Disruptions, Redundancy Strategies and Performance of Small Firms: Evidence from Uganda

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We study the impact of firm-specific business disruptions on the performance of small emerging market firms and test the effectiveness of building in redundancies to buffer against disruptions. Managerial disruptions result in the absence of the entrepreneur-owner, whereas operational disruptions lead to shortage of critical resources, e.g., inventory or electricity. We propose the use of relational redundancy – i.e., the availability of a trusted and capable person whom the entrepreneur-owner has an existing relationship with, who can manage the business in her absence – to recover from managerial disruptions. We also examine whether resource redundancy – e.g., maintaining safety stock or electricity backup – helps recover from operational disruptions. In the absence of publicly available data, we hand-built a panel dataset by interviewing 646 randomly selected small firms over four time periods in Kampala, Uganda. We find that disruptions are highly prevalent and have a statistically and economically significant effect on firm performance. When a firm faces multiple exogenous and severe disruptions in a six month period, its monthly sales decreases by 13.8% (p = 0.013) and its sales growth decreases by 18.8 percentage points (p = 0.070). Importantly, we find that both managerial and resource redundancies can help firms build resilience against the negative impact of disruptions. In some cases firms with high levels of redundancy are able to completely overcome the negative effect of disruptions on sales and sales growth. We discuss implications for entrepreneurs, policy makers and for large multinationals that buy from or sell to small emerging market firms.

Key words: business disruptions; redundancy strategies; small firms; firm resilience; emerging markets; natural experiments

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1. Introduction

Firm-specific disruptions – such as an unplanned absence of a key manager or a sudden supply crisis – as well as macro-level business disruptions – such as natural disasters or pandemics – can greatly hurt small firms, hampering their sales and operations and hurting their relationships with customers and suppliers. The ongoing Covid-19 pandemic has brought to light the severe impact of macro-level disruptions on small firms (Bartik et al. 2020). However, little is known about the types of firm-specific disruptions faced by small firms, entrepreneurial ventures and privately held firms. And, even less is known about how frequent they are, how they affect the performance of these firms or how they might best be buffered against. Small firms in emerging markets are especially vulnerable to firm-specific disruptions, yet there is no empirical research about such disruptions in this context.

To address this gap, our study answers three important questions: (1) What types of firm-specific business disruptions do small firms in emerging markets face and how frequent are they? (2) What is the impact of business disruptions on the performance of these firms, i.e., what are the downside losses? (3) To what extent can having appropriate redundancies in place help such firms build resilience against the impact of disruptions?

While better management of downside losses is important for firms of all sizes and in all markets, it is especially critical in emerging markets. Small firms run by entrepreneurs – most with less than ten employees – account for around ninety percent of businesses and over forty percent of employment in emerging economies (Alibhai et al. 2017). These small firms tend to be centrally managed by the entrepreneur-owner (herein referred to as *entrepreneur*), use basic management practices and have fairly simple operational structures. Small emerging market firms cover a wide range of sectors and include retailers, pharmacies, fast food outlets, repair shops and hairdressers. Importantly, these firms play a key role in the global provision of goods alongside multinationals – as distributors that enable reaching customers in new or distant markets and as suppliers that enable sourcing of local materials (Sodhi and Tang 2014, Viswanathan et al. 2010). Yet, the productivity gap between large and small firms in emerging markets is larger than in developed markets (International Trade Centre 2018).

Studies on small firms in emerging markets have so far focused on improving their performance (upside gains), primarily through interventions aimed at alleviating financial and human capital constraints. These include access to capital grants (De Mel et al. 2008), bank loans (Banerjee et al. 2015), business training (Anderson et al. 2018, McKenzie and Woodruff 2016) and management consulting (Bloom et al. 2013). However, the downside losses that can be avoided when these firms face disruptions have received little attention. To the best of our knowledge, ours is the first study to analyse the operating environment of small firms in emerging markets with a view to reducing their downside losses due to disruptions.

A critical challenge in answering our research questions is the unavailability of data. Firm-specific disruptions (i.e., idiosyncratic disruptions) and redundancy strategies are notoriously difficult to measure. For publicly listed firms, researchers have used press releases and proprietary data on risks to identify disruptions (Hendricks and Singhal 2005a, Wang et al. 2021) and financial indicators as proxies for redundancies (Hendricks et al. 2009). This is not an option for small firms. Therefore, we hand-built a panel dataset through periodic in-depth one-on-one survey interviews and business audits with the entrepreneurs who ran 646 small firms in Kampala, Uganda. Our analysis is based on data from four survey rounds, conducted at six month intervals, between June 2015 and November 2016. We collected detailed information on firm-specific events of different types that disrupted the day-to-day activities of the firms. We define *business disruptions*, or simply *disruptions*, as firm-specific events which are *exogenous* (i.e., abrupt and unpredictable) and *severe* (i.e., of sufficiently long duration and high intensity). In our surveys, we also record the presence of redundancies that are appropriate for small emerging market firms.

Depending on the business activities that are affected, we categorise business disruptions as either *managerial disruptions* or *operational disruptions*.[1] Managerial disruptions (e.g., sickness of the entrepreneur or sickness/death of her relatives) reduce the entrepreneur's ability to perform all day-to-day managerial activities, often leading to temporary closure of the business. These disruptions not only impede the entrepreneur's ability to sell the firm's goods and services but also limit her ability to manage the firm's operating resources. Operational disruptions (e.g., electricity outages, supply shortages or employee sickness), on the other hand, lead to a shortage of critical operational resources. They can affect stock or bring production to a standstill, and can lead to loss of customers. Given the different ways in which managerial and operational disruptions impact firms' operations, we expect them to require different forms of redundancy.

We introduce the concept of *relational redundancy* as a measure of the availability of someone who can be trusted to adequately cover for the entrepreneur in her absence by managing all parts of the business. In our context, this backup could be someone whom the entrepreneur has an existing relationship with, such as a business partner or an immediate family member. We hypothesise that having relational redundancy in place allows firms to buffer against managerial disruptions. In addition, we measure *resource redundancy* as the extent to which a firm maintains reserves of resources – such as multiple suppliers, safety stock, electricity backup or pool of temporary employees. We expect that having resource redundancy in place will help firms recover from operational disruptions by maintaining continuity in production and sales.

We find that firms in our sample frequently face business disruptions due to idiosyncratic, firm-specific events, which are distinct from industry wide or macro-level disturbances. On average, 54% of the 646 firms in our sample faced at least one disruption in a six month period and 17% faced multiple (two or more) such disruptions. In our data sample, managerial disruptions are twice as prevalent as operational disruptions. Around 40% of the entrepreneurs in our sample reported at least one managerial disruption in a period of six months. Although firm-specific disruptions are

[1] See Online Appendix A1 for more details on this classification process and analysis.

prevalent and the risks associated with such disruptions are more diversifiable through building in redundancies than are the risks associated with macro disruptions, we find that firms do not exhibit high levels of relational or resource redundancy. On average, only 15% of the firms in our sample have a high level of relational redundancy and less than 10% of them have a high level of resource redundancy. These low levels of redundancy could be in part attributable to the absence of accurate estimates of both the negative impact of disruptions and the benefits of building in redundancy (Simchi-Levi et al. 2014).

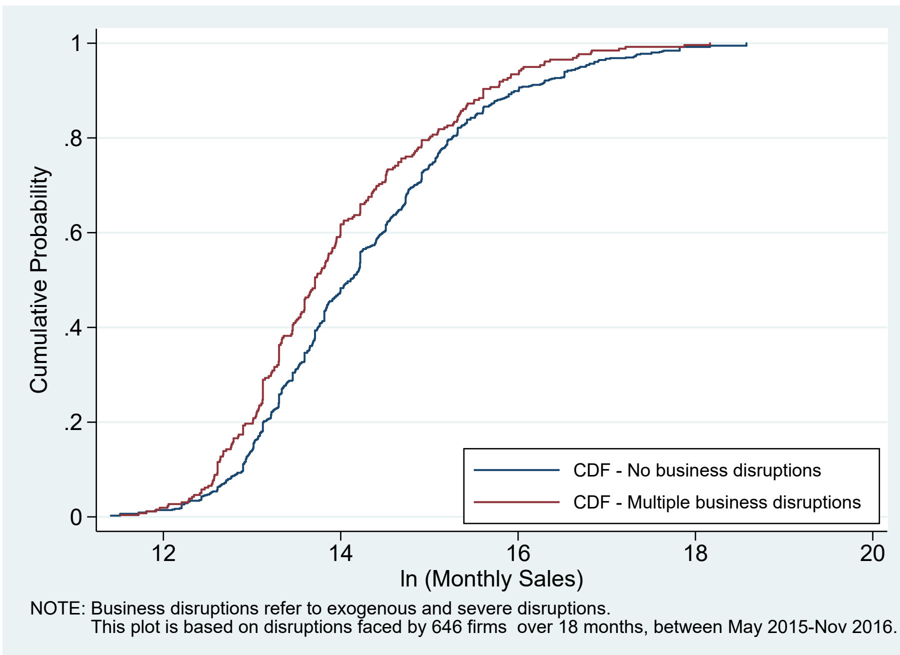

Figure 1.1 Cumulative Distribution Function of ln(monthly sales) of firms that face no business disruptions versus those that face multiple disruptions.

Figure 1.1 plots the CDFs of the natural logarithm of sales of firms in our sample that either faced no disruption (in blue) or multiple disruptions (in red) in a six month period. It suggests that disruptions hurt sales and highlights a pattern of clear stochastic dominance. By considering exogenous disruptions and carefully controlling for firm characteristics and macro-level temporal conditions that the firms faced through panel fixed effects regressions, we find that disruptions have an economically and statistically significant negative impact on the financial performance of firms in our sample. When a firm faces multiple disruptions in a six month period, its monthly sales at the end of this period reduces by 13.8% on average ($p = 0.013$), and its sales growth decreases by 18.8 percentage points on average over the six months ($p = 0.070$), compared to when it does not face disruptions. While one might expect business disruptions to hurt the performance of small firms, the magnitude of this effect is striking. Barrot and Sauvagnat (2016) find that sales growth for publicly listed firms in the U.S. drop by 3.3 percentage points in six months following a natural disaster such as a hurricane. Thus, when an entrepreneur in our sample faces multiple firm-specific business disruptions, the impact on sales growth is six times that of the impact of a natural disaster on the sales growth of publicly listed U.S. firms. The average monthly sales of firms in our sample is 3.6 million UGX ($\sim$ 1000 USD). Considering this, the negative impact of disruptions on monthly sales corresponds to over two months of rent paid or the monthly salary for three full-time employees at these firms. Our results suggest that small firms in emerging markets are at a substantial risk of facing not only frequent, but also large, downside losses due to business disruptions.

We find that both relational and resource redundancies can significantly help small firms in emerging markets buffer against disruptions. When a firm in our sample faces one or more managerial disruptions and lacks relational redundancy, it experiences a reduction in sales of 9.6% on average ($p = 0.053$). In contrast, if it has a high level of relational redundancy, it can completely overcome the negative impact of managerial disruptions on sales. In addition, a firm that has a high level of relational redundancy experiences a 40.9 percentage points higher sales growth over a six month period ($p = 0.067$) during which it faces one or more managerial disruptions, compared to when it faces such disruptions and lacks relational redundancy. For firms facing one or more operational disruptions, sales is 80.6% higher ($p = 0.061$) when they have a high level of resource redundancy as compared to when they lack such redundancy. Further, when firms face one or more operational disruptions and lack resource redundancy, they see a reduction in sales growth of 89.7 percentage points ($p = 0.039$). Firms with high level of resource redundancy are able to completely buffer against these losses. Thus having redundancy in place can make the difference between negative and positive sales growth for a firm when it faces disruptions.

Through our unique, hand collected data, we are able to shed new light on the operating environment of small firms in emerging markets. We bring to attention the alarming frequency with which these firms face a diverse range of business disruptions and the massive downside losses faced by them due to disruptions. We then estimate the economic gains from building firm resilience by having appropriate redundancies in place. In doing so, our study highlights a novel way to improve the performance of small firms in emerging markets. Our work complements existing studies that focus on increasing the upside gains to such firms by alleviating their financial and human capital constraints (McKenzie and Woodruff 2013, Banerjee et al. 2015).

In Section 2 below, we build our hypotheses and also discuss our contribution to the literature. In Section 3, we outline our research design, including the empirical strategy employed to assess the impact of business disruptions and the buffering effect of having redundancies in place. Section 4 contains results and robustness checks. We conclude the study in Section 5.

2. Relevant Literature and Contributions

Our work builds on the existing literature – in operations management and economics – on business disruptions and redundancies that firms can set in place to buffer against them. We develop and test new theory motivated by both our extensive fieldwork, in the context of small emerging market firms, and the prior literature. Below, we first discuss the literature on disruptions and our contribution to it, and then the literature on redundancies and how we contribute.

2.1. Business disruptions faced by small emerging market firms

What we know about the types, frequency and impact of supply chain disruptions and of personal events that impact leaders of publicly listed firms cannot be translated directly to the context of small firms in emerging markets, for two main reasons. First, by virtue of the structure of these firms, the types of disruptions they face will differ from those faced by large firms. Second, in contrast to firms operating in developed markets, small emerging market firms tend to operate in volatile environments plagued with political and economic instability, inadequate public infrastructure, poor health conditions and rampant disease (Collins et al. 2009,Marmot 2015). Such conditions not only constrain their odds of advancement, but also leave them more susceptible to disruptions. At present, little is known about the operating environment of small emerging market firms and the business disruptions they face. Our study seeks to help fill this gap in theory and evidence.

Hendricks and Singhal (2005a) find that press announcements of supply chain disruptions in publicly listed firms are associated with negative operating performance (e.g., decreases in income, sales and sales growth). Similarly, Hendricks and Singhal (2005b) and Wang et al. (2021) link supply chain disruptions with negative stock returns and increases in equity risk. These authors argue that supply chain disruptions can result in stockouts and service interruptions, resulting in lower customer satisfaction, loyalty and trust, and eventually in lower sales. Other researchers have made similar arguments and provided empirical evidence based on data from financial statements, linking operational disruptions to negative firm performance. For example, Barrot and Sauvagnat (2016) find that the sales growth of publicly listed firms in the U.S. drops when they – or their suppliers – face a natural disaster.

Based on this body of prior work, we expect disruptions to negatively affect the operations of small firms in emerging markets. While upstream supply chain disruptions leading to supply shortages are one aspect of operational disruptions that small firms could be exposed to, we expect these firms to encounter other types of firm-specific operational disruptions which may be rarer in large firms. These could include thefts, electricity outages and building damage. Small emerging market firms typically compete with many local firms and operate under high resource constraints, which would further intensify when they face operational disruptions. For example, thefts, electricity outages and supply shortages would further shrink working capital, affect stock, increase costs and reduce customer satisfaction and loyalty.

Next, consider disruptions that a business owner or a manager may face due to an unexpected personal event – such as a sudden sickness or a serious accident. Bennedsen et al. (2006) find that the death of a firm's top manager (or her immediate family member) is associated with decreases in sales growth and operating profits. Jones and Olken (2005) find that the exogenous death (e.g., due to heart attack or plane crash) of a country's top manager (i.e., its national leader) impacts its growth rate. When the leaders of large companies and entire countries influence their economic performance, it is conceivable that entrepreneurs who own and manage small firms also individually influence business outcomes.

Organizationally, small firms tend to be simple and undiversified, with control concentrated in the hands of their entrepreneur-owners. The fates – and fortunes – of these highly centralized firms thus tend to be influenced heavily by the entrepreneur and her personality, decisions and relationships (Miller 1983). In contrast, professional managers in large firms have specific duties and qualified support staff. Based on the central role and visibility of entrepreneurs in small firms, we expect that the personal shocks that an entrepreneur faces will likely impact all aspects of the business. The entrepreneur's absence from the business impedes her ability to sell the firm's goods and services and may also result in temporary closure of the business. It can also result in a breakdown of resource management – e.g., managing stock, working capital, machinery or employees – as well as relational exchanges with customers or suppliers. Given the lack of financial records, purchase contracts and formal reputation ratings, the buying process in emerging markets especially depends on relational exchanges (Viswanathan et al. 2010). Thus, for an emerging market entrepreneur, managerial disruptions can be costly, and are likely to impact sales and sales growth.

Our classification of disruptions as managerial and operational allows us to provide actionable managerial insights for small firm owners and policy makers, and highlights the value of considering managerial disruptions, which have to date been ignored in the operations management literature.[2]

2.2. Redundancy strategies relevant for small emerging market firms

While we expect business disruptions to negatively impact firm performance, it is unlikely that all firms will be equally worse off. One entrepreneur may suffer a disruption that hurts her business substantially, while another may experience a disruption of similar type and intensity, and yet be able to recover from it with little (if any) negative impact. An important underlying reason for

[2] Dimensionality reduction using exploratory factor analysis (see Online Appendix A1) further indicates a clear separation between operational disruptions and managerial disruptions.

this variation may be that entrepreneurs are less or more able to buffer their business activities against disruptions depending on the redundancy strategies they have in place. These strategies can be proactively implemented by firms to insulate their normal day-to-day activities from the damaging effects of disruptions. Through insights gained via our early field work in Kampala prior to designing our study, we classify redundancy strategies as resource redundancy or relational redundancy.[3]

Analytical and conceptual work in operations management suggests that firms can buffer their operations against supply chain disruptions by diversifying procurement processes, increasing flexibility in sourcing, improving supplier reliability, maintaining safety stock, developing backup production options, building strategic partnerships and purchasing insurance (Tang 2006, Sheffi and Rice Jr 2005, Tomlin 2006). Hendricks et al. (2009) use financial proxies to measure firms' supply chain resilience and find that greater operational slack and vertical relatedness are associated with less negative stock market reaction following a supply chain disruption announcement. Wang et al. (2021) also find that extensive sharing of subtier suppliers increases financial risk of the focal firm from supply shocks. Building on the operations management literature on redundancies or slack, we define resource redundancy as a strategy associated with increasing the reserves of the different resources (e.g., materials, supplies, employees) needed to make and deliver a firm's offerings to customers. In our setting, we expect that having multiple suppliers to source the same item, keeping safety stock, maintaining a backup electricity generator or having access to a pool of temporary workers would classify as appropriate resource redundancy. If a firm has such resource redundancy in place when it experiences an operational disruption, we expect that its operations are more likely to continue in a normal fashion.

Next we turn to redundancies that can buffer against managerial disruptions. We define relational redundancy as the extent to which a firm plans to cover for the focal manager's – or, in our case, entrepreneur's – unexpected absence by appointing someone suitable who can maintain continuity in business operations. Given the central role of the entrepreneur in her business, a suitable cover would need to be trustworthy and capable. Trustworthiness of the owner cover would ensure that the entrepreneur is not exploited in her vulnerable situation (Barney and Hansen 1994) and a capable owner cover would ensure continuity in business operations (Anderson and Weitz 1989). For a small emerging market firm, someone the entrepreneur has an existing relationship with – such as a business partner or an immediate family member – is likely to be both trustworthy and capable enough to cover for the entrepreneur in her absence. In related work in development economics, Kinnan and Townsend (2012) suggests that rural households in emerging markets recover from

[3] We validated this classification scheme through a data-driven exploratory factor analysis, detailed in Online Appendix A2.

expenditure shocks by borrowing from a trusted network of relatives and friends, while in the family business literature, resource adjustment between family and business is referred to as "social capital" (Brewton et al. 2010). Our conceptualization of relational redundancy is different from either of these concepts. We consider close family members or business partners as owner cover in that they can *manage* the business in the owner's absence instead of providing or sharing resources. If a firm has such cover (or relational redundancy) in place when it experiences a managerial disruption, we expect that its business operations can continue smoothly.

We gather measures of disruptions and redundancies in small emerging markets firms discussed above and build a detailed survey-based panel dataset. This is to our knowledge is the first paper to shed light on the performance effects of managerial and operational disruptions and the benefits of relational redundancy or resource redundancy in building resilience against disruptions in small emerging markets firms. In doing so, we highlight ways to reduce vulnerability of such firms that have limited social safety-nets, unaffordable loans and insurances, and limited financial and human resources to cope with disruptions (Collins et al. 2009). Further, by developing the concept of relational redundancy, we add theory and evidence for a new form of resilience that can be widely used (Van Der Vegt et al. 2015).

3. Research Design

3.1. Identification Strategy

To identify the impact of business disruptions on the performance of small firms in emerging markets, we use the following fixed effects specification:[4]

$$y_{ijkt} = \alpha_i + \boldsymbol{\beta D_{it}} + \zeta_{kt} + \eta_{jt} + \epsilon_{ijkt} \tag{1}$$

Here y_{ijkt} denotes a financial outcome – either log of sales or sales growth – of firm i in location j and sector k in survey round t. The α_i are firm fixed effects. D_{it} is a disruption measure for firm i in survey round t. Depending on the specification, D_{it} can be a count of the number of business disruptions or it can be a vector of two dummy variables indicating if a firm faced exactly n disruptions for $n = 0$ $(base\ case), 1, or\ multiple$ (≥ 2). D_{it} can span across managerial, operational or both disruption types. ζ_{kt} are sector-time fixed effects and η_{jt} are location-time fixed effects. The model errors are denoted as ϵ_{ijkt}. We cluster the errors at the firm level to account for serial autocorrelation in errors and correct for heteroskedasticity by using heteroskedasty-robust standard errors.

[4] See Barrot and Sauvagnat (2016) and Jack and Suri (2014) for similar specifications. These studies assess the impact of natural disasters on supply chain networks and the use of mobile money to smooth household consumption due to household level shocks, respectively.

To identify the impact of business disruptions on financial outcomes, it is critical that D_{it} is exogenous, i.e., uncorrelated with ϵ_{ijkt}. Naturally, many disruptions may be endogenous, i.e., anticipated and acted upon in advance and correlated with the temporal conditions of the firm. For example, a hair salon owner may expect a seasonal sales slump after Christmas and, thus, plan her father's cataract surgery for January when she can get away without severely disrupting her business. This 'disruption' event is not very surprising to the entrepreneur and so she plans accordingly. To address such issues related to foreseeable disruptions, we consider only exogenous (i.e., abrupt and unpredictable) disruptions, in D_{it}. These disruptions represent random shocks to the operations of a firm. Further, among exogenous disruptions, we only consider those that are severe, because non-severe events are not likely to be disruptive. Thus, D_{it} includes only exogenous and severe disruptions. When D_{it} is a vector indicating if a firm faced zero, one or multiple disruptions, the base case of no (zero) business disruptions contains observed disruptions that are either predictable or less severe. Endogenous or less severe disruptions in the regression errors can only induce omitted variable bias if they are correlated with exogenous and severe business disruptions. Given the exogeneity of business disruptions, we do not expect such a correlation.[5]

Despite limiting our focus to exogenous disruptions, we face two additional challenges to identification. First, while business disruptions are exogenous events, the likelihood of facing certain types of disruptions may depend on firm and entrepreneur characteristics. For example, smaller firms or poorer entrepreneurs may face more disruptions; also, disruptions due to employee sickness are likely to be more prevalent in firms with more employees. We take advantage of the panel structure of our dataset and include firm fixed effects, which control for all time-invariant characteristics (both observed and unobserved) of the firms and their entrepreneur-owners, as well as for the average effect of all time-varying characteristics. Thus, in Equation 1, firm fixed effects sweep out the effect of observed and unobserved entrepreneur and firm characteristics – such as ability of the entrepreneur, size and sector of the firm, family size, etc. – which could be correlated with both the number and types of disruptions and with financial outcomes.

Second, although unanticipated by the entrepreneur, some disruptions may arise due to temporal changes in a firm's environment. For example, an entrepreneur might be unaware of new import taxes levied on her supplies that may lead to a sector-wide shortage of supplies. We control for two main sources of such macro-level disruptions – disruptions to the local market economy and disruptions to the business sector economy by including sector-time and location-time fixed effects where 'time' denotes the survey round. These fixed effects subsume time fixed effects and control for seasonality in sales, which might further vary by industry or by location.

[5] In our data, the correlation between the number of exogenous disruptions and the number of endogenous disruptions is -0.005 (p = 0.918).

Conditional on firm, time, sector-time and location-time fixed effects, we argue that the exogenous firm-specific disruptions in Equation 1 allow us to identify the average impact of firm-specific business disruptions on firm performance. Next, to assess the buffering effect of redundancies, we use the following specification:

$$y_{ijkt} = \alpha_i + \boldsymbol{\gamma D_{it}} + \boldsymbol{\lambda R_{it}} + \boldsymbol{\mu D_{it} * R_{it}} + \boldsymbol{\rho X_i} + \boldsymbol{\sigma D_{it} * X_{it}} + \zeta_{kt} + \eta_{jt} + \phi_{ijkt} \tag{2}$$

In Equation 2, depending on the specification, D_{it} can be a count variable or a dummy variable that indicates whether firm i faces one or more (≥ 1) managerial disruptions (operational disruptions) in survey round t. For some disruptions, D_{it} can also be a vector of two dummy variables indicating if a firm faced exactly n disruptions for $n = 0, 1, or\ multiple$ (≥ 2). R_{it} is a vector of two dummy variables that indicate whether firm i has a low or high level of relational redundancy (resource redundancy) in survey round t. The omitted case is no redundancy. As before, we include firm fixed effects α_i, sector-time fixed effects ζ_{kt} and location-time fixed effects η_{jt}.

To correctly assess the buffering impact of redundancy strategies, we need to address an additional empirical challenge. It is possible that some firm and entrepreneur characteristics (indicated as X_{it} in Equation 2) allow entrepreneurs to buffer against disruptions. For example, having a larger family can allow the entrepreneur to more easily seek financial assistance from family members when a disruption occurs. A larger family can also increase the chances that the entrepreneur has an immediate family member who can cover for her in her absence (thus increasing relational redundancy). Similarly, firms with better business practices or insurance cover might be able to buffer against disruptions and may also be more likely to build redundancy. Entrepreneur or firm characteristics that are correlated with our redundancy strategies and help buffer against the impact of disruptions through channels other than our redundancy strategies could confound our estimates of the coefficient of redundancy in Equation 2. Therefore, we control for the five most likely sources of such bias – family size, firm size, business practice score, establishment score (i.e., a measure of how established the firm is) and insurance cover score – by including an interaction of each of these variables with our measure of disruptions, D_{it} – and partial out the effect of our redundancy strategies of interest.

3.2. Study Context, Sample and Survey Overview

Uganda is a lower income emerging economy in East Africa that has experienced strong annual GDP growth in recent years and a sharp rise in entrepreneurial activity. However, Ugandan entrepreneurs tend to face numerous constraints to growth, including firm-specific shocks (Global Entrepreneurship Moniter 2015). Kampala, the capital of Uganda, is the country's economic center and contributes 50 percent of the country's GDP. Thus, Kampala was identified as an ideal location for our study.

It is notoriously difficult to obtain data on small firms in emerging markets. First and foremost, there is a dearth of publicly available data on emerging market entrepreneurs, let alone on the types, frequency and impact of business disruptions they face. Also, there is no data on the redundancy strategies these small firms might benefit from using. Census data collection efforts typically target firms with over twenty employees (Li and Rama 2015). As a result, the most common type of firm in this context (i.e., firms with under ten employees) tends to get excluded from government data collection efforts. Most small emerging market firms are not formally registered, which increases the difficulty of including them in official surveys. To surmount these problems, a substantial part of our research involved doing a field study and collecting high quality data on the ground.

We selected firms into the study using a two-stage process. First, in the sample recruitment survey, we used a geographically exhaustive sampling approach to select a random sample of around 4,000 small firms. Each of these firms was owned and run by an English-speaking entrepreneur and operated out of a physical structure (see Online Appendix A3 for details on the sample recruitment survey). We used an *establishment score* based on entrepreneur and business characteristics (e.g., formal education, startup capital, years of operation, physical location) to rate how established each firm was. Based on this score, we divided the firms into three terciles. To obtain a heterogenous mix of small emerging market firms, we contacted a random sample of 400 firms each in the top and bottom terciles. Of these, 646 firms agreed to participate in our study.[6]

Our study timeline was roughly 18 months. We visited the entrepreneur-owners (the *respondents* to our surveys) of the 646 firms in our study four times (at six-month intervals) between June 2015 and November 2016, as noted in Figure 3.1. The same respondent answered our survey questions in the baseline and the three follow-up surveys.[7] More details on the survey process is provided in Online Appendix A3.

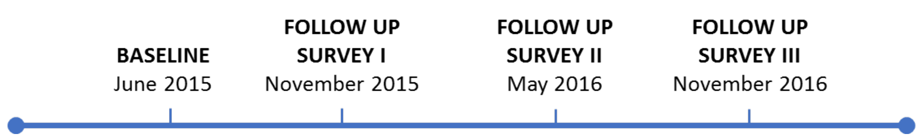

Figure 3.1 Timeline of the study.

[6] We find that firms in our sample are very similar to those in the recruitment sample (see Online Appendix A4). This suggests that our sample is representative of the small firms operating in Kampala that fit our inclusion criteria.

[7] The recruitment and baseline surveys are also part of a larger study.

3.3. Variables

3.3.1. Business Disruptions We define *business disruptions* as firm specific disruptions that are exogenous and severe. To inform our study and survey collection, we conducted numerous focus groups and interviewed over two dozen entrepreneurs across greater Kampala during the design phase of our study (i.e., prior to launch). Based on this field work, we created a comprehensive set of eight disruption types. As described in Section 2, we classified these disruption types into two categories – *managerial disruptions* (sickness of the entrepreneur, sickness of a relative, death of a relative) and *operational disruptions* (electricity outage, supply shortage, employee sickness, theft, building damage).[8]

During each business site visit in the three follow-up survey rounds, our enumerators noted down detailed information on disruptions based on the descriptions provided by the respondent. This includes details on what the disruption was and how it unfolded, its exogeneity, severity, cost and which parts of the business were affected (see Online Appendix A3 for details). Due to our focus on understanding the characteristics of disruptions faced by small firms, our data on disruptions is highly granular compared to that in earlier field studies (e.g., Jack and Suri (2014) and Gertler and Gruber (2002) that study disruptions to households in emerging markets).

In our surveys, we explicitly measure the exogeneity of all disruptions using two questions – how unpredictable the disruption was and how abruptly it occurred. We define disruptions as *exogeneous* if they are surprising and unfold in quick succession. For example, events such as heart attacks, strokes, miscarriages, thefts or electric short circuits are coded as exogenous disruptions; whereas infectious diseases, ongoing cancer and diabetes-related treatments, normal pregnancies or seasonal shortages of supplies are coded as endogenous (see Online Appendix A3 for details). In Figure 3.2, we see that exogenous disruptions are frequent across all disruption types. In fact, on average 65% of the firms in our sample faced at least one exogenous disruption in a six month period.

Using the rich text descriptions in our data, we display the prevalence of sicknesses and deaths across different causes of managerial disruptions in Figure 3.3. Surprisingly, over 10% of the entrepreneurs report a fatal road accident involving close family or close friends during the 18-month period of our study.[9] Assuming an average owner in our sample has 100 close family and

[8] During our survey visits, we asked the entrepreneurs to inform us of any other business disruption they may have experienced. No new disruption types were uncovered through these checks. We included political events in our original list of business disruptions and collected data on them. However, we do not include them in our analysis because it is difficult to disentangle firm-specific disruptions due to political events from the macro political situation. For example, Ugandan national elections took place in February 2016, affecting the political and business environment across Kampala. We find that firms located in areas that faced higher number of violent political events during elections saw a decline in their sales in the survey round following the election (see Online Appendix A5).

[9] This is an underestimate because: (i) We only captured details of deaths for which the owner was away from the

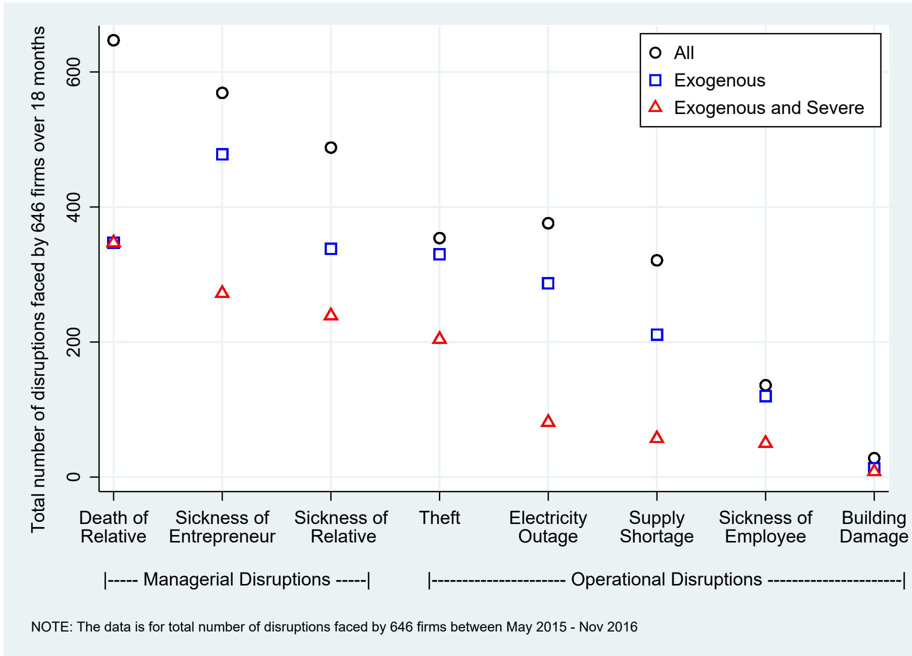

Figure 3.2 Prevalence of disruptions by exogeneity, severity and type.

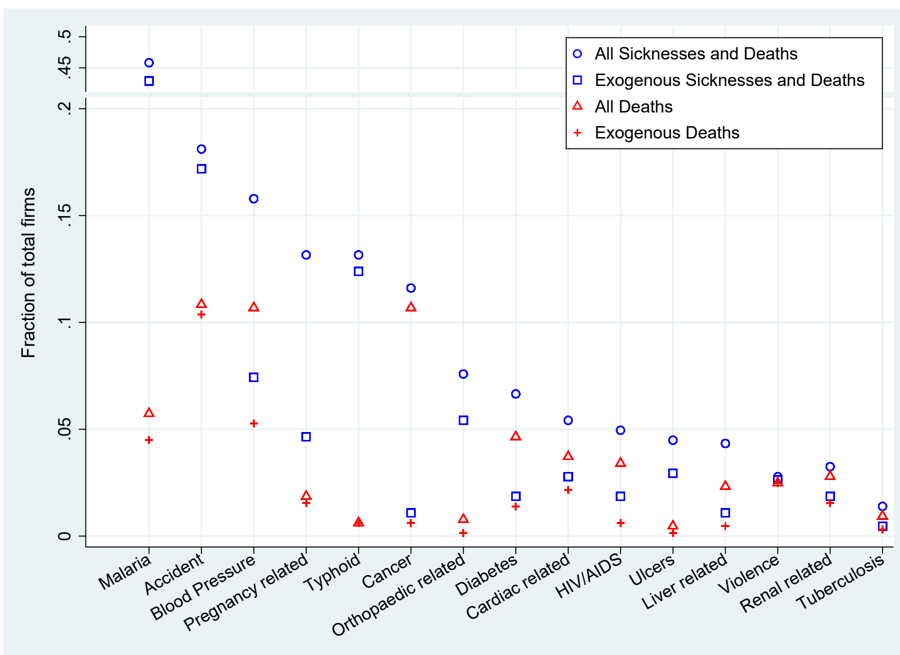

Figure 3.3 Prevalence and causes of managerial disruptions – based on disruptions faced by 646 entrepreneurs between May 2015 and November 2016.

friends, the probability of a fatal road accident in a year in Uganda is around 0.07%. In comparison,

business for at least half a day (see Online Appendix Table A3.1), and (ii) 20% of the owners reported facing more than one death among close family members or close friends in a 6-month period but we only collected details of the death of the person closest to the owner.

the probability of a fatal road accident in the U.S. was 0.01% in the year 2016.[10] In a similar analysis of operational disruptions, we find that about 25% of the firms in our sample experience major thefts in which they are either completely robbed or lost a significant amount of assets. Moreover, 10% of the firms face at least one exogenous electricity outage that last more than three consecutive days.

We measure severity of disruptions based on their characteristics. For example, sicknesses (including deaths) that are life threatening, lead to hospitalization, or involve being bed-ridden for at least 3-4 days are considered severe. Thefts and building damages that lead to loss or damage of machinery, vehicles, business premises and valuables are classified as severe. Electricity outages that last at least a week and supply shortages that last at least 40 days are considered as severe (see Online Appendix A3 for details). From Figure 3.2, we find that around half the disruptions faced by the small firms that comprise our sample are exogenous and severe business disruptions. Based on the frequency of the disruptions and the parts of the business they impact, we expect managerial disruptions and thefts to have the most impact. Building damage, on the other hand, is an impactful but very low frequency event (see Online Appendix A1 for a classification of disruptions by frequency and severity).

Table 3.1 summarises the frequency of business disruptions across our three follow-up survey rounds, along with firm and entrepreneur characteristics.[11] Strikingly, within a six-month period, on average 54% of the entrepreneurs faced at least one exogenous and severe disruption and 17% faced multiple such disruptions. Across the two disruption categories, on average an entrepreneur faced two managerial disruptions and one operational disruption in the 18 months of our study period (i.e., two major disruptions per year). In stark contrast, Andrew Wu (2016) finds that publicly listed firms in his sample faced five operational shocks on average in a 20 year period (i.e., 0.25 major disruptions per year). This comparison highlights the highly volatile nature of the business environment of small firms in emerging markets.

From our early field work prior to the start of the study, we learnt that firms are more likely to encounter multiple disruptions across different disruption types than within the same type, in a short time period. In order to manage time and respondent fatigue, when entrepreneurs faced multiple disruptive events of the same type in a six-month period, we only focused on the most severe event, leading to under-reporting of business disruptions. This is a limitation of the data and a tradeoff made by us between collecting detailed information on each disruptive event and

[10] http://www.iihs.org/iihs/topics/t/general-statistics/fatalityfacts/state-by-state-overview

[11] In Online Appendix A6, we compare characteristics of the subsample of firms that faced business disruptions and the subsample that did not. The only differences were in age, number of children and number of dependents. These differences are accounted for by our firm fixed effects.

collecting surface information on all events. Having detailed data on each event enables us to clearly assess its exogeneity and severity. From our data, we find that 50% of the disruptions occurred in conjunction with disruptions of another type. In contrast, the same type of disruption occurs in two consecutive periods only 12% of the time. Thus, within a time period, we expect under-reporting of disruptions of the same type to be even lower.

3.3.2. Redundancy Strategies Drawing on theory and on our extensive fieldwork prior to the study, we pre-identified strategies that increase the levels of relational redundancy and resource redundancy of small firms in emerging markets. For each pre-identified redundancy strategy, the enumerator read out a scripted description of the strategy and asked if the entrepreneur currently used the strategy. The enumerator recorded a binary value for whether the strategy was in place for the six months preceding the survey round, and noted down a compulsory text explanation of how the strategy was implemented and for how long (including anecdotal or physical evidence provided by the entrepreneur). By only considering redundancy strategies that were in place for at least six months, we ensure that redundancies were in place before disruptions occurred.

Based on our discussion in Section 2, we use two measures of redundancies. *Relational redundancy* measures the availability of a trustworthy and competent person to cover for the entrepreneur in her absence. We code this variable into three levels: “None” if the entrepreneur has neither an immediate family member (spouse, parent, sibling or a grown child) nor a business partner who can cover for her; “Low” if she has one of these two types of cover; and “High” if she has both. *Resource redundancy* measures the operational reserves maintained by the firm, which can help it to swiftly recover from operational disruptions. The reserves that we measured were an identified pool of temporary hires, multiple suppliers, safety stock, and backup power. These enable a firm to recover from sickness of an employee, supply shortages and electricity outages.[12] Based on the number of reserves in place, we code resource redundancy into three levels: “None” if the entrepreneur has none of these strategies; “Low” if she has up to two; and “High” if she has more than two in place. Data on resource redundancy was only collected in the second and third follow-up survey rounds.

3.3.3. Firm Sales Similar to prior field studies on small firms in emerging markets (McKenzie and Woodruff 2016, Drexler et al. 2014), we measure sales for the full calendar month prior to the survey date.[13] To reduce recall bias and overcome the general lack of financial records in these research contexts, we obtained two measures of firm sales – monthly recall and monthly anchored

[12] Note that our redundancy strategies allow firms to swiftly recover from disruptions, as opposed to reducing the likelihood of disruptions occurring. Since disruptions related to theft or building damage are best addressed by precautionary measures, in our regressions to test for effectiveness of resource redundancy, we leave these disruptions out.

[13] We consider sales as the amount of money collected. Credit to customers is not considered as sales.

sales (as in Anderson et al. 2021). Monthly anchored sales was obtained by considering weekly and daily sales of the firm (see Online Appendix A3 for details). We construct an index of monthly sales by averaging an entrepreneur's monthly recall sales and the anchored sales estimates. We then use the natural logarithmic of monthly sales, i.e., *ln(monthly sales)* as our measure of sales. For our second outcome, we take the difference in ln(monthly sales) over six months to obtain *sales growth* (as a ratio).

While disruptions may also affect other performance measures such as costs and profits, we focus on sales and sales growth for three reasons. First, the literature on supply chain disruptions suggests that disruptions should have a direct impact on sales by affecting customers, production and inventory. Sales is the most prevalent outcome variable in these studies (see Section 2). Second, since emerging market entrepreneurs do not usually keep complete financial records, sales (or the money collected from customers) is salient and more straightforward for an entrepreneur to recall. This makes sales a very widely used performance measure for small firms in emerging markets (e.g., see McKenzie and Woodruff 2016). Third, sales estimates are easier to collect using a shorter survey as compared to estimates of costs or profits. Since we built comprehensive survey sections to measure disruptions and redundancies, we kept a shorter survey section for collecting financial information – to be mindful of respondent fatigue.

3.3.4. Controls We measure several control variables that are included in our analysis (see Equation 2). In the baseline survey, we noted the background of the firm and entrepreneur including *firm size* i.e., number of business partners and employees, and *family size* of the entrepreneur. We also collected information on 27 different activities (e.g., record keeping, financial planning, marketing efforts, employee management, operational efficiency) that we use to construct a *business practices score*. As noted earlier, from the sample recruitment survey, we obtained each firm's *establishment score* based on entrepreneur and business characteristics such as formal education of the entrepreneur, startup capital, years of operation and physical location of the business. In each follow-up survey round, we captured information on five types of formal or informal insurance cover that entrepreneurs might have in place to recover from disruptions – alliances with community members, alliances with similar businesses, health insurance, business insurance, and alternate sources of income. For each insurance type, after verifying whether it had been in place for at least six months preceding the survey, the enumerator coded a binary variable indicating whether it had been implemented. The extent of *insurance cover* of a firm in a six month period is measured as the sum of these five insurance type dummies. Our redundancy strategies assess the ability of firms to recover swiftly from disruptions by maintaining relational coverage or resource reserves. Insurance, on the other hand, can provide capital to firms after a disruption, as opposed to a path to immediate recovery. Due to this fundamental difference in how insurance and our redundancy constructs help firms recover from a disruption, we measure them separately.

We face attrition in the data over time. Most of the attrition was because entrepreneurs were either not reachable or refused to participate in the follow-up surveys. This included 7% of the firms in our second follow-up survey and 21% in our third follow-up survey. In addition, at the time of our last follow-up survey round, 6% of the firms in our sample had closed down. While half of these closed because of non-survival, in the remaining cases the entrepreneur either found a salaried job or decided to pursue higher education. These attrition rates are on the lower side compared to those in other recent studies in emerging markets (e.g., see Drexler et al. 2014, Jack and Suri 2014). Despite attrition, the average characteristics of the firms that remain in our sample are comparable over time (see Table 3.1).

4. Results and Discussion

4.1. The Effect of Business Disruptions on Firm Sales

In Table 4.1, we report the impact of business disruptions on monthly sales and sales growth (using Equation 1). Columns (1) - (5) display the impact of disruptions on ln(monthly sales). From the linear model in column (1), we find that monthly sales decrease by 5.4% per disruption (p = 0.027).[14] In column (2), we test the non-linear relationship between disruptions and sales by including a quadratic term for disruptions. The quadratic term is negative and statistically significant. This provides clear evidence of a non linear relationship between disruptions and sales. As the number of disruptions increases, incremental increases in the number of disruptions has more negative impact on sales.

Next, we separate one and multiple disruptions to explicitly test for the non-linear effects of disruptions on sales without forcing a parametric relationship. A firm may have faced exactly n disruptions in a six month period, where n = 0 (base case), 1, or multiple (two or more) disruptions. In column (3) we find that when firms face multiple disruptions, their monthly sales reduce by 13.8% (p = 0.013). As few firms face more than two disruptions in a six month period, we use dummies for one and multiple disruptions for testing the non-linear effect of disruptions in our data. We find no evidence that firms in our sample are unable to cope with one disruption, in a six month period. [15]

In column (4), we segregate the disruptions as managerial and operational. We find that when a firm faces multiple managerial disruptions it results in a significant negative impact on monthly

[14] We use the standard formula $(e^{\beta} - 1)$ to obtain percentage change in regressions with log dependent variables, in our case Ln(Sales).

[15] Although the likelihood of multiple severe disruptions of the same type in a six month period is very low, it might lead to under-reporting of disruptions in our data. To the extent that there is under-reporting, it can bias our estimates for disruptions.

Table 3.1 Summary statistics per survey round

	2015 Nov		2016 May		2016 Nov	
	Mean	SD	Mean	SD	Mean	SD
Financial outcomes						
Monthly sales: Self-Reported (UGX)	4,119,088	10,683,857	4,562,057	14,456,263	4,070,766	9,399,822
Monthly sales: Anchored (UGX)	3,424,560	7,072,789	4,620,177	13,207,469	4,299,702	8,779,130
Sales Growth over 6 months (ratio)	-.029	.903	.031	.947	.127	.792
Entrepreneur characteristics						
Female	.444	.497	.410	.492	.416	.493
Age (years)	31.6	8.20	32.1	8.26	32.6	7.98
Education: Primary	.241	.428	.247	.432	.260	.439
Education: High School	.497	.500	.490	.500	.493	.500
Education: College and above	.260	.439	.261	.439	.245	.431
Married	.521	.500	.517	.500	.551	.498
Children (#)	4.98	3.36	5.02	3.38	5.24	3.37
Firm characteristics						
Sector: Retail	.509	.500	.490	.500	.480	.500
Sector: Services	.359	.480	.370	.483	.368	.483
Sector: Others	.132	.377	.140	.387	.152	.394
Years Operating (#)	5.69	4.52	5.85	4.64	6.04	4.76
Total employees (#)	1.60	3.66	2.07	4.16	1.95	3.72
Business Practices (score out of 27)	6.16	4.90	6.06	4.86	6.01	4.90
Insurance Cover (score out of 5)	.663	.764	.685	.799	.586	.720
Business Disruptions						
Sickness of Entrepreneur	.158	.365	.195	.396	.123	.328
Sickness of Relative	.153	.361	.148	.355	.116	.321
Death of Relative	.189	.392	.207	.405	.224	.417
Sickness of Employee	.109	.312	.089	.285	.044	.207
Theft	.116	.321	.146	.354	.095	.294
Building Damage	.005	.068	.007	.083	.002	.046
Supply shortage	.031	.173	.037	.188	.034	.181
Electricity Outage	.057	.233	.052	.223	.029	.170
Redundancies Adopted						
Immediate Family to Cover	.342	.400	.277	.381	.271	.379
Business Partners	.263	.441	.271	.445	.268	.444
Multiple Suppliers	.	.	.569	.496	.457	.499
Safety Stock	.	.	.211	.408	.093	.291
Power Backup	.	.	.259	.439	.216	.412
Pool of Temporary Hires	.	.	.184	.388	.114	.318
Observations	646		575		473	

Note: All financial outcomes are windsorised at one percent (1 USD $\sim$ 3,500 UGX). Business disruptions refer to disruptions that are exogenous and severe. Data on resource redundancy is not available for the first survey round.

sales. On average, the monthly sales of a firm reduces by 20.8% (p = 0.002) when it faces multiple managerial disruptions as compared to the base case when it does not face managerial disruptions. This highlights the central role of the entrepreneur in small firms. We do not find a statistically significant negative effect of operational disruptions on monthly sales. It is likely that some operational disruptions (such as building damages) would have a high negative impact on firm performance compared to other operational disruptions (such as employee sickness). Due to too few data points in each disruption type, we are unable to test the impact of different disruption types separately (see Online Appendix A1 for regression results of high frequency disruptions).

Table 4.1 Impact of business disruptions on firm sales and sales growth

Disruptions	(1) Ln(Sales)	(2) Ln(Sales)	(3) Ln(Sales)	(4) Ln(Sales)	(5) Ln(Sales)	(6) Sales Growth	(7) Sales Growth	(8) Sales Growth	(9) Sales Growth	(10) Sales Growth
Count (#)	-0.056**	0.069				-0.061	0.112			
	(0.03)	(0.06)				(0.04)	(0.09)			
Count Squared		-0.050**					-0.069**			
		(0.02)					(0.03)			
One			0.050					0.116		
			(0.05)					(0.08)		
Multiple			-0.148**					-0.188*		
			(0.06)					(0.10)		
One Managerial				0.005					0.058	
				(0.05)					(0.08)	
Multiple Managerial				-0.233***					-0.188	
				(0.08)					(0.13)	
One Operational				-0.033					-0.103	
				(0.05)					(0.09)	
Multiple Operational				-0.020					-0.235	
				(0.13)					(0.24)	
One Recent					0.070					0.119
					(0.05)					(0.08)
Multiple Recent					-0.216**					-0.372**
					(0.09)					(0.18)
One Not-Recent					-0.086*					-0.078
					(0.05)					(0.08)
Multiple Not-Recent					-0.202**					-0.194
					(0.09)					(0.14)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector X Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location X Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,624	1,624	1,624	1,624	1,624	1,548	1,548	1,548	1,548	1,548
R-squared	0.866	0.866	0.867	0.866	0.867	0.293	0.296	0.299	0.296	0.301
Number of firms	643	643	643	643	643	627	627	627	627	627

Note: All disruptions in our regressions are exogenous and severe. *Count* and *Count Squared* are continuous variables. All other disruptions-related variables in the table are dummy variables indicating whether disruptions in the category occurred in a six month period or not. FE refers to fixed effects. For sales growth, we lose observations when firms have missing data in consecutive periods. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Next, in column (5), we test whether the negative impact of business disruptions is driven by recent disruptions. The impact of multiple recent disruptions (that took place in the three months prior to the survey date) is negative and significant. Note that non-recent multiple disruptions (that took place three to six months prior to the survey date) also continue to impact sales, over three months later. This shows that the negative impact of multiple disruptions is persistent. Firms find it difficult to bounce back to normal operations. Disruptions can cause temporary business shutdowns or absences of the entrepreneur. This can in turn lead to inefficient management of the firm and loss of existing customer base. We find that over 30% of entrepreneurs in our surveys who face managerial disruptions report that their relationships with existing customers are affected by the disruptions. On average they report worse relationships with a third of their existing customers.

We use a similar sequence of specifications in columns (6) – (10) of Table 4.1, to measure the impact of disruptions on sales growth. In column (6), we do not find a statistically significant linear impact of disruptions on sales growth. However, in column (7), we find that disruptions have a strong negative and non-linear impact on sales growth. After segregating disruptions as one or multiple in column (8), we find that when a firm faces multiple disruptions, its sales growth reduces by 18.8 percentage points over six months ($p = 0.070$). As before we find no evidence that firms in our sample are unable to cope with one disruption in a six month period. In column (9), after segregating the disruptions as managerial and operational, we find that the effect for both disruption categories on sales growth is negative but not statistically significant. In column (10), we find that recent multiple disruptions have highly negative and significant impact on sales growth.

Our results in Table 4.1 indicate that business disruptions have a strong negative and non linear impact on the performance of firms in our sample. When a firm faces multiple disruptions, its monthly sales and sales growth reduces significantly. The magnitude of the impact depends on the type of disruption and its recency.

4.2. The Buffering Role of Redundancies

In Table 4.2, we examine the impact of disruptions on the performance of firms with varying levels of redundancies (using Equation 2). The disruptions and redundancy in columns (1) – (4) refer to managerial disruptions and relational redundancy, respectively. Disruptions and redundancy in columns (5) and (6) correspond to operational disruptions and resource redundancy, respectively. In columns (7) and (8), we show a combined analysis where we include both managerial and operational disruptions. In columns (1) and (2), a vector of two dummy variables indicate whether a firm faced exactly n managerial disruptions in a six month period, where $n = 0$ (base case), 1, or multiple (two or more) disruptions. We are unable to categorize operational disruptions as zero, one and multiple because of too few data points. Firms in our sample faced a low frequency of operational disruptions and we have resource redundancy data in the last two survey rounds. Thus, in columns (3) – (8), we combine one and multiple disruptions and measure disruptions as a binary variable that indicates whether a firm faced at least one managerial (or operational) disruption in a six month period. The covariates in Table 4.2 – family size, firm size, business practice score, establishment score and insurance score – are mean centered, thus the buffering effect of redundancies when firms face disruptions is estimated and reported at the mean value of these covariates.[16]

Overall, we find statistical evidence that high levels of redundancies enable firms to build resilience and thus buffer against the negative impact of disruptions as compared to the base case

[16] With the exception of insurance score, these controls are measured only at baseline and are therefore time-invariant in our data. The main effect of controls that are time-invariant is absorbed by the firm fixed effects, so they cannot be separately estimated. Equation 2 includes a main effect for insurance score.

Table 4.2 Buffering effect of relational and resource redundancies against disruptions

	Managerial Disruptions				Operational Disruptions		All Disruptions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth
Disruptions								
One Managerial	-0.035	0.024						
	(0.06)	(0.10)						
Multiple Managerial	-0.413***	-0.415**						
	(0.11)	(0.18)						
One or More Managerial			-0.101*	-0.043			-0.041	0.039
			(0.05)	(0.09)			(0.07)	(0.14)
One or More Operational					-0.358	-0.897**	-0.294	-0.724*
					(0.23)	(0.43)	(0.21)	(0.40)
Redundancy Levels								
Low Relational	0.169*	0.038	0.180*	0.056			0.327**	0.460*
	(0.10)	(0.16)	(0.10)	(0.16)			(0.14)	(0.27)
High Relational	0.042	-0.270	0.042	-0.266			-0.064	-0.114
	(0.14)	(0.23)	(0.14)	(0.23)			(0.24)	(0.45)
Low Resource					0.029	-0.059	0.030	-0.061
					(0.06)	(0.11)	(0.06)	(0.11)
High Resource					-0.103	-0.081	-0.121	-0.131
					(0.13)	(0.25)	(0.13)	(0.23)
Disruptions X Redundancy Levels								
One Managerial X Low Relational	-0.059	-0.069						
	(0.11)	(0.19)						
One Managerial X High Relational	0.224	0.340						
	(0.14)	(0.24)						
Multiple Managerial X Low Managerial	0.154	0.196						
	(0.18)	(0.30)						
Multiple Managerial X High Relational	0.479**	0.701						
	(0.24)	(0.44)						
One or More Managerial X Low Relational			-0.031	-0.068			-0.202	-0.416
			(0.10)	(0.18)			(0.14)	(0.29)
One or More Managerial X High Relational			0.265**	0.409*			0.516**	0.654
			(0.13)	(0.22)			(0.21)	(0.42)
One or More Operational X Low Resource					0.347	0.749	0.268	0.575
					(0.25)	(0.48)	(0.23)	(0.43)
One or More Operational X High Resource					0.591*	1.178**	0.509*	1.010*
					(0.32)	(0.57)	(0.29)	(0.54)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector X Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location X Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Family Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Firm Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Business Practice Score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Establishment Score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Insurance Score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,583	1,530	1,583	1,530	986	933	986	933
R-squared	0.873	0.299	0.870	0.286	0.931	0.441	0.934	0.474
Number of Firms	620	610	620	610	558	518	558	518

Note: All disruptions in our regressions are exogenous and severe. All disruptions-related variables in the table are dummy variables indicating whether firms faced *one*, *multiple* (≥ 2) or *one or more* (≥ 1) disruptions of the disruption category in a six month period. The base case is *no* disruptions. All redundancy-related variables in the table are dummy variables indicating whether firms had *low* or *high* level of redundancy in a six month period, with a base case of *no* redundancy. FE refers to fixed effects. Family size, firm size, business practice scores, establishment scores and insurance scores are continuous variables, centered around their means. Thus the buffering effect of redundancy when firms face disruptions is estimated and reported at the mean value of these covariates. All control variables, except for insurance score, were collected at baseline and are time-invariant. Therefore, we are unable to estimate the main effect of these variables. The main effect of insurance score is controlled for in the regressions. In columns (1) - (4), data from all the three survey rounds are used. In columns (5) - (8), the estimates are based on data from the last two survey rounds. Robust standard errors, clustered by firm, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

of having no redundancy. In fact, we are unable to reject the null hypothesis that high relational redundancy allow a firm to completely overcome the negative impact of multiple managerial disruptions on monthly sales. More formally, focusing on monthly sales in column (1), we are not able to reject the null hypothesis, $H_0 : \gamma + \mu = 0$ in Equation 2 at the ten percent significance level. We are also unable to reject the null hypothesis that high relational redundancy allow a firm to completely overcome the negative impact of one or more managerial disruptions, in column (3). In other words, in column (3), we find that when a firm faces one or more managerial disruptions and does not have relational redundancy in place, its sales goes down by around 9.6% (p = 0.053). But when the firm has a high level of relational redundancy in place, it is able to completely buffer against the negative impact of managerial disruptions.

In column (2), we find a statistically significant negative impact of multiple managerial disruptions on sales growth. The positive coefficient on multiple managerial disruptions interacted with a high level of relational redundancy is not statistically significant at the ten percent significance level. However, in column (4), we find that sales growth of a firm when it faces one or more managerial disruptions and has a high level of relational redundancy is 40.9 percentage points higher (p = 0.067) than its sales growth when it faces such disruptions but lacks relational redundancy. The direct impact of relational redundancy on sales is positive and significant. It is possible that family members or business partners who cover for the entrepreneur during disruptions are also able to participate in the business during normal operations and improve sales.

Next we turn to resource redundancy. We are unable to reject the null hypothesis that a high level of resource redundancy allows firms to completely overcome the negative impact of operational disruptions on sales growth (see column (6)). Thus in column (6), we find that when a firm faces one or more operational disruptions and does not have resource redundancy, its sales growth goes down by around 89.7 percentage points. But when the firm has a high level of resource redundancy in place, it is able to completely buffer against the negative impact of operational disruptions. In column (5), we see that the monthly sales of a firm when it faces operational disruptions and has a high level of resource redundancy in place is 80.6% higher (p = 0.061) as compared to when it faces such disruptions but lacks resource redundancy.[17]

Given the exogeneity of disruptions, managerial disruptions should be uncorrelated with operational disruptions. We find this to hold true in our data – the correlation between the number of managerial and operational disruptions is 0.026 (p = 0.284) (see Online Appendix A1 for correlation table of disruption types). Thus, running separate regressions for managerial disruptions and operational disruptions does not introduce bias. Separating the analysis for managerial and

[17] Regression coefficient is obtained using the standard formula ($e^{\beta} - 1$) to obtain percentage change in regressions with log dependent variables, in our case Ln(Sales).

operational disruptions is in line with earlier studies, such as Gertler and Gruber (2002) or Hendricks and Singhal (2005b), which assess the impact of only one type of disruption – health-related household-level disruptions and supply chain disruptions, respectively – thus assuming independence from all other types of disruptions. To further confirm that omitted disruptions are not creating bias, in columns (7) and (8) of Table 4.2, we provide a combined analysis, where we include managerial and operational disruptions together. For this analysis, we only have data for two time periods as resource redundancy was measured in the last two survey rounds. As expected, we find that our results for resource redundancy in columns (7) and (8) remain very similar to estimates reported in columns (5) and (6). In column (7), we find that the buffering impact of high relational redundancy on sales when a firm faces one or more managerial disruptions remains positive and significant. As data from two time periods is used to estimate the coefficients for managerial disruptions and relational redundancy in columns (7) and (8), the estimates differ slightly from the those in columns (3) and (4).

Finally, in Online Appendix A7, we also test if cross-redundancy can buffer against disruptions – i.e., we test the buffering effect of relational redundancy when firms face operational disruptions and we test the buffering effect of resource redundancy when firms face managerial disruptions. We do not find any evidence for the buffering effect of cross-redundancies. Thus, in line with our hypotheses, our analysis suggests that the buffering effect of relational redundancy is specific to managerial disruptions and the buffering effect of resource redundancy is specific to operational disruptions.

4.3. Robustness Tests

Small firms in emerging markets often have intermittent sales. The firm fixed effects in Equations 1 and 2 control for the time-invariant characteristics of firms in our sample. We also control for sector and location specific macroeconomic trends using location-time and sector-time fixed effects. However, to ensure that our results are not merely a manifestation of the intermittent sales, unobserved time-varying characteristics and unobserved changes in the macro environment of small firms, we conduct a placebo test. Within each time period, we estimate the probability of a firm facing one disruption or multiple disruptions in the original data. Using these probability estimates, we randomly generate two binary variables – 'one disruption' and 'multiple disruptions' – for each firm in each time period. We then test whether these randomly generated disruptions have an impact on sales and sales growth using our specification in Equation 1. We did 100 replications and have reported the mean and standard error of the coefficients below in Table 4.3. If our results were driven by unobserved time-varying characteristics of the firms rather than by disruptions, we would expect negative and statistically significant coefficients for the randomly generated disruptions as

Table 4.3 Placebo test – Impact of disruptions on firm performance

	Placebo Test		Past Sales	
	(1) Ln(Sales)	(2) Sales Growth	(3) Ln(Past Sales)	(4) Past Sales Growth
One disruption	-0.002	-0.001	-0.111	-0.146
	(0.004)	(0.004)	(0.070)	(0.122)
Multiple disruptions	-0.007	0.000	0.033	0.032
	(0.005)	(0.006)	(0.112)	(0.203)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Sector X Time Fixed Effects	Yes	Yes	Yes	Yes
Location X Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,624	1,548	989	959
Number of firms	643	627	565	536

Standard errors from 100 replications in parentheses in columns (1) and (2). Robust standard errors in parentheses in columns (3) and (4). Data from the last survey round was dropped in columns (3) and (4) because we do not have data for future disruptions for this period. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

well. However, in columns (1) and (2) of Table 4.3, we find that the randomly generated disruptions are not associated with sales or sales growth.

We do not control for past sales in our analysis. Given the exogeneity of business disruptions, we do not expect past sales to be correlated with the number of disruptions; therefore it should not be a correlated omitted variable. We test this in columns (3) and (4) of Table 4.3, by examining the association between disruptions and past sales (past sales growth). As expected, we find no evidence for such an association. Thus, we are confident that business disruptions are well classified as exogenous, are uncorrelated with past sales and have a significant negative impact on sales and sales growth, which cannot be explained by other unobserved time-varying characteristics of the firms or their macro environment. Furthermore, when sales growth is used as a dependent variable, regression errors do not contain sales from the past period. Redundancies could also be correlated with past sales. After controlling for firm fixed effects, sector-time and location-time fixed effects, we find no evidence of redundancies being correlated with past sales (see Online Appendix A8).

Entrepreneurs might justify lower sales by saying they suffered more disruptions. Likewise, entrepreneurs with high levels of redundancies in place might report inflated sales. This type of misreporting would induce measurement error. As explained in Podsakoff and Organ (1986), systematic misreporting across the three time periods is unlikely in our data because of the complexity in the data and its panel structure, along with the non-linear relationships tested in the analysis. Most of the responses to our survey questions are objective, which minimizes potential bias from misreporting. Also, all our measures of disruptions and redundancies are accompanied by multiple follow-up questions, detailed text descriptions, scale reordering and rigorous verification steps. We also measure sales in multiple ways. For our analysis, we use strict thresholds to code disruptions and redundancies, based on the responses to specific survey questions; how we would code these measures was unknown to the entrepreneurs (and to the enumerators) during the survey. We also model complex non-linear relationships over multiple time periods while including firm fixed effects, dummy variables and multiple interaction variables as controls. For the results to be driven by misreporting, the entrepreneurs would have to systematically under- or over-report sales while factoring in the effects of these complex controls. Furthermore, they would need to do so consistently across three time periods while answering probing questions posed by our enumerators. Such an attempt at misreporting would require an unrealistically high cognitive load.

Table 4.4 Impact of redundancies and disruptions on firm sales for firms with accounting books

	All Disruptions		Managerial Disruptions		Operational Disruptions	
	(1) Ln(Sales)	(2) Sales Growth	(3) Ln(Sales)	(4) Sales Growth	(5) Ln(Sales)	(6) Sales Growth
One Disruption	-0.002	0.024				
	(0.06)	(0.10)				
Multiple Disruptions	-0.209***	-0.260*				
	(0.07)	(0.11)				
At Least One Disruption			-0.093	-0.066	-0.528	-1.422**
			(0.07)	(0.12)	(0.33)	(0.57)
Low Redundancy			0.179	0.090	0.005	-0.155
			(0.13)	(0.22)	(0.10)	(0.17)
High Redundancy			0.103	-0.165	-0.238	-0.342
			(0.17)	(0.29)	(0.16)	(0.31)
At Least One Disruption X Low Redundancy			-0.052	-0.084	0.507	1.215**
			(0.13)	(0.23)	(0.34)	(0.61)
At Least One Disruption X High Redundancy			0.265*	0.406	0.844**	1.782**
			(0.15)	(0.27)	(0.40)	(0.73)
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Controls	-	-	Yes	Yes	Yes	Yes
Observations	1,037	992	1,018	983	628	593
R-squared	0.868	0.294	0.871	0.300	0.929	0.444
Number of Firms	414	406	404	397	359	331

Note: In columns (1) and (2), we assess the average effect of all disruptions together. In columns (3) and (4), disruptions refer to *managerial disruptions* and redundancy refer to *relational redundancy.* In columns (5) and (6), disruptions refer to *operational disruptions* and redundancy refer to *resource redundancy.* All disruptions in our regressions are exogenous and severe. All disruptions-related variables in the table are dummy variables indicating whether firms faced *one*, *multiple* or *one or more* disruptions of the disruption category in a six month period. The base case is *no* disruptions. All redundancy-related variables in the table are dummy variables indicating whether firms had *low* or *high* level of redundancy in a six month period, with a base case of *no* redundancy. The controls used in the regressions are the same as those in Table 4.1 and Table 4.2. In columns (1) - (4), data from all the three survey rounds are used. In columns (5) - (6), the estimates are based on data from the last two survey rounds. Robust standard errors, clustered by firm, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

To further rule out the possibility of systematic misreporting of sales data by the entrepreneurs, we run our specifications using a sub-sample of firms that used accounting books to regularly track sales. Since these firms keep accounting books irrespective of our surveys (and the survey dates were not communicated with the entrepreneurs in advance), we would expect less systematic misreporting and little difference in the responses for self-reported and anchored sales estimates. We confirm that the self-reported and anchored sales estimates of these firms are highly correlated at 0.91 (p = 0.000). As seen in Table 4.4, regression results for this sub-sample are comparable to those in Table 4.1 and Table 4.2, with generally lower significance, likely due to the smaller sample size.

Sample selection and resulting bias in estimates due to attrition can be of concern if attrition is correlated with time-varying characteristics that are not controlled for in our fixed effects model. In general, for short panels, conditional on fixed-effects and independent variables, it is not unreasonable to assume that errors are independent of attrition (Wooldridge 2010, p. 830). Nonetheless, we run a robustness test using only firms that were surveyed in all three periods. Such a balanced panel gives us similar results to those in Table 4.2 (see Online Appendix A9). Further, in Online Appendix A10, we report results using inverse probability weighting (IPW) with weights based on the likelihood of attrition, to confirm that our results are not affected by survivor bias.

To confirm that our results are not being driven by the difference in enumerators' surveying styles or in their interactions with the entrepreneurs, we add enumerator fixed effects to our specifications. We obtain similar results (see Online Appendix A11). Our results also go through when a higher threshold is used to measure the exogeneity of disruptions, i.e., a threshold of 90th percentile instead of 75th (see Appendix A12).

5. Conclusions and Implications

In this paper, we have taken a first step at characterizing the operating environment of small firms in emerging markets, bringing attention to the nature, frequency and impact of business disruptions that they face. We find that business disruptions are not only frequent but have a significant negative impact on sales and sales growth of the firms in our sample. Strikingly, the frequency of disruptions and the magnitude of their impact is many times larger for the small firms that comprise our sample than for larger firms in developed markets.

Importantly, our results show that building relational redundancy and resource redundancy are highly effective ways for small firms in emerging markets to build resilience against business disruptions. Back-of-the-envelope calculations suggest that these strategies are also cost effective. For example, firms in our sample have a 40% chance of facing one or more managerial disruptions in a six month period. Considering this probability and the negative impact of managerial disruptions (9.6% reduction in monthly sales), which is completely buffered against by having a high level of relational redundancy in place, a firm should be willing to invest on average 3.8% of its monthly sales into building relational redundancy. With the baseline monthly sales for firms in our sample, this corresponds to 133,000 UGX ($\sim$ 38 USD) – the equivalent of about two-thirds of the monthly income for a household head in Uganda (Ugandan Bureau of Statistics 2013). As a family member only spends a few days to cover for an entrepreneur during her absence, building relational redundancy is cost effective. Similarly, firms in our sample have a 20% chance of facing one or more operational disruptions in a six month period. When firms face operational disruptions but do not have resource redundancy, their sales growth reduces by 89.7 percentage points. Yet, when firms have high resource redundancy, they are able to completely buffer against these disruptions. Considering our estimates of the reduction in sales growth and the probability of operational disruptions, a firm should be willing to invest up to 18 percentage points of sales growth into building resource redundancy. This is sufficient to purchase a small solar home system to provide power backup, or to employ a temporary worker for a few weeks.

The redundancies we identified have already been implemented by some firms in our sample, and thus, it is likely that other emerging market firms can also implement these strategies. Training entrepreneurs on the risks associated with disruptions and the benefits of building redundancies can guide them in their decisions to put redundancies in place. Such training can be easily undertaken by policy makers and NGOs in these regions. Such entities already offer the entrepreneur-owners of small firms business support programs and mentorship, which enable skills development, improved access to financing, and market linkages (USAID 2018). Several multinational companies currently work with small emerging market firms in their supply chains (Sodhi and Tang 2014). These multinationals can also train, incentivise and support small firms in their network to build redundancies to improve their own supply chain resilience. There is little research that brings an operations management lens to the domain of entrepreneurship. One exception is Yoo et al. (2016) who analyse how entrepreneurs can balance between investing their time to achieve growth vs. in improving processes to reduce crises. Our work adds to this nascent stream of research by building new knowledge on disruptions and redundancies in the context of small firms in emerging markets.

Practitioners in both risk management and finance are increasingly viewing small emerging market firms as a key future growth area for new product offerings in risk analytics, insurance, and financial lending (Microinsurance Network 2018). An effective financial product customized to this market segment necessitates a thorough understanding of the risks that these firms face, the cash-flow effect of these risks and potential mitigation strategies. Our study contributes directly to the growth of this industry. Small firms in emerging markets are disproportionately understudied because of the lack of credible data (International Trade Centre 2018). To overcome this, we collected detailed data on the operations of the small firms in our sample using business audits and recall-based one-on-one interviews with the owners of the firms. There are inherent limitations to survey-based datasets and empirical models, which can be improved with better access to secondary data. Despite the many checks we have in place, the self-reported nature of our data could result in bias. Future research on small firms can identify careful approaches to obtain accurate estimates of sales and other performance measures using secondary data. Randomized or quasi-experimental variation in exposure to redundancy strategies can also reduce the potential bias in the estimates.

The operations management literature has focused heavily – and mostly through theoretical work – on how firms can build what we term as 'resource redundancy' to buffer against supply chain disruptions. We broaden the concept of redundancy by introducing relational redundancy, which acknowledges that disruptions not only affect resources but can also affect the manager. Implementing relational redundancy strategies is a feasible and effective way to improve the resilience of centrally managed small firms to managerial disruptions. Naturally, disruptions arising from individual crises that affect key personnel in large firms are also likely to be detrimental to these firms' operational continuity and relationships with their suppliers and customers. Future research can assess ways to buffer against managerial disruptions in large firms. For instance, rather than having purchasing managers dedicated by product category, it may be beneficial to have a reserve of managers who are familiar with multiple product categories and can maintain operations during disruptions.

In this paper, we have shed light on three fundamental and high-level research questions. Future research can delve deeper and unearth many interesting questions on individual disruption types and redundancy strategies. They can also test the cost effectiveness of different redundancy strategies by collecting detailed data on costs and profits. While our empirical estimates are specific to our sample, the key takeaways can be generalized to small firms operating in other geographies as well. There will be some differences, however. For examples, higher mortality rates and lack of medical infrastructure in Africa might make managerial disruptions more frequent in small firms in Africa than in Asia. Future research can study the economic, political, social and cultural differences across geographies and how they impact the vulnerability of small firms.

The World Bank estimates that there are between 365-445 million small firms in emerging markets. These firms constitute a large portion of the overall GDP in emerging markets and employ the majority of the labour force. Yet very little is known about their operating environments and the idiosyncratic, firm-specific disruptions that they are constantly battling. Our work provides a stepping stone towards developing management strategies to increase resilience of small firms against business disruptions. We also highlight the need for more balanced policies to support small emerging market firms. Such policies should not only target increasing the upside gains of these firms, but also decreasing their downside losses by building in redundancies. Given the sheer number of small firms in emerging markets and their contribution to the economy, there remains much scope for future research in this area.

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