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

Online Appendix

A1. Exploratory Factor Analysis I – Identifying Groups of Disruptions

In the absence of prior literature on how business disruptions affect small firms in emerging markets, we develop new theory on the types of disruptions and their expected impact on firm performance based on our field work. Further, we use an exploratory factor analysis to identify the types of disruptions that impact businesses in a similar manner, which we can then categorize into different groups.

Factor analysis describes variation in observed, correlated variables in terms of a lower number of unobserved variables or factors. We are unable to use exploratory factor analysis directly on the types of disruptions in our dataset because the business disruptions used in our analysis are exogenous events, which are therefore uncorrelated with one another. Table A1.1 below shows this (expected) lack of correlation between disruption types.

	Owner Sickness	Relative Sickness	Relative Death	Theft	Supply Shortage	Electricity Outage	Employee Sickness	Building Damage
Owner Sickness	1.000							
Relative Sickness	0.081*	1.000						
Relative Death	0.045	0.009	1.000					
Theft	0.051	0.022	-0.004	1.000				
Supply Shortage	-0.010	-0.009	0.051	0.011	1.000			
Electricity Outage	-0.000	0.020	-0.011	-0.006	0.036	1.000		
Employee Sickness	0.015	-0.008	0.069	-0.002	0.041	0.025	1.000	
Building Damage	-0.030	-0.003	0.008	0.027	-0.013	-0.015	-0.024	1.000

Bonferroni-adjusted significance levels. *** p<0.01, ** p<0.05, * p<0.1

Table A1.1: Correlations between different disruption types

To conduct exploratory factor analysis, we use additional data obtained on each disruption event to examine which parts of the business were affected when a disruption occurred (i.e., the business activities interrupted by a given disruption) and then group together the disruption types that impact business activities in a similar manner. In the Event Verification section of our surveys, for each disruption reported by the respondent (an entrepreneur in our sample), we asked which of the following business activities were interrupted by the disruption: (1) relationship with customers; (2) relationship with suppliers; (3) stock; (4) availability of working capital; (5) payment of debt; (6) investments and business growth plans; (7) sales loss; and (8) temporary closure of business. All measures of interrupted activities were binary (“Yes” or “No”), except for sales loss (measured as a value on a 0-10 ordinal scale) and temporary closure of business (measured in total days closed).[1]

Using these additional measures, we conduct an exploratory factor analysis on interrupted business activities for subset of the data where a business disruption (exogenous and severe disruption) occurs. The dataset used to conduct exploratory factor analysis has 1250 rows and eight columns. Each row corresponds to a disruption that a firm faced in a six-month period and each column corresponds to an interrupted business activity.

First, we obtain factor loadings on the interrupted business activities using polychrolic correlations (because interrupted business activities mostly have discrete values) and maximum likelihood estimation method (Everitt and Hothorn 2011, Ch. 5). This allows us to identify the latent variables or factors, i.e., groups of interrupted business activities, that are affected together when disruptions occur. Based on the scree plot of the analysis, we consider two factors and we consider a factor loading threshold of 0.3. There is a lack of consensus on the right factor loading threshold (see Howard 2016 for a review), we choose 0.3 as the threshold because factor loadings in the analysis are generally low. In most cases, there is a difference of over 0.2 between the primary and alternative factor loadings, which adds confidence to the factor groupings.

interrupted activities	**Factor 1**	**Factor 2**
Relationship with customers	**0.370**	0.222
Relationship with suppliers	**0.365**	
Stock	**0.380**	
Availability of working capital	**0.587**	0.259
Payment of debt	**0.463**	
Investments and business growth plans	**0.387**	
Sales loss	0.118	**0.809**
Temporary closure of business		**0.363**

Missing values in the table are negligible loading values.

Table A1.2: Factor loadings on interrupted business activities

Table A1.2 displays the results of this analysis, including the factor loadings. Two factors were uncovered: Factor 1 included six of the interrupted business activities (relationship with customers, relationship with suppliers, stock, availability of working capital, payment of debt, investments

[1] Please note we have not used any of the interrupted business activities in the paper's main regression analyses because: (a) these measures are included solely for verification and checking purposes; and (b) this data is only available for the subset of firms that reported a disruption (i.e., they are conditional on a disruption event being recorded). The sales and sales growth values used in our regression tables are different from the sales loss measure obtained in the Event Verification section. Sales loss is a number on an ordinal scale based on the respondent's assessment of how much sales was lost due to a given business disruption. By contrast, the dependent variables in our regression analysis use monthly sales and sales growth values – obtained in a different section of our surveys and measured for all firms in our sample independent of any disruption event.

and business growth plans); while Factor 2 was comprised of the remaining two activities (sales loss, temporary closure of business). The pattern of results suggests that disruptions can impact performance of firms in two ways. Disruptions that affect business activities that load onto Factor 1 can indirectly affect sales by impacting the firm's operating resources (e.g., human, physical, financial). On the other hand, disruptions that affect business activities that load onto Factor 2 can directly affect sales by impeding the entrepreneur's ability to sell the firm's goods and services.

Next, we identify which disruptions map onto Factor 1 and Factor 2. A factor score is first computed for every disruption (1250 in total).[2] The factor score represents a disruption's relative standing (or ranking) on the factor. A highly positive factor score for a disruption (on one of the two factors) indicates the disruption has a strong impact on the interrupted activities that load onto the factor. On the other hand, if a disruption has a highly negative factor score then it indicates the disruption has a weak impact on the interrupted business activities which load onto that factor.

For each factor, we first identify disruptions that have highly positive factor scores (i.e., values above the median for all factor scores in the positive range). Next, for each disruption type, we calculate the proportion of disruptions that have highly positive factor scores associated with Factor 1 and Factor 2. We plot these proportions in Figure A1.1. This allows us to examine which disruption types strongly impact the interrupted activities that load onto the two factors.

The patterns displayed in Figure A1.1 indicate that a large proportion of disruptions due to owner sickness, the sickness of an owner's relative, and the death of an owner's relative have highly positive factor scores associated with Factor 2, i.e., these disruptions directly affect sales by impeding the entrepreneur's ability to sell the firm's goods and services. Since these disruptions load together onto Factor 2 and they limit the owner-managers' availability, we classify these disruptions as **managerial disruptions**. In addition to impacting Factor 2, managerial disruptions, especially owner sickness and the sickness of an owner's relative, also impact Factor 1, i.e., these disruptions also limit the operating resources of a firm. For the small firms in our sample, this pattern highlights the central role played by entrepreneur-owners in running their businesses, both in maintaining sales and in managing the firm's operating resources.

Figure A1.1 also suggests that the remaining four disruption types (theft, supply shortage, electricity outage, employee sickness) tend to be more aligned with Factor 1 (to varying degrees), i.e., these disruptions limit the operating resources (e.g., human, physical, financial) of a firm. In

[2] Building damage is a very low frequency disruption (we only observed eight instances of exogenous building damages in our data). Given the low number of data points, we do not include building damage in our factor analysis.

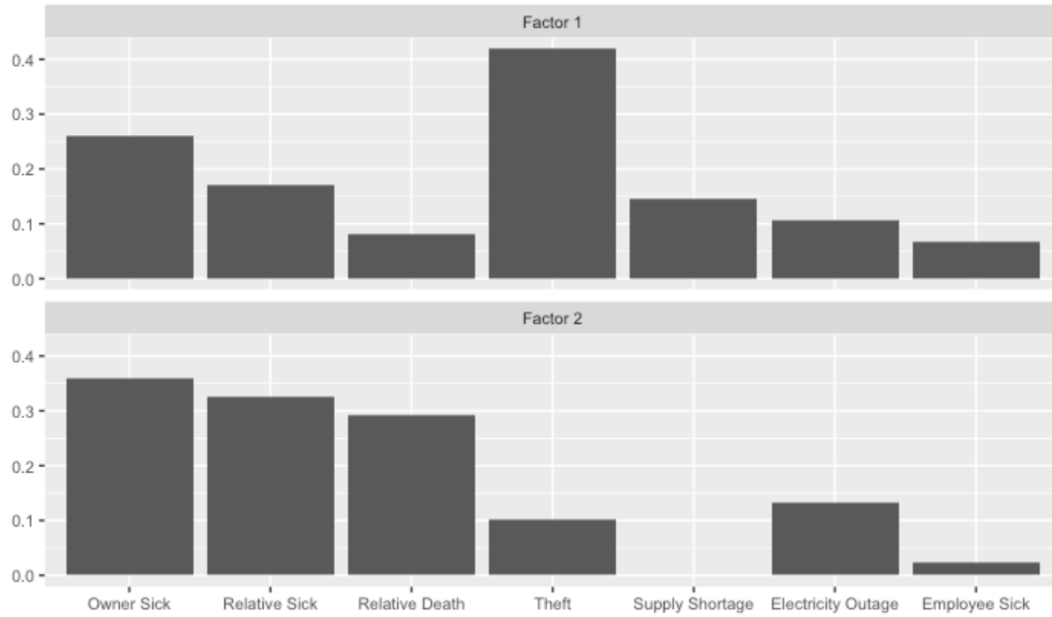

Figure A1.1: Plot of the proportion of disruptions of each disruption type that have a positive and high factor score in each factor

particular, we find that a large proportion of thefts have highly positive factor scores associated with Factor 1. Given that these four disruption types can be grouped together within Factor 1, and they constrain the operating resources of a firm, we classify them as **operational disruptions**.

Classification of Disruptions based on Frequency and Severity Using the descriptive results above, we can classify disruptions based on their frequency and the expected severity of their impact on sales and sales growth. In particular, based on Figure A1.1, one can assign different types of disruptions as having "very high", "high", "moderate" or "low" severity. For instance, a high proportion of disruptions due to owner sickness exhibit highly positive scores across both the factors. This suggests that owner sickness can be categorized as a very high impact disruption. After owner sickness, relative sickness and theft appear to have high impact across both factors. Disruptions due to a relative's death, electricity outage and supply shortage are expected to have a moderate impact. Finally, one might expect low impact from disruptions due to employee sickness.

Building damage is a very low frequency disruption (we only observed eight instances of exogenous building damages in our data). Because of the low number of data points, we do not include building damage in our factor analysis. However, on manually inspecting the responses to interrupted business activities for the eight instances of building damage, we find that they interrupt most of the activities. Therefore, we classify building damage as a very high impact, low frequency disruption.

Next, based on expected severity and frequency, we place disruptions in four groups as shown in Figure A1.2 – (i) high-frequency, high-impact disruptions (owner sickness, relative sickness, theft), (ii) high-frequency, low-impact disruptions (relative death), (iii) low-frequency, high-impact disruptions (building damage), and (iv) low-frequency, low-impact disruptions (supply shortage, electricity outage, employee sickness). Figure A1.2 suggests that managerial disruptions (such as owner sickness and relative sickness) and thefts need to be managed most effectively as they are likely to hurt performance of small emerging market firms the most.

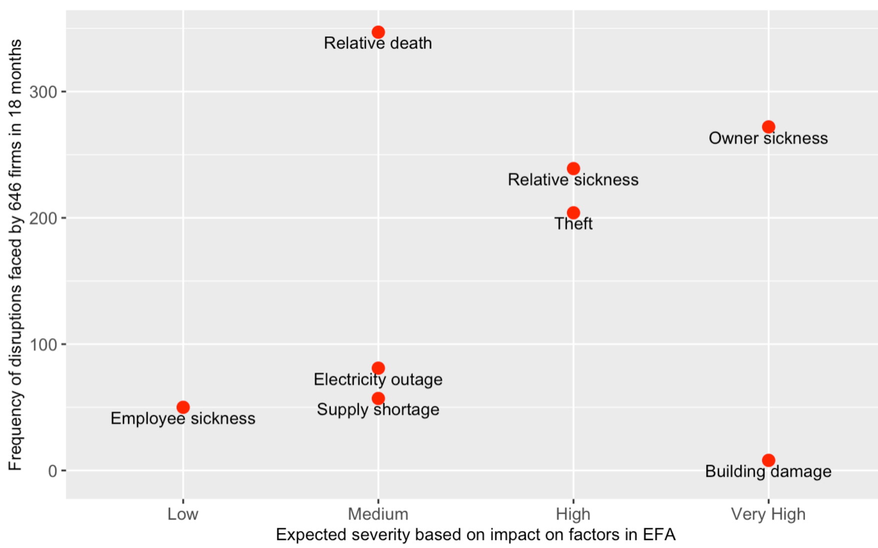

Figure A1.2: Vulnerability Map – Frequency and Expected Severity of Different Disruption Types.

In Table A1.3, we summarize regression results for the impact of these four categories of disruptions on sales and sales growth (as in the paper). In the regressions, we control for firm, location-time and sector-time fixed effects. As displayed in columns (1) and (2) of Table A1.3, on average, firms in our sample see a decrease in sales and sales growth when they face 'high-frequency, high-impact' disruptions. Please note that there are only eight 'low-frequency, high-impact' disruptions, so as a result the estimate might not be reliable. In columns (3) and (4) of Table A1.3, we examine the impact of the four types of high frequency disruptions individually. We only find a strong negative main effect of disruptions related to owner sickness on sales and sales growth of the firms in our sample.

Disruptions	(1) Ln(Sales)	(2) Sales Growth	(3) Ln(Sales)	(4) Sales Growth
High frequency high impact	-0.070**	-0.095*		
	(0.03)	(0.06)		
High frequency low impact	-0.046	0.025		
	(0.05)	(0.08)		
Low frequency high impact	0.390	0.333		
	(0.31)	(0.46)		
Low frequency low impact	-0.056	-0.144		
	(0.06)	(0.11)		
Owner sickness			-0.159***	-0.177*
			(0.06)	(0.09)
Relative sickness			-0.008	0.030
			(0.06)	(0.10)
Relative death			-0.048	0.020
			(0.06)	(0.08)
Theft			-0.019	-0.113
			(0.07)	(0.11)
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	1,624	1,548
Number of firms	643	627	643	627

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A1.3: Impact of disruptions classified by frequency and expected impact

A2. Exploratory Factor Analysis II – Identifying Groups of Redundancy Strategies

In this analysis, we examine the underlying constructs in our pre-identified redundancy strategies: (1) cover for the owner by an immediate family member; (2) cover for the owner by business partner; (3) having multiple suppliers; (4) keeping safety stock; (5) maintaining electricity backup; and (6) having a temporary pool of employees.

Since redundancy strategies are expected to reduce the negative impact of disruptions, we first identify the subset of disruptions that interrupted few (four or less) of the business activities (which we checked as part of the Event Verification section in our surveys). The logic is that if a given disruption did not strongly interrupt business activities, then the firm may have had strategies in place to buffer against these otherwise damaging events. We then conduct an exploratory factor analysis on the redundancy strategies that the firms in this subset had in place to obtain the groups of redundancy strategies. Based on the scree plot of the analysis, we consider two factors. We consider a factor loading threshold of 0.3 (Howard 2016). Table A2.1 displays the factor loadings for each of the six redundancy strategies.

The factor loadings suggest that the redundancy strategies generally separate across two factors. The first factor is availability of backup resources, namely, multiple suppliers, safety stock and electricity backup. We therefore classify these redundancy strategies grouped together within Factor 1 as **resource redundancy**. The second factor is a cover for the entrepreneur-owner during their absence by someone trustworthy and capable that she has a close relationship with, such as an immediate family member or a business partner. We therefore classify these redundancy strategies grouped together within Factor 2 as **relational redundancy**.

Redundancy Strategies	Factor 1	Factor 2
Owner cover by Immediate Family	0.119	**0.378**
Owner cover by Business Partner		**0.447**
Has Multiple Suppliers	**0.406**	0.155
Has Safety Stock	**0.456**	
Has Electricity Backup	**0.306**	0.286
Has Temporary Employee Pool		

Missing values in the table are negligible loading values.

Table A2.1: Factor loadings for redundancy strategies

A3. Data Collection Details

Survey Process In each survey round, a team of twenty-five trained enumerators filled out survey responses using hand-held electronic tablets as they interviewed the respondents, i.e., the entrepreneur-owners of the businesses in our sample. Our survey structure ensured extensive verification checks to reduce any recall bias, data manipulation or contamination. To enhance consistency for our measures, we used different question formats and multiple response scales for each measure. Each numeric or scale response was also accompanied by a detailed text response to explain the selection. The enumerators were supervised in the field by a research manager who reviewed the data on a daily basis. Outliers, anomalies, or data entry mistakes were immediately clarified either with the enumerator or entrepreneur. Every week, independent auditors also cross-checked a random subset of 10% of the surveys with the entrepreneurs. Finally, after the data was collected from a survey round, two research assistants (who were blind to the research design) independently reviewed every response provided for the key variables – exogeneity and severity of disruptions, redundancy measures and control variables. Discrepancies were brought to the attention of the authors and discussed with the research manager in Uganda – who subsequently followed up with the entrepreneur to confirm the information. To maintain interest and reduce attrition, after each completed survey, the participating entrepreneur was offered a small 'thank you gift' (mobile top up card worth $2).

Sample Recruitment Survey First, using a geographically exhaustive sampling approach from January to March 2015, a team of 15 enumerators went door-to-door seeking out small firms across the greater Kampala area. Approximately 20,000 businesses were approached during this stage, with a view to identify suitable firms to enable a broad research agenda on small firms in emerging markets, which includes this study as well as other projects. Enumerators were sent to "business hot spots" where many small firms operate. They then approached any small firm operating out of a physical structure (e.g., small shop, shipping container, or larger retail space) and asked to speak in English with the entrepreneur running the firm.[3] Entrepreneurs who met these two inclusion criteria were given a sales pitch about potential business development services and the opportunity to apply for future participation (as part of a different project) by completing a thirty-minute sample recruitment survey conducted by the enumerator. We obtained 4,103 responses to this survey. After confirming that the firms were in fact operational and exchanged money for an offering (i.e., real customers were currently paying for their products/services) and performing other data checks, a total of 3,936 firms were recruited at this stage. As discussed in the paper in Section 3.3.1, our sample was derived from these 3,936 firms. Firms in our sample did not receive any business service intervention during our study period.

Enumerators The enumerators in our survey rounds are graduates from the top universities in Uganda with several years of experience in field-based data collection. Prior to starting each of our follow up survey rounds, they were trained for 1-2 weeks on the content and logic of our electronic survey. Over the next month, the team of enumerators physically visited all firms in our sample and interviewed the entrepreneurs. Each follow-up survey took about 90 minutes on average.

Business Disruptions For each type of disruption, the enumerator read out its scripted description and asked the entrepreneur if they had faced a disruption of that kind in the previous six months, and if so, how many. In cases where entrepreneurs face multiple disruptions of a type within six months, the enumerator focused on the most severe disruption for further questioning. In order to manage time and not capture every small disruptive event, we included specific severity thresholds in our scripted descriptions of disruptions. For example, we excluded sicknesses that required the entrepreneur to be absent from the business for less than half a day and electricity outages that lasted less than two days for further questioning. The threshold used for each disruption type is detailed in Table A3.1 below. Our enumerators were trained to probe and obtain details that helped verify if a given disruption really occurred.

Disruption type	**Threshold**
All managerial disruptions	Owner was away from the business for at least half a day
Sickness of employee	Employee was away from the business for at least two consecutive days
Electricity outage	Power outages in locality of the business that lasted at least two consecutive days
Supply shortage	Shortage of at least one product that lasted at least a week
Theft	Incident of theft or burglary in the business
Building damage	Incidences of fire, flooding or building collapse at the business site

Table A3.1: Thresholds used to Collect Data on Disruptions

[3] The enumerators were instructed to exclude firms operating in mobile street stands, roadside carts, or other non-permanent structures.

Based on the entrepreneur's description of a disruption, our enumerator marked the unpredictability and abruptness of the disruption on a 0-10 ordinal scale. We created a composite variable by taking the average of the response to these two questions. *Exogeneous* disruptions are disruptions with a minimum score of six (out of 10) – also the 75th percentile value – for the composite variable. Thus, our focus was on disruptions that were surprising and unfolded in quick succession. In Table A3.2 below, we provide detailed examples of exogenous disruptions in each disruption type.

Disruption category	**Disruption type**	**Exogenous Disruptions** (Exogeneity Score>=6)	**Endogenous Disruptions** (Exogeneity Score<6)
Managerial Disruptions	Sickness of Entrepreneur or Relative	- Very abrupt and unpredictable onset of sickness. (e.g., Accident, Heart-attack, Miscarriage) - Abrupt with gradual onset of the sickness over 3-4 days. (e.g., Malaria, Typhoid) - Unexpected diagnosis of a disease that showed symptoms over a few weeks. (e.g., Diagnosis of cancer, blood pressure, diabetes)	- Expected sickness. (e.g., Childbirth without complications) - Flare-up associated with an existing condition. (e.g., AIDS, Cancer, Diabetes)
	Death of Relative	- Very abrupt and unpredictable death. (e.g., Accident, Stroke, Heart-attack) - Abrupt onset of sickness over a few days followed by death.	- Expected death due to old age or known terminal ailment. - Expected death due to worsening condition from long-term ailment.
Operational Disruptions	Sickness of Employee	- Very abrupt and unpredictable onset of sickness. (e.g., Accident, Heart-attack, Miscarriage) - Abrupt with gradual onset of the sickness over 3-4 days before condition worsened. (e.g., Malaria, Typhoid) - Unexpected diagnosis of a disease which may have shown symptoms over a few weeks. (e.g., Diagnosis of cancer, blood pressure, diabetes)	- Expected sickness. (e.g., Childbirth without complications) - Flare-up associated with an existing condition. (e.g., AIDS, Cancer, Diabetes)
	Supply Shortage	- Very surprising, product always available when ordered. - Surprising, shortage uncommon in time of year.	- Predictable, suppliers informed apriori. - Predictable, seasonal product.
	Electricity Outage	- Very abrupt outage. (e.g., Blow-up of transformer, damage to electric poles) - Surprising, outages are rare or never last more than few hours.	- Not surprising, electric maintenance was expected. - Not surprising, outages common in neighborhood or season.
	Theft	- Very surprising, thefts rare in neighborhood. - Surprising, thefts occur rarely.	- Not surprising, common in neighborhood. - Not surprising, recent thefts in neighborhood.
	Building Damage	- Very surprising and abrupt source of damage. (e.g., Electric short circuits, fire) - Unexpected damages from sources that do not usually cause damage. (e.g., Rains)	- Expected damage due to seasonal weather patterns. - Expected damage, old infrastructure.

Table A3.2: Exogenous versus Endogenous disruptions

Our enumerators marked the severity of each disruption on a 0-10 ordinal scale. For sickness-related disruptions, the ordinal scale options describe disease characteristics that indicate increasing levels of severity. Sicknesses (including deaths) that are life threatening, lead to hospitalization, or involve being bed-ridden for at least 3-4 days are considered severe. Such events correspond to a score of six and above on the ordinal scale (also the 75th percentile). For theft and building damage, the ordinal scale options describe the extent of damage to the firm's physical property and goods. Disruptions that lead to loss or damage of machinery, vehicles, business premises and valuables are classified as severe. For electricity outages and supply shortages, the number of days that a disruption lasts is used to assess its severity. Disruptions that last beyond the 75th percentile of this measure are classified as severe. This corresponds to electricity outages that last at least a week and supply shortages that last at least 40 days.

Sales Data Collection For the monthly recall sales estimate, the enumerator asked the entrepreneur to report all the money collected into the business in the last month. To arrive at the monthly anchored sales estimate, the enumerator also asked the entrepreneur to report sales in the best week and worst week in the last month, and sales in the best, worst and the typical day during the last month. Our electronic survey was pre-programmed to calculate and store sales values in three recall windows: (i) monthly window – monthly recall sales value, (ii) weekly window – average of the best week and worst week during the last month, multiplied by 4.25 (average number of weeks in a month) and (iii) daily window – sales in a typical day multiplied by the number of days the business operates in a week and by 4.25 weeks per month. The enumerator presented these three different sales estimates to the entrepreneur, who used them to guide her monthly anchored sales estimate. Triangulating by first anchoring on the three estimates and then adjusting the monthly sales estimate through an iterative process has the advantage of increasing the precision of performance measures of small firms (Anderson et al. 2021).

A4. Differences in Characteristics of Firms in our Sample and in the Recruitment Sample

In Table A4.1, using paired t-tests, we assess whether the 646 firms in our sample are systematically different in characteristics from the sample of 3,936 firms in the recruitment sample. Apart from a small difference in the age of the entrepreneurs and in years of operation, we do not find any significant differences in the two samples. This suggests that our sample is fairly representative of the small firms operating in Kampala that meet our inclusion criteria.

	Our Sample		Recruitment Sample		Difference	
	mean	sd	mean	sd	b	t
Number of employees	.85	2.3	.7	1.7	.14	(1.5)
Age (years)	33	8.2	30	8.1	2.2***	(6.3)
Years operating	5.7	4.5	4.3	4.9	1.4***	(7.3)
Education	5.9	1.7	5.9	1.7	.017	(.23)
Married	.52	.5	.51	.5	.013	(.61)
Children	2.2	2	2.1	2.2	.11	(1.3)
Gender	.44	.5	.48	.5	-.031	(-1.5)
Sector: Agriculture	.0077	.088	.0069	.083	.00081	(.22)
Sector: Construction	.0031	.056	.004	.063	-.00086	(-.36)
Sector: Manufacturing	.084	.28	.072	.26	.011	(.96)
Sector: Retail	.51	.5	.54	.5	-.035	(-1.6)
Sector: Services	.36	.48	.34	.48	.015	(.73)
Sector: Wholesale	.037	.19	.028	.17	.0087	(1.1)
Observations	646		3936		4582	

Table A4.1: Differences in characteristics of firms in our sample and in the recruitment sample

A5. Impact of National Elections on Firm Performance

Although we collected data on political events in the vicinity of the firms in our surveys, we do not consider political events as firm specific business disruptions. Political events are macro level or systemic shocks to these firms. Between the first and second round of our surveys on business disruptions (collected in Nov 2015 and May 2016, respectively), Uganda had its national elections – in February 2016.

Using the data on violent political events reported by firms in our sample, we assess whether a firm location was highly disrupted during the national elections. We consider locations as highly disrupted during elections if more than a quarter of the firms in our sample operating in the location witnessed political events that were violent around the election time. We then test how the sales of firms in the locations that faced disruptions during elections vary over time.

Our sample includes data on small firms from 15 locations in the greater Kampala region. Among these locations, four were hotspots of election-related disruptions: 1. Bwaise, Karelwe, Mulago area, 2. Central Business District, 3. Najjanankumbi, and 4. Wandegeya, Makerere area. We use a dummy variable to indicate if the location of a firm was in one of these hotspots. We use the following regression model to assess if the sales and sales growth of the firms in locations that were hotspots for election-related disruptions varied over the three survey rounds, where data on the second survey round was collected shortly after the national elections:

$$\begin{aligned} y_{ijkt} = \alpha_i + \beta Election.Disruption.Hotspot_j + \boldsymbol{\gamma Survey.Round_t} \\ + \boldsymbol{\delta Election.Disruption.Hotspot_j * Survey.Round_t} + \zeta_{kt} + + \epsilon_{ijkt} \end{aligned} \tag{1}$$

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. $Election.Disruption.Hotspot_j$ is a dummy variable that indicates if location j became a hotspot of election related disruptions. $Survey.Round_t$ is a categorical variable that indicates the survey round (with the first survey round in Nov 2015 as the base case). The α_i are firm fixed effects. They 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. Because of the firm fixed effects, we are unable to estimate the coefficient for $Election.Disruption.Hotspot_j$, which is time-invariant. ζ_{kt} are sector-time fixed effects. They control for disruptions to the business sector in a time period. 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.

In Table A5.1, we see some evidence that businesses located in hotspots of election-related disruptions had lower sales growth (by 22.1 percentage points ($p = 0.119$)) in the survey round following the national elections, i.e., in May 2016, than other locations. This is after controlling for differences in time invariant characteristics of the firms as well as any sector wide impact of elections (by inclusion of Sector X Time fixed effects). The coefficients for sales and sales growth for firms located in the hotspots in time periods after the elections in negative, but not statistically significant at the ten percent significance level. We also find that all firms in our sample report higher sales and sales growth nine months after the elections (in Nov 2016) compared to right before the elections (in Nov 2015).

Future research can study the impact of such systemic disruptions on performance of small firms in more detail.

	(1) Ln(Sales)	(2) Sales Growth
Survey round in May 2016	0.074	0.152
	(0.07)	(0.11)
Survey round in Nov 2016	0.179***	0.221**
	(0.07)	(0.09)
Election Disruption Hotspots X Survey round in May 2016	-0.082	-0.243
	(0.09)	(0.16)
Election Disruption Hotspots X Survey round in Nov 2016	-0.007	-0.078
	(0.10)	(0.13)
Observations	1,543	1,486
Number of firms	574	565
Firm Fixed Effects	Yes	Yes
Sector X Time Fixed Effects	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5.1: Impact of systemic disruptions – Violence and unrest due to national elections in February 2016

A6. Baseline characteristics of firms that faced disruptions and those that did not

Table A6.1 shows that the means of most observable firm characteristics do not differ for the subsample that faced disruptions and the subsample that did not. The differences in the number of dependents, number of children and age of entrepreneur are controlled for on average using the firm fixed effects.

	Firms without Disruptions		Firms with Disruptions		Difference	
	mean	sd	mean	sd	b	t
ln(Baseline Sales)	14	1.1	14	1.2	-.22	(-1.9)
ln(Baseline Profits)	11	4.2	11	4.6	-.49	(-1.1)
Owner's characteristics						
Female	.47	.5	.44	.5	-.031	(-.64)
Age (years)	34	9.6	32	7.8	-1.9*	(-2.1)
Education: Primary	.25	.43	.24	.43	-.0058	(-.14)
Education: High School	.5	.5	.5	.5	-.0039	(-.079)
Education: College and above	.25	.44	.26	.44	.0078	(.18)
Owner married	.54	.5	.52	.5	-.022	(-.45)
Children (number)	4.4	3.2	5.1	3.4	.68*	(2.1)
Dependents (number)	2.5	2.4	3.3	2.7	.8***	(3.3)
Firm characteristics						
Sector: Agriculture	.0077	.088	.0078	.088	.00006	(.0069)
Sector: Construction	.0077	.088	.0019	.044	-.0058	(-.73)
Sector: Manufacturing	.054	.23	.091	.29	.037	(1.6)
Sector: Retail	.58	.5	.49	.5	-.085	(-1.7)
Sector: Services	.32	.47	.37	.48	.055	(1.2)
Sector: Wholesale	.038	.19	.037	.19	-.0016	(-.087)
Years operating	5.8	5	5.7	4.4	-.17	(-.36)
Total employees (number)	1.2	2.4	1.7	3.9	.45	(1.6)
Observations	130		516		646	

Table A6.1: Paired t-tests of average baseline characteristics of firms that faced disruptions versus those that did not face disruptions

A7. Testing the Buffering Impact of Cross Redundancies

In Table A7.1, we test if resource redundancy can help firms buffer against managerial disruptions and if relational redundancy can help firms buffer against operational disruptions. We do not find evidence for such cross redundancy effects.

	Managerial Disruptions		Operational Disruptions	
	(1)	(2)	(3)	(4)
	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth
One or more disruptions	0.035	-0.024	-0.039	-0.185
	(0.12)	(0.21)	(0.08)	(0.13)
Low Redundancy	0.074	-0.048	0.183**	0.027
	(0.08)	(0.14)	(0.09)	(0.15)
High Redundancy	0.081	-0.115	0.132	-0.117
	(0.16)	(0.25)	(0.13)	(0.22)
One or More Disruptions X Low Redundancy	-0.048	0.067	-0.232	-0.063
	(0.13)	(0.23)	(0.17)	(0.33)
One or More Disruptions X High Redundancy	-0.201	0.313	-0.045	-0.007
	(0.27)	(0.43)	(0.18)	(0.25)
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
Disruptions X Controls	Yes	Yes	Yes	Yes
Observations	986	933	1,583	1,530

Note: In columns (1)–(2), *disruptions* refer to *managerial disruptions* and in columns (3)–(4), *disruptions* refer to *operational disruptions*. In columns (1)–(2), *redundancy* refer to *resource redundancy* and in columns (3)–(4), *redundancy* refer to *relational redundancy*. Family size, firm size, business practice scores, establishment scores and insurance scores are continuous variables, centered around their means. Thus the buffering effect of redundancies when firms face disruptions is estimated and reported at the mean value of these covariates. All control variables, except insurance score were collected at baseline and are time invariant. Therefore, we are unable to estimate the main effect of these variables. Main effect of insurance score is controlled for in the regressions. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7.1: Impact of cross redundancies on disruptions

A8: Correlation between Redundancy and Past Sales

We check for correlation between past period sales and current period redundancy in our fixed effects model which controls for firm, time, sector-time and location-time fixed effects. Coefficients for ln(past monthly sales) in Table A8.1 are not significantly different from zero for both relational and resource redundancy.

	(1)	(2)
	Relational Redundancy	Resource Redundancy
Ln(Past Monthly Sales)	0.016	-0.018
	(0.02)	(0.06)
All fixed effects	Yes	Yes
Observations	1,611	989
R-squared	0.842	0.681
Number of Firms	639	565

Both the regressions include firm fixed effects, sector-time fixed effects and location-time fixed effects. Redundancy is measured as a continuous variable here. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8.1: Association between redundancy and past period sales

A9: Regression Results using Balanced Panel

			Relational Redundancy		Resource Redundancy	
	(1) Ln(Sales)	(2) Sales Growth	(3) Ln(Sales)	(4) Sales Growth	(5) Ln(Sales)	(6) Sales Growth
One Disruption	0.029	0.109				
	(0.05)	(0.08)				
Multiple Disruptions	-0.141**	-0.208*				
	(0.06)	(0.11)				
At Least One Disruption			-0.100*	-0.067	-0.358	-0.897**
			(0.05)	(0.10)	(0.23)	(0.43)
Low Redundancy			0.148	0.004	0.032	-0.060
			(0.10)	(0.18)	(0.06)	(0.11)
High Redundancy			0.043	-0.258	-0.100	-0.080
			(0.15)	(0.25)	(0.13)	(0.25)
At Least One Disruption X Low Redundancy			0.011	0.026	0.347	0.749
			(0.11)	(0.19)	(0.25)	(0.48)
At Least One Disruption X High Redundancy			0.256*	0.436*	0.591*	1.178**
			(0.14)	(0.24)	(0.32)	(0.58)
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Controls	-	-	Yes	Yes	Yes	Yes
Observations	1,331	1,295	1,326	1,292	885	851
R-squared	0.863	0.206	0.865	0.211	0.923	0.374
Number of Firm	459	456	457	454	457	436

Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A9.1: Impact of redundancy and disruptions on firm sales for a balanced panel

A10: Weighted Regression to address Attrition

We use inverse probability weighting (IPW) to account for attrition in our surveys (Wooldridge 2010). For each time period, we first use the full set of baseline characteristics (listed in Table 3.1 in the paper) to predict attrition using a logit model. We then obtain predicted probabilities of attrition and use their inverses as weights in our regression models. This method has been widely used in the literature to deal with selection due to attrition and selection into treatment (e.g., Gertler et al. (2014), Jensen (2012), Jack and Suri (2014)). The method is based on the assumption that observable baseline characteristics are a good predictor of attrition in subsequent survey rounds. Below in Table A10.1, we list results from our weighted regressions. We find that the estimates remain similar to those in Tables 4.1 and 4.2 in the paper. Some estimates lose significance; this can be attributed to loss of about 40-60 observations as some firms have one or more missing baseline characteristics due to which their weights could not be calculated.

			Relational Redundancy		Resource Redundancy	
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth
One Disruption	0.027	0.121				
	(0.05)	(0.08)				
Multiple Disruptions	-0.158**	-0.181				
	(0.07)	(0.12)				
At Least One Disruption			-0.087	-0.034	-0.378	-0.931*
			(0.06)	(0.10)	(0.26)	(0.48)
Low Redundancy			0.183*	0.042	0.033	-0.034
			(0.10)	(0.17)	(0.07)	(0.12)
High Redundancy			0.051	-0.262	-0.105	-0.069
			(0.15)	(0.25)	(0.15)	(0.28)
At Least One Disruption X Low Redundancy			-0.038	-0.060	0.395	0.817
			(0.11)	(0.20)	(0.29)	(0.54)
At Least One Disruption X High Redundancy			0.232*	0.350	0.605*	1.196*
			(0.14)	(0.25)	(0.36)	(0.64)
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Controls	-	-	Yes	Yes	Yes	Yes
Observations	1,564	1,494	1,543	1,494	946	897
R-squared	0.875	0.301	0.875	0.309	0.932	0.454
Number of Firms	414	406	404	397	359	331

Results from reweighting the data using IPW to account for attrition. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A10.1: Regression results with Inverse Probability Weighting

A11: Regression with Enumerator Fixed Effects

			Relational Redundancy		Resource Redundancy	
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth
One Disruption	0.071	0.131*				
	(0.05)	(0.08)				
Multiple Disruptions	-0.143**	-0.212**				
	(0.06)	(0.10)				
At Least One Disruption			-0.069	-0.044	-0.277*	-0.673**
			(0.04)	(0.08)	(0.16)	(0.29)
Low Redundancy			0.117	-0.082	0.024	-0.044
			(0.09)	(0.14)	(0.05)	(0.10)
High Redundancy			-0.018	-0.355*	-0.054	-0.071
			(0.12)	(0.19)	(0.10)	(0.21)
At Least One Disruption X Low Redundancy			-0.018	0.012	0.271	0.490
			(0.09)	(0.15)	(0.20)	(0.35)
At Least One Disruption X High Redundancy			0.188*	0.271	0.581**	1.089**
			(0.10)	(0.18)	(0.24)	(0.43)
Enumerator Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector X Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location X Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Controls	-	-	Yes	Yes	Yes	Yes
Observations	1,624	1,548	1,583	1,530	986	933
R-squared	0.876	0.362	0.880	0.345	0.934	0.499
Number of Firms	643	627	620	610	558	518

Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A11.1: Regression results with enumerator fixed effects

A12. Regression with Higher Threshold of Exogeneity for Disruptions

			Relational Redundancy		Resource Redundancy	
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth	Ln(Sales)	Sales Growth
One Disruption	0.067	0.106				
	(0.05)	(0.07)				
Multiple Disruptions	-0.228**	-0.348**				
	(0.09)	(0.15)				
At Least One Disruption			-0.079	-0.083	-0.276	-0.184
			(0.06)	(0.10)	(0.18)	(0.29)
Low Redundancy			0.205**	0.051	0.032	-0.035
			(0.09)	(0.16)	(0.06)	(0.11)
High Redundancy			0.053	-0.241	-0.066	0.009
			(0.14)	(0.23)	(0.13)	(0.24)
At Least One Disruption X Low Redundancy			-0.150	-0.012	0.306	0.100
			(0.13)	(0.21)	(0.22)	(0.37)
At Least One Disruption X High Redundancy			0.384**	0.649**	0.327	0.041
			(0.15)	(0.26)	(0.31)	(0.45)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector X Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Location X Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Disruption X Controls	-	-	Yes	Yes	Yes	Yes
Observations	1,624	1,548	1,583	1,530	986	933
R-squared	0.867	0.298	0.871	0.283	0.931	0.434
Number of Firms	643	627	620	610	558	518

Robust standard errors, clustered by firm, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A12.1: Regression results with highly exogenous disruptions

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