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Abstract

Online surveys are an alternative to traditional in-person data collection. However, abrupt transitions between modes may have unintended consequences. This study examines the impact of a sudden shift from in-person to online survey administration in Zambia prompted by the COVID-19 pandemic. Using a panel of 1,719 firm responses from five rounds of in-person business opinion surveys (2019–early 2020) and five subsequent rounds conducted online, we assess how this mode change affected response rates and data quality. We find that the shift led to a sharp decline in response rates, particularly among rural firms and sectors with limited digital capacity. However, data quality, measured by item nonresponse, improved significantly under the online mode. These findings highlight the trade-offs involved in survey mode transitions in developing country contexts. While online platforms present important opportunities for cost-effective data collection and improved quality, their effectiveness may be hindered by gaps in digital infrastructure and low levels of digital literacy.

Keywords: *Survey Mode Effects, COVID-19, Business surveys, Digital divide, Zambia.*

JEL Codes : *C83, D22, O55, O33*

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1.0 Introduction

Business surveys play an important role in assessing the general direction of economic changes and provide valuable information to policymakers. These surveys are an important means of assessing the macroeconomic environment and expectations by major stakeholders in the private sector (firms). This information also is critical for monetary authorities in anchoring inflation expectations. Business tendency surveys are also key in generating timely information on short-term economic developments and have become more informative and useful in tracking and anticipating macroeconomic changes as an input in monetary policy formulation (D'Souza and Voll, 2021; Irving Fisher Committee on Central Bank Statistics et al., 2009; Omana and Mall, 2015). As with all surveys, the mode of data collection is a critical aspect that may determine whether the survey is successfully undertaken or not.

A mix of face-to-face and online data collection methods has been used for surveys conducted in various African countries. For example, the Afrobarometer survey provides an important example of physical data collection in numerous countries, including Zambia. It employs in-person interviews conducted in respondents' preferred languages to ensure broad national coverage. This mode of data collection is especially effective in reaching remote areas and contributes significantly to the representativeness of the survey. High response rates have been reported in both urban and rural regions, and the approach facilitates the inclusion of older and potentially less digitally literate individuals who may be less reachable through online platforms (Afrobarometer, 2022). However, online methods are usually adopted to optimize efficient allocation of resources and time for surveying. Particularly, during events such as the COVID-19 pandemic and with the rising uptake of technology, remote surveys are even more feasible and are gaining popularity. However, issues of representativeness and under coverage arise in developing countries due to lower internet penetration compared to developed regions. This leads to skewed participation with online samples more likely to over-represent younger, urban, and more educated respondents while excluding large segments of the population (Bethlehem and Biffignandi, 2011; Elliott, 2018).

Business surveys also employ a wide range of data-collection modes which vary across countries and have evolved over time. Recent years have seen a shift toward increased use of computers in data collection, self-administration, and adoption of mixed-mode designs (Smith and Kim, 2015). In developed economies, online and web-based surveys are predominantly utilized due to high internet penetration and digital literacy (Couper and Bosnjak, 2010). The growing popularity of web surveys is largely driven by cost efficiency. Typically, respondents receive an electronic invitation with a link to an interactive questionnaire that they complete and submit online. Alongside web surveys, telephone and mail interviews remain in use, and face-to-face interviews are employed for high-quality data or sensitive topics. Mixed-mode approaches are also common to optimize coverage and response rates (Küfner et al., 2025). In contrast, developing and emerging market economies primarily rely on mixed-mode and face-to-face interviews due to limited internet access. Mixed-mode surveys in these contexts often combine computer-based methods with internet, telephone, mail, and postal approaches to balance cost, reach, and response rates (Mariasingham et al., 2025). Online surveys are gradually gaining traction, particularly in urban areas with better internet connectivity.

Online survey uptake in Zambia is relatively new, with adoption influenced by factors such as internet accessibility, digital literacy, and infrastructural limitations. Zulu et al. (2022) note that, while online platforms like WhatsApp and Google Forms are gaining popularity due to their cost-effectiveness and convenience, their reach remains limited, particularly in rural areas where internet penetration is low. The study also notes that the use of snowball sampling techniques, while helpful in expanding reach, may not fully overcome these limitations. Furthermore, research by Kayombo and Mwiinga (2021) on online assessments at a Zambian university during the COVID-19 era indicates that students' acceptance of online methods was influenced by prior exposure to digital platforms with distance learners and postgraduate students more receptive. However, the study notes that challenges such as inconsistent internet connectivity and limited access to digital devices were reported, affecting the overall effectiveness of online surveys and assessments. These studies underscore the early stages of online survey adoption in Zambia and the need for targeted interventions to address the existing barriers. With an internet penetration rate of 63.1 subscriptions per 100 inhabitants as of mid-June 2024, the successful implementation of online surveys in Zambia will depend on continued improvements in digital infrastructure and access (Zambia Information and Communications Technology Authority, 2024).

Honesty when submitting survey responses and data quality are other outcomes influenced by the mode of data collection. In this respect, physical surveys are usually considered superior. Face-to-face interviews allow for trust between the data collector and respondents but may cause respondents to shy away from revealing answers they are not certain about. Therefore, removing the interviewer may prompt more honest answers from the respondents (Heerwegh, 2009). Empirical studies support this. Removing the live interviewer tends to reduce social desirability bias resulting in more candid answers (Zhang et al., 2017). In that sense, data collected online can sometimes be more reliable for certain questions. However, in some circumstances, without an interviewer present, respondents may misinterpret the questions or lose motivation to answer truthfully (Jones et al., 2016). Overall, trade-offs need to be carefully measured: physical surveys usually excel in representativeness and often completeness of data (missingness) while online/telephone surveys offer speed, lower cost, and sometimes greater honesty on sensitive questions. This is further supported by Couper (2008) who observed that self-administered online surveys often yield higher reporting rates of sensitive behaviors compared to interviewer-administered modes. Therefore, understanding the strength and implications of either method will support the collection of quality data by researchers.

Though the factors discussed above are generalizable to surveys, business surveys face some unique challenges due to their focus on enterprises rather than individuals. Common challenges include non-response bias as businesses may refuse to participate due to time constraint or perceived lack of benefit (Seiler, 2010). These surveys are also affected by mode effects where face-to-face, telephone or online data collection can influence quality alongside issues such as errors in question interpretation or misreporting. Further, the cost and logistical demands of administering business surveys require considerable resources and trained personnel. Other challenges specific to business surveys that have been identified include dealing with large firms which may have multiple departments, complicating the identification of appropriate respondents and potentially leading to inconsistent answers. Strategic bias can also arise when firms intentionally overstate or understate expectations to influence policy or safeguard competitive positions. The complexity of some survey questions, which often ask for expectations about future conditions such as demand or prices might also require subjective judgment from respondents while confidentiality concerns are heightened as businesses tend to be more cautious about sharing internal data even when anonymized (Snijkers et al., 2013). This makes business surveys more complex and underpins the need for careful analysis of modal shifts on survey responses.

Like many other central banks, the Bank of Zambia conducts business surveys. One of these is the Quarterly Survey of Business Opinion and Expectations (QSBOE). This survey provides input into the central bank's evaluation of the prevailing business environment and short-term economic expectations held by businesses. It covers major economic sectors and the results are meant to augment real sector analysis in the assessment of macroeconomic developments for monetary policy decisions. Since its inception in 1993, the QSBOE has been conducted using physically administered paper-based questionnaires. Response rates have generally been high, above 80 percent against the target of 75 percent. Prior to the COVID-19 pandemic, plans were underway to transition to electronic data collection. The aim was to increase efficiency in data collection and processing, as well as minimize the cost of conducting surveys. Migration to electronic surveys was meant to be gradual while sensitizing respondents on the new survey methodology. However, following the advent of the COVID-19 pandemic and subsequent containment measures that included mobility restrictions, the transition to electronic data collection was immediately implemented by the Bank of Zambia. This research paper compares the effects of the drastic change in data collection method from physical in-person data collection to online (remote) surveys on survey response rates and data quality.

Using data from ten rounds of the QSBOE, five conducted between Q1 2019 and Q1 2020, and five during the subsequent quarters coinciding with the COVID-19 pandemic, we observe a marked decline in response rates, particularly among firms in less urbanized areas and in sectors with limited digital capacity. Despite the reduction in participation, the overall quality of responses improved, evidenced by a significant decline in item nonresponse following the transition. These findings suggest that, while the shift in survey mode may have reduced inclusivity, it enhanced data quality. A mixed-mode approach may, therefore, offer a viable solution for balancing inclusiveness and data reliability.

Our work relates to two main strands of literature. The first is that which explores the effect of shifts in data collection mode on response rates and data quality. The literature shows that there are considerable implications for both response rates and data quality when there is a shift in how data is collected. Face-to-face approaches often yield higher participation due to interpersonal interaction (de Leeuw, 2005) while web-based surveys typically report lower response rates, particularly among individuals with limited technological access or literacy (Couper, 2000; Manfreda et al., 2008). However, mixed-mode designs attempt to balance efficiency and coverage but can introduce complexities relating to mode comparability and respondent burden (de Leeuw, 2005; Dillman et al., 2014). Further, Schouten et al. (2009) and Tourangeau and Yan (2007) suggest that data quality may vary across modes due to social desirability bias issues, interviewer effects and inconsistent measurement across survey formats. Respondents unfamiliar with digital tools are also more likely to disengage or respond inconsistently, further compromising data integrity (Couper, 2000; Tourangeau et al., 2013). Thus, careful calibration is essential when transitioning between modes to minimise coverage error, measurement bias and the loss of data comparability (de Leeuw, 2005; Schouten et al., 2009). We contribute to this literature by demonstrating that, despite growing technological adoption and the increasing use of online platforms, digital modes of data collection still present substantial coverage limitations in a developing country context, underscoring the need for deliberate survey design choices that account for persistent infrastructure gaps and digital literacy barriers.

The second strand of literature we relate to explores how external shocks, such as, the Covid-19 pandemic affects data collection. The global COVID-19 pandemic introduced a significant external shock to survey operations, disrupting traditional in-person data collection methods due to public health concerns, mobility restrictions, and distancing protocols (Lau et al., 2021). Widely used face-to-face survey programs, including labor force and demographic health surveys, were largely suspended while longitudinal studies faced attrition due to communication breakdowns. In response, institutions swiftly adopted remote alternatives, such as telephone interviews, SMS-based tools, and online platforms like Qualtrics and Google Forms (Benzeval et al., 2021; Elliott and Vaitkus, 2020). These solutions maintained continuity and lowered health risks but introduced challenges, including digital coverage bias, increased nonresponse among marginalized populations, and higher item nonresponse or shortened instruments. To address these, researchers have applied statistical techniques like weighting adjustments (Kalton, 2020) and mode calibration strategies (Jäckle et al., 2021). Institutional responses also evolved: the World Bank launched high-frequency phone surveys, while national statistical agencies adopted hybrid models to balance safety and data robustness (United Nations Statistics Division, 2021). The pandemic highlighted both vulnerability of traditional methodologies and the need for more advanced survey strategies and we contribute to this discourse by highlighting how this evolved for Zambia during that period.

The remainder of the paper is structured as follows. Section 2 describes the data and outlines the two methods employed. Section 3 presents and discusses the results. Section 4 concludes.

2.0 Data and Methodology

2.1 Data description

The analysis is based on data from ten rounds (five in-person and five online) of the QSBOE survey with a total of 1,719 firm-level panel observations. The cross-sectional QSBOE is designed to capture the opinions of the business community with respect to performance in the previous quarter. It also captures the expectations/economic outlook for the next quarter as well as a year (12 months) ahead. The survey covers six sectors: agriculture, construction, manufacturing, merchants, services, and tourism. It is currently conducted in all the 10 Provinces of Zambia though inclusion was staggered with Western Province a recent addition within the last five years. As a result, the analysis does not include any firm from Western Province. The survey is conducted in English. The survey is also used to assess the business cycle and provides insight into the expectations channel of the monetary policy transmission mechanism. This is particularly useful in an inflation targeting monetary policy framework such as adopted by Zambia.

The original sampling frame was obtained from a list of registered private companies compiled by the Zambia Revenue Authority and stratified sampling techniques, by location and sector, were administered to select companies. To manage survey fatigue, the sampling frame was divided into two groups of 350 comparable firms, samples A and B, and are interviewed interchangeably twice per year. The responses are collected using a semi-structured questionnaire adapted to different sectors. The findings of the survey are shared with the Monetary Policy Committee and disseminated to the general public through the Central Bank website.

Summary statistics for the variables are presented in Table 1. The data is skewed towards observations collected in person at 75 percent and the firms are largely from the tourism sector. In terms of province, the highest proportion is drawn from the urban areas of Central (19%), Lusaka (16 %) and Copperbelt (14 %) with Muchinga, a relatively rural location, accounting for the least number of respondents (6 %). Most of the companies had been operational for more than five years. The sample is almost evenly distributed between the two sampling groups.

Table 1: Summary Statistics

Variable	Description	Frequency	Percent
Mode	Physical (in person)	1,293	75.22
	Online	426	24.78
Sector	Manufacturing	323	18.81
	Merchant	359	20.91
	Service	183	10.66
	Tourism	615	35.82
	Construction	35	2.04
	Agriculture	202	11.76
Province	Lusaka	274	15.94
	Copperbelt	248	14.43
	Southern	217	12.62
	Central	331	19.26
	Northwestern	151	8.78
	Eastern	133	7.74
	Luapula	140	8.14
	Northern	117	6.81
	Muchinga	108	6.28
Length Operational	Less than 12 months	6	0.35
	1-5 years	59	3.44
	More than 5 years	1,648	96.21
Sample Group	Group A	975	56.72
	Group B	744	43.28
Total		1,719	100.00

Source: Authors computation.

Notes: The table presents summary statistics of the main indicators used in the analysis. Physical data collection refers to data collected before the 2020Q1 QSBOE data collection phase, while online is the sample collected afterwards. Sample group A is interviewed in quarters 2 and 4 while sample group B is interviewed in quarters 1 and 3 of each survey year.

The dependent variable for the quality analysis is the degree of *item nonresponse* for each observation. To systematically quantify it, the extent of *missingness* within the dataset was computed. This approach counts the number of missing values per observation across the full set of variables, providing a numeric representation of data completeness. This approach helps to distinguish between random and systematic missing data mechanisms and is particularly useful for evaluating whether *missingness* is associated with key variables, which may indicate non-ignorable missing data processes. It should be noted that not all questions are applicable to all the respondents but are dependent on the sector of the firm. Hence, some observations have more *missingness* than others. However, this does not invalidate the analysis of the degree of *item nonresponse* across mode which should be unaffected.[2] The complete distribution of *missingness* for each variable is shown in Table A2 in the Appendix.

Factors that could affect responses include regional internet availability, firms' access to and use of computers, as well as the education level and age of the individual completing the survey on behalf of the firm. These factors have been highlighted in previous studies (Kayombo and Mwiinga, 2021; Zulu et al., 2022). However, except for the availability of the internet, partially captured through the location of the company, these variables are not available in the survey data and are, therefore, beyond our scope. We, therefore, control for three factors in different model specifications: sector of the firm, sample group to which it belongs and locality (province).

2.2. Methodology

Two approaches are employed to examine the impact of the abrupt shift from in-person to online survey administration on firm response rate and data quality. To assess the effect on survey participation, we compare response rates, defined as the proportion of sampled firms that completed the survey in each round, between the in-person and online modes. The response rate is very useful in monitoring the process of data collection and is a key quality indicator of surveys (United Nations, 2015). Ward (2006) also suggests that achievement of satisfactory response rates is key in the compilation of high-quality opinion survey data, further providing support for the use of this metric. Response rates are summarized separately for each mode. We also conduct subgroup analyses based on firm characteristics such as sector and province to determine whether the decline in responses was consistent or varied across segments of the business population. This descriptive analysis offers preliminary evidence of the effects of mode on participation and potential shifts in sample composition.

The second level of analysis investigates how the change in survey mode affects data quality. As described in the previous section, we use *item-level missingness* as a proxy for response reliability following the approach proposed by McDaniel and Rao (1980) who suggest that data quality can be assessed through item omission, response error,

[2] To confirm that *item nonresponse* is based on other pre-determined factors, we assessed whether the missing data is Missing Completely at Random (MCAR), following Little and Rubin (2019) and using Little's MCAR test, and the results indicate that the *missingness* is not completely random, implying that it is likely dependent on observed or unobserved variables.

and overall response completeness.[3] To evaluate the relationship between mode and data quality, we estimate the following linear regression:

$$M_i = \beta_0 + \beta_1 \text{mode}_i + \beta_2 \text{sector}_i + \beta_3 \text{location}_i + \beta_4 \text{sample group}_i + \epsilon_i \quad (1)$$

where M_i represents the *missingness* score for observation *i* and $mode_i$ is a binary indicator for survey mode (physical versus online). The variable $sector_i$ captures industry classification while geographic variations are captured through the inclusion of $location_i$. To account for firm sample group allocation, we include $sample\_group_i$. The error term ϵ_i captures unobserved factors. This model estimates the association between online administration and *item nonresponse*, net of compositional effects. We estimate three model specifications of increasing complexity. Model 1 is a naïve specification that includes only *missingness* and survey mode. Model 2 adds controls for sector while Model 3 incorporates location. We use heteroskedasticity-robust standard errors in all the different model specifications. The base categories were selected to reflect the group with the largest sample size, enhancing statistical stability of the estimates. As a robustness check to account for intra-group correlation (e.g., within A or B), we also estimate a variant of the model with standard errors clustered by sample group.

3.0 Empirical Results

3.1. Response Rates

Table 2 and Figure 1 summarize response rates by survey mode, distinguishing between physical (in-person) and online data collection methods. The results indicate a substantial decline in response rates between the two periods. We find that during the period when data collection was physical, the mean response rate was high, at 87.7 percent. In contrast, the mean response rate for the period when online surveys were introduced was markedly lower, at 31.22 percent. The physical data collection period also had a relatively low standard deviation (2.01), suggesting consistent participation of the respondents in all survey instances compared to a higher online standard deviation (7.40) of the online mode period which had greater variability in participation.

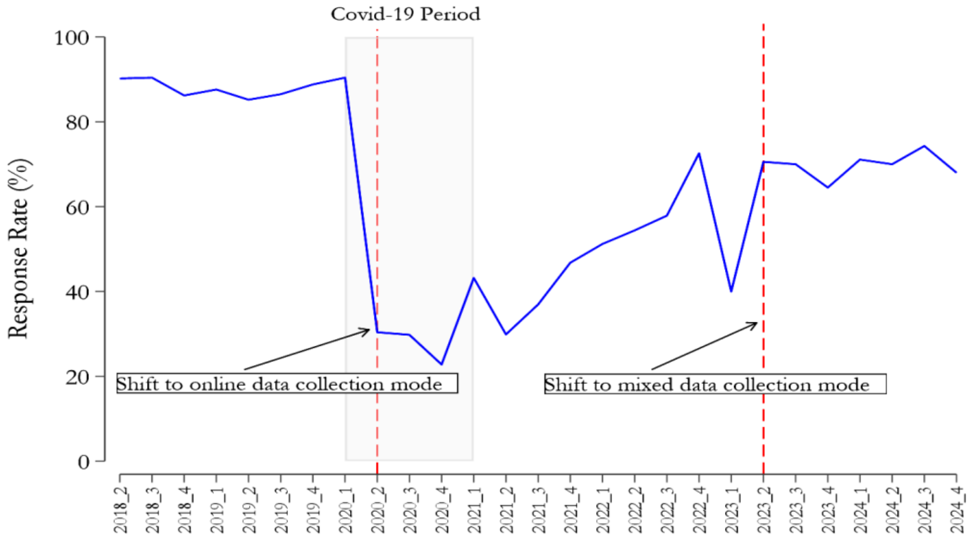
Table 2: Response Rates by Survey Mode

Mode of Data Collection	Mean	Std. Dev.	Minimum	Maximum
Physical (In- person)	87.70	2.01	85.2	90.4
Online	31.22	7.40	22.8	43.2

Source: Authors computation.
Notes: Std. Dev. refers to the standard deviation.

[3] The datasets used are cleaned versions of the original data and exclude certain responses such as “don’t know” or “not applicable,” which limits our ability to fully analyze satisficing behavior.

Figure 1: Trend in the QSBOE Response Rate



Source: Authors computation.
Notes: The figure shows the trend in the QSBOE response rate between 2018 and 2024. The shaded area covers the period during the COVID-19 global epidemic occurred.

The fall in the response rate is similar to the results from Haas et al. (2021) who compared the response burden between paper and web-based modes in establishment surveys and found that the web-based survey yielded lower response rates than paper-based surveys. The researchers argue that the lower response rate in the web-based survey could be an indication that respondents may have found them to be burdensome due to failure by some respondents to access the web survey using the links provided and challenges in navigating the web survey. It was concluded that, while administration using web-based surveys comes at a cost of low response rates, paper-based surveys produced high response rates as paper questionnaires did not require web access and may have served as visible reminders to complete the survey rendering them less burdensome. Harrell et al. (2007) also identified lack of internet access or internal security guidelines as factors that could hamper effective administration of web surveys in establishments leading to reduced response rates.

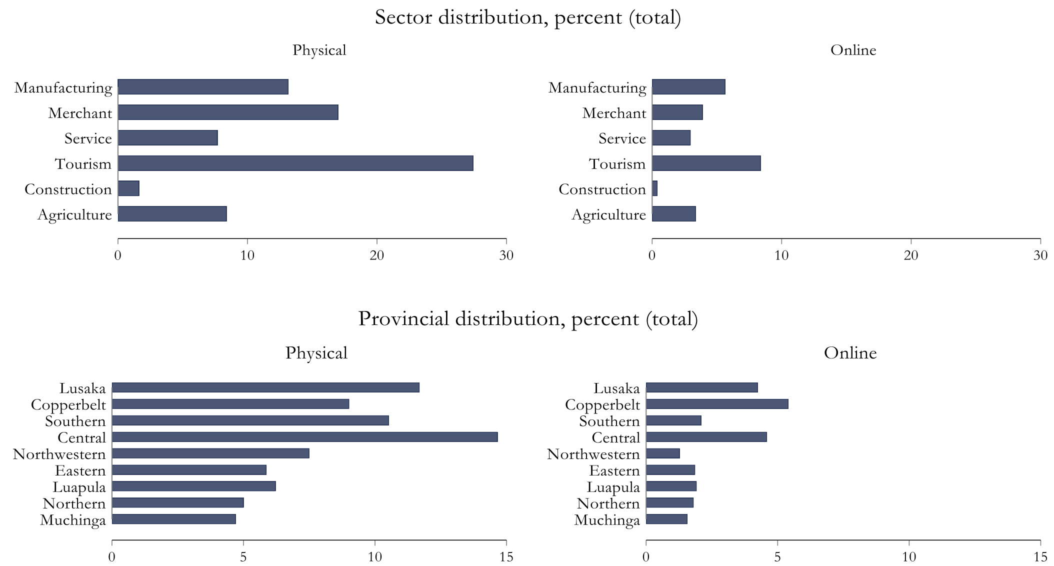
A more detailed breakdown of firm responses across the two distinct periods is provided in Table 3 and illustrated in Figure 2. Following the shift to online data collection, response rates declined across most sectors and locations. The most pronounced drop occurred in the construction sector where the number of respondents reduced to 7 from 28 across modes. By province, urban areas consistently recorded higher response rates, reflecting underlying disparities in internet access and digital literacy.

Table 3: Distribution of Firm Responses

		Mode of Data Collection			
		Physical		Online	
		No.	%	No.	%
Sector	Manufacturing	226	17.5	97	22.9
	Merchant	292	22.6	67	15.8
	Service	132	10.2	51	12
	Tourism	471	36.4	144	34
	Construction	28	2.2	7	1.7
	Agriculture	144	11.1	58	13.7
Location	Lusaka	201	15.5	73	17.1
	Copperbelt	155	12	93	21.8
	Southern	181	14	36	8.5
	Central	252	19.5	79	18.5
	Northwestern	129	10	22	5.2
	Eastern	101	7.8	32	7.5
	Luapula	107	8.3	33	7.7
	Northern	86	6.7	31	7.3
	Muchinga	81	6.3	27	6.3
Length of Operation	less than 12 months	6	0.5	0	0
	1-5 years	50	3.9	9	2.1
	more than 5 years	1,233	95.7	415	97.9
	Total	1,293	100	426	100

Source: Authors computation.
Notes: This table presents the distribution of firm response by mode of data collection.

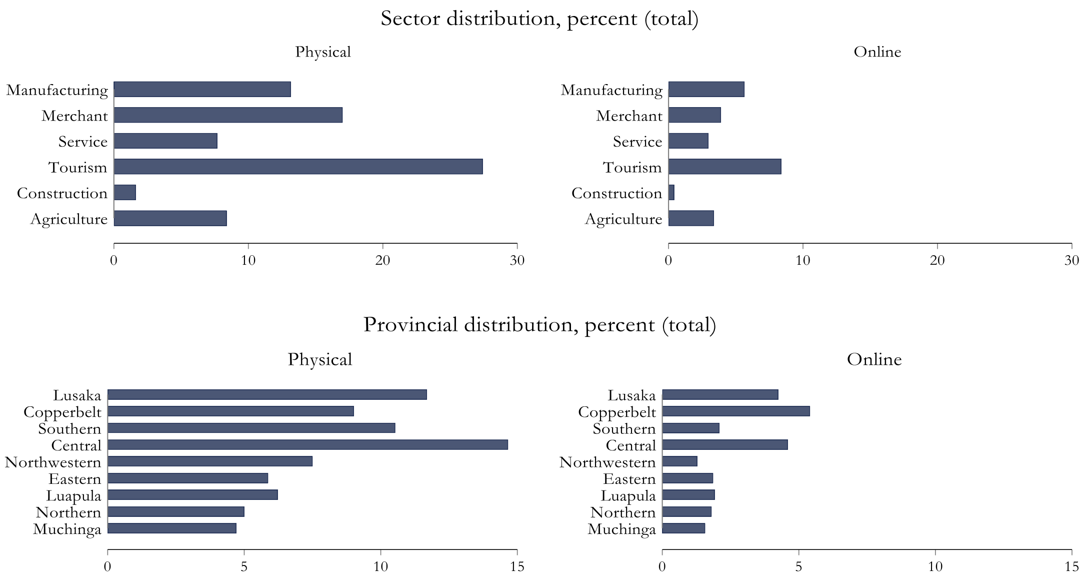
Figure 2: Distribution of Responses



Source: Authors computation.
Notes: The figure illustrates the distribution of responses by mode of data collection as a proportion of the total sample.

Notably, within-mode distributions also shifted. As a share of total responses in each period, participation increased between firms in the manufacturing and agriculture sectors, sectors which may be more digitally advanced (Figure 3). Similarly, there was a relative increase in responses in Lusaka and Copperbelt Provinces, the main urban centers. Mobility restrictions and the absence of physical data collection further limited the ability to recruit new firms to replace non-respondents. As noted in Bank of Zambia (2020), "...the poor response rate was compounded by the negative effects of the COVID-19 pandemic that disrupted normal business operations characterized mainly by remote work and the resultant closures of some companies mainly in the transport, services, tourism and hospitality sectors. Further, the COVID-19 induced travel restrictions resulted in the Survey being conducted electronically via email and telephone calls. This was the first time since inception (in 1993) that the Survey was conducted without physical contact with respondents..." (page 1).

Figure 3: Distribution of Responses within the Mode of Data Collection



Source: Authors computation.
Notes: The figure illustrates the distribution of responses for each mode of data collection within the subsample groups. The subsample group is the mode of data collection.

3.2 Mode Change and Data quality

We now examine the impact of the change in survey mode on the quality of data collected. The results of the linear regression with *item nonresponse* as the dependent variable are presented in Table 4. We find that online data collection is associated with significantly lower missing responses compared to physical surveys. This finding is consistent across the different model specifications and suggests that online surveys yield more complete responses possibly due to the structured nature of digital forms and increased respondent convenience (Couper, 2000; Dillman et al., 2014; Tourangeau et al., 2013). Online platforms often implement input validation and skip logic that help reduce unintentional *item nonresponse* (Shin et al., 2012). Sectoral effects further show that generally, firms in the manufacturing, merchants and agriculture sectors have significantly lower level of *item nonresponse* relative to the reference tourism sector. This implies stronger engagement or clearer survey relevance within these industries. Geographic variation reveals that respondents in the provincial capital of Lusaka exhibit significantly lower *missingness* than the base location, Central Province, potentially due to higher digital literacy and accessibility. Muchinga Province, a predominantly rural area, shows a substantial increase in missing responses, indicating survey completion challenges and supporting the importance of environmental/infrastructural considerations in survey design as discussed in De Groote (1996). The increasing R-squared values across models (0.007, 0.232, 0.261) demonstrates that sector and location contribute substantially to explaining *missingness* patterns. These findings align with prior research on missing data mechanisms, which emphasize the role of survey mode, sectoral participation, and geographic disparities in response completeness (Kilic et al., 2013; Laaksonen and Laaksonen, 2018).

Table 4: Correlates of *Item nonresponse*

	Dependent variable: Missing observations		
Mode: Base - Physical Data collection Online	Model 1	Model 2	Model 3
Data collection	-1.174***	-1.425**	-1.500**
	(0.37)	(0.63)	(0.62)
Sector: Base - Tourism Sector Manufacturing		-9.008***	-8.055***
		(0.42)	(0.48)
Merchant		-1.716***	-1.179***
		(0.41)	(0.42)
Service		-0.299	0.631
		(0.55)	(0.57)
Construction		-1.356	-1.178
		(1.50)	(1.46)
Agriculture		-2.980***	-2.777***
		(0.46)	(0.53)
Location: Base - Central Province			
Lusaka			-2.557***
			(0.49)
Copperbelt			-0.935*
			(0.56)
Southern			0.115
			(0.58)
Northwestern			-0.953
			(0.62)
Eastern			0.507
			(0.62)
Luapula			0.036
			(0.68)
Northern			0.804
			(0.72)
Muchinga			2.551***
			(0.82)
Sample Group: Base - Sample Group A Sample			
Group B	-0.559*	1.141	1.082
	(0.34)	(0.93)	(0.93)
Constant	30.575***	33.480***	33.404***
	(0.26)	(0.48)	(0.60)
Period Dummy	No	Yes	Yes
R-squared	0.007	0.232	0.261
N	1719	1717	1717

Source: Authors computation.

Significance levels * 10% ** 5% *** 1%. Standard errors in parentheses. Note: This table presents the correlates of *item nonresponse* estimated with robust standard errors. Similar results are obtained when we absorb for sample group.

The improvement observed may also reflect changes in data collection and processing procedures associated with the transition to online surveys. Prior to the shift, questionnaires were physically delivered to and collected from respondents with responses subsequently entered manually into the system, an approach prone to human error. Beginning in 2019, a hybrid method was introduced for some firms whereby questionnaires were emailed in advance and later collected through in-person visits. Following the full transition to remote data collection, Microsoft Forms were adopted during the period covered in this study, streamlining the process by eliminating manual data entry, reducing the likelihood of human error, and incorporating built-in validation checks, particularly for questions designated as mandatory.

Similar results are obtained from a linear regression model which absorbs for the sample group allocation. When we cluster the standard errors by sample group, the directional effects remain unchanged though the model loses statistical significance (Table 5). This may be due to the limited number of sample groups and the associated increase in standard errors from clustering, which reduces the model's statistical power.

We also estimate an interactions model between survey mode and location/ sector to explore whether the relationship between online data collection and *item nonresponse* varies by locality and by industry. The results presented in Table 6 show that, after controlling for interaction effects, the mode of data collection on its own does not significantly influence *missingness*. However, the interaction terms reveal notable geographic heterogeneity. While no significant variation emerges across sectors, online surveys conducted in Southern and Luapula provinces, and, to a lesser extent, in Muchinga Province, exhibit significantly lower *item nonresponse* values compared with physical surveys in the same areas. These findings suggest that the advantages of online administration are primarily location-specific rather than sector-specific, pointing to underlying differences in internet access, digital skills or respondent characteristics.

Table 5: Correlates of *Item Nonresponse* - Alternate Model Specification (Clustered Standard Errors)

	Dependent variable: Missing observations		
Mode: Base - Physical Data collection	Model 1	Model 2	Model 3
Online Data collection	-1.174	-1.425**	-1.500***
	(0.81)	(0.03)	(0.01)
Sector: Base - Tourism Sector			
Manufacturing		-9.008***	-8.055**
		(0.14)	(0.21)
Merchant		-1.716	-1.179
		(0.94)	(0.69)
Service		-0.299	0.631
		(0.18)	(0.13)
Construction		-1.356	-1.178
		(1.44)	(0.80)
Agriculture		-2.980	-2.777***
		(0.74)	(0.03)
Location: Base - Central Province			
Lusaka			-2.557
			(0.54)
Copperbelt			-0.935
			(0.69)
Southern			0.115
			(1.30)
Northwestern			-0.953
			(0.97)
Eastern			0.507
			(0.19)
Luapula			0.036
			(1.41)
Northern			0.804
			(0.58)
Muchinga			2.551
			(1.48)
Sample Group: Base - Sample Group A			
Sample Group	-0.559*	1.141**	1.082***
	(0.07)	(0.04)	(0.01)
Constant	30.575***	33.480***	33.404**
	(0.17)	(0.30)	(0.64)
Period Dummy	No	Yes	Yes
R-squared	0.007	0.232	0.261
N	1719	1717	1717

Source: Authors computation.

Significance levels * 10% ** 5% *** 1%. Standard errors in parentheses. Note: This table presents the results of an alternate model specification which clusters the standard errors by sample group. The results from a specification which absorbs for the sample group are similar to initial results presented in Table 4.

Table 6: Interaction Effects Between Survey Mode and Sector/ Location on *Item Nonresponse*

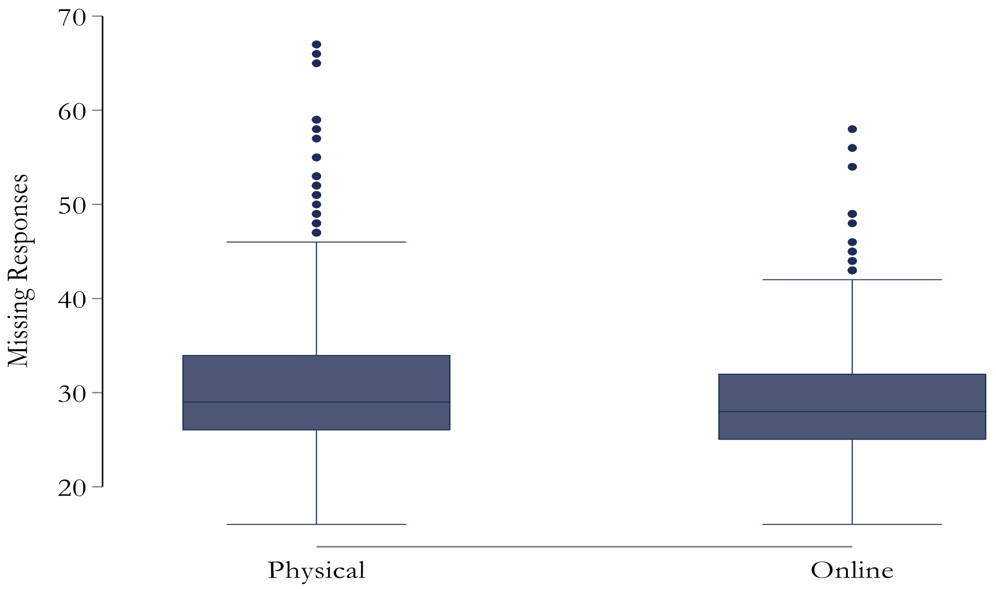
	Dependent Variable: Missing observations
Variable	Coefficient (Std. Error)
Mode: Base - Physical Data collection	
Online mode	0.231 (1.281)
Sector: Base - Tourism Sector	
Manufacturing	-8.104*** (0.577)
Merchant	-1.192** (0.483)
Service	0.450 (0.653)
Construction	-1.062 (1.789)
Agriculture	-2.883*** (0.617)
Mode and Sector Interactions	
Online and Manufacturing	0.034 (1.076)
Online and Merchant	-0.005 (1.009)
Online and Service	0.436 (1.364)
Online and Construction	-0.508 (2.240)
Online and Agriculture	0.179 (1.237)
Location: Base - Central Province	
Lusaka	-2.202*** (0.574)
Copperbelt	-0.482 (0.682)
Southern	0.673 (0.664)
Northwestern	-0.667 (0.688)
Eastern	0.943 (0.720)
Luapula	0.919 (0.809)
Northern	1.112 (0.821)
Muchinga	3.435*** (0.950)
Mode and Location Interactions	
Online and Lusaka	-1.618 (1.135)
Online and Copperbelt	-1.844 (1.266)
Online and Southern	-2.803** (1.274)
Online and Northwestern	-1.050 (1.521)
Online and Eastern	-1.936 (1.405)
Online and Luapula	-3.873*** (1.459)
Online and Northern	-1.449 (1.709)
Online and Muchinga	-3.729* (1.949)
Sample Group: Base - Sample Group A	
Sample B	1.012 (0.919)
Constant	33.032*** (0.637)
Period Dummy	Yes
R-Squared	0.263
N	1,717

Source: Authors computation.

Significance levels * 10% ** 5% *** 1%. Robust standard errors in parentheses. Note: This table presents the results of an alternate model specification with interaction terms.

To further model *nonresponse*, we generate a variable that counts the number of missing values per observation (row) across the specified list of variables. We then compare the mean number of missing values between two groups defined by the variable mode. Consistent with the regression results, respondents in the physical mode exhibit significantly more missing data than those in the online mode (Figure 4). This supports the conclusion that data quality or completeness differs between the two survey modes.

Figure 4: Distribution of Missing Data by Mode of Collection



Source: Authors computation.
Notes: The figure illustrates the distribution of missing data by mode of collection.

Lastly, we examine the occurrence of straight-lining, a phenomenon in survey research where respondents provide uniform answers across multiple questions indicating disengagement and suggesting compromised data quality. Prior studies have highlighted the importance of distinguishing valid straight-lining from satisficing behavior, emphasizing its role in survey methodology and data quality assessment (Reuning and Plutzer, 2020; Silber and Kraemer, 2024).[4] We found that the mean within-observation standard deviation was 55.72 for the physical mode and 54.38 for the online mode. This difference is not statistically significant, indicating that there is no evidence of differential straight-lining behavior between the two modes. Both groups exhibited comparable levels of response variability. This suggests that data quality, in terms of response differentiation, was broadly similar across modes (Table A1 in the Appendix).

We, however, note some limitations in the results. While the findings are robust to the different specifications applied, they may have been affected by selection bias related to the characteristics of firms that were able to respond as highlighted in previous works (Luiten and Schouten, 2013; Tourangeau et al., 2013). In particular, the post-transition sample may be biased due to difficulties in contacting some firms during the pandemic, either because of incorrect/ outdated email contact information or staff turnover. Nevertheless, biodata on all participating firms was routinely collected prior to the mode change, which we believe helps mitigate some of this bias. Another potential source of bias stems from the likelihood that firms able to respond online may have had higher levels of digital literacy or education, making them less prone to *item*

[4] Satisficing theory explains survey response errors by arguing that answering questions optimally requires substantial cognitive effort—interpreting the question, retrieving relevant information, forming a judgment, and selecting an appropriate response. While some respondents fully engage in these steps, others reduce their cognitive effort, leading to less accurate or lower-quality responses (Heerwegh and Loosveldt, 2008).

nonresponse. However, this possibility has not yet been formally assessed and could be investigated in future work once firm level linkage is undertaken.[5]

4.0 Conclusion

We examined the impact of an abrupt shift in data collection mode from physical/in person collection to online/remote data collection. Using data from ten rounds of the survey fieldwork, five before the shift and five after, we find that the change in data collection strategy led to a drop in response rates but resulted in overall improvement in the quality of data, proxied by item nonresponse. These findings highlight both the challenges and benefits associated with online data collection, particularly in contexts where internet access, digital infrastructure or participant familiarity with digital platforms may be limited. The response rate drop was further exacerbated by the COVID-19 pandemic, which negatively affected business operations. In the QSBOE context, limited sensitization before the shift may have also contributed to the decline in response rates. Additionally, some firms did not respond due to changes in staffing levels during the COVID-19 period. This observation is consistent with Luiten and Schouten (2013) who show that introducing a new data collection mode can reduce response rates, particularly when respondents are inexperienced or insufficiently prepared for the transition and argue that a tailored approach is a more effective way of managing response rates. However, after easing of COVID-19 restrictions, physical interactions resumed, and this combined with continuous sensitization, have led to a gradual recovery in the response rates (Figure 1).

The findings have important policy implications for the design and implementation of business surveys in low and middle-income country contexts. Given the persistent reliance on physical data collection, particularly among firms in less urbanized regions and those with limited digital capacity, national policy efforts to expand digital survey infrastructure must be matched with targeted investment in connectivity, digital literacy, and institutional trust. In this regard, online usage in Zambia may be enhanced by the various initiatives currently underway such as the provision of public free Wireless local area network (WLAN) technology (Wi-Fi), improvements in the availability of internet fiber connections and integration of Information and Communication Technology (ICT) education in both elementary and tertiary institutions (Nyemba et al., 2020; Zambia Information and Communications Technology Authority, 2024).

In addition, the relatively low uptake of online surveys highlights the risk of under-representing certain segments of the private sector especially rural or smaller informal firms if digital-only approaches are pursued. Policymakers and statistical agencies should therefore adopt mixed-mode strategies that preserve the inclusiveness of traditional methods while incrementally building the foundation for broader digital engagement. This is supported by De Groote (1996) who stated that survey methodologies must be tailored to the specific conditions of rural areas in developing countries to achieve cost-effective and reliable data collection. The study advocates for

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[5] Firm-level linkage will rely on unique firm identifiers which were not collected in the survey rounds. In future work, we plan to use other firm identification details such as the name of the firm, sector and location to create a unique identifier across surveys.

adaptive survey designs that consider local contexts, suggesting that flexibility in sampling methods and data collection techniques can lead to more accurate and efficient surveys. Doing so not only enhances the representativeness and resilience of data systems but also supports more responsive and evidence-informed decision-making in times of crisis or disruption. Further, the stability and magnitude of response rates in the physical and mixed mode reaffirms the continued relevance of in-person methods, especially when high response rates are critical for the validity and representativeness of survey findings.

Other policy recommendations from this study concern strategies to enhance firm compliance and reduce survey response burden. As noted in the Organisation for Economic Co-operation and Development (2003), the quality of business survey data is closely linked to respondents' willingness to cooperate. While participation is often voluntary, compelling firms to respond through legal enforcement may negatively affect both the quality and timeliness of responses. The most effective approach to improving response rates is to minimize the burden of participation, primarily through well-designed questionnaires and rotation of survey subjects. It is also essential that firms perceive the data they provide as valuable for their own operations and for macroeconomic analysis. United Nations (2015) similarly argue that reducing response burden is imperative to maintain participation. To this end, questionnaires must be accessible, clearly worded, and relevant to respondents. Simplifying the structure, content, and mode of delivery of questionnaires can significantly improve both participation and completion rates.

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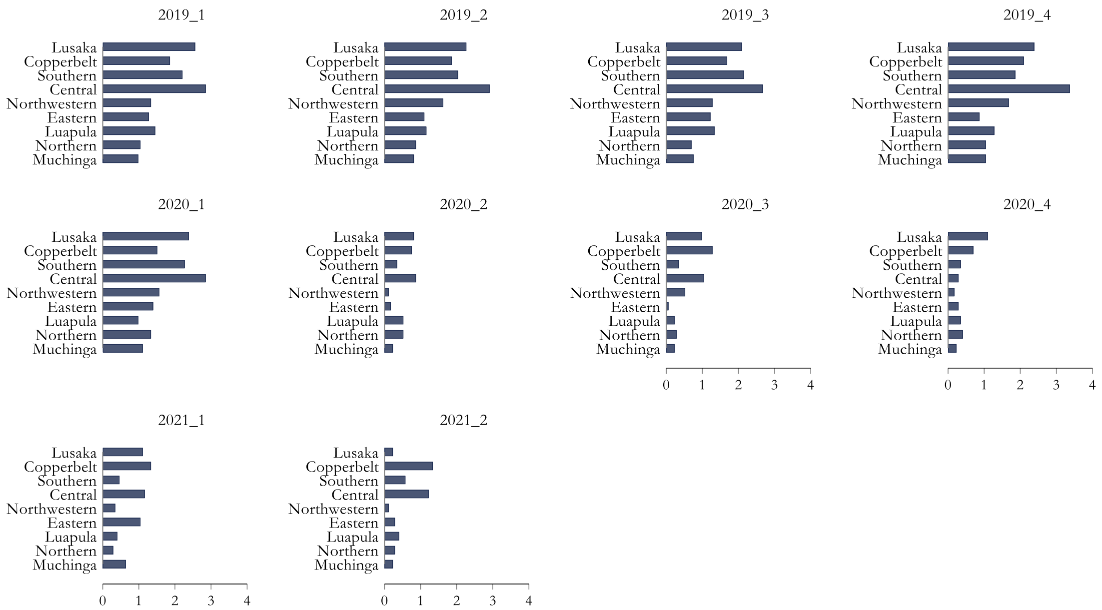
Appendices

Figure A1: Responses by Location and Survey Quarter

Source: Authors computation.

Figure A2: Responses by Sector and Survey Quarter



Source: Authors computation.

Table A1: Two-sample t-test comparing response variation between Physical and Online groups

Group	N	Mean	Std. Dev.	Std. Error	95% CI Lower	Upper
Physical	1,293	55.72	27.69	0.77	54.21	57.23
Online	426	54.38	27.51	1.33	51.76	57.00
Combined	1,719	55.39	27.64	0.67	54.08	56.69
Difference (Phys - Online)		1.34		1.54	–1.69	4.37

Source: Authors computation.
Note: $t = 0.87$, degrees of freedom = 1717, two-tailed p-value = 0.39. The results indicate that there is no statistically significant difference between groups.

Table A2: Number of Missing Variables by Survey Mode

No.	Variable	Physical		Online	
		Number	%	Number	%
1	sector	0	0	2	0.47
2	id	2	0.15	0	0
3	Category	521	40.29	142	33.33
4	dtmdate	1293	100	426	100
5	mainactivity	1039	80.36	355	83.33
6	principactivity	10	0.77	3	0.7
7	servilength	4	0.31	2	0.47
8	diversifyprincipal	87	6.73	59	13.85
9	caputcurr	1048	81.05	330	77.46
10	caputexp	1054	81.52	333	78.17
11	constractpast	1265	97.83	418	98.12
12	constactnext	1272	98.38	418	98.12
13	outputpast	944	73.01	287	67.37
14	outputnext	947	73.24	291	68.31
15	volsalespast	989	76.49	348	81.69
16	volsalesnext	1001	77.42	352	82.63
17	volservicepast	730	56.46	231	54.23
18	volservicenext	759	58.7	242	56.81
19	domsalespast	951	73.55	285	66.9
20	domsalesnext	956	73.94	289	67.84
21	exportspast	1122	86.77	348	81.69
22	exportsnext	1119	86.54	348	81.69
23	avginputcostspast	115	8.89	25	5.87
24	avginputcostsnext	150	11.6	39	9.15
25	wagespast	64	4.95	11	2.58
26	wagesnext	108	8.35	22	5.16
27	avgsellpricepast	102	7.89	17	3.99
28	avgsellpricenext	129	9.98	35	8.22
29	profitabilitypast	85	6.57	18	4.23
30	profitabilitynext	126	9.74	31	7.28
31	stockspast_raw	974	75.33	294	69.01
32	stocksnext_raw	976	75.48	297	69.72
33	inventoriespast_stocks	831	64.27	279	65.49
34	inventoriesnext_stocks	833	64.42	280	65.73
35	newordpast	1084	83.84	342	80.28
36	newordnext	1095	84.69	346	81.22
37	completedprojpast	879	67.98	299	70.19
38	completedprojnext	900	69.61	298	69.95
39	importspast	1077	83.29	374	87.79
40	importsnext	1095	84.69	376	88.26
41	workinprogpast	891	68.91	302	70.89
42	workinprognext	905	69.99	304	71.36
43	levelinvesttotalpast	681	52.67	200	46.95
44	levelofworkcappast	222	17.17	61	14.32
45	levelinvestonmachinpast	352	27.22	94	22.07
46	levelinvestonbuildpast	316	24.44	99	23.24
47	levelinvesttotalnext12	185	14.31	66	15.49
48	levelofworkcapnext12	210	16.24	53	12.44
49	levelinvestonmachinnext12	320	24.75	79	18.54
50	levelinvestonbuildingsnext12	288	22.27	83	19.48
51	limitfactor	34	2.63	10	2.35
52	investfinancesource	83	6.42	27	6.34
53	workcapitasourcel	95	7.35	24	5.63
54	competdegree	34	2.63	12	2.82
55	pricelevelnext	135	10.44	28	6.57
56	factorexplain	103	7.97	19	4.46
57	pricelevelnext12	197	15.24	41	9.62

No.	Variable	Physical		Online	
		Number	%	Number	%
58	factorexplainnext12	153	11.83	36	8.45
59	creditavailpast	268	20.73	67	15.73
60	creditavailnext	364	28.15	82	19.25
61	lendingratespast	266	20.57	67	15.73
62	lendingratesnext	355	27.46	94	22.07
63	exchgrate	203	15.7	38	8.92
64	exchgratefactors	173	13.38	43	10.09
65	economicperformnext12	202	15.62	60	14.08
66	labourpast	63	4.87	9	2.11
67	labournext	86	6.65	24	5.63
68	labournext12	149	11.52	49	11.5
69	category	772	59.71	284	66.67
70	newcontpast	1281	99.07	421	98.83
71	newcontnext	1285	99.38	424	99.53
72	levelinvesttotalPast	835	64.58	308	72.3

Source: Authors computation.

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