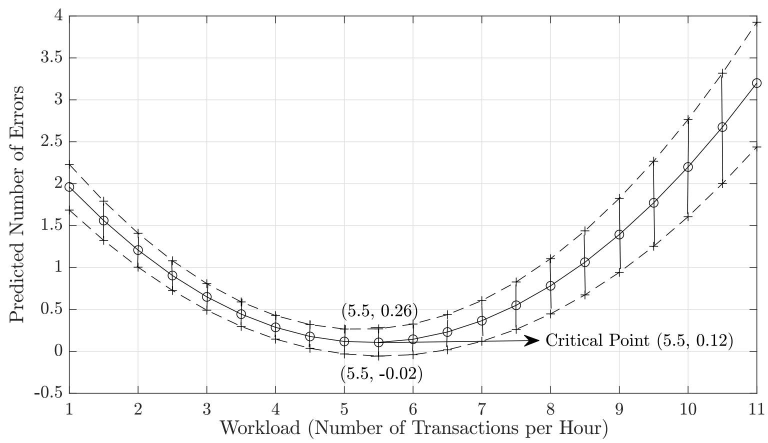

Figure 2: Predicted Number of Errors by Workload

Finally, whether estimated with or without the IVs, we find that the nonlinear model has a better goodness-of-fit than the linear one (adjusted R^2 = 0.429 vs. 0.455 in Columns 1 and 2, 0.558 vs. 0.59 in Columns 3 and 4), which further supports our U-shaped relationship hypothesis instead of a linear relationship. Furthermore, we have conducted a partial F test for the quadratic model and find that the p-value is 0.02. This test result suggests that we can reject the null-hypothesis that the quadratic model does not significantly differ the linear model at the 0.05 level. We also conduct various robustness checks of the U-shaped relationship (e.g., spline regression, two-line test), which we detail in Section 5.4. For the control variables, employees with a higher cumulative workload tend to have lower error rates, which is consistent with our expectations from the theory on learning. The coefficient of the number of hours worked turns out to be insignificant, probably because we have already normalized our dependent variable to an hourly basis.

5.3 Workload Impact Discussion and Subset Analysis

What mechanisms are behind our empirical results? We first present the detailed text descriptions of the operational risk events in our data set under extremely high- and low-workload environments in Tables 13

Table 2: Impact of Workload on Error Rate

	Main Model without IV		Main Model with IV	
	(1) Linear	(2) Non-linear	(3) Linear	(4) Non-linear
Dependent Variable	Error Rate	Error Rate	Error Rate	Error Rate
Load	-0.054*	-0.241*	-0.104***	-0.513***
	(0.023)	(0.104)	(0.026)	(0.090)
$Load^2$	–	0.196*	–	0.487***
	–	(0.085)	–	(0.081)
Cum_load	-0.067**	-0.062**	-0.132***	-0.194***
	(0.024)	(0.022)	(0.029)	(0.037)
Work_hour	0.084	0.092	0.106	0.115
	(0.071)	(0.080)	(0.079)	(0.082)
Residual1			0.112*	0.087*
			(0.049)	(0.038)
Residual2				0.043*
				(0.018)
Risk Type (%)	Yes	Yes	Yes	Yes
Line of Business	Yes	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Month Year FE	Yes	Yes	Yes	Yes
N	9,954	9,954	9,954	9,954
adj. R^2	0.429	0.455	0.558	0.590

1. Standard errors in parentheses
2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and 14, respectively. Among the 29 risk events that happened under extremely high workload conditions (the top 10% highest workload observations), where each employee handles between 7.25 to 25.34 transactions per hour, employees tend to make errors or exhibit quality degradation due to cognitive multitasking. For example, the risk event "Issued RMB 3 million business loan with maturity date as the next day" (item 1) or "Issued RMB 1 million business loan without an interest rate" (item 10) are such errors. Despite the variety of risk events in this table, most of them seem to be simple mistakes due to negligence related to ED&PM-type risk events, which neither enhances the performance of employees nor appears malicious. By contrast, among the 11 risk events under low workload (the bottom 10% of workload observations) shown in Table 14), where each employee handles around 0.317 to 1.21 transactions per hour, employees tend to commit performance-seeking violations. As a case in point, the risk event "Client manager issued RMB 5 million loans without the branch manager's signature" (item 1) shows that the client manager used discretion without proper approval to issue the loan to the customer, probably in an attempt to reach a certain performance target. In fact, all the risk events here are related to issuing more loans, an area that is a major component of employees' income incentives. Such behavior of inappropriately issuing loans belongs to CP&BP-type risk events. When we broadly define high and low workloads by the sample mean, we find similar results. When workload is below the sample average, CP&BP events account for 71.3% of all events observed; when workload is above the sample average, however, this percentage falls to 37.4%.

These summary statistics prompt us to more rigorously examine the impact of workload on the occurrence of the two risk types (ED&PM and CP&BP), separately. We first use the same independent variables as in Equation (5) and adopt a seemingly unrelated regression (SUR) of the proportions of either ED&PM or CP&BP events because the two risk events are not independent within the same employee-month unit of analysis.[7] We present our model specifications as follows:

$$ED\&PM(\%)_{ijt} = a_0 + a_1 Load_{ijt} + a_2 Load_{ijt}^2 + a\boldsymbol{X}_{ijt} + f_i + g_j + h_t + \rho_{ijt}, \tag{6}$$

$$CP\&BP(\%)_{ijt} = c_0 + c_1 Load_{ijt} + c_2 Load_{ijt}^2 + \boldsymbol{c}\boldsymbol{X}_{ijt} + k_i + l_j + m_t + \vartheta_{ijt}. \tag{7}$$

We regress the percentage of ED&PM or CP&BP events on the linear and nonlinear workload terms and baseline covariates ($\boldsymbol{X}_{ijt}$) and control for the employee, branch, and month-year fixed effects. Columns 1 and 2 in Table 3 show the results. The coefficients of *Load* are significantly positive for ED&PM (0.156) and significantly negative for CP&BP (-0.618). The coefficients of $Load^2$ are significantly positive for ED&PM (0.092) and insignificant for CP&BP (0.302). These results suggest that the percentage of ED&PM risk events has a U-shaped relationship in workload with the critical point as 0.85 standard deviations below the sample mean (i.e., $0.156/(2\times 0.092) = 0.85$), and the percentage of CP&BP risk events monotonically decreases with workload. This finding offers evidence of a mechanism supporting our hypothesis. That is, when workload is low, it predominantly reduces operational risk, because 1) it stimulates employees to avoid making cognitive errors such as ED&PM-type risk events, and 2) it inhibits performance-seeking-related events, such as CP&BP errors, which are the most frequent type of errors under low workload.

[7] We thank the anonymous AE for this suggestion.

When workload is high, increase in workload induces more operational risk events because it increases cognitive-error-related events, such as the ED&PM type, which is the biggest component of errors under high workload.

Table 3: SUR Models on ED&PM (%) and CP&BP (%)

	(1) ED&PM (FE)	(2) CP& BP (FE)	(3) ED&PM	(4) CP&BP
Dependent Variable	Error Percentage (%)	Error Percentage (%)	Error Percentage (%)	Error Percentage (%)
Load	0.156***	-0.618***	0.205***	-0.674***
	(0.027)	(0.085)	(0.036)	(0.097)
$Load^2$	0.092***	0.302	0.102***	0.341
	(0.013)	(0.264)	(0.024)	(0.274)
Cum_load	-0.124***	-0.043***	-0.101**	-0.039**
	(0.013)	(0.008)	(0.037)	(0.014)
Work_hour	0.106	0.087	0.094	0.082
	(0.097)	(0.084)	(0.090)	(0.077)
Residual1	0.094*	0.076*	0.085*	0.081*
	(0.041)	(0.033)	(0.037)	(0.035)
Residual2	0.049*	0.041*	0.043*	0.035*
	(0.021)	(0.017)	(0.018)	(0.015)
Rural/Urban	–	–	0.114***	0.067***
	–	–	(0.025)	(0.013)
Edu_lvl	–	–	-0.115	-0.094**
	–	–	(0.102)	(0.034)
Exp_lvl	–	–	0.054	0.062*
	–	–	(0.060)	(0.027)
GDP	–	–	0.061	0.053
	–	–	(0.070)	(0.072)
Profit	–	–	0.073	0.059
	–	–	(0.063)	(0.051)
Business Line Dummy	Yes	Yes	No	No
Employee FE	Yes	Yes	No	No
Branch FE	Yes	Yes	No	No
Month Year FE	Yes	Yes	No	No
N	9,954	9,954	9,954	9,954
adj. R^2	0.213	0.225	0.221	0.233

1. Standard errors in parentheses
2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Besides the aforementioned fixed-effects models, we use two SUR regression models to understand what employee-specific characteristics may affect the occurrence of ED&PM and CP&BP events. In particular, we examine three variables, namely, education level (i.e., high school, bachelor's, master's, and doctorate), experience level (i.e., years of related financial-industry working experience), and working environment (i.e., whether the employee's branch is in a rural or an urban area.

Table 4: Additional Subsample Analyses

	(1) Data Entry	(2) Reporting	(3) Operation Failure	(4) Individual Deposit and Withdrawal	(5) Individual Credit and Loan	(6) Individual Sales of Wealth Mgnt	(7) Business Deposit and Withdrawal	(8) Business Credit and Loan
Dependent Variable	Error Percentage (%)	Error Percentage (%)	Error Percentage (%)	Error Rate	Error Rate	Error Rate	Error Rate	Error Rate
Load	0.187***	0.141***	0.102***	-0.497***	-0.483***	-0.495***	-0.496***	-0.488***
	(0.029)	(0.021)	(0.013)	(0.071)	(0.062)	(0.070)	(0.072)	(0.069)
$Load^2$	0.143***	0.119***	0.082***	0.452***	0.463***	0.461***	0.459***	0.466***
	(0.022)	(0.018)	(0.012)	(0.051)	(0.055)	(0.052)	(0.046)	(0.047)
Cum_load	-0.121***	-0.140***	-0.202***	-0.101***	-0.113***	-0.109***	-0.107***	-0.119***
	(0.015)	(0.019)	(0.028)	(0.012)	(0.018)	(0.014)	(0.016)	(0.017)
Work_hour	0.095	0.089	0.091	0.105	0.112	0.108	0.106	0.111
	(0.078)	(0.072)	(0.075)	(0.089)	(0.091)	(0.082)	(0.090)	(0.088)
Residual1	0.095*	0.081*	0.086*	0.074*	0.082*	0.077*	0.080*	0.075*
	(0.041)	(0.035)	(0.037)	(0.032)	(0.035)	(0.033)	(0.035)	(0.032)
Residual2	0.046*	0.051*	0.042*	0.045*	0.043*	0.049*	0.050*	0.046*
	(0.020)	(0.022)	(0.018)	(0.019)	(0.018)	(0.021)	(0.021)	(0.020)
Line of Business	Yes	Yes	Yes	–	–	–	–	–
Risk Type(%)	–	–	–	Yes	Yes	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,954	9,954	9,954	2,140	2,018	1,968	1,936	1,892
adj. R^2	0.384	0.391	0.380	0.439	0.442	0.437	0.409	0.430

1. Standard errors in parentheses
2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Columns 3 and 4 in Table 3 present the results. First, the coefficients of *Load* and $Load^2$ are consistent with those in Columns 1 and 2. Second, employees working in a rural branch (coefficient = 0.067) who have lower education levels (coefficient = -0.094) and higher experience levels (coefficient = 0.062) are more likely to cause CP&BP-related risk events than those employees working in an urban branch who have higher education levels and lower experience levels. Third, employees who work in a rural branch as opposed to an urban branch (coefficient = 0.114) are also more likely to be responsible for ED&PM-related risk events. We find no significant associations between either education level or experience level and ED&PM occurrence. Furthermore, we conduct various additional subsample analyses. In particular, we divide ED&PM into the three risk types labeled by the focal bank—(i) data-entry errors, (ii) failed mandatory reporting, and (iii) operation failure—and we employ SUR fixed-effects models for estimation. The results shown in Columns 1 through 3 in Table 4 support the finding in Table 3. We also delve into the five lines of business. Columns 4 through 8 in Table 4 show the results of these subsample analyses. All the models support the finding of a U-shaped effect of workload on risk occurrence in all lines of business.

5.4 Robustness Checks

We conduct additional robustness checks in terms of alternative models, an alternative workload measure and instrumental variables, and additional control variables. All results remain consistent.

5.4.1 Alternative Models

First, we consider the joint estimation of the risk error rate and severity through a seemingly unrelated regression (SUR) because the error rate and the severity of the risk events can be correlated. We specify the models as follows:

$$ErrorRate_{ijt} = \beta_0 + \beta_1 Load_{ijt} + \beta_2 Load^2_{ijt} + \beta \boldsymbol{X}_{ijt} + \kappa_i + \phi_j + \omega_t + u_{ijt}, \tag{8}$$

$$Severity_{ijt} = b_0 + b_1 Load_{ijt} + b_2 Load^2_{ijt} + \boldsymbol{bX}_{ijt} + \psi_i + \rho_j + \mu_t + \nu_{ijt}, \tag{9}$$

where $Severity_{ijt}$ is the average severity level of operational risk events for employee i at branch j in month t. The mean of *Severity* is 3.56 per event, and the standard deviation is equal to 11.2. Figures 3 and 4 in Appendix A further show the average severity score distribution by risk type and business line, separately. Despite the variation, all risk events are likely to cause losses for the bank if they are not caught or corrected.

We present our estimation results in Columns 1 and 2 of Table 5. We find the impact of workload on error rate to be consistent with our main model, but workload has no statistically significant impact on risk severity. Why is the effect of workload on severity absent? We read the text descriptions for some intuitions, and find the severity level for most risk events depends primarily on the financial aspect of the risk rather than the operational aspect. For example, one such risk event, "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 characteristic that is not controllable either by the bank employees or by operational characteristics. Another example, "Issued RMB 500,000 loan with 0 interest rate," has a severity score of 5. Again, the severity score of 5 here is mainly determined by the current interest rate, on which the workload of employees would have limited impact.

Table 5: Alternative Models

	SUR Models		Zero-inflated Poisson
	(1) Error Rate	(2) Severity	(3) Count
Dependent Variable	Error Rate	Severity	Error Num.
Load	-0.579***	0.597	-0.475***
	(0.048)	(0.416)	(0.071)
Load^2	0.512***	0.316	0.432***
	(0.040)	(0.449)	(0.054)
Cum_load	-0.052***	-0.048***	-0.102***
	(0.013)	(0.003)	(0.010)
Work_hour	0.084	0.061	0.093
	(0.069)	(0.058)	(0.087)
Residual1	0.086*	0.073*	0.079*
	(0.037)	(0.032)	(0.034)
Residual2	0.042*	0.036	0.041*
	(0.018)	(0.029)	(0.017)
Tran.num	–	–	0.215***
	–	–	(0.054)
Risk Type (%)	Yes	Yes	Yes
Business Line Dummy	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes
Month Year FE	Yes	Yes	Yes
N	9,954	9,954	9,954
adj. R^2	0.556	0.301	0.282

1. Standard errors in parentheses

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

We further conduct robustness checks with a zero-inflated Poisson regression, because 1) the risk occurrence can be considered as a count data type, and 2) most operational risk measurement models use a compound Poisson process to capture the convolution of risk occurrence and severity (Cruz, 2002). Since our data set contains many zeros for non-occurrence, we adopt the zero-inflated Poisson regression. We present the respective results in Column 3 of Table 5. As can be seen, the coefficient of $Load^2$ is significant and positive (0.432), whereas the coefficient of *Load* is significant and negative (-0.475). These results support our U-shaped impact of workload on error rate.

In addition to SUR and zero-inflated Poisson, we also use a spline regression of workload on error rate. A spline regression can be viewed as an extension of linear models that are used to characterize specific nonlinear relationships. It has the 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 6a shows the spline regression results. As can be seen, the coefficient of workload for the piece-wise linear function when workload is low is negative, starting from -9.145 at a 5% significance level, and it increases to positive, with a value of 4.536 at a 5% significance level. This finding is consistent with a U-shape hypothesis. Furthermore, we conduct a two-line test and Lind test. The two-line test is used to test the U-shaped relationship between x (independent variable) and y (dependent variable) with two separate lines that characterize the low and high value of x. The two-line test follows Simonsohn (2016). We obtain a p-value of 0.017 for the left line and 0.022 for the right line, which suggests the statistical significance of a U-shape. The Lind test is another method to test the U-shaped relationship, which characterizes both necessary and sufficient conditions for such a relationship. Following Lind and Mehlum (2010), we conduct the Lind test to validate the quadratic specification, and we obtain a p-value of 0.025 for the test, which rejects the null hypothesis of a monotone or inverse U-shape (see Table 6b).

5.4.2 Alternative Workload Measure and Instrumental Variables

We consider an alternative utilization-based measure of workload, which is operationalized as

$$Load_{2ijt} = Load_{ijt} / Load.cap_{ij}, \tag{10}$$

Table 6: Alternative U-shape Testing

(a) Spline Regression

Dependent Variable	Error Rate
0%-10%	-9.145*
	(4.011)
10%-20%	-5.784*
	(2.537)
20%-30%	-2.867*
	(1.257)
30%-40%	-1.046*
	(0.459)
40%-50%	-0.803*
	(0.352)
50%-60%	-0.101*
	(0.044)
60%-70%	0.246*
	(0.107)
70%-80%	1.912*
	(0.838)
80%-90%	4.536*
	(1.989)
90%-100%	9.224
	(10.022)
N	9,954
$adj.R^2$	0.251

1. Standard errors in parentheses

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

3. The results of control variables are omitted due to page constraint.

(b) Lind and Mehlum U-shape Testing on Error Rate and Workload

	Lower bound	Upper bound
Interval	-0.524	15.415
Slope	-0.001	0.003
t-value	-2.012	1.953
$P > \|t\|$	0.021	0.024

Specification $f(x) = x^2$ Extreme point: 0.532

Overall test of presence of a U shape: t-value = 1.97, P > |t|=0.025

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

where the workload capacity $Load.cap_{ij}$ is defined as 95% of the maximum monthly workload throughout the entire study period (i.e., the number of transactions divided by the number of hours worked in the corresponding month) (a similar measure is used in Berry and Tucker, 2016). We then calculate the quadratic term $Load_2^2$ and use it and $Load_2$ to replace $Load^2$ and $Load$ in our main model. Note that, similar to other independent variables, we mean-center the alternative load measure and its squared value for interpretation purposes. The results are shown in Columns (1) and (2) of Table 7. As can be seen, the coefficient of the linear term is significant and negative, and the coefficient of the quadratic term is significant and positive, supporting the U-shaped relationship between workload and error rate. Interpreting the two coefficients, the critical point is equal to 0.545 ($0.505/(2 \times 0.463)$). In addition, the estimation results for all other variables remain consistent with our main estimation.

In addition, we consider six alternative IVs as a robustness check. They are the linear and quadratic terms of the monthly average temperature near the branch location (see Cachon et al., 2019), the amount of precipitation,[8] and one-month lagged workload. We show consistent results in Column 3 of Table 7.

Table 7: Alternative Workload Measure and Instrumental Variables

	Alternative Load		Alternative IVs
	(1) Linear	(2) Non-linear	(3)
Dependent Variable	Error Rate	Error Rate	Error Rate
Load	–	–	-0.532***
	–	–	(0.074)
$Load^2$	–	–	0.496***
	–	–	(0.068)
$Load_2$	-0.108***	-0.505***	–
	(0.025)	(0.083)	–
$Load_2^2$	–	0.463***	–
	–	(0.075)	–
Cum_load	-0.140***	-0.199***	-0.124***
	(0.021)	(0.036)	(0.030)
Work_hour	0.103	0.111	0.116
	(0.071)	(0.079)	(0.013)
Residual1	0.106*	0.081*	0.086*
	(0.045)	(0.035)	(0.037)
Residual2	–	0.039*	0.041*
	–	(0.017)	(0.017)
Risk_Type (%)	Yes	Yes	Yes
Line of Business	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes
Month Year FE	Yes	Yes	Yes
N	9,954	9,954	9,678
adj. R^2	0.545	0.588	0.511

1. Standard errors in parentheses
2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4.3 Additional Control Variables and Other Checks

We first replace the fixed effects in our original model with additional employee-related characteristics (in terms of education level, experience level, rural/urban setting) and branch-characteristics (in terms of local

[8] We gather our weather data from https://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

quarterly GDP and monthly branch profit) and run the regression analysis again. Column 1 of Table 11 in Appendix A shows results that are consistent with our main results. Noteworthy here is that the dummy variable rural/urban is positively correlated with the error rate, which suggests that the rural areas are subject to more operational risk events. In addition, employees with higher levels of education are less likely to make errors (the correlation is -0.103 under the non-linear model).

We next consider alternative risk-type variables. We categorize our risk events into ten types via text mining, and reestimate our fixed-effects models, i.e., replace the four percentage variables of risk types in the main model (i.e., percentages of data-entry errors, failed mandatory reporting, operation failure, and aggressive sales) with ten new percentage variables yielded by text mining analysis. The details of the text mining analysis can be found in Appendix B. We show our estimation results in Column 2 of Table 11 in Appendix A. We find that the non-linear effects are consistent with our main estimation.

Furthermore, we consider the interaction effects of the cumulative workload and current workload to check if the effect of workload depends on cumulative learning. We find no statistically significant effects of the interaction term, and the effects of all the other variables remain the same (see Column 3 of Table 11 in Appendix A). Moreover, we include the lagged error variable to address the potential serial correlation of the error rates. In particular, to reduce the concern regarding Nickell bias for the dynamic panel, we estimate the regression model with the IV estimator of Anderson and Hsiao (1981), and we find that the lagged error term turns out to be statistically insignificant. All other results remain robust (Column 4 of Table 11). As additional robustness checks, we also consider the impact of cubic workload, which turns out be statistically insignificant (Column 5 of Table 11). We also delete the two branches with the highest number of errors. The results are congruent with our main results (Column 6 of Table 11). Finally, to control for heteroskedasticity in errors across months and allow for the correlation of errors across branches in any month, we conduct two-way clustering at both the branch and month level as a robustness check. We show consistent results in Column 7 of Table 11.

6 Discussion on the Optimal Staffing Level

Currently, the bank normally conducts qualitative controls of operational risk management based on managers' personal experience rather than by using a quantitative model (McKinsey, 2020). Therefore, one goal of our paper is to demonstrate the value of incorporating evidence-based results in a quantitative staffing model. In particular, our empirical results suggest a U-shaped relationship between the workload and error rate. Using this finding, we propose a resource allocation model to help branch managers make optimal staffing decisions to reduce operational risk losses. Let us first be clear about an important assumption of our model. Our optimization model considers a simplified scenario where all the risk events cause financial losses purely based on their severity level. In practice, however, whether or not the risk events are materialized depends on the time difference between the occurrence of events and the time they are caught by auditing. If the audit department captures the risk events in time and corrects them, these events will no longer cause actual losses. Simplified as it is, we make this assumption because 1) we do not observe actual losses in our data, and 2) banks consider all the relevant events to decide on capital provision for operational risk. Hence, our proposed staffing model can also potentially help reduce operational risk capital provision.

To estimate the potential losses, as mandated by regulations, a bank typically uses a frequency distribution to project the total number of loss events in a 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. In fact, we validate this independence assumption between the frequency and severity variables in our data set by means of the Chi-squared test. The p-value of Chi-squared test is 0.4125 at the employee level and 0.3271 at the branch level, which suggests that we fail to reject the null hypothesis that the frequency is independent of the severity. The total loss is then computed by the convolution of these two distributions using a compound model. In our case, the operational risk losses $L_{i_k jt}$ of employee i_k from line of business k at branch j in month t could be written as follows:

$$L_{i_k jt} = \sum_{n=1}^{N_{i_k jt}} X_n, \quad \text{for} \quad t = 1, ..., 16, \quad j = 1, ...49, \tag{11}$$

where X_n is the severity of each risk event for every employee at every branch during every month, and $N_{i_k jt}$ is the monthly number of the risk events. The monthly risk error rate (the number of events divided by the number of transactions) is found to be affected by the workload (a division of the number of transactions by the staffing level and working hours) through a U-shaped relationship, based on our empirical investigation. In other words, keeping the transaction number and working hours constant, optimally changing the staffing levels for each line of business k at each branch j in each month t, denoted as $\boldsymbol{S} = \{S_{111}, ..., S_{kjt}, ...\}$, affects the error rate as follows:

$$ErrorRate_{i_k jt}(\mathbf{S}) = \beta_0 + \beta_1 Load_{i_k jt}(\boldsymbol{S}) + \beta_2 Load^2_{i_k jt}(\boldsymbol{S}) + \boldsymbol{\beta X}_{i_k jt} + \kappa_{i_k} + \phi_j + \omega_t + u_{i_k jt}.$$

Given that

$$N_{i_k jt}(\boldsymbol{S}) = Tran_{i_k jt} \cdot ErrorRate_{i_k jt}(\boldsymbol{S}),$$

we can then obtain the number of operational risk events. With both X_n and $N_{i_k jt}(\boldsymbol{S})$ defined, the total loss for all the branches over time is

$$L(\boldsymbol{S}) = \sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{i_k=1}^{S_{kjt}} \sum_{n=1}^{N_{i_k jt}(\boldsymbol{S})} X_n.$$

Since X_n are assumed to be i.i.d, the expected total loss should be

$$E[L(\boldsymbol{S})] = \sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{i_k=1}^{S_{kjt}} N_{i_k jt}(\boldsymbol{S}) E[X_n]. \tag{12}$$

In our study, we focus on the optimal staffing rules with the same service capacity (675 employees). The objective function is

$$\min_{\boldsymbol{S}} \sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{i_k=1}^{S_{kjt}} N_{i_k jt}(\boldsymbol{S}). \tag{13}$$

Our focal bank currently makes the staffing decision one quarter in advance. Employees are dedicated to the particular line of business and branch within each quarter; however, this staffing decision is purely based on the manager's experience and does not use any quantitative risk model. Consequently, the workload of some business lines and branches might be either too high or too low relative to the risk-minimizing staffing level.

Therefore, we propose new staffing rules that add more flexibility to the staffing processes. In particular, we consider three types of staffing rules: (i) full flexibility (employees can switch across any business lines and branches), (ii) flexibility across business lines within the same branch, and (iii) flexibility across branches within the same business line. Employees may switch business lines and/or branches every month or every quarter.

As a benchmark case, we keep the current staffing decisions unchanged, and equally split the workload among the employees within the same business line and the branch. In other words, we balance the workload without changing the staffing. The total number of risk events is estimated to be 1,390 across 49 branches over 16 months (i.e., 1.77 events per branch per month). Is the assumption about the balanced workload reasonable? The daily operation of the bank branch under study could be considered as a multi-server queueing system, whereby customers arrive at the branch and wait to be served by one of the employees in a particular business line. In this case, the workload of each individual in the business line is mainly determined by their service rates. Since the level of the branch under study handles only basic personal and business banking, the service rates among employees within the same business line do not significantly differ. In particular, the standard deviations of workload measures among employees are 0.423 (individual wealth management), 0.204 (individual deposit/withdrawal), 0.365 (individual credit/loan), 0.249 (business deposit/withdrawal), and 0.402 (business credit/loan) for the five business lines. These values are much smaller than the overall standard deviation of the number of transactions handled per hour (i.e., 1.471). Therefore, we can see that the service rate variation is relatively small within each business line, and the overall variation is mainly caused by the cross-business-line variation. Although the benchmark case with balanced workloads is an ideal scenario, it may still serve as a relatively good approximation of actual practice. Later, we extend this approximation to take into account workload variability within business lines and show consistent improvement.

We then compare this benchmark case with the three types of new staffing rules, allowing employees to switch their lines of business or their branches every month. Specifically, we consider a full flexibility

Table 8: Staffing Rule Implications

	Monthly Staffing Rules			Quarterly Staffing Rules		
	Full Flexibility	Business Line Switch	Branch Switch	Full Flexibility	Business Line Switch	Branch Switch
Number of Events	1,251	1,336	1,321	1,302	1,346	1,332
Percentage Decrease	10.0%	3.9%	5.0%	6.3%	3.2%	4.2%

staffing rule, a flexibility rule across business lines within the same branch, and a flexibility rule across branches within the same business line, respectively, and separately minimize the objective function shown in Equation (13) every month. Table 8 shows the results. The objective function values in terms of the total number of risk events drop to 1,251 (a 10.0% decrease from the benchmark case), 1,336, (a 3.9% decrease), and 1,321, (a 5.0% decrease), respectively.

Next, we perform similar comparisons and allow employees to switch their lines of business or their branches every quarter. The optimized total numbers of risk events of the three flexibility rules drop to 1,302 (a 6.3% decrease from the benchmark case), 1,346 (a 3.2% decrease), and 1,332 (a 4.2% decrease), respectively.

We also try to consider the workload variability within business lines. In particular, we use the historical variance of workload within each business line to introduce the workload variability under the proposed staffing rules and keep the overall workload variance of each business line fixed. Specifically, we define each employee's workload as the average workload (i.e., total number of transactions divided by number of employees) plus or minus a small perturbation δ, then based on the historical workload variance of a particular business line, we can compute the value of this perturbation δ. We then use the workload to estimate the error rate and quantify the impact as compared to the current practice with a total of 1,441 risk events under the same workload variability level. We find that adding this variability actually generates a greater positive impact of our proposed staffing rules; however, the magnitude of this positive impact is quite small. Specifically, we find that employing a flexible staffing rule can reduce the number of operational risk events by 3.5% to 10.6% under workload variability, see Table 12 in Appendix A.

What is the financial impact of the flexible staffing rule? We believe that our flexible staffing rule benefits both in terms of reducing operational risks and capital requirements, and that this benefit should outweigh the cost.

First, the savings from the reduced operational risks can be economically significant. We find that employing a flexible staffing rule can reduce the number of operational risk events by 3.2% (i.e., a reduction of 0.057 events per branch per month) to 10% (i.e., a reduction of 0.177 events per branch per month) from the benchmark case under different scenarios. The average operational risk loss per event in our focal bank is 356,500 RMB (approximately 53,475 USD, it is found by muiplying average severity score of 3.56 per event times 100,000 RMB). Therefore, the loss reduction across the 49 branches is 1.79 ($0.057 \times 49 \times 12$) to 5.57 ($0.177 \times 49 \times 12$) million USD per year.

Second, the saving on capital requirement is also likely to be substantial. Banks can control the frequency of operational risk events to reduce the capital requirements. Per Basel II, commercial banks should typically set aside 15% of annual gross income to account for operational risks (PwC, 2016). Using the financial impact calculated above, we estimate that the saving on capital requirement would be between 0.26 ($15\% \times 1.79$) and 0.83 ($15\% \times 5.57$) million USD per year in our focal bank.

Third, the cost of moving to our flexible staffing should be low. Our suggested staffing rule does not imply hiring additional workers. It simply switches workers' business lines and branches. Besides, most of the workers are already cross-trained and are prepared to switch business lines in our focal bank. The training costs have already been accounted for. Furthermore, employees can easily switch branches, which tend to be located in close proximity to the cities. Admittedly, switching branches may not be free (e.g., banks may provide some travel allowance or incentives). Even if we only allowed business line switch in our staffing rule, we would still directly reduce potential operational risk loss by approximately 1.79 million USD per year in our focal bank, and indirectly reduce capital requirements by 0.26 million USD.

We think our rules build on practical assumptions that are both realistic and feasible. First, managers do not need to make a perfect prediction of workload to balance the workload. To fit the model, one only needs to first forecast the monthly or quarterly average transaction volume, and estimate the regression model for the error rate with historical data. In fact, in practice, banks generally forecast their monthly or quarterly average transaction volume to plan for their operational decisions in the following month or quarter. Second, most of the employees are cross-trained and are prepared to switch business lines or even branches. During the internship or the first one to two years for new employees, their jobs are usually rotation-based as an onboarding practice. In fact, 64% of the 675 employees in our sample have worked across business lines during our study period. Employees may also switch branches, especially between branches in proximity. However, switching between branches is admittedly rather infrequent (only around 11.85% of the 675 employees in our study have ever switched branches). Third, our staffing rules allow employees to switch between business lines and/or branches either every quarter, which is consistent with current practice, so that banks can determine which rules to adopt based on their own business situation. Our focal bank generally makes its staffing decisions one quarter in advance and typically does not revise the decisions later. In other words, employees are dedicated to a business line and a branch each quarter. Lastly, the flexible staffing rule should indirectly improve worker compensation, making it easy for the employees to accept it because it helps employees avoid getting penalized for errors. For these reasons, we believe our flexible staffing rules should be feasible.

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. 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 the workload will reduce the error rate; however, when the overall workload is high, increasing the workload increases the error rate. We further discover the following mechanism behind this finding. When the workload is low, it predominantly reduces operational risk (i.e., an increase in workload leads to risk reduction), because 1) it stimulates employees to avoid making cognitive errors, such as the ED&PM type of risk events, and 2) it inhibits performance-seeking-related events, such as CP&BP errors, which are the most frequent type of errors under low workload. When the workload is high, the promotion effect dominates, because it increases cognitive-error-related events, such as those of the ED&PM type, which is the biggest component of errors under high workload. Although we find a U-shaped relationship between workload and error rate, we do not observe a 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 banks' current staffing decisions create avoidable operational risk events because of imbalanced workloads among branches. We therefore propose a capital allocation model to help make optimal staffing decisions to reduce operational risk losses under the same service capacity (number of employees). In general, we find that keeping the risk severity level the same, employing a flexible staffing rule can significantly reduce operational risk losses by more than 3% from the benchmark case under different scenarios. In particular, we can achieve performance improvement by adding even a little bit of flexibility to the process by allowing employees to either switch their business lines in the same branch or switch branches within the same business lines on a quarterly basis.

Our study makes the following contributions to the literature. To the best of our knowledge, our paper is the first empirical work that analyzes the causes of operational risks officially defined by Basel II from an OM perspective in the banking industry, while the previous studies tended to model operational risk as an exogenous probability distribution. In particular, we establish a causal link between workload, an important work environment factor that can be adjusted by staffing decisions, and the error rate of operational risk events. Second, we revisit a growing area in operations management—the impact of workload on operational performance—and broaden our understanding of the importance of the workload in staffing decisions in the financial industry, which is understudied in the empirical OM literature. We particularly examine the mechanisms through which workload affects operational risk events. Third, our empirical study enables us to explain the variation in operational risk events, so that we can build a capital allocation model to re-optimize bank staffing levels to improve operational risk management. Therefore, our paper provides a novel consideration for the labor optimization literature: staffing to avert operational risk events.

Finally, it is important to understand the limitations of our work and establish future research directions. First, although our data set is unique with respect to its collection of operational risk events, we only cover the categories of data-entry errors, accounting errors, failed mandatory reporting, and negligent loss of client assets, which are mainly caused by bank workers. Clearly, there are still other types of operational risk events that we did not study in this paper. For example, "External Fraud" is committed by a third-party. "Damage to Physical Assets" entails those losses arising from natural disasters or terrorism/vandalism. "Business Disruption and System Failures" incur losses arising from the disruption of business/system failure. These events are mainly exogenous and beyond the scope of this paper. An interesting future research direction could be to conduct field experiments to study internal or external fraud events and explore incentive issues. Moreover, if detailed time stamp information (e.g., 10:30 a.m. on March 3, 2014) for each transaction is available, future work can study the relationship between employees' multitasking behaviors and operational risk. Second, our data does not contain customer demographic information because it is too sensitive for most banks to share. Future research with more granular-level data on customer demographic information can focus on how customer-side heterogeneity would affect workload and thus operational risks. Third, future research can consider using granular information on employee compensation to identify how the compensation structure can influence the error rate of operational risk events, especially those related to performance-seeking. Fourth, our work focuses on the workload and operational risk events in physical branches. Given the growing adoption of online and mobile banking, it is worth examining how online and mobile banking channels would affect operational risk. Fifth, our optimization model considers a simplified scenario wherein all risk events cause losses purely based on their severity level. Future research might consider studying a more sophisticated model that considers the impacts of random event occurrence and auditing time, so that it can study the consequent materialized losses. Finally, our optimal staffing policy ignores other implications of changing staffing levels, such as profit and customer satisfaction, in our optimization model because the focus of our model is to illustrate the importance of considering operational risk losses when banks make staffing-level decisions. However, these features could serve as potential future research directions.

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Appendix A: Tables and Figures

Table 9: 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%
Damage to Physical Assets	504	0.41%
Business Disruption & System Failures	2,236	1.83%
Execution, Delivery, & Process Management	23,921	19.53%

Note. ORX is the largest operational risk association in the financial services sector (see https://managingrisktogether.orx.org/).

Table 10: First-stage Regressions of *Load*

Dependent Variable	Main $Load_1$	Main $Load_1^2$	Alternative $Load_2$	Alternative $Load_2^2$
E-visits	0.412***	0.215***	0.409***	0.202***
	(0.091)	(0.036)	(0.088)	(0.030)
Haus_load	0.102***	0.089***	0.101***	0.081***
	(0.026)	(0.013)	(0.021)	(0.010)
Haus_loadsq	0.079***	0.034***	0.083***	0.031***
	(0.023)	(0.004)	(0.027)	(0.003)
Cum_load	0.023*	0.028	0.022*	0.022
	(0.010)	(0.020)	(0.009)	(0.019)
Work_hour	0.079*	0.054*	0.083*	0.050*
	(0.0357)	(0.023)	(0.036)	(0.021)
Risk_Type (%)	Yes	Yes	Yes	Yes
Business_Line_Dummy	Yes	Yes	Yes	Yes
Employee_FE	Yes	Yes	Yes	Yes
Branch_FE	Yes	Yes	Yes	Yes
Month_Year_FE	Yes	Yes	Yes	Yes
N	9,954	9,954	9,954	9,954
$adj.R^2$	0.443	0.345	0.437	0.339
Prob>Chi-sq	<0.001	<0.001	<0.001	<0.001

1. Standard errors in parentheses
2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Additional Control Variables and Other Checks

	(1) Additional Controls	(2) Text Mining	(3) Cumulative Workload	(4) Lagged Error	(5) Cubic Load	(6) 47 Branches	(7) Two-way Clustering
Dependent Variable	Error Rate	Error Rate	Error Rate	Error Rate	Error Rate	Error Rate	Error Rate
Load	-0.657***	-0.639***	-0.317***	-0.574***	-0.233***	-0.487***	-0.524***
	(0.128)	(0.103)	(0.032)	(0.072)	(0.014)	(0.024)	(0.071)
$Load^2$	0.610***	0.607***	0.294***	0.541***	0.216***	0.426***	0.489***
	(0.102)	(0.089)	(0.041)	(0.069)	(0.026)	(0.018)	(0.062)
Cum_load	-0.104***	-0.063***	-0.132***	-0.129***	-0.135***	-0.112***	
	(0.015)	(0.011)	(0.021)	(0.022)	(0.019)	(0.013)	(0.028)
Work_hour	0.079	0.092	0.104	0.108	0.115	0.124	
	(0.063)	(0.077)	(0.092)	(0.096)	(0.101)	(0.093)	(0.012)
Residual1	0.085*	0.089*	0.081*	0.082*	0.074*	0.085*	0.083*
	(0.037)	(0.039)	(0.035)	(0.035)	(0.032)	(0.037)	(0.036)
Residual2	0.041*	0.046*	0.040*	0.042*	0.035*	0.042*	0.039*
	(0.017)	(0.020)	(0.017)	(0.018)	(0.015)	(0.018)	(0.016)
Rural/Urban	0.191***						
	(0.021)						
Edu_lvl	-0.103**						
	(0.037)						
Exp_lvl	0.060						
	(0.072)						
GDP	0.041						
	(0.050)						
Profit	0.061						
	(0.069)						
Load×Cumulative Workload			-0.0174				
			(0.0105)				
Lag_error				-0.522			
				(0.415)			
Load_cubic					0.063		
					(0.059)		
Risk Type (%)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Line of Business	No	Yes	Yes	Yes	Yes	Yes	Yes
Employee FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Month Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
N	9,954	9,954	9,954	9,954	9,954	9,376	9,954
adj. R^2	0.435	0.230	0.538	0.586	0.544	0.531	0.510

1. Standard errors in parentheses
2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Staffing Rule Implications (under Workload Variability)

	Monthly Staffing Rules			Quarterly Staffing Rules		
	Full Flexibility	Business Line Switch	Branch Switch	Full Flexibility	Business Line Switch	Branch Switch
Number of Events	1,288	1,379	1,364	1,345	1,390	1,374
Percentage Decrease	10.6%	4.3%	5.3%	6.7%	3.5%	4.6%

Table 13: Operational Risk Events under High Workload

1	Issued RMB 3 million 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 entering client information into the system.
6	Did not record the withdrawal client ID number.
7	Client manager issued a business loan of RMB 100,000 to a company with an expired license.
8	Deposit without currency tag.
9	Issued RMB 500,000 business loan on 12/2014 with maturity date as 12/2013.
10	Issued RMB 1 million business loan without an interest rate.
11	Opened new account with wrong client name.
12	Issued RMB 100,000 personal loan to a client with credit card delinquency of 43,817.65.
13	Issued RMB 1 million business loan without borrower's name.
14	Issued RMB 1 million business loan without the loan usage.
15	XXX did not log out of computer system after the transaction was concluded.
16	XXX did not lock the safe of the client.
17	Opened the ATM machine without locking it.
18	Issued RMB 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 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 of computer system when leaving for home.
28	An account deposit without a client ID.
29	Issued RMB 1 million business loan with maturity date as the previous month.

Table 14: Operational Risk Events under Low Workload

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

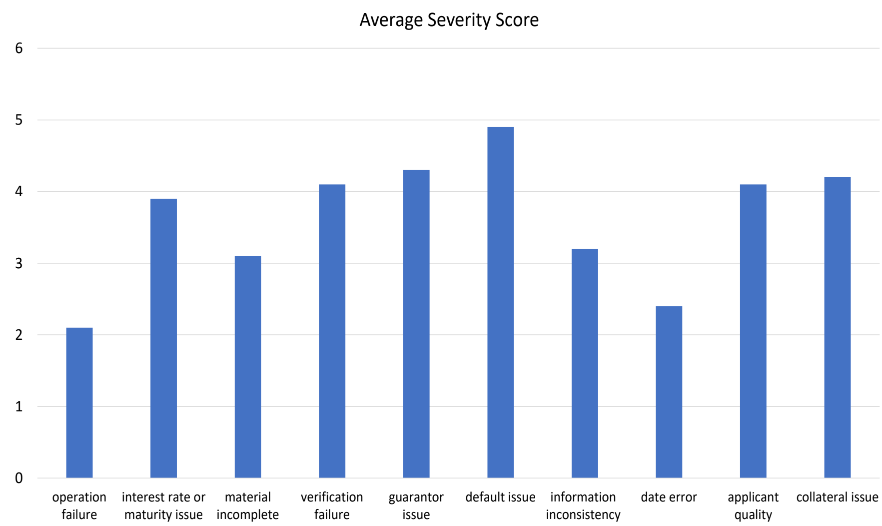

Figure 3: Average Severity Scores by Risk Type

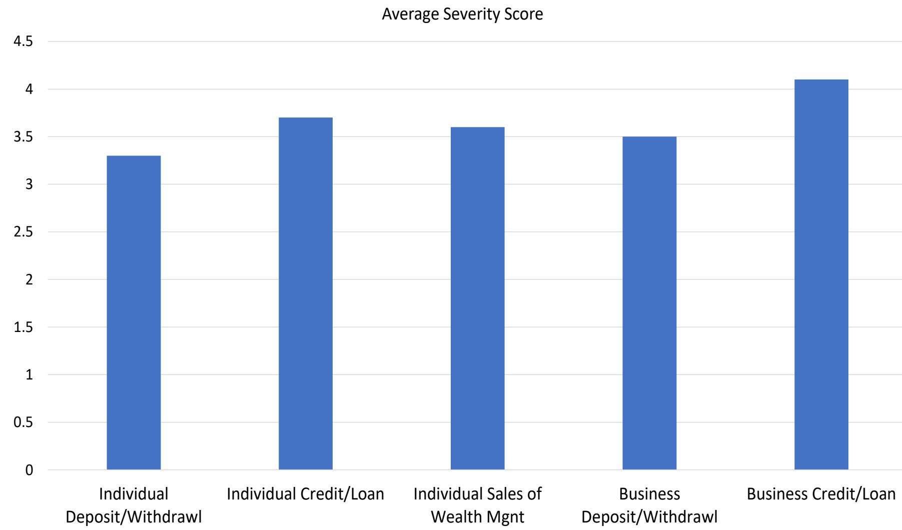

Figure 4: Average Severity Scores by Business Line

Appendix B: Text Mining of Risk Events

In this part, we further conduct text mining analysis of our risk events. Utilizing the text mining analysis, we now classify all the risk events in our data set into ten types, as shown in Figure 5. Specifically, we apply the Han Language Processing (HanLP) package contained in Python to analyze the Chinese event description. We first use the POS tagger to identify the part of speech of each word in each event description in terms of nouns, noun phrases, and verbs. We then use an association mining algorithm, following Manning and Schutze (1999), to further cluster the candidate features. The association mining here finds correlations within a set of data. After obtaining the feature (topic) of each event, we use association mining to group similar features together. In the end, we ask contacts in our focal bank to label the topics of all events according to the ten types. We summarize our algorithm in the following table.

Algorithm 1 Topic Extraction

Input: Event description E
For: Sentence $I \in E$
State: POS tagger for each word in I
State: Select nouns, verbs, noun phrases, and verb phrases in I as candidates for features of E
State: Association mining to group items in E that appear together frequently to find features (itemsets)
EndFor
Output: Set of features f of event E

Finally, the ten risk event types can be further classified into two general types of operational risk events, according to the definition of The Basel Committee,[9] namely "clients, products, and business practices" (CP&BP) and "execution, delivery, and process management" (ED&PM). Five types—verification failure, guarantor issue, applicant quality, default issue, and information inconsistency (a total of 542 events)—belong to CP&BP since they are special examples of "Fiduciary breaches/guideline violations, account churning, failure to investigate client per guidelines, etc." (level 3 category in the link of footnote 9). The remaining five types—operation failure, interest rate or maturity issue, date error, collateral issue, and material incomplete (a total of 1245 events)—are grouped into ED&PM because they are special examples of "Data entry, maintenance or loading error, delivery failure, etc." (level 3 category in the link of footnote 9). Note that our data set only contains risk events occurring in the physical branches, and it does not include those that happened through the online banking system.

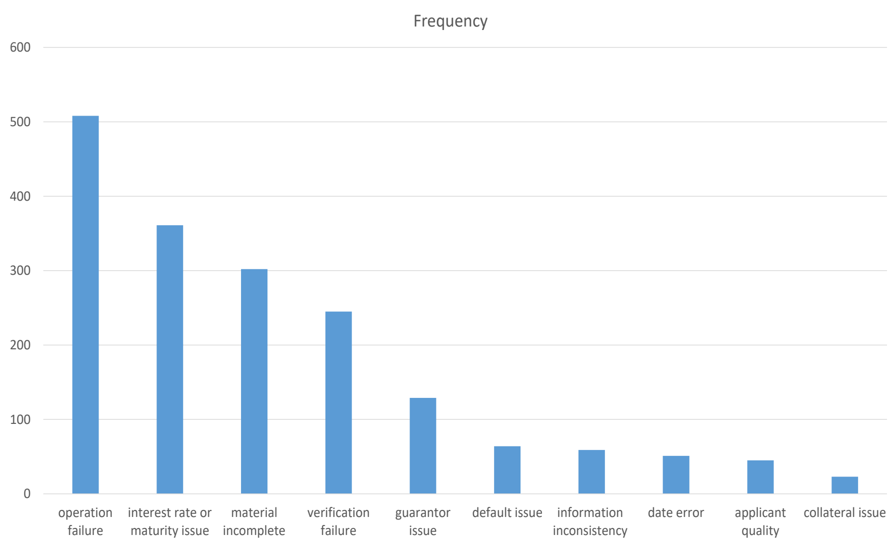

Figure 5: Risk Types Via Text Analysis

[9]https://www.bis.org/bcbs/qisoprisknote.pdf (pages 12—13).