Highlights

Navigating the corporate disclosure gap: Modelling of Missing Not at Random Carbon Data

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- Only around 65% of companies report their carbon emissions and the undisclosed data is most likely missing not at random (MNAR) due to voluntary act of reporting.
- We use multiple imputation with Heckman’s model approach to improve the prediction of corporate Scope 1 and Scope 2 emissions.
- Multiple imputation with Heckman’s model performs best among tested approaches if data is missing not at random.
- We achieve accuracy gains (Root mean squared error (RMSE)) of up to 30% and up to 40% higher coverage (for 95% confidence intervals) relative to existing models (median, linear regression) if data is missing not at random.
Navigating the corporate disclosure gap: Modelling of Missing Not at Random Carbon Data

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\section*{Abstract}
Corporate carbon emissions data is disclosed by approximately 65\% of large and mid-sized companies globally, despite being a key indicator of corporate climate performance. With investors increasingly looking to integrate climate risk into their investment strategies and risk reporting, this creates demand for robust prediction models that can generate reliable estimates for missing carbon disclosures. However, these estimates lack transparency and are frequently used in the investment decisions process with the same confidence as corporate reported data. As disclosures remain mostly voluntary and the propensity to disclose is shaped by several factors (e.g. size, sector, geography), missing emissions data should be assumed to be ‘missing not at random’ (MNAR). However, widely used estimation methods (e.g. linear regression models) typically do not correct for MNAR bias and do not accurately reflect the uncertainty of estimated data. The objective of this paper is to address these issues: (1) account for the uncertainty of the missing data and thus obtain regression coefficients by multiple imputation (MI) (2) correct for potential bias by using MI algorithms based on Heckman’s sample selection model introduced by Galimard et al. (3) estimate missing carbon disclosures with linear models based on MI and report on the uncertainty of predicted values, measured as the length of the prediction interval. In the simulation, our approach resulted in an accuracy gain based on root mean squared error of up to 30\%, and up to a 40\% higher coverage rate than the existing models. When applied to commercial data, the results suggested up to 20\% higher coverage for proposed methods.

\textit{Keywords:} Multiple Imputation, Missing Data, Missing Not at Random, Carbon Emissions, Sustainable Investment
Sustainable investment directs investment capital to companies that manage climate-related risks and opportunities effectively by including non-financial indicators (e.g., carbon emissions) in the investment decision process (Schoenmaker and Schramade, 2018). Mounting pressure from asset owners, governments and society more widely has contributed to the rapid proliferation of sustainable investment strategies, with a record $155bn raised globally in the third quarter of 2020 (Refinitiv, 2021). This has created a growing demand for high-quality sustainability data to underpin these strategies. However, non-financial reporting is not yet standardized and remains largely voluntary, resulting in incomplete, "noisy" datasets (see e.g. Li and Polychronopoulos, 2020).

Therefore, for investors to meet their sustainability and risk management objectives, it is important that accurate data is available for all companies in the investible universe. However, corporate carbon emissions, which is a crucial climate-related indicator, is only disclosed by approximately 65% of listed companies\(^1\). To fill the gap between the available and required data, it is common practice to replace missing emissions values with estimates. The methods used to predict such missing emissions vary across data providers, but tend to fall under one of three categories:

1. sector median or median carbon intensity estimation, where missing values are predicted based on the reported emissions within the respective peer group (Busch et al., 2018).
2. regression analysis, where missing values are predicted using various linear models with predictors based on the financial, energy consumption, and historical emissions data (Kalesnik et al., 2020) (the corresponding regression coefficients are typically obtained using complete case analysis (CCA) or single imputation (SI) techniques), and
3. input-output models, where the sectors’ total direct emissions and energy consumption are used to derive their carbon intensities, reflecting the emissions associated with one dollar of gross output (Liu and Fan, 2017).

Data providers typically do not disclose the details of their models’ assumptions and corresponding uncertainty, which can lead to a misplaced per-

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\(^1\)Based on All Word Index 2018. Non-financial reporting is most advanced for listed equities and similar issues are present across other asset classes.
ception that estimated and reported emissions are equally accurate (Kalesnik et al., 2020). In particular, quantitative investment strategies - such as investment against specific climate-focused indices - typically treat estimated and disclosed data in the same way. This is concerning, given some of the discrepancies in datasets across different data providers that have been identified in several studies (e.g. Busch et al., 2018 and Berg et al., 2019). Consequently, without a good understanding of the estimation process and associated uncertainty, investors may struggle to make fully informed decisions when choosing a data provider, and to select the one whose estimation model is most suitable for their purposes (Busch et al., 2018).

Another concern with the current emissions estimation models is that they are often built based on only the observed data within the sample, i.e., without accounting for the uncertainty of missing values. This matter has been highlighted in a recent publication by Hoepner and Rogelj (2021), in which the authors recommended that emissions estimation models embed a precautionary principle to discourage the lack of disclosure. In practice, not accounting for missing data during a model estimation may lead to biased and inefficient estimates of model parameters such as regression coefficients and an underestimation of standard errors, resulting in incorrect confidence intervals (White et al., 2011). In this paper, we focus on linear regression, which can perform well as a prediction tool if obtained model parameters are unbiased, and efficient (Greene, 2003, Section 6.6). Therefore, if missing data are not handled properly, the resulting linear prediction model may produce inaccurate estimates.

Incomplete datasets are the norm rather than the exception in social, behavioural and medical sciences. To address aforementioned issues related to missing data, imputation techniques, which replace missing observations with plausible values, have been the subject of extensive research in the statistical literature since the 1970s (see e.g. Rubin, 1976 and Gleason and Staelin, 1975). However, imputation may lead to a situation where an imputed dataset is treated as if it was complete, which makes imputation “seductive and dangerous” (Rubin et al., 1983, p.8), since the inherent uncertainty of the imputation process may be overlooked. Therefore, multiple imputation (MI), where several imputed datasets are created, should be the preferred technique as it accounts for the uncertainty of the missing values.

According to Rubin’s framework, missing data can be classified into three
categories:

1. missing completely at random (MCAR),
2. missing at random (MAR), where the probability of the data being missing depends on the observed data, and
3. missing not at random (MNAR), where the probability of the data being missing depends on both the observed and the unobserved data.

Carbon emissions data cannot be classified as MCAR, since there is extensive research on the (observed) drivers that compel companies to disclose their emissions. This research suggests that the biggest motivator for disclosure tends to be regulatory pressure (see Prado-Lorenzo et al., 2009 and Venturelli et al., 2019). Several countries such as Brazil have succeeded in increasing disclosure rates by providing a wide range of incentives – either through legislation or changes in the regulatory regime (Araya, 2006). The positive impact on disclosure has also been credited to stakeholder activism, especially effective if initiated by investors (Flammer et al., 2019), the industry’s environmental sensitivity and companies’ international operations (Araya, 2006). Moreover, highly carbon-intensive industries tend to be more regulated and publicly pressured to report their data, leading to higher disclosure rates within those industries (Noronha et al., 2013).

However, the exact determinants of corporate carbon disclosures within each sector are difficult to identify, and therefore the majority of related studies consider the carbon emission data to be MNAR (e.g. Allen et al., 2017 and Saka and Oshika, 2014). The voluntary decision to disclose is a form of self-selection, which could lead to bias, since companies with a relatively high level of emissions might be reluctant to disclose this information (Matsumura et al., 2014 and Clarkson et al., 2008). Companies are also less likely to report their emissions if the cost of measuring and collecting this information exceeds the potential benefit (often the case for low carbon-intensive industries or smaller out-of-public-eye firms) (Matsumura et al., 2014).

When dealing with MNAR data, it is crucial to account for potential bias during the prediction process (Heckman, 1976). However, the current methods used by data providers when estimating missing emissions data typically do not systematically correct for this and the predicted data risk being inaccurate. Moreover, most commercially available datasets rely on CCA or SI techniques to estimate prediction model parameters, which do not
account for the uncertainty caused by the data incompleteness. This results in prediction intervals that do not adequately reflect estimates’ uncertainty.

To address these challenges, the objective of this paper is to predict the missing carbon emissions values with a regression model using parameters obtained with multiple imputation (MI) techniques. To account for the potential non-randomness of the observed sample, we use MI algorithms based on Heckman’s sample selection model introduced in Galimard et al. (2016) and extended in Galimard et al. (2018). Finally, to reflect the uncertainty of our estimation, we report the length of the prediction interval for each predicted value.

The remainder of this paper is organized as follows. Section 2 presents the theoretical foundations related to Heckman’s model and multiple imputation. The methods proposed by Galimard et al. are discussed in detail. Section 3 introduces the 2018 carbon emissions data (n = 6547) used for this study, which was curated by the London Stock Exchange Group for use in investment solutions (LSEG data). In section 4, we describe the design of a simulation study and evaluation methods that were applied. To further assess the accuracy of our prediction models, we apply the proposed methods to LSEG data, and, for companies which started reporting their emissions data the following year (n = 423 for Scope 1 and n = 447 for Scope 2), we compare the estimated values with the reported 2019 emissions. In section 5, we present results for the simulation and the empirical study. In the last section, we discuss our findings.

1. Methods

We introduce the applied methods by first giving an overview of Heckman’s model, also known as the sample selection method, which corrects for the bias in not randomly selected samples (Heckman 1976). We then discuss the basic multiple imputation algorithm and its extensions proposed by Galimard et al. (2016, 2018). Finally, the predict then combine (PC) procedure (Miles 2016) is presented, which we later use to obtain the final estimates of the missing values and their standard errors.

1.1. Heckman’s model

Let $Y_i, i = 1, \ldots, n$, be an incomplete set of continuous outcome variables and $R_i'$ the associated selection latent variable, where the outcome is missing
\((R_i = 0)\) if \(R_i' < 0\) and observed \((R_i = 1)\) otherwise. Thus, vector \(Y\) can be divided into two parts: \(Y_{\text{miss}}\) \((n_0 \times 1)\) containing all \(Y_i\) for which \(R_i = 0\) and \(Y_{\text{obs}}\) \((n_1 \times 1)\) with all the values of \(Y_i\) where \(R_i = 1\). The joint outcome and selection model is defined as

\[
R_i' = X_i^s \beta^s + \varepsilon_i^s \\
Y_i = X_i \beta + \varepsilon_i
\]

with \(\begin{pmatrix} \varepsilon^s \\ \varepsilon \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \sigma \varepsilon \\ \rho \sigma \varepsilon & \sigma^2 \varepsilon \end{pmatrix} \right) \), \hspace{1cm} (1)

where \(X_i^s\) is a vector \((1 \times q)\) of covariates associated with the missingness, \(X_i\) is a vector \((1 \times p)\) of outcome covariates, \(\beta^s\) is a \((q \times 1)\) vector of selection coefficients, \(\beta\) is a \((p \times 1)\) vector of outcome coefficients, \(\rho\) is the correlation between the error terms, \(\varepsilon_i^s\) is the error term of the selection model, \(\sigma^2 \varepsilon\) is its variance and \(\varepsilon_i\) is the error of the outcome model. The variance of the selection latent variable \(\sigma^2 \varepsilon\) is set to 1 since only the sign of \(R_i'\) is observed (Cameron and Trivedi, 2005, Section 16.5). The model requires \(X_i \neq X_i^s\), which is known as exclusion restriction (see Section 1.1.1). By the properties of the bivariate normal distribution

\[
E [R_i' | Y_i] = X_i^s \beta^s + \rho \frac{\sigma \varepsilon}{\sigma \varepsilon} (Y_i - X_i \beta), \hspace{1cm} (2)
\]

which implies that if the correlation \(\rho\) is not 0, the missingness depends on the outcome and the observed data (MNAR mechanism). If \(\rho = 0\), the missingness depends on the observed data only and the corresponding mechanism is MAR. As \(\rho\) further deviates from 0, bias becomes stronger (Galimard et al., 2016). The probability of a value being observed is estimated using a probit model and is given by

\[
P (R_i = 1 | X_i) = \Phi (X_i^s \beta^s), \hspace{1cm} (3)
\]

where \(\Phi\) is the standard normal cumulative distribution function and \(\phi\) its density. Consequently, Heckman derives the conditional mean and the variance of the outcome variable as

\[
E (Y_i | X_i, X_i^s, R_{yi} = 1) = X_i \beta + \rho \sigma \varepsilon \lambda_i \hspace{1cm} (4)
\]

\[
Var (Y_i | X_i, X_i^s, R_{yi} = 1) = \sigma^2 \varepsilon (1 - \rho^2 \delta_i) \hspace{1cm} \text{with } \delta_i = \lambda_i (\lambda_i + X_i^s \beta^s) \hspace{1cm} (5)
\]
where $\lambda_i$ is defined as inverse Mills ratio (IMR) with
\[ \lambda_i = \frac{\phi(X_i^s \beta^s)}{\Phi(X_i^s \beta^s)}. \]  

(6)

It is important to note that the $\text{Var}(Y_i)$ in Eq.(5) is homoskedastic, which needs to be corrected for during the variance estimation process. To obtain the model parameters, Heckman proposed two-step estimation and maximum-likelihood (ML) methods which are presented in the sections below.

1.1.1. Two-step (2-Step) Estimation

The process of obtaining the two-step estimator is as follows:

1. From the probit selection Equation (3) estimate $\hat{\beta}^s$ using ML. For each observation obtain IMR ($\hat{\lambda}_i$) as defined in Equation (6).
2. Estimate $\hat{\beta}$ and $\hat{\beta}_\lambda$ from the following linear equation:
\[ Y_i = X_i \beta + \hat{\lambda}_i \beta + \eta_i, \eta_i \sim N(0, \sigma_\eta^2) \]  

(7)

where $\beta_\lambda = \rho \sigma_\varepsilon$ is the coefficient of Mills ratio (i.e., 'correction term' associated with probability of observing the value) and $\eta_i$ is the error term with variance $\sigma_\eta^2 = \sigma_\varepsilon^2 (1 - \rho^2 \delta_i)$.

Since $\hat{\lambda}_i$ is obtained using covariates $X_i^s$, to avoid collinearity issues in the second step, the model requires exclusion restrictions where a different set of covariates is used in selection and outcome equation (Cameron and Trivedi, 2005, Section 16.5). In practice, it is often suggested to use at least one more variable ($q = p + 1$) in the selection equation, which has no significant relation with the outcome (Galimard et al., 2016). However, finding such a variable in the real world has been shown to be challenging (Liu, 2020). For further details see Cameron and Trivedi (2005).

1.1.2. Maximum Likelihood (ML)

Since Heckman’s model is fully parametric, it is possible to derive ML estimates of the joint model parameters $\theta = (\beta, \beta^s, \rho)$ from the bivariate normal distribution. The bivariate selection model has the likelihood function
\[ L = \prod_{i=1}^{n} \{ Pr[R'_i \leq 0] \}^{1-R_i} \{ f(Y_i \mid R'_i > 0) \times Pr[R'_i > 0] \}^{R_i} \]  

(8)
where the first component corresponds to the observations with the unobserved outcome variable \((Y_{\text{miss}})\) and the second to the complete observations \((Y_{\text{obs}})\) \cite{Cameron:2005}. The ML is more efficient than the two-step estimator but computationally more expensive. Today, computational cost is not an issue but the two-step estimator is considered more robust, since the ML may not converge at all or converge to a local rather than a global maximum \cite{Henningsen:2019}.

1.2. Multiple Imputation

Multiple imputation techniques are motivated by Bayes’ theory and their standard implementation provides unbiased inference if the missing data are MAR \cite{Liu:2015}. Let \(\theta\) be a parameter of interest, which could be estimated if the entire population observed. To obtain an unbiased and efficient parameter of interest \(\hat{\theta}\), despite the incomplete sample, the MI approximates the complete-data posterior mean with an average, using a small number of imputed data sets.

Consequently, any multiple imputation algorithm consists of three steps:

1. generation of \(m\) multiply-imputed data sets,
2. estimation of the parameters of interest \(\theta\) for each data set separately and
3. calculation of the aggregated estimates.

The final estimate of the parameter of interest is an approximation of the mean in Eq.(4) with an average as

\[
\hat{\theta} = \frac{1}{m} \sum_{j=1}^{m} \hat{\theta}_j
\]  \hspace{1cm} (9)

where \(m\) is the total number of the imputed data sets and \(\hat{\theta}_j\) is the estimate obtained from the \(j^{th}\) imputation. Using Rubin’s rules one can approximate the total variance of \(\hat{\theta}\) such that:

\[
\text{Var}(\hat{\theta}) = W + \left(1 + \frac{1}{m}\right) B
\]  \hspace{1cm} (10)

where \(W\) is the within-imputation variance \(W = (1/m) \sum_{j=1}^{m} \text{Var}(\hat{\theta}_j)\) and \(B\) is the between-imputation variance \(B = (1/(m-1)) \sum_{j=1}^{m} (\hat{\theta}_j - \hat{\theta})^2\).
The total variance accounts for three sources of uncertainty: the variance caused by observing the sample rather than the entire population \( (W) \), the additional variance caused by the missing values \( (B) \) and the extra simulation variance \( (B/m) \) caused by the fact that \( \hat{\theta} \) is estimated for a finite \( m \) \cite{VanBuuren2018}. The single imputation techniques do not capture the between-imputation part of the variance and therefore often result in too small standard errors \cite{White2011}. It is important to note that for the model used in the first step of the MI algorithm to result in proper imputation, it is required that both the imputed values and imputation model’s parameters are drawn from a distribution. Consequently, each set of imputed data will be based on a different set of model parameters, which are drawn at each iteration from their respective Bayesian posterior \cite{Carpenter2007}. The imputed data should be then drawn from the Bayesian posterior distribution with uninformative priors for the model parameters \cite{White2011}.

### 1.2.1. Multiple Imputation using Heckman’s Model

Selection of an imputation model strongly depends on the type of data at hand. If the data is MNAR, the standard MI techniques will not be satisfactory, as the obtained estimates tend to be biased. To address this issue, in their first paper \cite{Galimard2016} proposed a MI algorithm using Heckman’s two-step estimation. Algorithm is built out of three main steps: \( \beta^* \) and \( \lambda_i \) estimation, \( \beta, \beta_\lambda \) estimation and imputation step. In the first step, the algorithm follows the 2-Step estimation procedure to obtain estimates of \( \beta^* \) and \( \lambda_i \). As shown in Eq.(5), the variance of the outcome equation in the second step is not homeostatic and the algorithm corrects for this using a Cholesky decomposition (for details see \cite{Galimard2016}, Annex A). In the second step, to obtain model parameters \( (\beta, \beta_\lambda) \) for each imputation model the algorithm follows steps of the initial MI algorithm under the normal linear model proposed by Rubin \cite[p.167]{Rubin2004}. Thirdly, the imputation is then performed as specified in the second Step of the Eq.(7) with the parameters obtained in the previous steps.

As stated earlier, the advantage of the two-step approach is its computational efficiency. However, this method is often susceptible to collinearity, and additional exclusion restrictions need to be implemented \cite{Ogundimu2019}. Moreover, the uncertainty of the first step \( \beta^* \) is not accounted for in the second step and may lead to biased estimates \cite{Galimard2016}.
Consequently, in their second paper [Galimard et al. (2018)] followed up with an algorithm for MI based on maximum likelihood estimation. In the first step of the algorithm, Heckman’s model parameters $\theta = (\beta, \beta_s, \sigma_\epsilon, \rho)$ are estimated using ML. In the second step, the parameters for each imputation model are drawn from normal distribution. In the third step, the imputation is performed, following this same logic as in 2-Step estimation.

In our study, we apply both of the proposed algorithms since each offers a different set of advantages. To compare their performance with other MI methods, we also implemented MI using predictive mean matching [Van Buuren, 2018] and random forest [Doove et al., 2014], which implicitly assume a MAR mechanism. Both of these methods are hot deck methods, meaning that the imputed values are limited only to the already observed data.

1.3. Final Prediction

The performance of an imputation technique should not be evaluated based on the proximity of the imputed and true values since the imputation of missing data is not the same as their prediction. The aim of the imputation is to account for the uncertainty resulting from the incomplete data, whereas prediction tries to minimise the distance between the true and predicted values [Van Buuren, 2018]. Therefore, in practice, the final estimates rather than imputed missing values are used to replace the missing observations. The final estimates can be easily obtained from the models fitted to multiply-imputed data [Miles, 2016]. For each missing value $Y_i$, the final predicted value is estimated as the average of the predicted values $\hat{Y}_{ij}$ across the $m$ imputed data sets with

$$\hat{Y}_i = \frac{1}{m} \sum_{j=1}^{m} \hat{Y}_{ij} = \frac{1}{m} \sum_{j=1}^{m} X_i \hat{\beta}_j = X_i \hat{\beta}$$

(11)

where $\hat{\beta}_j$ is the vector of coefficients obtained for the data set $j$, $j = 1, \ldots, m$. In the case of multiple imputation, the standard error of prediction should account for both; the within and between-variance of the prediction. To combine the estimation of the standard errors from multiply imputed data [Miles, 2016] proposed the predict then combine (PC) procedure which follows Rubin’s rule. The total variance of the prediction can be calculated as:

$$V_{\hat{Y}_i} = V_{W_i} + V_{B_i} \left( 1 + \frac{1}{m} \right)$$

(12)
with the within \((V_{W_i})\) and the between-variance \((V_{B_i})\) given as

\[
V_{W_i} = \frac{1}{m} \sum_{j=1}^{m} \hat{se}_{ij}^2
\]

\[(13)\]

\[
V_{B_i} = \frac{1}{m-1} \sum_{j=1}^{m} \left( \hat{Y}_{ij} - \hat{Y}_i \right)^2
\]

\[(14)\]

The estimated standard error of the prediction \( \hat{se}_{ij} \) from imputed data set \( j \) in Eq.\((13)\) is calculated as in the standard linear model:

\[
\hat{se}_{ij}^2 = \sqrt{\sigma^2 + \left( X_i [\sigma^2 (X_{obs} X_{obs}^\top)^{-1}] X_i^\top \right)}.
\]

\[(15)\]

where \( X_{obs} \) is a \((n_1 \times p)\) matrix of outcome covariates for the observed part of the sample.

Finally, the prediction interval (PI) is obtained using a t-distribution with

\[
PI = \hat{Y}_i \pm t_{(\lambda/2, df)} \times \sqrt{V_{\hat{Y}_i}}
\]

\[(16)\]

where \( t_{\lambda/2} \) is the \((1 - \frac{\lambda}{2})\)-quantile of t distribution with \( df \) degrees of freedom.

2. Data

2.1. Data Overview

For this study, we use the 2018 data set of 6547 companies, which was curated by the London Stock Exchange Group (LSEG) for use in investment solutions. We focus on Scope 1 and Scope 2 emissions, which refer to emissions resulting directly from company activity and emissions resulting from its energy consumption, respectively. Companies with reported emissions value constituted 39% of the sample. For each of the companies, the following covariates are available: Region, Size, Industry, SuperSector, Sector, SubSector, RevenueUSD and FirstActivity. All the covariates are categorical except RevenueUSD (for details see Annex Table 6). Prior to

The sample includes additional micro companies, which are not included in All World Index.
the analysis, we checked whether the common support criterium is satisfied, meaning that for each category within categorical variables, observations with reported and missing emission values were present. The observations without common support have been excluded from the analysis (less than 2% of the total sample).

The probability of the emissions being observed varies significantly depending on the Size of the company. Therefore, to investigate the impact of the level of missingness in the sample on the precision of the prediction, we also analysed data for each size category separately. The summary of the analysed data sets can be found in Table 1 where the size of the company is denoted by $L$ for large, $M$ for medium, $S$ for small and $U$ for micro.

Table 1: Overview of the data and in particular reported and missing values according to the Size of the company.

| Size | $n$  | Scope 1 | | Scope 2 | |
|------|------|---------|---------|---------|---------|
|      | $n_1$| $n_0$   | % reported | $n_1$ | $n_0$   | % reported |
| L    | 1343 | 950     | 393 | 71% | 948 | 395 | 71% |
| M    | 1694 | 927     | 767 | 55% | 923 | 771 | 55% |
| S    | 2085 | 508     | 1577 | 24% | 504 | 1581 | 24% |
| U    | 1425 | 169     | 1256 | 12% | 167 | 1258 | 12% |
| Total| 6547 | 2554   | 3993 | 39% | 2542 | 4005 | 39% |

2.2. Variable Selection Process

For each analysed data set, we considered all the available covariates as predictor variables in the outcome and selection equation. For this purpose, we used the stepwise regression (stepwise selection) approach, where predictors are iteratively added and/or removed from the prediction model. The process is terminated when further improvements in the model fit are no longer statistically significant [Efron and Hastie 2016]. In this study, we applied both-directions stepwise selection, which is a hybrid of forward and backward selection.

The selection was performed with the stepAIC function from the MASS package, which uses the AIC as the model performance evaluation criterion. For each analysed dataset, we performed variable selection separately for the outcome and selection equation (emissions model and disclosure probability
model). For the outcome equation, we conducted a variable selection based on a linear model. For the selection equation, we fit a probit model to the data at every step of the selection. The process has been repeated for both Scope 1 and Scope 2 separately.

The stepwise selection based on the AIC criterion does not guarantee that all the selected variables will be statistically significant. Therefore, the authors of the stepAIC function, Venables and Ripley (2013, section 6.8), recommend manual removal of insignificant variables. Selected in this way, outcome and selection variables for all datasets met the exclusion restriction criterion required for the 2-Step Heckman model.

3. Simulation Study

The objective of this simulation study is to evaluate the performance of the selected and alternative imputation techniques in various scenarios for the MAR and MNAR mechanisms. In each scenario, $N$ independent data sets were generated based on the LSEG data.

3.1. Data-generating process

In the LSEG dataset, covariates are complete and were used in the simulation without any modifications. The jointly distributed error terms, $\varepsilon$, $\varepsilon^s$ were generated from the bivariate normal distribution specified in Eq. (1) with $\rho$ equal to 0, -0.3 and -0.6, corresponding to a MAR, Light MNAR and Heavy MNAR mechanism respectively. We assume a negative correlation between the selection and outcome equations to reflect the empirical research suggesting that companies with a higher level of emissions are less likely to report their data. To evaluate the performance of the methods when the missingness mechanism is different from specified in Heckman’s model, we use the approach proposed by Ganjali and Ranji (2008), which uses a Bernoulli distribution for $R_i$ with a function of $Y_i$ as its parameter $P(R_i = 1)$. This fourth scenario is named Non-Heckman in our notation. In the Results section and Discussion, we collectively refer to the Light MNAR, Heavy MNAR and Non-Heckman scenario as MNAR scenarios.

For each subset and the Total dataset, we fitted Heckman’s model (ML estimation) and obtained vectors of estimates $\hat{\beta}$ and $\hat{\beta}^s$. The estimated $\hat{\sigma}_s$ was between 1.44 and 1.64 for all the datasets. For each missingness mechanism,
we generated data under three scenarios of $\sigma^2_\varepsilon$: 1, 2.5 and 4. The $\hat{\beta}^s$ were used directly from the ML Heckman’s estimation to keep the same missingness level and distribution within each sample, and the binary missingness variable $R_i$ was estimated accordingly with $R_i = 1$ if $P(R_i = 1) \geq 0.5$. For $\hat{\beta}$, we drew a vector from $\beta \sim N(\hat{\beta}, \hat{se}(\hat{\beta})^2)$ and defined it as $\beta^*$. The outcome variable $Y_i$ was generated according to the outcome equation $Y_i = X_i \beta^* + \varepsilon_i$. The missingness indicator $R_i$ was generated according to the following selection equation: $X_i \beta^* + \varepsilon_i \geq 0$, then $R_i = 1$; $R_i = 0$ otherwise. The predictors in $X_i$ and $X_i^s$ were selected as specified in Section 2.2 and Annex in Table 8, except for the Total dataset where SubSector (113 categories) was replaced by the Sector (40 categories) variable for computational efficiency of the simulation (in the empirical study SubSector is used). For each model, we also added an intercept. For the Non-Heckman scenario, the missingness indicator $R_i$ was generated using Bernoulli distribution with parameter $P(R_i = 1) = \Phi(c + 0.45 * \Delta Y_i)$ for $i = 1, \ldots, n$ where $\Delta Y_i = \bar{Y}_{\text{sector}(Y_i)} - Y_i$. Here, $\bar{Y}_{\text{sector}(Y_i)}$ is the average emission for the Sector to which observation $Y_i$ belongs. To obtain a similar level of missingness as in the original data $c$ for Total dataset is equal to $-0.5, 0.6$ for $L$, $0.15$ for $M$, $-0.9$ for $S$ and $-1.6$ for $U$. Generating the probability of data being observed as a function of $\Delta Y_i$ allowed us to ensure that within each Sector observations with emissions above the average level are less likely to be observed, following the same hypothesis as the other implemented MNAR mechanisms.

A total of $N = 500$ datasets were generated under each missingness scenario and value of $\sigma^2_\varepsilon$. The entire data-generating process was repeated separately for Scope 1 and Scope 2.

3.2. Computational Setting

The analysis was performed with the R statistical software, version 4.0.3, including the following packages: mice [van Buuren et al., 2015], sampleSelection [Toomet et al., 2008] and miceMNAR [Galimard and Resche-Rigon, 2018].

3.3. Analysis Methods

The complete simulated data were first saved, before the deletion of some values, to later serve as a benchmark. The incomplete data were then analysed with the following methods:
1. Single Imputation (SI):
   - Linear model (LM) consisting of imputation based on the linear model prediction, with the least squares estimates calculated from the observed data. Imputations were obtained with the norm.predict function from the mice package.
   - Heckman’s model with maximum likelihood estimation (Hml) as described in (Galimard et al., 2016). Imputations were obtained with the hecknorm function from the miceMNAR package.

2. Multiple Imputation (MI) with imputation performed five times for each missing value:
   - MI using Predictive Mean Matching (MIPmm) consisted of imputations from a small list of candidates, which are chosen based on their proximity to the predictive mean (for details see Van Buuren, 2018). Imputations were obtained with the pmm function from the mice package.
   - MI using Random Forest (MIRF) consists of imputation, where the predictive mean is now calculated by a tree model instead of a regression model (for details see Doove et al., 2014). Imputations were obtained with the rf function from the mice package with the default number of 10 trees in each random forest.
   - MI using Heckman’s model with maximum likelihood estimation (MIHml) based on (Galimard et al., 2018). Imputations were obtained with the hecknorm function from the miceMNAR package.
   - MI using Heckman’s two-step model estimation (MIH2step) based on (Galimard et al., 2016). Imputations were obtained with the hecknorm2step function from the miceMNAR package.

The missing values were then predicted using linear models with coefficients obtained from an analysis of the imputed datasets. For the MI methods, the final coefficient estimates were obtained using Rubin’s rule. In the Annex, Table (8) summarises the predictors used for each of the models, which were selected according to the procedure described in Section(2.2). The final estimates of the missing values based on the MI methods were obtained with the PC procedure described in the Methods section. As stated earlier, sector median estimation (Median) and LM are currently widely used.
approaches for the estimation of missing emissions. Therefore, we additionally implemented median estimation, where the missing values were estimated with the median of the observed emissions within the (Sub-) Sector peer group. Based on the coefficients obtained from the imputation analysis, the same set of predictors were used for the imputation for the linear prediction models. We then evaluated the performance of each method.

First, we evaluated the above methods in terms of accuracy of the estimated parameters $\theta$ (coefficients). For this purpose, we computed the empirical mean of the parameter estimates ($\bar{\theta}$), relative bias (RBias %), the root mean square of estimated (model) standard errors ($SE_m$), empirical standard error ($SE_e$), coverage rate (CR %) and the root mean square error (RMSE). To calculate these metrics, we use formulas provided in Morris et al. (2019). The coverage rate was estimated for a $\alpha = 0.05$ confidence level, which implies that, according to the property of randomisation validity, exactly 95% of intervals should cover the true $\theta$ (Morris et al. 2019). The root mean of the squared model standard errors is often also called “average model SE” and should be close to $SE_e$ since $E[SE_m^2] = SE_e^2$. If the $SE_m$ is systematically underestimated, this suggests a bias, which may lead to undercoverage, meaning that the true value of the parameter is not significantly often covered by the confidence interval. In the case when $SE_m < SE_e$, Morris et al. (2019) recommends using the relative error in the average model SE ($RE_{SE_m}$) as an informative performance measure.

The accuracy of the models’ predictions in each data-generating setting was evaluated with the coverage rate of the nominal 95% confidence intervals (CR%), the average length of the prediction interval (PI), the mean relative error (RE), and the root mean square error (RMSE). The prediction intervals for each missing variable was calculated according to Eq. (16). Since RE is a measure relative to the true value, it reports much higher values for the observations with very small true values, i.e. RE is sensitive to small true values. In contrast, RMSE penalises heavily high absolute variation between the estimate and its true values, regardless of the true values. Therefore, it is often used to report the overall error of the prediction model.

4. Results

In this section, we present the results of the simulation study for the Scope 1 Total dataset, including all data-generating scenarios. To test our approach
beyond the simulation, we report results obtained from the application of the proposed methods to the original 2018 LSEG data. The results for the data sub-sets (Scope 1), based on company size, and Scope 2 Total dataset can be found in the Annex.

4.1. Simulation

Estimation of Coefficients

Table 2 and Fig 1 present results of $\beta_{\text{Revenue}}$ estimation for the Total dataset. With MAR mechanism ($\rho = 0$), all methods except MIRF appeared to give unbiased estimates of $\beta_{\text{Revenue}}$ (with relative bias (Rbias) less than 2%). In Light MNAR ($\rho = -0.3$) and Heavy MNAR ($\rho = -0.6$), only Hml, MIHml and MI2Step appeared to consistently give unbiased estimates across all the values of $\sigma^2_\epsilon$. The estimates obtained with methods not based on Heckman’s model appeared to be biased and their bias increased with $\rho$ and $\sigma^2_\epsilon$. In Non-Heckman scenario, Hml and MIHml appeared to be unbiased (or almost unbiased i.e., $Rbias$ less than 2.5%), whereas bias of MI2Step was much lower than of the other methods not based on Heckman’s model. As expected, the MIHml was more efficient (smaller $SE_m$) than MIH2Step. To sum up, if data is MNAR, proposed approaches estimated coefficients with lower bias than alternatives.

For all scenarios, due to the exclusion of between-variance, the $SE_m$ for LM and Hml was smaller than that for MI methods. $SE_m$ was smaller than $SE_e$ for all the methods, suggesting that $SE_m$ of all models was underestimated. The relative error ($RE_{SE}$) was higher for single imputation methods.

The coverage rate (CR) was below its nominal value (95%) for all the methods, with especially low value for all methods except MIHml and MI2Step in Heavy MNAR and Non-Heckman scenarios ($CR \leq 56\%$) when $\sigma^2_\epsilon > 1$. The proposed MIHml and MI2Step performed best with relatively high coverage rate across all scenarios in comparison to other tested methods.

In the MAR scenario, the RMSE was the lowest for LM or MIPmm for all values of $\sigma^2_\epsilon$, suggesting a smaller estimation error across all 500 datasets. In non-Heckman scenarios, the RMSE of methods based on Heckman’s model was lower than the other methods and MIHml tended to have the lowest RMSE among all the methods and across all values of $\sigma^2_\epsilon$. In general, higher
value of $\sigma^2$ brought an increase in $SE_m$, $SE_e$ and RMSE across all the methods. The results for the sub-samples are detailed in the Annex.

For the Total dataset, we obtained the coefficient estimates for all 42 variables. For each categorical covariate with a total of $k$ categories, $k-1$ coefficients were estimated. To summarise results for all the categories, Table 3 presents the median of the relative bias (median of Rbias) across all the categories of each covariate. As before, Hml, MIHml and MI2Step performed better than other methods for most covariates across MNAR scenarios, resulting in lower median relative bias. The results for coefficients estimation for Scope 2 emissions were very similar to Scope 1 and similar trends were observed for the sub-sets. The results are detailed in the Annex.

Table 2: Total Scope 1: Simulation results for $\beta_{\text{Revenue}} = 1.00$ estimates

| Methods | Mean Rbias | $SE_m$ | $SE_e$ | $RE_{SE}$ | CR | RMSE |
|---------|------------|--------|--------|-----------|----|------|
| LM      | 1.12       | 5.74   | 0.51   | 6.77      | 92.47 | 0.20 | 6.29 |
| MAR     |            |        |        |           |     |      |
| MIPnum  | 1.05       | 4.74   | 1.43   | 5.94      | -75.93 | 9.80 | 5.16 |
| MIRF    | 0.94       | -6.23  | 3.27   | 8.54      | -61.71 | 48.00 | 7.04 |
| Hml     | 1.01       | 0.75   | 0.84   | 4.80      | -82.50 | 42.20 | 2.87 |
| MIHml   | 1.00       | 0.25   | 2.13   | 4.50      | -52.67 | 88.20 | 2.25 |
| MIH2Step| 1.00       | 0.25   | 2.23   | 4.76      | -53.15 | 88.00 | 2.35 |
| Light   |            |        |        |           |     |      |
| MIPnum  | 1.11       | 10.73  | 1.33   | 9.21      | -85.56 | 0.00 | 10.98 |
| MIRF    | 1.00       | 0.25   | 2.28   | 7.32      | -55.19 | 91.20 | 3.10 |
| Hml     | 1.00       | 0.25   | 0.87   | 6.91      | -87.41 | 56.00 | 2.32 |
| MIHml   | 1.00       | 0.25   | 1.92   | 6.76      | -71.60 | 87.80 | 2.02 |
| MIH2Step| 1.00       | 0.25   | 2.20   | 7.01      | -68.02 | 89.20 | 2.25 |
| MNAR    |            |        |        |           |     |      |
| LM      | 0.91       | 9.22   | 0.48   | 7.50      | -83.60 | 0.00 | 9.39 |
| MIPnum  | 0.90       | -10.22 | 1.38   | 7.81      | -82.33 | 0.00 | 10.06 |
| MIRF    | 0.77       | -25.19 | 2.71   | 16.85     | -83.92 | 0.00 | 23.31 |
| Hml     | 0.99       | -1.24  | 0.85   | 11.94     | -92.88 | 21.20 | 6.49 |
| MIHml   | 0.99       | -1.24  | 4.50   | 11.78     | -61.80 | 85.20 | 4.78 |
| MIH2Step| 0.95       | -5.23  | 5.32   | 9.47      | -43.82 | 76.60 | 7.20 |

Mean = Average estimate $\beta_{\text{Revenue}}$ (rounded to 2 digits), Rbias = Average relative bias (%), $SE_m$ = Root mean square of the estimated standard errors $\times 10^2$, $SE_e$ = Empirical standard error $\times 10^2$, CR = Coverage rate (based on 95% confidence interval), $RE_{SE}$ = relative error of $SE_m$(%), RMSE = Root mean square error $\times 10^2$. 

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### 1.b) $\sigma^2_{\varepsilon} = 2.5$

| Methods     | Mean Rbias | SEm $\times 10^2$ | SEe $\times 10^2$ | RESE | CR | RMSE |
|-------------|------------|--------------------|--------------------|------|----|------|
| LM          | 1.00 -0.25 | 0.82 5.71         | -85.64 46.80      | 2.41 |
| MIPmm       | 0.99 -1.24 | 2.28 5.41         | -57.86 85.40      | 2.89 |
| MRF         | 0.88 -12.22 | 3.51 11.74       | -70.10 10.80      | 12.63|
| Hml         | 1.01 0.75  | 1.16 7.18         | -83.84 36.40      | 4.82 |
| MIIHml      | 1.01 0.75  | 3.57 6.59         | -65.83 85.00      | 3.36 |
| MIIH2Step   | 1.00 -0.25 | 3.57 6.21         | -42.51 90.20      | 3.64 |

#### Light MNAR

| LM          | 1.10 -0.25 | 0.80 9.08         | -91.19 0.00       | 9.96 |
| MIPmm       | 1.09 8.73  | 2.21 8.24         | -73.18 6.40       | 8.84 |
| MRF         | 0.97 -3.24 | 3.58 7.95         | -54.97 79.40      | 4.65 |
| Hml         | 1.00 -0.25 | 1.17 6.94         | -83.14 41.80      | 4.37 |
| MIIHml      | 1.00 -0.25 | 3.39 6.46         | -47.52 88.00      | 3.52 |
| MIIH2Step   | 1.00 -0.25 | 3.51 6.69         | -47.53 89.00      | 3.61 |

#### Heavy MNAR

| LM          | 1.19 18.71 | 0.75 14.83       | -94.94 0.00       | 19.31|
| MIPmm       | 1.18 17.71 | 2.08 13.97       | -85.11 79.40      | 18.19|
| MRF         | 0.87 -12.22 | 3.82 12.06       | -57.60 54.20      | 7.61 |
| Hml         | 1.00 -0.25 | 1.21 11.70       | -89.66 46.00      | 3.81 |
| MIIHml      | 1.00 -0.25 | 2.84 11.37       | -75.02 87.80      | 3.13 |
| MIIH2Step   | 1.00 -0.25 | 3.38 11.33       | -70.17 93.00      | 3.35 |

#### Non-MNAR

| LM          | 0.81 -19.20 | 0.73 12.61       | -94.21 0.00       | 19.29|
| MIPmm       | 0.81 -19.20 | 2.00 13.20       | -84.85 83.20      | 18.83|
| MRF         | 0.68 -32.17 | 2.59 21.81       | -88.12 0.00       | 31.96|
| Hml         | 0.99 -1.24  | 1.22 18.84       | -93.52 30.80      | 9.47 |
| MIIHml      | 0.99 -1.24  | 4.88 18.95       | -73.25 83.20      | 8.59 |
| MIIH2Step   | 0.93 -7.23  | 8.90 14.73       | -39.58 78.40      | 11.39|

### 1.c) $\sigma^2_{\varepsilon} = 4$

| Methods     | Mean Rbias | SEm $\times 10^2$ | SEe $\times 10^2$ | RESE | CR | RMSE |
|-------------|------------|--------------------|--------------------|------|----|------|
| LM          | 1.00 -0.25 | 0.82 5.71         | -85.64 46.80      | 2.41 |
| MIPmm       | 0.99 -1.24 | 2.28 5.41         | -57.86 85.40      | 2.89 |
| MRF         | 0.88 -12.22 | 3.51 11.74       | -70.10 10.80      | 12.63|
| Hml         | 1.01 0.75  | 1.16 7.18         | -83.84 36.40      | 4.82 |
| MIIHml      | 1.01 0.75  | 3.57 6.59         | -65.83 85.00      | 3.36 |
| MIIH2Step   | 1.00 -0.25 | 3.57 6.21         | -42.51 90.20      | 3.64 |

#### Light MNAR

| LM          | 1.19 18.71 | 0.75 14.83       | -94.94 0.00       | 19.31|
| MIPmm       | 1.18 17.71 | 2.08 13.97       | -85.11 79.40      | 18.19|
| MRF         | 0.87 -12.22 | 3.82 12.06       | -57.60 54.20      | 7.61 |
| Hml         | 1.00 -0.25 | 1.21 11.70       | -89.66 46.00      | 3.81 |
| MIIHml      | 1.00 -0.25 | 2.84 11.37       | -75.02 87.80      | 3.13 |
| MIIH2Step   | 1.00 -0.25 | 3.38 11.33       | -70.17 93.00      | 3.35 |

#### Heavy MNAR

| LM          | 0.81 -19.20 | 0.73 12.61       | -94.21 0.00       | 19.29|
| MIPmm       | 0.81 -19.20 | 2.00 13.20       | -84.85 83.20      | 18.83|
| MRF         | 0.68 -32.17 | 2.59 21.81       | -88.12 0.00       | 31.96|
| Hml         | 0.99 -1.24  | 1.22 18.84       | -93.52 30.80      | 9.47 |
| MIIHml      | 0.99 -1.24  | 4.88 18.95       | -73.25 83.20      | 8.59 |
| MIIH2Step   | 0.93 -7.23  | 8.90 14.73       | -39.58 78.40      | 11.39|

#### Non-MNAR

| LM          | 0.74 -26.18 | 0.80 15.86       | -94.39 0.00       | 26.21|
| MIPmm       | 0.74 -26.18 | 2.34 16.45       | -85.78 0.00       | 26.74|
| MRF         | 0.63 -37.15 | 2.66 24.45       | -89.12 0.00       | 37.78|
| Hml         | 0.98 -2.24  | 1.46 23.46       | -93.78 37.20      | 11.83|
| MIIHml      | 0.98 -2.24  | 5.21 23.46       | -77.79 82.00      | 11.63|
| MIIH2Step   | 0.90 -10.22 | 11.63 17.90      | -35.03 74.80      | 14.81|

Mean = Average estimate $\beta_{Revenue}$ (rounded to 2 digits), Rbias = Average relative bias (%), $SEM = \text{Root mean square of the estimated standard errors} \times 10^2$, $SEe = \text{Empirical standard error} \times 10^2$, CR = Coverage rate (based on 95% confidence interval), $RESE = \text{relative error of } SEM(\%)$, RMSE = Root mean square error $\times 10^2$. 

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Figure 1: Total Scope 1: Boxplot over simulations for $\hat{\beta}_{Revenue}$. Red dotted lines denote the true value of the coefficient.
Table 3: Total Scope 1: Median relative bias (% Rbias) for variable coefficients estimates across all the categories of selected predictors

\[ \sigma^2_\varepsilon = 2.5 \]

| Sector (40 categories) | Region (8 categories) | FirstActivity (4 categories) |
|------------------------|-----------------------|-----------------------------|
| MAR Light Non-         | MAR Light Heavy Non-  | MAR Light Heavy Non-        |
| Light Heavy Non-       | Light Heavy Non-      | Light Heavy Non-            |
| MNAR MNAR Heckman     | MNAR MNAR Heckman     | MNAR MNAR Heckman           |
| LM                     | 0.04 1.31 2.44 -4.98  | -1.39 -16.36 -32.40 -23.01 |
| MIPmm                  | -0.24 1.98 3.40 -2.72  | -2.10 -17.21 -32.49 -23.65 |
| MIRF                   | -21.16 -18.59 -20.32 -11.89 | -34.47 -44.50 -61.39 -46.37 |
| Hml                    | 0.01 0.06 -0.99 0.10   | -1.83 -0.94 -0.94 -3.40 |
| MIFhml                 | 0.00 0.11 -0.18 -0.66  | -1.90 -1.69 -1.33 -2.04 |
| MIR2Step               | -0.34 -0.45 -0.37 -1.35 | -1.39 -0.22 -0.52 -7.77 |

Results for \( \sigma^2_\varepsilon = 1 \) and \( \sigma^2_\varepsilon = 4 \) are enclosed in the Annex

**Prediction Accuracy**

Table 4 presents the results for the prediction accuracy for the Total dataset. As expected, the average length of prediction interval (PI) based on MI methods was wider than for single imputation methods. Moreover, PI tended to increase with \( \sigma^2_\varepsilon \) for all methods. The average prediction interval length for LM was the lowest across all the methods and scenarios, whereas the highest RE and RMSE appeared to be associated with the Median based estimation. The MIRF had the highest CR across all the methods for most scenarios (except Non-Heckman); however, its relatively high RMSE suggested that the high CR was caused by the length of the prediction interval and not high prediction accuracy.

With the MAR mechanism, LM showed the lowest CR (72.5-87.7%) within each scenario, which was well below the nominal coverage rate (95%). The coverage of the MI methods fluctuated between approx. 90% and 99% conditional on \( \sigma^2_\varepsilon \). Across all values of \( \sigma^2_\varepsilon \), Median and MIRF had the highest RE and RMSE and all the other methods reported similar values.
Table 4: Total: Simulation results for the predicted missing Scope 1 emissions values.

| Method | MAR | Light MNAR | Heavy MNAR | Non-Heckman |
|--------|-----|------------|------------|-------------|
|        | RE  | RMSE      | CR         | PI          | RE  | RMSE      | CR         | PI          |
| Median | 68.03 | 2.57 | - | - | 60.07 | 2.44 | - | - | 61.27 | 2.33 | - | - | 25.06 | 2.89 | - | - |
| LM     | 17.77 | 1.00 | 87.72 | 3.09 | 17.07 | 1.09 | 83.91 | 3.06 | 18.40 | 1.32 | 72.25 | 2.97 | 10.85 | 1.19 | 78.75 | 3.00 |
| MIPmm  | 17.98 | 1.00 | 95.19 | 3.96 | 17.29 | 1.08 | 92.68 | 3.88 | 18.15 | 1.31 | 81.15 | 3.64 | 10.88 | 1.19 | 88.32 | 3.74 |
| MIRF   | 23.63 | 1.09 | 99.00 | 5.59 | 20.04 | 1.06 | 99.22 | 5.64 | 18.29 | 1.18 | 94.11 | 5.60 | 12.65 | 1.42 | 93.80 | 5.14 |
| Hml    | 17.66 | 1.00 | 95.06 | 3.93 | 17.91 | 1.00 | 95.24 | 3.95 | 17.16 | 0.98 | 95.79 | 4.01 | 9.53 | 1.01 | 95.08 | 3.97 |
| MIHml  | 17.71 | 1.00 | 95.25 | 3.97 | 17.93 | 1.00 | 95.48 | 4.00 | 17.14 | 0.99 | 96.21 | 4.10 | 9.48 | 1.00 | 96.13 | 4.16 |
| MIH2Step | 17.89 | 1.00 | 95.29 | 3.98 | 18.11 | 0.99 | 95.43 | 3.99 | 17.27 | 0.98 | 95.68 | 3.99 | 9.93 | 1.07 | 94.05 | 4.05 |
| Median | 104.21 | 2.85 | - | - | 148.31 | 2.68 | - | - | 171.89 | 2.56 | - | - | 30.06 | 3.46 | - | - |
| LM     | 43.44 | 1.58 | 78.03 | 3.88 | 36.60 | 1.72 | 73.41 | 3.85 | 47.13 | 1.58 | 78.03 | 3.88 | 18.79 | 2.12 | 57.66 | 3.68 |
| MIPmm  | 44.65 | 1.58 | 95.11 | 6.24 | 36.37 | 1.72 | 92.50 | 6.11 | 46.12 | 1.58 | 95.11 | 6.24 | 18.82 | 2.12 | 79.96 | 5.54 |
| MIRF   | 52.91 | 1.64 | 97.63 | 7.42 | 48.08 | 1.66 | 97.54 | 7.45 | 49.88 | 1.91 | 94.77 | 7.30 | 20.43 | 2.32 | 82.56 | 6.35 |
| Hml    | 43.15 | 1.58 | 85.77 | 4.64 | 44.65 | 1.58 | 86.00 | 4.66 | 59.46 | 1.57 | 86.76 | 4.72 | 14.83 | 1.60 | 86.13 | 4.74 |
| MIHml  | 43.19 | 1.58 | 91.98 | 5.54 | 44.61 | 1.58 | 92.21 | 5.58 | 58.57 | 1.57 | 93.01 | 5.70 | 14.83 | 1.60 | 92.94 | 5.81 |
| MIH2Step | 43.87 | 1.58 | 95.28 | 6.29 | 45.75 | 1.57 | 95.39 | 6.29 | 68.63 | 1.56 | 95.59 | 6.29 | 25.48 | 1.71 | 93.42 | 6.35 |
| Median | 130.56 | 3.11 | - | - | 138.90 | 2.92 | - | - | 129.58 | 2.82 | - | - | 31.14 | 3.97 | - | - |
| LM     | 68.19 | 2.00 | 72.49 | 4.37 | 60.23 | 2.18 | 67.73 | 4.33 | 42.92 | 2.64 | 54.06 | 4.19 | 24.82 | 2.85 | 45.47 | 4.05 |
| MIPmm  | 68.97 | 2.00 | 95.10 | 7.89 | 60.30 | 2.17 | 92.46 | 7.73 | 42.82 | 2.63 | 82.49 | 7.21 | 24.83 | 2.85 | 73.65 | 6.67 |
| MIRF   | 81.67 | 2.05 | 96.93 | 8.88 | 71.88 | 2.10 | 96.54 | 8.87 | 44.98 | 2.44 | 92.57 | 8.62 | 26.26 | 3.03 | 74.76 | 7.22 |
| Hml    | 67.79 | 2.00 | 79.53 | 5.08 | 72.55 | 2.00 | 79.78 | 5.10 | 49.67 | 2.00 | 80.37 | 5.15 | 18.56 | 2.06 | 79.20 | 5.19 |
| MIHml  | 67.68 | 2.00 | 90.28 | 6.64 | 72.45 | 2.00 | 90.48 | 6.68 | 49.78 | 2.00 | 91.19 | 6.81 | 18.58 | 2.06 | 90.78 | 6.98 |
| MIH2Step | 68.68 | 2.00 | 95.29 | 7.90 | 73.53 | 1.99 | 95.37 | 7.95 | 60.54 | 1.97 | 95.58 | 7.95 | 19.45 | 2.21 | 92.42 | 7.95 |

RE = Average relative error for all $Y_{miss}$ (%), PI = Average length of the prediction interval, RMSE = Root mean square error, CR = Coverage rate (%)

With the MNAR mechanisms, for each value of $\sigma^2$, MIHml, MIH2Step and Hml had lower RMSE than the other methods. The PI of MIH2Step was higher than that of MIHml across all the MNAR scenarios and values of $\sigma^2$, which tended to result in a higher coverage rate for MIH2Step. The MIPmm had the lowest coverage rate among all MI methods. For larger variance in Heavy MNAR and Non-Heckman scenario, MIH2Step had higher coverage than MIRF but also higher PI, suggesting inefficiency in the estimation. In summary, MI methods based on Heckman’s model tend to have relatively high coverage and small PI in comparison to other tested methods if data is MNAR.

The results for the data sub-sets were similar and are detailed in the Annex. In general, a higher level of data missingness did not increase the RMSE of the estimates. Only for LM, the CR significantly decreased with the level of missingness.

4.2. Empirical Study Results: 2018 LSEG Data

For the empirical part of our study, we have applied the methods described in Section 3.3 to the original 2018 LSEG Scope 1 and Scope 2 data. It is important to note that the MAR mechanism cannot be ruled out for LSEG
data, based on testing $\hat{\rho} = 0$ (for Scope 1 p-value = 0.99 and for Scope 2 p-value = 0.48, $\hat{\rho}$ obtained with Heckman’s ML estimation).

Fig. 2 presents a boxplot of the relative prediction interval length (relative PI) ($100\% \times \frac{\text{PILength}}{\text{PredictedValue}}$) for the Scope 1 and Scope 2 estimates of all missing values in the LSEG dataset. As expected, the relative PI was smaller for single imputation methods than for MI methods with its average value for Scope 1 of 47.75% (Scope 2: 36.42%) for LM, 57.29% (Scope 2: 46.08%) for Hml, 93.58% (Scope 2: 63.40%) for MIRF, 76.15% (Scope 2: 56.21%) for MIPmm, 71.02% (Scope 2: 50.06%) for MIHml and 75.45% (Scope 2: 54.46%) for MIH2step. Among MI methods, MIHml had the lowest relative PI for both Scope 1 and Scope 2. The variation in relative prediction interval values was smaller for Scope 2 than Scope 1 across all the methods, which can be explained by smaller variation of the reported values.

Figure 2: Empirical results: Boxplots of the relative prediction interval length according to the method for the Total data set.

In practice, the evaluation of the accuracy of emissions prediction models is often performed retrospectively, after a company starts to report its data (e.g. Kalesnik et al., 2020). Thus, for companies that disclosed their emissions for the first time in 2019 ("first-time reporters"), we compared the reported values (2019) with the obtained estimates (2018). The sample size ($n_{2019}$) for Scope 1 was 423 and for Scope 2 was 447. In our analysis, we did not adjust for a year effect to avoid inclusion of any additional bias. Due
to a small sample size available for this exercise, the following results should not be considered conclusive.

Fig. 3 shows the 2018 estimated values against the corresponding 2019 reported values. It can be also seen that estimates based on multiple imputation methods are distributed more closely to the diagonal line with slope equal to 1 (2018 estimate = 2019 reported value), suggesting higher estimation accuracy. For Scope 1, LM had the highest correlation ($\rho$ Pearson correlation) among all the methods. For Scope 1 among MI methods, MIPmm and MIHml had the highest correlation $\rho = 0.812$ and MIHml had the highest $\rho = 0.646$ for Scope 2.

The detailed results of prediction accuracy for the first-time reporters are presented in Table 5. We have also included the results for prediction accuracy of the joint Scope 1 and Scope 2 estimates (Scope 1 + 2). In terms of coverage rate, MIPmm performed better than MIHml, whereas MIRF performed better than both MI methods based on Heckman’s model for all estimates.

Across all the methods, only MIRF had CR above (Scope 1, Scope 1 + 2) or close to (Scope 2) the nominal rate (95%). Similar to what we have seen in simulation, the comparatively high coverage of MIRF was caused by its wide prediction interval but not higher accuracy, since its RMSE was higher than for other methods. All the methods except MIRF and Median had very similar RMSE values for Scope 1, 2 and 1 + 2. The LM exhibited substantial undercoverage, but a relatively low RMSE, which indicated that its prediction errors were not much higher than for the other methods. The value of Spearman correlation behaved similarly to Pearson and was almost the same for all the methods except MIRF and Median for Scope 1, 2 and 1 + 2. It is important to note that the 2019 data may vary from the true 2018 values and thus the coverage rate could be reflected incorrectly. Scope 1 + 2 estimates tend to have higher CR and lower RMSE than Scope 1 and Scope 2 estimates.
Figure 3: Empirical results. Estimated 2018 values vs reported 2019 values for the *Total* data set.

In the Annex in Table 24, we present results for estimation accuracy within the subsets. For each of the subsets, the RMSE of all methods was higher in comparison to their value in the *Total* sample, with Median having the highest RMSE value across all the samples. Similarly to results in
the simulation study, the CR of LM decreased significantly with the level of missingness in the sample since the model was fitted to a smaller number of observations, causing the estimated SE and, consequently PI to decrease. CR varied much less across the subsets for the methods other than LM and their PI tended to increase with the level of missingness. The higher level of missingness did not necessarily lead to an increase in RE across the methods. The sample with the highest RMSE was \( U \) (12% of the data observed); however, the coverage rate across the MI methods in that sample was still pretty high, varying between 77.55% for MIHml in Scope 1 and 98.04% for MIRF in Scope 2. Across all methods and samples, CR for Scope 2 tended to be higher than for Scope 1 whereas RMSE, Pearson and Spearman Correlations tended to be lower.

In the last step of our analysis, we considered the relative error of the estimates according to the Industry to which companies belong. The results for Scope 1 and Scope 2 are presented in Fig.4. In general, for Scope 1 and Scope 2 all methods except Median and MIRF performed similarly for most industries. For Scope 1, the industries with highest variation between the methods were Technology, where Median and MIRF performed worse than other methods, as well as Telecommunication (59.8% Obs.) and Utilities (59.0% Obs.) where Median performed better than the other methods. Financial industry had the highest RE, which can be explained by the metric sensitivity to small reported values (Scope 1 median 7.9).
Table 5: Empirical study results: Accuracy of the 2018 estimates with respect to the 2019 reported values in the Total Sample.

| Obs/\% | n2019 | Methods | CR | PI | RE_{min} | RE_{mean} | RE_{max} | RMSE | Pearson Corr. | Spearman Corr. |
|--------|-------|---------|----|----|----------|-----------|----------|------|---------------|---------------|
|        |       | Median  |    |    | 8.04     | 18.14     | 34.15    | 2.70 | 0.64          | 0.68          |
|        |       | LM      | 70.45 | 3.80 | 6.49     | 13.48     | 24.37    | 1.86 | 0.81          | 0.81          |
|        |       | MIP/mm  | 88.65 | 6.07 | 6.29     | 13.45     | 23.92    | 1.86 | 0.81          | 0.81          |
| Scope1 | 39    | MIRF    | 97.16 | 8.32 | 7.18     | 14.59     | 23.90    | 2.00 | 0.80          | 0.79          |
|        |       | Hml     | 78.01 | 4.52 | 6.45     | 13.47     | 23.13    | 1.86 | 0.81          | 0.81          |
|        |       | MIH2Step| 84.40 | 5.41 | 6.62     | 13.55     | 23.44    | 1.86 | 0.81          | 0.81          |
|        |       | Median  |    |    | 5.62     | 13.22     | 29.15    | 2.64 | 0.29          | 0.42          |
|        |       | LM      | 75.84 | 3.46 | 4.10     | 8.79      | 16.91    | 1.59 | 0.73          | 0.69          |
|        |       | MIP/mm  | 88.59 | 5.30 | 4.22     | 8.61      | 16.76    | 1.59 | 0.73          | 0.69          |
| Scope 2 | 39    | MIRF    | 93.51 | 6.38 | 4.48     | 9.85      | 18.01    | 1.65 | 0.73          | 0.68          |
|        |       | Hml     | 83.89 | 4.28 | 4.54     | 8.93      | 16.97    | 1.58 | 0.72          | 0.69          |
|        |       | MIH2Step| 85.91 | 4.71 | 4.36     | 8.91      | 17.04    | 1.59 | 0.73          | 0.69          |
|        |       | Median  |    |    | 4.92     | 11.23     | 21.34    | 2.34 | 0.55          | 0.64          |
|        |       | LM      | 78.49 | 3.37 | 3.50     | 7.44      | 13.55    | 1.43 | 0.82          | 0.80          |
|        |       | MIP/mm  | 90.07 | 4.70 | 3.51     | 7.44      | 13.60    | 1.44 | 0.82          | 0.80          |
| Scope 1 + 2 | 39 | MIRF    | 95.04 | 6.41 | 3.84     | 8.34      | 14.96    | 1.56 | 0.81          | 0.78          |
|        |       | Hml     | 85.58 | 4.18 | 3.20     | 7.64      | 13.83    | 1.44 | 0.82          | 0.80          |
|        |       | MIH2Step| 88.89 | 4.53 | 3.66     | 7.51      | 13.77    | 1.44 | 0.82          | 0.79          |

RE = relative error (%), PI = Average length of the 95% prediction interval, RMSE = Root mean square error, CR = Coverage Rate (%)

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Figure 4: Empirical results. Relative Error per Industry for the Total data set.

| Industry  | Obs. % | n_{2019} | mean  |
|-----------|--------|----------|-------|
| BscM      | 41.6   | 51       | 13.8  |
| CnsG      | 40.1   | 62       | 11.2  |
| CnsS      | 33.6   | 44       | 10.5  |
| Fnnc      | 36.4   | 78       | 7.9   |
| HltC      | 34.8   | 24       | 10.4  |
| Inds      | 39.0   | 87       | 11.4  |
| Ol&G      | 53.2   | 14       | 14.1  |
| Tchn      | 34.7   | 32       | 9.1   |
| Tlcm      | 59.8   | 11       | 10.2  |
| Utlt      | 59.0   | 20       | 15.0  |

BscM: Basic Materials, CnsG: Consumer Goods, CnsS: Consumer Services, Fnnc: Financials, HltC: Health Care, Inds: Industrials, Ol&G: Oil & Gas, Tchn: Technology, Tlcm: Telecommunications, Utlt: Utilities
5. Discussion

This paper proposed a new way to estimate missing corporate carbon emissions data to account for the potential non-randomness of the observed sample and appropriately reflect the uncertainty of the estimates of the missing values. This paper showed that if data are MNAR, the proposed multiple imputation approaches using Heckman’s model can lead to a more accurate estimation of the missing corporate carbon emissions values. Moreover, reporting the length of the prediction intervals is likely to improve the transparency of the predicted values, while being simple for investors to understand. We have also shown that MI methods can reflect more accurately the uncertainty of the obtained estimates (through a wider prediction interval) than corresponding single imputation methods, and they resulted in a higher coverage rate.

Currently used methods that predict missing emission values, such as a linear model, are typically only based on the disclosed emissions values. Therefore, these methods do not account for the uncertainty of the missing data and tend to overlook potential bias. To address these issues, we decided to derive the required linear prediction model based on an analysis of the data with multiple imputation (MI) methods for MNAR data using Heckman’s model with maximum likelihood (MIHml) and two-step estimation (MIH2Step). To reflect the uncertainty of the predicted values, we proposed to report the corresponding length of the prediction interval.

Our conclusions were drawn by examining different methods and scenarios. In the empirical literature, emissions data are often considered to be missing not at random. However, the non-randomness of the observed sample is not testable from the data and the performance of the proposed methods against MAR and MNAR assumption thus needed to be tested with a simulation study. In the simulation, we implemented four data missingness scenarios, namely MAR, Light MNAR (data-generation based on Heckman’s approach with \( \rho = -0.3 \)), Heavy MNAR (\( \rho = -0.6 \)) and a Non-Heckamn scenario (MNAR mechanism where the probability of observing the data is a function of the emissions value). To compare the performance of the proposed MI methods with other techniques, we also implemented MI based on random forest (MIRF) and predictive mean matching (MIPmm) as well as single imputation (SI) using a linear model (LM) and Heckman’s model with maximum likelihood (Hml). Each of the methods have been tested in terms
of the accuracy of regression coefficients estimation. The resulting prediction models were then evaluated in terms of their prediction accuracy and were also compared with the results from a sector median (Median) estimation, a popular approach used by data providers.

The simulation study has shown that the proposed MIHml and MIH2Step methods appeared to improve the accuracy of parameter estimation if the data were MNAR. The estimates of coefficients obtained with Hml, MIHml and MIH2Step seemed to be unbiased or have significantly lower bias than other methods across all missingness scenarios. MIRF, MIPmm and LM tended to result in biased estimates when data were MNAR. When the MAR mechanism was applied, all MI methods except MIRF performed equally well and their coverage rate was much higher than single imputation methods. This result was anticipated since MI methods include the between-variance when estimating standard errors (i.e., MI methods have larger standard errors than those resulting from single imputation); thus, their confidence intervals reflect the uncertainty of the estimates more accurately.

Moreover, if the data were MNAR, the prediction models based on MIH2Step and MIHml appeared to have a smaller prediction error than other methods. In all the samples and scenarios, Median estimation was the method with the highest RMSE. As expected, MI has a greater length of the prediction interval than SI approaches due to the inclusion of the between-imputation variance. Thus, the coverage rate was higher for MI methods. However, SI Hml performed significantly better in terms of coverage than LM, which showed significant undercoverage in all simulation scenarios and samples. Therefore, neither LM nor Median (currently used by the industry) performed well in the simulation, suggesting that the proposed methods can bring improvements when being applied to corporate emissions estimation.

The methods implemented in this paper are subject to several constraints. We have shown that the relevant literature provides some evidence to support our MNAR assumption for corporate emission data; however, due to its non-testability, a MAR mechanism cannot be ruled out. Moreover, even though it is possible to approximate the distribution of the observed emissions data with a normal distribution, we cannot test Heckman’s assumption about the normality of the error terms in the complete sample since the missing data cannot be observed. Furthermore, finding covariates, which would allow
to satisfy the exclusion restriction for 2-Step estimation, may prove to be difficult in practice.

In conclusion, the proposed Heckman’s model based methods may result in more reliable estimates of missing carbon emissions than currently used techniques. The MI methods more accurately reflect the uncertainty of the estimation process and therefore provide investors with a better understanding of estimates’ quality. The limited results from the empirical study, based on only 10% of the missing sample that was observed in the following year, suggested that multiple imputation methods resulted in a higher coverage rate of the estimates than single imputation methods. Across all the methods, $MIH2Step$ had the lowest RMSE and relatively high coverage rate. Further research based on time-series data (with bigger sample size) should be conducted.
6. Annex

6.1. Data

Table 6: London Stock Exchange Data (2018) Overview

| Name                        | Description                                           | Type    | Details                  |
|-----------------------------|-------------------------------------------------------|---------|--------------------------|
| Carbon Emissions Scope 1    | Log transformed Scope 1 Carbon Emissions (MT CO2 equivalent) | Numeric | Min: 2.31, Mean: 10.95, Max: 19.39, Observed: 39 % |
| Carbon Emissions Scope 2    | Log transformed Scope 2 Carbon Emissions (MT CO2 equivalent) | Numeric | Min: 2.35, Mean: 11.22, Max: 17.58, Observed: 39 % |
| Country                     | Location of the Headquarters                          | Factor  | 51 levels                |
| Region                      | Carbon Region                                         | Factor  | 8 levels                 |
| Market                      | Stage of the Regional Market Development              | Factor  | 5 levels                 |
| IndustryName                | Industry                                              | Factor  | 10 levels                |
| SuperSectorName             | Super-Sector                                          | Factor  | 20 levels                |
| SectorName                  | Sector                                                | Factor  | 40 levels                |
| SubSectorName               | Sub-sector                                            | Factor  | 113 levels               |
| LogRevenue                  | Log Transformed Annual Revenue ($M)                   | Numeric | Min: 11.34, Mean: 21.38, Max: 26.97 |
| FirstActivity               | Time period of Company’s IPO or First Trade Recorded Date | Factor  | 4 levels                 |
| SizeMarker                  | Size category of the company                          | Factor  | L, M, S, U               |

3The first (recorded) trade of the companies have been captured in the database since 1981. The initial public offering (IPO) dates are only recorded for the USA companies and the first trade date is available for the majority of companies. In most cases, the date of the IPO and the first trade is the same, however it is not a rule.
### 6.2. Evaluation Metrics

Table 7: Measure applied for methods performance in the simulation

| Measure                        | Abb. | Definition                                      | Estimate                                                                 |
|--------------------------------|------|------------------------------------------------|--------------------------------------------------------------------------|
| Relative bias (%)             | Rubias | $\frac{\sum_{i=1}^{N} (\hat{\theta}_i - \theta)}{N}$ | $\frac{1}{N} \sum_{i=1}^{N} (\hat{\theta}_i - \theta)^2 100\%$       |
| Root mean squared error       | RMSE | $\sqrt{E\left( (\hat{\theta} - \theta)^2 \right)}$ | $\sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{\theta}_i - \theta)^2}$       |
| Empirical SE                 | $SE_e$ | $\sqrt{\text{Var}(\hat{\theta})}$ | $\sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{\theta}_i - \bar{\theta})^2}$ |
| Average model SE             | $SE_m$ | $\sqrt{E[\text{Var}(\hat{\theta})]}$ | $\sqrt{\frac{1}{N} \sum_{i=1}^{N} \text{Var}(\hat{\theta})}$         |
| Relative error of $SE_m$ (%) | RE$_{SE_m}$ | $(\frac{SE_m}{SE_e} - 1)$ | $(\frac{SE_m}{SE_e} - 1) 100\%$                                        |
| Coverage rate (%)            | CR   | $Pr\left( \hat{\theta}_{\text{low}} \leq \theta \leq \hat{\theta}_{\text{upp}} \right)$ | $\frac{1}{N} \sum_{i=1}^{N} 1 \left( \hat{\theta}_{\text{low},i} \leq \theta \leq \hat{\theta}_{\text{upp},i} \right) 100\%$ |

#### Prediction Accuracy

| Measure                        | Abb. | Definition                                      | Estimate                                                                 |
|--------------------------------|------|------------------------------------------------|--------------------------------------------------------------------------|
| Average Relative Error (%)     | RE   | $\frac{1}{N} \sum_{i=1}^{N} |Y_{ij} - \hat{Y}_{ij}|}{Y_{ij}}$ | $\frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{n_0} \sum_{j=1}^{n_0} |Y_{ij} - \hat{Y}_{ij}| ight) 100\%$       |
| Root mean squared error        | RMSE | $\sqrt{E\left( (\hat{Y} - Y)^2 \right)}$ | $\sqrt{\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{n_0} (\hat{Y}_{ij} - Y_{ij})^2}$ |
| Coverage rate (%)              | CR   | $Pr\left( \hat{Y}_{\text{low},j} \leq Y_j \leq \hat{Y}_{\text{upp},j} \right)$ | $\frac{1}{N} \sum_{i=1}^{N} \left( \frac{1}{n_0} \sum_{j=1}^{n_0} 1 \left( \hat{Y}_{\text{low},ij} \leq Y_{ij} \leq \hat{Y}_{\text{upp},ij} \right) \right) 100\%$ |
| Average prediction interval length | PI  | $\hat{Y}_{\text{upp},j} - \hat{Y}_{\text{low},j}$ | $\frac{1}{N} \sum_{i=1}^{N} (\frac{1}{n_0} \sum_{j=1}^{n_0} \hat{Y}_{\text{upp},ij} - \hat{Y}_{\text{low},ij})$ |

Formulas as presented in [Morris et al., 2019](#).
### 6.3. Imputation Methods

Table 8: Overview of the applied methods and corresponding predictors for each dataset

| Method                            | Abbr. | Imputations | Predictors |
|-----------------------------------|-------|-------------|------------|
| (Sub)Sector Median                | Median | 0           | L YS1      |
|                                  |       |             | M YS1      |
|                                  |       |             | S YS1      |
|                                  |       |             | U YS1      |
|                                  |       |             | Total YS1  |
|                                  |       |             | L YS2      |
|                                  |       |             | M YS2      |
|                                  |       |             | S YS2      |
|                                  |       |             | U YS2      |
|                                  |       |             | Total YS2  |
|                                  |       |             | Total YS1+2|
| Linear Model                     | LM    | 1           | L YS1      |
|                                  |       |             | M YS1      |
|                                  |       |             | S YS1      |
|                                  |       |             | U YS1      |
|                                  |       |             | Total YS1  |
|                                  |       |             | L YS2      |
|                                  |       |             | M YS2      |
|                                  |       |             | S YS2      |
|                                  |       |             | U YS2      |
|                                  |       |             | Total YS2  |
|                                  |       |             | Total YS1+2|
| MI Predictive Mean Matching      | MIPmm | 5           | S YS2      |
|                                  |       |             | U YS2      |
|                                  |       |             | Total YS2  |
|                                  |       |             | Total YS1+2|
| MI Random Forest                 | MIRF  | 5           | S YS2      |
|                                  |       |             | U YS2      |
|                                  |       |             | Total YS2  |
|                                  |       |             | Total YS1+2|
| Heckman’s ML Estimator          | Hml   | 1           | L YS1      |
|                                  |       |             | M YS1      |
|                                  |       |             | S YS1      |
|                                  |       |             | U YS1      |
|                                  |       |             | Total YS1  |
|                                  |       |             | L YS2      |
|                                  |       |             | M YS2      |
|                                  |       |             | S YS2      |
|                                  |       |             | U YS2      |
|                                  |       |             | Total YS2  |
|                                  |       |             | Total YS1+2|
| MI Heckman’s ML Estimator       | MIHml | 1           | L RS1      |
|                                  |       |             | M RS1      |
|                                  |       |             | S RS1      |
|                                  |       |             | U RS1      |
|                                  |       |             | Total RS1  |
|                                  |       |             | L RS2      |
|                                  |       |             | M RS2      |
|                                  |       |             | S RS2      |
|                                  |       |             | U RS2      |
|                                  |       |             | Total RS2  |
|                                  |       |             | Total RS1+2|
| MI Heckman’s Two-Step Estimator | MIH2Step | 1         | L RSI      |
|                                  |       |             | M RSI      |
|                                  |       |             | S RSI      |
|                                  |       |             | U RSI      |
|                                  |       |             | Total RSI  |
|                                  |       |             | L RSI      |
|                                  |       |             | M RSI      |
|                                  |       |             | S RSI      |
|                                  |       |             | U RSI      |
|                                  |       |             | Total RSI  |
|                                  |       |             | Total RSI+2|

Median was used only for prediction (not imputation). Otherwise, same set of predictors was used for imputation and prediction model. Each model included an intercept. $Y_{S1}$ Scope 1 outcome, $Y_{S2}$ Scope 2 outcome, $R_{S1}$ Scope 1 selection, $R_{S2}$ Scope 2 selection. Variables: r selected for simulation, e selected for Empirical study, b selected for both.
### 6.4. Simulation Prediction Accuracy: Total Scope 2

Table 9: *Total*: Simulation results for the predicted missing Scope 2 emissions values.

| Method          | σ² | RE | RMSE | CR | PI | RE | RMSE | CR | PI | RE | RMSE | CR | PI |
|-----------------|----|----|------|----|----|----|------|----|----|----|------|----|----|
| MAR             | 2.5|    |      |    |    |    |      |    |    |    |      |    |    |
| lm              | 129| Median 21.38 | 2.25 | - | - | 19.62 | 2.15 | - | - | 18.18 | 2.07 | - | - |
| Light MNAR      | 129| LM 8.74 | 1.00 | 87.68 | 3.08 | 9.06 | 1.10 | 83.21 | 3.05 | 11.21 | 1.37 | 69.54 | 2.95 |
|                | 129| MIIF 9.58 | 1.05 | 95.16 | 3.95 | 9.03 | 1.10 | 92.12 | 3.87 | 11.15 | 1.30 | 80.49 | 3.59 |
|                | 129| He.heckman 8.75 | 1.00 | 95.08 | 3.94 | 8.99 | 1.08 | 95.75 | 3.85 | 10.24 | 1.29 | 93.76 | 4.69 |
|                | 129| MIRF 8.73 | 1.00 | 95.39 | 3.99 | 8.48 | 1.00 | 95.60 | 4.02 | 8.16 | 0.98 | 96.29 | 4.12 |
|                | 129| MIHml 8.73 | 1.00 | 95.41 | 4.00 | 8.49 | 1.00 | 95.50 | 4.00 | 8.16 | 0.98 | 95.67 | 4.00 |
|                | 129| MIH2Step 8.76 | 1.00 | 95.41 | 4.00 | 8.49 | 1.00 | 95.50 | 4.00 | 8.16 | 0.98 | 95.67 | 4.00 |
| Medium          | 2.5| LM 14.85 | 1.58 | 77.98 | 3.88 | 14.72 | 1.75 | 72.60 | 3.84 | 17.53 | 2.16 | 57.04 | 3.71 |
|                | 129| MIIF 14.89 | 1.58 | 95.11 | 6.24 | 14.73 | 1.74 | 92.03 | 6.10 | 17.51 | 2.16 | 80.14 | 5.66 |
|                | 129| He.heckman 14.81 | 1.58 | 92.21 | 5.58 | 14.37 | 1.58 | 92.41 | 5.62 | 13.75 | 1.57 | 86.78 | 4.72 |
|                | 129| MIRF 14.86 | 1.58 | 95.78 | 4.64 | 14.38 | 1.58 | 86.06 | 4.67 | 13.76 | 1.57 | 86.78 | 4.72 |
|                | 129| MIHml 14.81 | 1.58 | 95.41 | 6.32 | 14.39 | 1.58 | 95.46 | 6.32 | 13.72 | 1.56 | 95.61 | 6.31 |
|                | 129| MIH2Step 14.88 | 1.58 | 95.41 | 6.32 | 14.39 | 1.58 | 95.46 | 6.32 | 13.72 | 1.56 | 95.61 | 6.31 |
| Large           | 4  | Median 26.20 | 2.85 | - | - | 24.88 | 2.44 | - | - | 24.18 | 2.38 | - | - |
|                | 129| LM 15.79 | 1.61 | 96.48 | 6.80 | 14.80 | 1.70 | 95.26 | 6.75 | 16.60 | 2.06 | 88.34 | 6.43 |
|                | 129| MIIF 14.85 | 1.58 | 95.78 | 4.64 | 14.38 | 1.58 | 86.06 | 4.67 | 13.76 | 1.57 | 86.78 | 4.72 |
|                | 129| He.heckman 14.81 | 1.58 | 92.21 | 5.58 | 14.37 | 1.58 | 92.41 | 5.62 | 13.75 | 1.57 | 86.78 | 4.72 |
|                | 129| MIRF 14.86 | 1.58 | 95.78 | 4.64 | 14.38 | 1.58 | 86.06 | 4.67 | 13.76 | 1.57 | 86.78 | 4.72 |
|                | 129| MIHml 14.81 | 1.58 | 95.41 | 6.32 | 14.39 | 1.58 | 95.46 | 6.32 | 13.72 | 1.56 | 95.61 | 6.31 |
|                | 129| MIH2Step 14.88 | 1.58 | 95.41 | 6.32 | 14.39 | 1.58 | 95.46 | 6.32 | 13.72 | 1.56 | 95.61 | 6.31 |

RE = Average relative error for all Ymiss (%), PI = Average length of the prediction interval, RMSE = Root mean square error, CR = Coverage rate (%)
6.5. Simulation Parameter Estimation: Scope 2 Total

Figure 5: Total Scope 2: Boxplot over simulations over $\hat{\beta}_{\text{Revenue}}$. Red dotted lines denotes true value of the coefficient.
### 6.6. Simulation Parameter Estimation: Sub-sets

#### Table 10: L Scope 1: Simulation results for $\beta_{\text{Revenue}} = 0.875$ estimates

| Method       | $S^2 = 1$ | $S^2 = 2.5$ | $S^2 = 4$ |
|--------------|-----------|-------------|-----------|
| Mean Rbias   | $S_E^m$, $S_E$, $S_{RE}$, $S_{RMSE}$ | Mean Rbias   | $S_E^m$, $S_E$, $S_{RE}$, $S_{RMSE}$ | Mean Rbias   | $S_E^m$, $S_E$, $S_{RE}$, $S_{RMSE}$ |
| Light       |           |             |           |
| MAR         | 0.80      | 0.16        | 0.15      |
| MIHF        | 0.87      | 0.19        | 0.18      |
| Bias        | 0.87      | 0.23        | 0.22      |
| MIH0        | 0.88      | 0.27        | 0.26      |
| MIH0.5      | 0.86      | 0.21        | 0.20      |
| Mean Rbias  | 0.87      | 0.19        | 0.18      |
| MNAR        | 0.87      | 0.19        | 0.18      |
| MIHF        | 0.87      | 0.19        | 0.18      |
| Bias        | 0.87      | 0.19        | 0.18      |
| MIH0        | 0.88      | 0.19        | 0.18      |
| MIH0.5      | 0.86      | 0.19        | 0.18      |
| Mean Rbias  | 0.87      | 0.19        | 0.18      |
| MIH2Step    | 0.87      | 0.19        | 0.18      |
| Bias        | 0.87      | 0.19        | 0.18      |
| MIH0        | 0.88      | 0.19        | 0.18      |
| MIH0.5      | 0.86      | 0.19        | 0.18      |

#### Table 11: L Scope 1: Median relative bias (%) for variable coefficients estimates across all the categories of selected predictors

| Sector (40 categories) | Region (8 categories) | First Activity (4 categories) |
|-------------------------|-----------------------|-----------------------------|
| MAR                     | Light                 | Heavy                       |
| MNAR                    | Non-Heckman           | MNAR                        |
| Non-Heckman             |                       |                             |

#### Mean = Average estimate $\beta_{\text{Revenue}}$ (rounded to 2 digits), Rbias = Average relative bias (%), $S_E^m$ = Root mean square of the estimated standard errors $\times 10^2$, $S_E =$ Empirical standard error $\times 10^2$, CR = Coverage rate (based on 95% confidence interval), $RE_{SE} =$ relative error of $S_E^m$(%), RMSE = Root mean square error $\times 10^2$.
Table 12: L Scope 1: Median relative bias (% Rbias) for variable coefficients estimates across all the categories of selected predictors

\[ \sigma^2 = 2.5 \]

|                | Sector (40 categories) | Region (8 categories) | First Activity (4 categories) |
|----------------|------------------------|-----------------------|-------------------------------|
|                | MAR Light Heavy Non-MNAR | MAR Light Heavy Non-MNAR | MAR Light Heavy Non-MNAR |
| LM             | 14.32 16.59 16.32 -13.00 | -2.95 2.73 8.93 -3.22 | 2.53 25.46 47.22 -13.63 |
| MIPmm          | 13.87 16.16 15.61 -12.88 | -4.29 -9.34 1.44 -1.78 | 2.93 27.15 48.95 -17.47 |
| MIRF           | 4.33 5.97 4.66 -22.90 | -28.30 -36.16 -47.68 -19.20 | -16.41 -14.83 32.97 -28.50 |
| Hml            | 14.41 16.07 15.29 -12.73 | 2.52 3.60 -2.10 4.43 | -5.18 -5.85 -2.69 -8.66 |
| MIHml          | 14.48 16.44 15.89 -11.30 | -2.90 -5.32 -3.85 -3.60 | 2.67 2.14 3.11 -11.75 |
| MIH2Step       | 14.69 16.13 15.68 -9.20 | -4.17 -3.60 -2.72 2.70 | 3.31 2.71 2.40 -7.10 |

Table 13: L Scope 1: Median relative bias (% Rbias) for variable coefficients estimates across all the categories of selected predictors

\[ \sigma^2 = 4 \]

|                | Sector (40 categories) | Region (8 categories) | First Activity (4 categories) |
|----------------|------------------------|-----------------------|-------------------------------|
|                | MAR Light Heavy Non-MNAR | MAR Light Heavy Non-MNAR | MAR Light Heavy Non-MNAR |
| LM             | 14.61 17.41 16.78 -14.31 | -2.64 3.04 12.79 -6.68 | 2.83 31.77 59.13 -22.21 |
| MIPmm          | 14.58 16.82 15.95 -14.10 | -7.85 -10.65 4.66 -9.95 | 3.36 33.62 60.74 -22.52 |
| MIRF           | 4.22 5.85 4.40 -24.56 | -30.62 -37.63 -54.48 -23.76 | -16.18 -5.67 44.40 -54.83 |
| Hml            | 14.66 17.16 15.61 -12.38 | 3.22 -0.96 -2.62 -7.65 | -6.50 -4.91 0.59 -10.86 |
| MIHml          | 14.83 16.74 16.06 -10.74 | -2.17 -3.98 -5.59 -3.98 | 2.94 3.34 3.01 -17.15 |
| MIH2Step       | 14.34 16.78 16.13 -8.80 | -4.97 -3.17 -2.54 4.96 | 3.90 2.61 3.00 -9.22 |

**Comment:** For Sector variable, only in Non-Heckman scenario, when \( \sigma^2 \neq 1 \) MIHml, Hml and MIH2Step had lower median relative bias than other methods. For Region variable, MIHml and MIH2step tended to have lower lower median relative bias than MIRF and LM in Heavy MNAR and Non-Heckman scenario. For FirstActivity variable, in Light and Heavy MNAR scenario Hml, MIHml and MIH2Step tended to perform better than LM, MIPmm and MIRF.

**Comment:** For Sector variable, Hml, MIHml and MIH2Step had lower median relative bias than other methods across all MNAR scenarios and values of \( \sigma^2 \). For Market, MIHml and MIH2step performed better than other methods across all the MNAR scenarios and values of \( \sigma^2 \). MIH2Step had lower median relative bias than other methods in Heavy MNAR and Non-Heckman scenarios.
### Table 14: M Scope 1: Simulation results for $\beta_{Revenue} = 1.077$ estimates

| Method          | Mean Rbias | $SE_{\beta}$ | $SE_{RE}$ | CR | RMSE |
|-----------------|------------|--------------|-----------|----|------|
| **MAR**         |            |              |           |    |      |
| MAR             | 1.04       | 3.45         | 3.33      | 52.7 | 5.27 |
| MIIB            | 0.08       | -16.31       | 5.65      | 17.74 | 19.09 |
| Hail            | 1.07       | -0.67        | 2.23      | 9.93  | 54.40 |
| MIIBa           | 1.06       | 2.60         | 4.99      | 3.05  | 92.00 |
| MHIBb           | 1.07       | -0.67        | 4.46      | 9.35  | 92.20 |
| **Light**       |            |              |           |    |      |
| Light           | 1.08       | 2.60         | 3.18      | 7.29  | 54.40 |
| MIINAR          | 0.93       | -16.37       | 5.87      | 13.71 | 36.40 |
| Hail            | 1.07       | -0.67        | 2.26      | 8.10  | 59.80 |
| MIIBa           | 1.06       | 2.40         | 4.36      | 4.11  | 92.20 |
| MHIBb           | 1.08       | 2.60         | 4.32      | 7.91  | 92.80 |
| **Heavy**       |            |              |           |    |      |
| Heavy           | 1.13       | 4.03         | 3.02      | 7.76  | 60.60 |
| MIINAR          | 0.98       | -9.02        | 2.99      | 5.49  | 12.40 |
| Hail            | 1.07       | -0.67        | 2.32      | 7.71  | 54.60 |
| MIIBa           | 1.08       | 2.60         | 4.31      | 4.10  | 92.20 |
| MHIBb           | 1.08       | 2.60         | 4.29      | 7.22  | 92.80 |
| **Non-Heckman** |            |              |           |    |      |
| Non-Heckman     | 0.98       | -9.02        | 2.99      | 5.49  | 12.40 |
| MIINAR          | 0.98       | -16.37       | 5.87      | 13.71 | 36.40 |
| Hail            | 1.02       | -5.31        | 2.52      | 14.49 | 60.00 |
| MIIBa           | 1.08       | 2.60         | 4.30      | 4.09  | 92.20 |
| MIH2Step        |          |              |           |    |      |
| MIH2Step        | 0.99       | -8.10        | 2.99      | 5.49  | 12.40 |
| **LM**          |            |              |           |    |      |
| LM              | 0.99       | -9.02        | 2.99      | 5.49  | 12.40 |
| MIINAR          | 0.98       | -16.37       | 5.87      | 13.71 | 36.40 |
| Hail            | 1.02       | -5.31        | 2.52      | 14.49 | 60.00 |
| MIIBa           | 1.09       | 1.19         | 6.53      | 9.81  | 40.40 |
| MIH2Step        |          |              |           |    |      |
| MIH2Step        | 0.99       | -8.10        | 2.99      | 5.49  | 12.40 |

Mean = Average estimate $\beta_{Revenue}$ (rounded to 2 digits), Rbias = Average relative bias (%), $SE_m$ = Root mean square of the estimated standard errors $\times 10^2$, $SE_e$ = Empirical standard error $\times 10^2$, CR = Coverage rate (based on 95% confidence interval), $RE_{SE}$ = relative error of $SE_m$(%), RMSE = Root mean square error $\times 10^2$. 

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Table 15: $M$: Median relative bias ($\%$ Rbias) for estimated coefficients across all categories

\[ \sigma^2\varepsilon = 1 \]

| Method | Sector (39 categories) | Market (4 categories) |
|--------|------------------------|-----------------------|
|        | MAR Light Heavy Non-   | MAR Light Heavy Non-   |
|        | MNAR MNAR Heckman      | MNAR MNAR Heckman      |
| LM     | 1.40 1.61 2.12 1.00    | 0.76 -8.88 -17.84 -7.45 |
| MIPmm  | 0.00 1.10 1.82 1.31    | -3.71 -13.50 -23.25 -7.10 |
| MIRF   | -16.00 -15.37 -13.70 -11.68 | -40.34 -46.67 -52.77 -32.52 |
| Hml    | 0.36 0.26 0.96 0.29    | 1.20 1.04 0.46 -5.16   |
| MIHml  | 1.61 1.37 1.75 0.80    | 0.76 -0.38 -0.52 -4.18  |
| MIH2Step | 1.17 1.03 1.69 0.90  | -0.79 -0.81 -2.42 -7.49 |

\[ \sigma^2\varepsilon = 2.5 \]

| Method | Sector (39 categories) | Market (4 categories) |
|--------|------------------------|-----------------------|
|        | MAR Light Heavy Non-   | MAR Light Heavy Non-   |
|        | MNAR MNAR Heckman      | MNAR MNAR Heckman      |
| LM     | 1.37 2.13 3.20 2.82    | 1.04 -14.09 -28.01 -15.55 |
| MIPmm  | 0.54 0.67 2.35 2.79    | -3.40 -18.99 -33.53 -14.20 |
| MIRF   | -15.38 -14.07 -10.37 -10.68 | -38.11 -47.90 -54.56 -37.88 |
| Hml    | 0.32 0.01 1.34 0.59    | 2.47 1.17 0.91 -10.71   |
| MIHml  | 1.09 0.72 1.38 1.43    | 1.10 0.22 -0.95 -7.99    |
| MIH2Step | 0.51 0.30 1.37 1.93  | -1.34 -2.19 -4.68 -11.44 |

\[ \sigma^2\varepsilon = 4 \]

| Method | Sector (39 categories) | Market (4 categories) |
|--------|------------------------|-----------------------|
|        | MAR Light Heavy Non-   | MAR Light Heavy Non-   |
|        | MNAR MNAR Heckman      | MNAR MNAR Heckman      |
| LM     | 0.90 2.38 3.48 3.83    | 1.24 -18.32 -34.98 -22.44 |
| MIPmm  | 0.38 1.35 2.84 3.62    | -2.85 -23.33 -40.05 -21.20 |
| MIRF   | -15.04 -12.84 -9.72 -11.02 | -36.03 -48.47 -56.28 -44.12 |
| Hml    | 0.46 0.52 1.01 1.17    | 5.86 2.30 1.48 -12.62   |
| MIHml  | 0.78 0.86 1.59 1.19    | 0.32 -1.09 -0.58 -11.61  |
| MIH2Step | 0.47 0.59 1.19 2.95  | -1.73 -2.18 -4.45 -15.83 |

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Table 16: Simulation results for $\beta_{Revenue} = 1.165$ estimates

| Method | Mean $\hat{\beta}_{Revenue}$ | SE $\hat{\beta}_{Revenue}$ | RSE $\hat{\beta}_{Revenue}$ | CR | RMSE $\hat{\beta}_{Revenue}$ |
|--------|-------------------------------|-----------------------------|-----------------------------|----|-----------------------------|
| MIPH   | 1.02 -10.77 5.09       | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 |
| MIRF   | 0.89 -21.64 6.00       | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 |
| BCE    | 0.89 -21.64 6.00       | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 |
| Non-   | MIPH   | 1.02 -10.77 5.09       | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 |
| MIRF   | 0.89 -21.64 6.00       | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 |
| BCE    | 0.89 -21.64 6.00       | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 | 0.00 -22.74 5.71 |

Mean = Average estimate $\beta_{Revenue}$ (rounded to 2 digits), Rbias = Average relative bias (%), $SE_{m}$ = Root mean square of the estimated standard errors $\times 10^2$, $SE_{\epsilon}$ = Empirical standard error $\times 10^2$, CR = Coverage rate (based on 95% confidence interval), $RE_{SE}$ = relative error of $SE_{m}$(%), RMSE = Root mean square error $\times 10^2$. 

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Table 17: $S$: Median relative bias ($\%$ Rbias) for estimated coefficients across all categories

| Variable | Sector ($39$ categories) | FirstActivity ($4$ categories) |
|----------|---------------------------|--------------------------------|
|          | MAR Light Heavy Non-MNAR MNAR MNAR Heckman | MAR Light Heavy Non-MNAR MNAR MNAR Heckman |
| Method   | LM | MIPmm | MIRF | Hml | MIHml | MIH2Step | LM | MIPmm | MIRF | Hml | MIHml | MIH2Step |
| $\sigma_\varepsilon^2 = 1$ | | | | | | | | | | | | |
| LM       | -22.49 | 0.62 | 1.29 | 0.06 | -22.41 | -4.71 | -7.80 | -12.15 | | | | | |
| MIPmm    | -23.24 | 0.02 | -0.14 | 0.11 | -23.71 | -7.64 | -10.38 | -12.77 | | | | | |
| MIRF     | -21.84 | 0.19 | -1.16 | -1.13 | -15.91 | 8.26 | 7.19 | -0.73 | | | | | |
| Hml      | -21.99 | 0.59 | 0.38 | -0.22 | -17.52 | -0.91 | -1.06 | -5.56 | | | | | |
| MIHml    | -22.09 | -0.15 | -0.20 | -0.11 | -15.79 | -0.12 | -0.55 | -4.99 | | | | | |
| MIH2Step | | | | | | | | | | | | | |
| $\sigma_\varepsilon^2 = 2.5$ | | | | | | | | | | | | | |
| LM       | 0.15 | 1.34 | 2.39 | -0.25 | -2.67 | -8.36 | -12.18 | -24.73 | | | | | |
| MIPmm    | -0.21 | 0.22 | 0.65 | -0.26 | -5.29 | -10.42 | -15.05 | -24.77 | | | | | |
| MIRF     | -38.08 | -37.36 | -35.94 | -44.64 | -20.11 | -48.88 | -51.98 | -34.22 | | | | | |
| Hml      | -1.38 | 2.08 | 1.98 | -1.57 | 8.87 | 6.93 | 9.30 | -15.24 | | | | | |
| MIHml    | 0.78 | 0.60 | 0.68 | -1.00 | -2.25 | -3.69 | -3.17 | -11.36 | | | | | |
| MIH2Step | -0.23 | 1.43 | -0.01 | -2.17 | -0.98 | -1.28 | -0.01 | -16.33 | | | | | |
| $\sigma_\varepsilon^2 = 4$ | | | | | | | | | | | | | |
| LM       | 0.18 | 2.17 | 2.95 | -0.60 | -3.37 | -10.57 | -15.34 | -33.54 | | | | | |
| MIPmm    | -1.00 | 0.32 | 1.17 | -2.21 | -5.85 | -13.66 | -17.24 | -31.21 | | | | | |
| MIRF     | -37.48 | -35.27 | -35.39 | -39.94 | -18.15 | -39.24 | -51.84 | -38.80 | | | | | |
| Hml      | 1.22 | 3.36 | 1.96 | -3.40 | 9.11 | 12.63 | 8.01 | -15.15 | | | | | |
| MIHml    | 0.54 | 0.62 | 0.32 | -2.53 | -2.42 | -2.61 | -2.50 | -18.65 | | | | | |
| MIH2Step | -0.36 | 0.32 | 0.99 | -1.40 | -1.22 | -1.26 | -1.95 | -24.82 | | | | | |

**Comment:** For Sector variable, MIHml and MIH2Step tended to have lower median relative bias than other methods except MIPmm in Light MNAR and Heavy MNAR scenario. For Non-Heckman scenario, LM does performed better than all the other methods. For the FirstActivity variable, MIHStep2 and MIHml had lower median relative bias than other methods under Light MNAR and Heavy MNAR scenario. In the Non-Heckman scenario, Hml, MIHml and MIH2Step had lower relative biased than LM, MIPmm and MIRF across all values of $\sigma_\varepsilon^2$. 
Table 18: $U$ Scope 1: Simulation results for $\beta_{\text{Revenue}} = 0.837$ estimates

| Methods | Mean | Rbias | $\sigma_m$ | $\sigma_e$ | $\sigma_{RE}$ | CR | RMSE |
|---------|------|-------|-----------|-----------|-------------|----|------|
| MAR     | 0.84 | 0.83  | 0.83  | 0.83  | 0.83  | 0.83 | 0.83 |
| MIPmm   | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| MIRF    | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| Hml     | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| MIHml   | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| MIH2Step| 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| LM      | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| Light   | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| MNAR    | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| Heavy   | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| MIH2Step| 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| LM      | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| Non-    | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |
| Heckman | 0.84 | 0.84  | 0.84  | 0.84  | 0.84  | 0.84 | 0.84 |

Mean = Average estimate $\hat{\beta}_{\text{Revenue}}$ (rounded to 2 digits), Rbias = Average relative bias (%), $SE_m$ = Root mean square of the estimated standard errors $\times 10^2$, $SE_e$ = Empirical standard error $\times 10^2$, CR = Coverage rate (based on 95% confidence interval), $RE_{SE}$ = relative error of $SE_m$(%), RMSE = Root mean square $\times 10^2$. 

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Table 19: Median relative bias (% Rbias) for estimated coefficients across all categories

| Sector (32 categories) | Method | MAR | Light | Heavy | Non-MNAR | MNAR | Heckman |
|------------------------|--------|-----|-------|-------|----------|------|---------|
| Variable               |        |     |       |       |          |      |         |
| $\sigma^2_\varepsilon = 1$ |        |     |       |       |          |      |         |
| LM                     |        | 0.74| -0.29 | -1.71 | -2.17    |      |         |
| MIPmm                  |        | -1.07| -1.28 | -4.06 | -8.58    |      |         |
| MIRF                   |        | -59.05| -59.18 | -61.41 | -54.64  |      |         |
| Hml                    |        | 0.49 | 0.79  | 0.09  | -0.94    |      |         |
| MIHml                  |        | 0.43 | 0.78  | 0.51  | -0.62    |      |         |
| MIH2Step               |        | -2.14| -2.64 | -0.88 | -2.41    |      |         |
| $\sigma^2_\varepsilon = 2.5$ |        |     |       |       |          |      |         |
| LM                     |        | 0.69 | -0.31 | -4.31 | -2.91    |      |         |
| MIPmm                  |        | -3.07| -3.22 | -4.29 | -6.66    |      |         |
| MIRF                   |        | -59.67| -57.71 | -60.11 | -52.69  |      |         |
| Hml                    |        | 2.40 | 2.71  | 0.77  | -0.39    |      |         |
| MIHml                  |        | 0.52 | 0.57  | 0.37  | -1.69    |      |         |
| MIH2Step               |        | -2.73| -1.68 | -0.93 | -3.60    |      |         |
| $\sigma^2_\varepsilon = 4$ |        |     |       |       |          |      |         |
| LM                     |        | 0.51 | -0.88 | -3.78 | -3.84    |      |         |
| MIPmm                  |        | -4.13| -5.02 | -7.40 | -8.35    |      |         |
| MIRF                   |        | -59.91| -58.60 | -62.25 | -42.96  |      |         |
| Hml                    |        | 2.43 | 4.77  | 1.57  | -1.00    |      |         |
| MIHml                  |        | 0.75 | 0.53  | 0.73  | -2.44    |      |         |
| MIH2Step               |        | -3.41| -1.92 | 0.17  | -5.94    |      |         |

**Comment:** For Sector variable, Hml, MIHml and MIH2Step performed better than other methods under Heavy MNAR scenario across all values of $\sigma^2_\varepsilon$. Hml and MIHml performed better than other methods in Non-Heckman scenario.
Figure 6: Boxplot over simulations over $\hat{\beta}_{Revenue}$. Red dotted lines denotes true value of the coefficient.

(a) $L$

(b) $M$

\begin{align*}
\sigma^2 &= 1 \\
\sigma^2 &= 2.5 \\
\sigma^2 &= 4
\end{align*}
Figure 9: Boxplot over simulations over $\hat{\beta}_{\text{Revenue}}$. Red dotted lines denotes true value of the coefficient.

(a) S

(b) U

$\sigma^2 = 1$

$\sigma^2 = 2.5$

$\sigma^2 = 4$
6.7. Simulation study results: prediction accuracy

Table 20: \(L\): Simulation results for the predicted missing emissions values.

| \(\sigma^2\) Method | MAR RE RMSE CR PI | Light MNAR RE RMSE CR PI | Heavy MNAR RE RMSE CR PI | NonHeckman RE RMSE CR PI |
|----------------------|-------------------|--------------------------|--------------------------|--------------------------|
| Median               | 27.21 2.18 - -   | 24.44 2.12 - -           | 21.27 2.11 - -           | 16.24 2.28 - -           |
| LM                  | 12.10 1.07 91.30 3.63 | 11.38 1.15 88.48 3.62     | 12.68 1.35 80.12 3.52     | 8.87 1.16 90.45 3.87     |
| MPIpnm              | 12.23 1.07 94.23 4.11 | 11.37 1.15 92.06 4.04     | 12.54 1.34 84.63 3.84     | 8.88 1.16 90.45 3.87     |
| 1 MIRF              | 13.14 1.11 97.61 5.17 | 11.60 1.15 97.42 5.17     | 12.09 1.31 95.39 5.07     | 9.35 1.24 94.55 4.67     |
| Hnl                 | 12.09 1.07 93.88 4.03 | 11.11 1.10 93.28 4.02     | 10.82 1.15 92.15 4.04     | 8.67 1.13 92.66 4.05     |
| MIHnl               | 12.05 1.07 95.09 4.29 | 11.12 1.10 94.36 4.25     | 10.89 1.16 93.16 4.23     | 8.74 1.14 94.42 4.36     |
| MIH2Step            | 12.14 1.07 95.08 4.28 | 11.11 1.09 94.64 4.28     | 10.77 1.14 93.54 4.26     | 8.72 1.14 97.21 5.33     |
| Median.1            | 45.01 2.33 - -   | 36.75 2.46 - -           | 29.31 2.52 - -           | 20.74 2.92 - -           |
| LM                  | 23.43 1.63 83.93 4.56 | 20.56 1.75 80.25 4.53     | 19.40 2.08 68.29 4.40     | 14.88 2.04 68.21 4.31     |
| MPIpnm              | 23.75 1.63 94.91 6.40 | 20.71 1.74 92.85 6.30     | 19.37 2.06 84.96 5.96     | 14.91 2.04 84.31 5.81     |
| 2.5 MIRF            | 25.50 1.65 96.80 7.14 | 21.63 1.74 95.96 7.12     | 19.24 2.03 91.61 6.87     | 15.35 2.11 87.08 6.34     |
| Hnl                 | 23.54 1.63 86.69 4.89 | 21.02 1.67 85.81 4.89     | 17.68 1.78 82.80 4.88     | 13.90 1.91 78.55 4.85     |
| MIHml               | 23.36 1.63 94.42 6.27 | 20.99 1.67 93.68 6.24     | 17.74 1.79 91.66 6.18     | 14.20 1.95 88.75 6.18     |
| MIH2Step            | 23.48 1.63 93.80 6.69 | 21.12 1.66 95.42 6.69     | 17.59 1.74 94.35 6.66     | 13.48 1.86 97.15 8.88     |
| Median.2            | 57.77 2.83 - -   | 48.74 2.93 - -           | 40.94 3.02 - -           | 24.46 3.49 - -           |
| LM                  | 35.41 2.04 79.19 5.13 | 31.28 2.19 75.10 5.08     | 24.74 2.61 62.08 4.94     | 19.51 2.74 55.15 4.73     |
| MPIpnm              | 35.81 2.04 95.14 8.07 | 31.66 2.18 93.06 7.94     | 24.86 2.60 85.03 7.50     | 19.55 2.74 79.37 7.07     |
| 4 MIRF              | 38.05 2.06 96.42 8.66 | 34.09 2.17 95.29 8.61     | 25.35 2.56 89.98 8.27     | 19.93 2.80 81.57 7.50     |
| Hnl                 | 35.53 2.04 83.09 5.43 | 33.44 2.09 80.45 5.42     | 24.45 2.24 76.52 5.40     | 17.56 2.50 68.46 5.31     |
| MIHml               | 35.35 2.04 94.02 7.73 | 33.31 2.09 93.14 7.66     | 24.48 2.25 90.69 7.56     | 17.89 2.54 85.12 7.37     |
| MIH2Step            | 35.44 2.04 96.01 8.44 | 33.84 2.07 95.62 8.44     | 24.52 2.19 94.36 8.36     | 16.90 2.42 97.29 11.78    |
Table 21: M: Simulation results for the predicted missing emissions values.

| Method        | RE  | RMSE | CR  | PI  | RE  | RMSE | CR  | PI  | RE  | RMSE | CR  | PI  |
|---------------|-----|------|-----|-----|-----|------|-----|-----|-----|------|-----|-----|
| **σ²**        | RE  | RMSE | CR  | PI  | RE  | RMSE | CR  | PI  | RE  | RMSE | CR  | PI  |
| Median        | 48.89 | 2.03 | -   | -   | 29.49 | 1.98 | -   | -   | 36.60 | 1.90 | -   | -   |
| LM            | 15.39 | 1.00 | 90.94 | 3.38 | 12.32 | 1.08 | 87.80 | 3.34 | 13.75 | 1.30 | 77.66 | 3.24 |
| MIPnum        | 16.44 | 1.00 | 95.63 | 4.05 | 12.36 | 1.07 | 93.56 | 3.97 | 13.43 | 1.28 | 85.44 | 3.72 |
| MIRF          | 22.25 | 1.07 | 96.71 | 5.36 | 13.68 | 1.06 | 98.81 | 5.35 | 12.95 | 1.19 | 97.54 | 5.21 |
| Hml           | 15.62 | 1.00 | 95.31 | 3.97 | 12.15 | 1.00 | 95.42 | 3.99 | 11.19 | 1.00 | 95.65 | 4.05 |
| MIHml         | 15.31 | 1.00 | 96.06 | 4.12 | 12.10 | 1.00 | 95.95 | 4.14 | 11.22 | 1.01 | 96.16 | 4.22 |
| MIH2Step      | 15.49 | 1.00 | 96.12 | 4.14 | 12.11 | 1.01 | 95.82 | 4.12 | 11.27 | 1.02 | 95.15 | 4.07 |
| Median        | 50.28 | 2.39 | -   | -   | 35.12 | 2.65 | -   | -   | 35.25 | 2.83 | -   | -   |
| LM            | 26.29 | 1.58 | 82.12 | 4.25 | 23.34 | 1.71 | 77.90 | 4.21 | 21.85 | 2.05 | 70.63 | 4.07 |
| MIPnum        | 26.77 | 1.58 | 95.49 | 6.35 | 23.77 | 1.70 | 93.26 | 6.22 | 21.41 | 2.03 | 84.72 | 5.81 |
| MIRF          | 30.94 | 1.63 | 97.36 | 7.25 | 26.54 | 1.66 | 96.99 | 7.18 | 21.28 | 1.90 | 93.52 | 6.91 |
| Hml           | 26.50 | 1.58 | 86.82 | 4.77 | 24.65 | 1.59 | 86.40 | 4.78 | 19.39 | 1.61 | 86.56 | 4.83 |
| MIHml         | 26.20 | 1.58 | 94.02 | 5.96 | 24.48 | 1.59 | 93.80 | 5.96 | 19.38 | 1.63 | 93.39 | 6.01 |
| MIH2Step      | 26.19 | 1.58 | 96.12 | 6.54 | 24.48 | 1.59 | 95.79 | 6.50 | 19.31 | 1.63 | 94.92 | 6.40 |
| Median        | 292.60 | 2.71 | -   | -   | 163.42 | 2.68 | -   | -   | 165.15 | 2.81 | -   | -   |
| LM            | 172.17 | 2.00 | 76.81 | 4.78 | 133.42 | 2.16 | 72.31 | 4.73 | 122.00 | 2.59 | 58.74 | 4.57 |
| MIPnum        | 179.01 | 2.00 | 95.46 | 8.01 | 143.16 | 2.15 | 93.13 | 7.84 | 131.04 | 2.57 | 84.48 | 7.33 |
| MIRF          | 214.96 | 2.04 | 96.77 | 8.73 | 183.31 | 2.10 | 96.03 | 8.64 | 171.24 | 2.42 | 91.55 | 8.25 |
| Hml           | 173.29 | 2.00 | 81.15 | 5.26 | 136.93 | 2.01 | 80.96 | 5.27 | 130.52 | 2.06 | 80.12 | 5.31 |
| MIHml         | 170.73 | 2.00 | 93.01 | 7.26 | 136.61 | 2.02 | 92.64 | 7.25 | 129.39 | 2.07 | 91.97 | 7.28 |
| MIH2Step      | 170.44 | 2.00 | 96.12 | 8.27 | 136.59 | 2.02 | 95.73 | 8.21 | 130.25 | 2.06 | 94.94 | 8.10 |

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Table 22: Simulation results for the predicted missing emissions values.

| $\sigma^2$ | Method    | MAR        | Light MNAR | Heavy MNAR | Non Heckman |
|------------|-----------|------------|------------|------------|-------------|
|            | RE RMSE CR PI | RE RMSE CR PI | RE RMSE CR PI | RE RMSE CR PI |
| 1          | Median    | 22.03 2.19 - | 21.34 2.11 - | 21.34 2.11 - | 18.90 2.07 - |
|            | LM        | 8.64 1.00 82.64 2.72 | 8.99 1.07 79.39 2.70 | 10.20 1.24 70.12 2.64 | 8.95 1.22 70.58 2.62 |
|            | MIIPmm    | 8.79 1.00 95.54 4.07 | 8.73 1.06 94.12 4.02 | 9.81 1.22 88.73 3.88 | 9.00 1.23 87.13 3.77 |
|            | MIIRF     | 12.67 1.28 98.92 6.76 | 11.47 1.23 99.33 6.80 | 10.68 1.27 99.49 6.79 | 10.78 1.53 97.69 6.87 |
|            | MIRL      | 8.63 1.00 95.11 3.94 | 8.45 0.99 95.34 3.96 | 8.12 0.97 96.05 4.02 | 8.20 1.12 93.33 4.10 |
|            | MIHML     | 8.64 1.00 95.89 4.12 | 8.46 0.99 96.23 4.16 | 8.12 0.97 96.99 4.25 | 8.88 1.10 96.75 4.85 |
|            | MIH2Step  | 8.63 1.00 96.23 4.20 | 8.45 0.99 96.35 4.20 | 8.12 0.97 96.66 4.19 | 8.34 1.14 96.92 5.16 |
| 2.5        | Median    | 28.10 2.55 - | 26.62 2.45 - | 25.36 2.45 - | 23.30 2.32 - |
|            | LM        | 15.53 1.58 72.03 3.42 | 15.08 1.69 68.49 3.40 | 16.63 1.96 58.66 3.33 | 15.68 2.19 49.42 3.24 |
|            | MIIPmm    | 15.83 1.58 95.38 6.37 | 14.96 1.67 93.80 6.29 | 16.37 1.93 88.17 6.05 | 15.74 2.20 77.49 5.50 |
|            | MIIRF     | 19.53 1.78 97.96 8.38 | 17.33 1.74 98.31 8.34 | 17.02 1.88 97.36 8.26 | 16.76 2.40 89.36 7.60 |
|            | MIRL      | 15.50 1.58 85.18 4.57 | 14.80 1.57 85.60 4.59 | 14.52 1.55 86.96 4.67 | 13.68 1.84 79.79 4.75 |
|            | MIHML     | 15.55 1.58 92.16 5.61 | 14.82 1.57 92.60 5.66 | 14.55 1.54 93.75 5.80 | 13.00 1.83 91.72 6.52 |
|            | MIH2Step  | 15.54 1.58 96.24 6.64 | 14.81 1.57 96.33 6.64 | 14.51 1.54 96.66 6.62 | 13.35 1.91 95.43 8.10 |
| 4          | Median    | 197.52 2.86 - | 29.47 2.84 - | 29.47 2.84 - | 22.98 3.66 - |
|            | LM        | 118.65 2.00 66.35 3.85 | 20.97 2.13 62.82 3.82 | 21.22 2.48 53.08 3.74 | 44.96 2.93 34.96 3.28 |
|            | MIIPmm    | 125.76 2.00 95.33 8.04 | 21.16 2.12 93.70 7.92 | 21.07 2.44 87.98 7.62 | 45.09 2.94 74.35 7.13 |
|            | MIIRF     | 165.72 2.16 97.31 9.58 | 24.23 2.15 97.44 9.61 | 21.86 2.35 95.78 9.48 | 46.06 3.08 82.57 8.45 |
|            | MIRL      | 117.13 2.00 78.39 4.95 | 21.47 1.99 78.85 4.97 | 19.56 1.96 80.46 5.07 | 44.85 2.36 83.87 6.79 |
|            | MIHML     | 119.57 2.00 90.03 6.65 | 21.60 1.99 90.48 6.69 | 19.61 1.96 91.79 6.86 | 43.93 2.44 92.11 9.71 |
|            | MIH2Step  | 118.16 2.00 96.24 8.40 | 21.58 1.99 96.33 8.39 | 19.54 1.95 96.65 8.38 | 44.21 2.65 98.27 19.55 |
Table 23: U: Simulation results for the predicted missing emissions values.

| σ^2   | Method       | RE | RMSE  | CR  | PI  | RE | RMSE  | CR  | PI  |
|-------|--------------|----|--------|-----|-----|----|--------|-----|-----|
|       | Light MNAR   |    |        |     |     |    |        |     |     |
| 1     | MIRF         | 293.04 | 1.81 | 98.65 | 9.37 | 200.47 | 1.86 | 98.66 | 9.35 |
|       | HML          | 175.95 | 1.12 | 93.32 | 3.90 | 139.97 | 1.12 | 93.57 | 3.93 |
|       | MIHML        | 175.89 | 1.12 | 95.11 | 4.35 | 140.59 | 1.12 | 95.28 | 4.36 |
|       | MIH2Step     | 175.66 | 1.12 | 96.13 | 4.67 | 139.24 | 1.12 | 96.06 | 4.64 |
| 2.5   | MIRF         | 336.82 | 2.18 | 98.14 | 10.47 | 387.11 | 2.27 | 97.77 | 10.42 |
|       | HML          | 264.01 | 1.67 | 82.91 | 4.46 | 419.65 | 1.66 | 83.37 | 4.48 |
|       | MIHML        | 265.75 | 1.66 | 96.96 | 5.92 | 523.90 | 1.66 | 94.36 | 5.92 |
|       | MIH2Step     | 267.58 | 1.66 | 96.63 | 7.37 | 518.49 | 1.66 | 96.69 | 7.36 |
| 4     | MIRF         | 331.47 | 2.50 | 97.69 | 11.49 | 221.93 | 2.63 | 96.96 | 11.39 |
|       | HML          | 290.86 | 2.07 | 75.88 | 4.79 | 237.70 | 2.06 | 76.48 | 4.83 |
|       | MIHML        | 291.03 | 2.07 | 96.02 | 6.99 | 238.75 | 2.06 | 96.09 | 6.99 |
|       | MIH2Step     | 292.18 | 2.07 | 96.91 | 9.32 | 237.67 | 2.06 | 96.95 | 9.29 |

|       | Heavy MNAR   |    |        |     |     |    |        |     |     |
| 1     | MIRF         | 293.04 | 1.81 | 98.65 | 9.37 | 200.47 | 1.86 | 98.66 | 9.35 |
|       | HML          | 175.95 | 1.12 | 93.32 | 3.90 | 139.97 | 1.12 | 93.57 | 3.93 |
|       | MIHML        | 175.89 | 1.12 | 95.11 | 4.35 | 140.59 | 1.12 | 95.28 | 4.36 |
|       | MIH2Step     | 175.66 | 1.12 | 96.13 | 4.67 | 139.24 | 1.12 | 96.06 | 4.64 |
| 2.5   | MIRF         | 336.82 | 2.18 | 98.14 | 10.47 | 387.11 | 2.27 | 97.77 | 10.42 |
|       | HML          | 264.01 | 1.67 | 82.91 | 4.46 | 419.65 | 1.66 | 83.37 | 4.48 |
|       | MIHML        | 265.75 | 1.66 | 96.96 | 5.92 | 523.90 | 1.66 | 94.36 | 5.92 |
|       | MIH2Step     | 267.58 | 1.66 | 96.63 | 7.37 | 518.49 | 1.66 | 96.69 | 7.36 |
| 4     | MIRF         | 331.47 | 2.50 | 97.69 | 11.49 | 221.93 | 2.63 | 96.96 | 11.39 |
|       | HML          | 290.86 | 2.07 | 75.88 | 4.79 | 237.70 | 2.06 | 76.48 | 4.83 |
|       | MIHML        | 291.03 | 2.07 | 96.02 | 6.99 | 238.75 | 2.06 | 96.09 | 6.99 |
|       | MIH2Step     | 292.18 | 2.07 | 96.91 | 9.32 | 237.67 | 2.06 | 96.95 | 9.29 |

|       | NonHeckman   |    |        |     |     |    |        |     |     |
| 1     | MIRF         | 293.04 | 1.81 | 98.65 | 9.37 | 200.47 | 1.86 | 98.66 | 9.35 |
|       | HML          | 175.95 | 1.12 | 93.32 | 3.90 | 139.97 | 1.12 | 93.57 | 3.93 |
|       | MIHML        | 175.89 | 1.12 | 95.11 | 4.35 | 140.59 | 1.12 | 95.28 | 4.36 |
|       | MIH2Step     | 175.66 | 1.12 | 96.13 | 4.67 | 139.24 | 1.12 | 96.06 | 4.64 |
| 2.5   | MIRF         | 336.82 | 2.18 | 98.14 | 10.47 | 387.11 | 2.27 | 97.77 | 10.42 |
|       | HML          | 264.01 | 1.67 | 82.91 | 4.46 | 419.65 | 1.66 | 83.37 | 4.48 |
|       | MIHML        | 265.75 | 1.66 | 96.96 | 5.92 | 523.90 | 1.66 | 94.36 | 5.92 |
|       | MIH2Step     | 267.58 | 1.66 | 96.63 | 7.37 | 518.49 | 1.66 | 96.69 | 7.36 |
| 4     | MIRF         | 331.47 | 2.50 | 97.69 | 11.49 | 221.93 | 2.63 | 96.96 | 11.39 |
|       | HML          | 290.86 | 2.07 | 75.88 | 4.79 | 237.70 | 2.06 | 76.48 | 4.83 |
|       | MIHML        | 291.03 | 2.07 | 96.02 | 6.99 | 238.75 | 2.06 | 96.09 | 6.99 |
|       | MIH2Step     | 292.18 | 2.07 | 96.91 | 9.32 | 237.67 | 2.06 | 96.95 | 9.29 |
### 6.8. Empirical Study Results

Table 24: Empirical study results: Accuracy of the 2018 estimates with respect to the 2019 reported values in Total Sample.

| Oracle β  | n₀ | n₂₀₁₈ | Methods | CR  | PI   | RE<sub>min</sub> | RE<sub>mean</sub> | RE<sub>max</sub> | RMSE | Pearson Corr | Spearman Corr |
|-----------|----|--------|---------|-----|------|-----------------|-----------------|-----------------|------|--------------|--------------|
| L         |    |        |         |     |      |                 |                 |                 |      |              |              |
|           |    |        |         | 69.00 | 4.54 | 7.25            | 13.76           | 23.01           | 1.90 | 0.82         | 0.82         |
|           |    |        |         | 91.76 | 6.34 | 7.36            | 13.68           | 22.30           | 1.90 | 0.82         | 0.81         |
|           |    |        |         | 94.12 | 7.18 | 8.57            | 13.23           | 22.81           | 1.97 | 0.81         | 0.84         |
|           |    |        |         | 82.35 | 4.83 | 5.62            | 14.57           | 23.12           | 1.90 | 0.82         | 0.82         |
|           |    |        |         | 89.59 | 6.01 | 8.47            | 14.05           | 21.70           | 1.91 | 0.81         | 0.82         |
|           |    |        |         | 92.94 | 6.48 | 5.49            | 14.18           | 24.02           | 1.92 | 0.84         | 0.82         |
| Scope 1   | 71 | 393    | 85      |     |      |                 |                 |                 |      |              |              |
|           |    |        |         | 68.12 | 3.96 | 7.28            | 12.28           | 21.56           | 1.93 | 0.81         | 0.82         |
|           |    |        |         | 85.23 | 4.97 | 3.98            | 9.45            | 13.80           | 1.61 | 0.80         | 0.79         |
|           |    |        |         | 86.36 | 5.3  | 4.09            | 7.87            | 14.18           | 1.64 | 0.79         | 0.75         |
|           |    |        |         | 81.82 | 4.39 | 2.91            | 6.59            | 14.47           | 1.66 | 0.79         | 0.76         |
|           |    |        |         | 90.59 | 6.01 | 8.47            | 14.05           | 21.70           | 1.90 | 0.81         | 0.82         |
|           |    |        |         | 92.94 | 6.48 | 5.49            | 14.18           | 24.02           | 1.92 | 0.84         | 0.82         |
| Scope 2   | 71 | 395    | 88      |     |      |                 |                 |                 |      |              |              |
|           |    |        |         | 77.17 | 3.95 | 3.64            | 9.14            | 17.89           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 92.13 | 5.63 | 3.73            | 9.52            | 18.63           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 84.25 | 6.07 | 4.20            | 9.95            | 18.11           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 90.59 | 6.84 | 7.05            | 15.40           | 31.10           | 1.95 | 0.78         | 0.78         |
| Scope 1   | 55 | 767    | 127     |     |      |                 |                 |                 |      |              |              |
|           |    |        |         | 64.56 | 3.57 | 6.46            | 14.18           | 24.83           | 1.89 | 0.75         | 0.74         |
|           |    |        |         | 88.19 | 6.59 | 6.46            | 15.65           | 29.46           | 2.08 | 0.78         | 0.78         |
|           |    |        |         | 86.06 | 7.57 | 6.04            | 15.36           | 29.85           | 2.09 | 0.78         | 0.79         |
|           |    |        |         | 77.72 | 4.83 | 6.22            | 16.42           | 31.18           | 2.12 | 0.78         | 0.78         |
|           |    |        |         | 85.24 | 6.07 | 4.20            | 9.95            | 18.11           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 90.59 | 6.84 | 7.05            | 15.40           | 31.10           | 1.95 | 0.78         | 0.78         |
| Scope 2   | 54 | 771    | 127     |     |      |                 |                 |                 |      |              |              |
|           |    |        |         | 77.17 | 3.95 | 3.64            | 9.14            | 17.89           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 92.13 | 5.63 | 3.73            | 9.52            | 18.63           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 84.25 | 6.07 | 4.20            | 9.95            | 18.11           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 90.59 | 6.84 | 7.05            | 15.40           | 31.10           | 1.95 | 0.78         | 0.78         |
| Scope 1   | 24 | 1577   | 159     |     |      |                 |                 |                 |      |              |              |
|           |    |        |         | 64.56 | 3.57 | 6.46            | 14.18           | 24.83           | 1.89 | 0.75         | 0.75         |
|           |    |        |         | 88.19 | 6.59 | 6.46            | 15.65           | 29.46           | 2.08 | 0.78         | 0.78         |
|           |    |        |         | 86.06 | 7.57 | 6.04            | 15.36           | 29.85           | 2.09 | 0.78         | 0.79         |
|           |    |        |         | 77.72 | 4.83 | 6.22            | 16.42           | 31.18           | 2.12 | 0.78         | 0.78         |
|           |    |        |         | 85.24 | 6.07 | 4.20            | 9.95            | 18.11           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 90.59 | 6.84 | 7.05            | 15.40           | 31.10           | 1.95 | 0.78         | 0.78         |
| Scope 2   | 24 | 1581   | 176     |     |      |                 |                 |                 |      |              |              |
|           |    |        |         | 64.56 | 3.57 | 6.46            | 14.18           | 24.83           | 1.89 | 0.75         | 0.75         |
|           |    |        |         | 88.19 | 6.59 | 6.46            | 15.65           | 29.46           | 2.08 | 0.78         | 0.78         |
|           |    |        |         | 86.06 | 7.57 | 6.04            | 15.36           | 29.85           | 2.09 | 0.78         | 0.79         |
|           |    |        |         | 77.72 | 4.83 | 6.22            | 16.42           | 31.18           | 2.12 | 0.78         | 0.78         |
|           |    |        |         | 85.24 | 6.07 | 4.20            | 9.95            | 18.11           | 1.58 | 0.63         | 0.62         |
|           |    |        |         | 90.59 | 6.84 | 7.05            | 15.40           | 31.10           | 1.95 | 0.78         | 0.78         |

RE = relative error (%), PI = Average length of the 95% prediction interval, RMSE = Root mean square error, CR = Coverage Rate (%)
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