PREDICTORS OF BUSINESS SUCCESS AMONG EDF RECIPIENTS IN IRAQ

IOM
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EXECUTIVE SUMMARY

This report describes the process and results of predicting business success among Iraqi small and medium-sized enterprises (SMEs) that received financial support from the International Organization for Migration (IOM) Enterprise Development Fund (EDF). The study serves as a proof-of-concept for the usefulness of applying machine learning models trained on self-reported survey data. Using baseline data from 1,628 grantees as input, Elastic Net and Random Forest models are employed to select the variables with the highest predictive power among a range of indicators capturing owner and firm characteristics, with the aim of estimating each firm's probability of success.[1]

A firm's success is assessed in two ways, both measured a year after the award of the grant: an increase in profits during the best month of the year and the achievement of the job creation goal established at baseline in the firm's business plan. While neither of these indicators provides a comprehensive picture of business success, they represent two distinct and complementary measures of firm growth. Job creation is a core programmatic objective for EDF and an important measure of the firm's size and productive capacity. Profits may take longer to materialize than job creation, as firms face increasing costs during their expansion phase, but are an important measure of financial sustainability, particularly in an economy where access to finance remains constrained and most businesses rely on profits to fund investment.

The findings show that these endline measures of business success can be accurately predicted using a Random Forest model trained on baseline survey data, whereas Elastic Net performs poorly. Random Forest works better in this case because it captures complex, non-linear relationships and interactions between variables that Elastic Net cannot. The Random Forest model achieved out-of-sample accuracy of 80 per cent.[2] These results highlight the complexity and non-linearity of the relationship between baseline business characteristics and outcomes at 12 months. The superior performance of the Random Forest model suggests that simple heuristics or rule-based eligibility criteria are likely to miss high-potential applicants. Instead, more flexible and adaptive models have the potential to improve targeting and programme efficiency.

While the study is not designed to causally identify what factors drive business success, we conduct exploratory analysis into the most important predictors of success. The results of the Random Forest model indicate that formal business practices, including having a written budget, employee contracts and official registration, are strong predictors of both profit growth and job creation. Additionally, there is a close relationship between scale and profits as dimensions of business success. Larger businesses, based on the number of employees at baseline, are more likely to increase profits, while initial profit levels help predict job creation outcomes. The size of the EDF grant is also a critical factor in business success across all estimated models.

A possible concern with the application of predictive models for programmatic purposes is that they may reinforce pre-existing biases that contribute to the economic exclusion of marginalized social groups. Because this study is only a preliminary investigation designed to establish the feasibility and relevance of such applications, we take the approach of explicitly modelling social and demographic variables including sex, age, displacement history and geographic location. We follow the same approach for the business sector because of the gendered nature of some productive sectors in the Iraqi context and to be sensitive to the rural-urban divide between agricultural and non-agricultural sectors. Understanding whether social characteristics are predictive of business success can help design interventions to promote economic inclusion, such as quotas or complementary programming to address the socioeconomic barriers faced by marginalized groups. The results indicate that businesses operating in southern governorates and those within the agriculture sector may face additional challenges in achieving job creation targets and profit increases. On the other hand, we surprisingly see little evidence of bias in model predictions by gender or displacement history. We caveat that this may be driven by the selected group of firms covered by our data, which is limited to firms awarded EDF grants.

Overall, the findings support piloting the integration of data-driven tools into EDF's selection and support processes, with a focus on fairness, flexibility and inclusion. Machine learning models offer a promising way to improve targeting by identifying high-potential businesses based on complex patterns in pre-award data, especially those that may be missed by traditional screening methods. However, predictive tools should complement, not replace, human judgment. Further research is needed to confirm whether the findings of this study extend to the broader pool of applicants for EDF grants and to develop more comprehensive measures of business success.

1 In simple terms, Elastic Net helps identify which factors matter most by filtering out less useful ones, especially when many are related with each other. Random Forest predicts outcomes by combining many simple algorithms known as decision trees, making it good at spotting complex, non-linear patterns in the data.

2 In contrast, the Elastic Net model showed lower predictive power, with accuracy ranging from 57 to 67 per cent. In the analysis, the Elastic Net model did not include fully interacted regressors, which may have limited its predictive power.

INTRODUCTION

The Enterprise Development Fund (EDF) supports economic recovery in areas of Iraq affected by conflict and forced population displacement, providing financial capital to small and medium-sized enterprises (SMEs) across various sectors to catalyse private sector growth and job creation. A key challenge for similar livelihood programmes is identifying the most promising businesses among a large pool of applicants while ensuring the inclusion of disadvantaged groups such as female or displaced entrepreneurs who may need additional support to address the specific challenges they face due to their social background. This study serves as a proof of concept to explore the feasibility, relevance and ethics of applying predictive machine learning models to inform EDF programming decisions.

The report uses baseline information collected from EDF-supported businesses at the time of award to predict endline performance a year later. The primary goal of this exercise is to determine what business characteristics predict future success in endline indicators, specifically job creation and increases in profit.[3] Relevant baseline characteristics include firm size, age in business, management practices, access to credit and the qualifications of the business owner. The results of the analysis will help EDF to better identify and support businesses that exhibit these promising traits, thereby enhancing the programme's overall efficacy.

In addition to business-related characteristics, it is crucial to recognize and understand the social barriers that create additional hurdles for entrepreneurs from marginalized groups and that may impede business success. This requires attention to social and demographic factors such as sex, age and migration history. This challenge is further complicated by geographic patterns in business viability, since many high-potential enterprises are in relatively stable regions and in large urban centres, rather than in areas more directly affected by conflict, displacement and livelihoods loss as a result of environmental degradation. These issues raise important questions about how to balance economic efficiency with inclusive recovery. In this study, we therefore also explore how social characteristics correlate with business success, in order to inform complementary, targeted interventions to address existing barriers. This approach ensures that all entrepreneurs, regardless of their social background, have an equal opportunity to succeed, promoting an inclusive recovery that leaves no one behind.

LITERATURE REVIEW

What constitutes business success can be subjective and contextual. Some authors focus on profit, others focus on growth, and several create an index combining indicators commonly used as observables of attainment. Predictors of business success can also be hard to quantify. For instance, the business owner's ability can be measured differently through financial literacy tests, reasoning tests or years of education (Fafchamps and Woodruff, 2017). Previous studies have aimed at estimating models for variables such as firm growth, business profit or a combination of indicators to find predictors of success. Most conclude that making this prediction based on observable characteristics of enterprises is an overly complicated task, as proposed models often have low predictive power (Wright et al., 2015). However, some characteristics can cast a light on high-growth potential firms.

The most common features with explanatory power are size, age, management practices, access to credit and the ability of the manager or business owner (McKenzie, 2017; Fafchamps and Woodruff, 2017; Cheraghali and Molnár, 2023; Wang and Guedes; 2024). More experienced businesses with better-qualified managers have higher success rates. Beyond the ability of the business owner, other personal characteristics like gender, attitude towards risk, and household wealth tend to play a part in the success of the business (McKenzie and Sansone, 2019). Previous studies have found that young men who score highly on ability tests are more likely to succeed as entrepreneurs, with some pointing out that this result stems from a cultural bias against female entrepreneurs and from women's lower optimism in their entrepreneurial projects, translating to a higher probability of trying to start a business for males (Nikolova, 2017; Lemma et al., 2022; Taghizadeh-Hesary et al., 2019; Kiefer et al., 2020). This finding highlights the important social and economic barriers faced by female entrepreneurs in many developing economies, including Iraq. Other factors influencing success are contextual and, therefore, less related to the business or business owner, including geographic location and industry sector (McKenzie, 2017; Yoo et al., 2023).

A specific branch of the literature studies possible predictors of success in the context of policy programmes that boost SMEs. Different types of interventions have been proven to have different outcomes on the likelihood of success of firms. When put in a cash or training programme context, some observable characteristics of businesses and business owners (gender, ability and age) tend to lose explanatory power, suggesting that these policy interventions may level the ground for business owners (McKenzie and Sansone, 2019). Additionally, cash grants can boost sales, profits, and employment and give a jumpstart to investment, all pointing to improved attainment (OECD, 2022; McKenzie, 2017). Customized advice and aids to visibility also have significant positive results on success (González-Uribe and Reyes, 2021).

Nonetheless, estimates from studies of business success in the context of intervention programmes – such as the present study – have a crucial methodological limitation. Their samples of SMEs include those qualified or choosing to participate in cash or training programmes, excluding, for example, those unable to apply due to lack of means, those self-selecting out of programmes, or underperforming firms, which leaves possibly biased coefficients (McKenzie, 2017; Scott et al., 2015; González-Uribe and Reyes, 2021). Given the complexity of measuring and predicting business success, some researchers have advised policymakers to aim interventions at easing the business environment, allowing for trial and error, instead of seeking to pick the most likely winners in the market (Nanda, 2010). Facilitating access to financial capital for SMEs in high-growth sectors plays an important role in this process, even when individual businesses have a high failure rate.

3 The success variables are two binary variables. First, a variable equal to one for those SMEs that reached or exceeded their commitment to hire workers (49%). Second, a variable equal to one for those SMEs with an increase in the profit in the best month of the year, one year after the baseline round (53%).

METHODOLOGY

The data for this report come from surveys with (SMEs that were awarded a grant from the EDF in Iraq from 2019 to early 2024. EDF business owners are interviewed throughout the process in three stages: at the time of award, at six months (midline) and at 12 months (endline). The data set includes businesses that completed all three rounds of interviews by February 2024, which results in a sample of 1,628 businesses per round.

EDF business owners' survey data at the baseline round is fed into elastic net regularization and random forest models. The selected variables from the baseline are then used to predict the success of the business at the endline (see details in McKenzie, 2017). This report focuses on two outcome variables: increases in profit in the best month of the year in United States dollars (USD) and achieving the firm's job creation commitment. The average values per survey round for profit and employee count are displayed in Table 1.[4] **It is important to highlight that the analysis is purely correlational and none of the findings should be interpreted as suggesting a causal relationship between predictors and outcomes.**

The focus on the *best month of the year* as the profit metric follows McKenzie (2017) and is intended to mitigate noise and seasonal fluctuations in self-reported income data. Still, it is important to highlight that this measure may overstate long-term business performance, especially for firms with irregular income patterns. Future analyses could consider complementary indicators such as median or average monthly profit to capture a more comprehensive picture of profitability, as well as looking at other financial measures of business performance, such as revenue growth, that may be more relevant for early-stage and expanding firms.

Table 1. Mean values for outcome variables

	Baseline	6 months	12 months
Number of employees	5.29	8.38	8.40
Binary for achieving hiring commitment	-	0.49	0.49
Profit (USD)	1849	2117	1993
Binary indicating increased profit	-	0.50	0.53

Note: Outcome variables for random forest and elastic net are binary variables indicating success in increasing profit and reaching the hiring commitment by the endline stage. The table provides the mean values for the variables of profit and number of employees (from which the outcome binaries are calculated) at each survey round. The mean values for the outcome binaries are shown in the last column.

RANDOM FOREST MODEL

Random forest (RF) is a machine learning model that uses multiple decision trees to improve the accuracy and reliability of predictions by averaging their results. A decision tree behaves like a series of yes or no questions used to make a prediction based on the baseline data. To predict business income in the midline and the endline using a decision tree, the model starts with variables from the baseline, such as whether the SME has a bank loan, a written budget, and the gender and age of the business owner. The tree splits the data recursively according to the values of relevant survey indicators. For instance, it may start with the indicator, "Do you have a loan from a bank?" If the answer is "Yes," the next question might be, "Do you have a written budget?" Based on the response, the following indicator might be, "What is the gender of the business owner?" And finally, ""How old is the business owner?" Each of these questions helps the decision tree narrow the prediction for the SME's profit by considering the most relevant factors step by step.

Instead of just one decision tree, a Random Forest uses many trees and combines their predictions to make the final decision.[5] The process begins by randomly selecting subsamples of SMEs and making predictions for each group.[6] Each tree predicts the value of a target variable (like profit or employment in the midline and the endline) based on variables from the baseline. The model iterates until an additional tree does not provide new information.[7] This model shows how important each variable is by measuring how much prediction accuracy changes when that variable is included or excluded.

LASSO AND ELASTIC NET MODELS

Elastic Net and LASSO are alternative models that can help choose the baseline variables that best predict the selected measures of business success, increased income and the achievement of the job creation goals set at baseline. LASSO is a method that helps make predictions by simplifying a linear regression model, keeping only the most informative baseline variables to predict profit and labor in the endline. LASSO adds a penalty term to the linear regression, balancing simplicity and accuracy by summing the absolute values of the coefficients multiplied by a regularization parameter. This process sets some coefficients to zero, and the remaining positives are considered relevant to predict midline and endline outcomes. LASSO iterates to minimize the objective loss function and returns a list of variables with non-zero coefficients.[8]

Elastic Net addresses LASSO's possible drawbacks by combining it with Ridge Regression. Ridge Regression adds the square of each coefficient as a penalty term, unlike LASSO, which uses absolute value. This means Ridge Regression keeps all coefficients, while LASSO turns some to zero. Elastic Net offers better regularization by combining and weighing these two types of penalties. The result is a list of non-zero coefficients chosen by the combined shrinking methods. Given that Elastic Net is an extension of LASSO, the following sections will show results from Elastic Net only.

4 Within the sample, 53 per cent of businesses increased their profit between baseline and endline, and 49 per cent reached or exceeded their job creation commitment.

5 For numbers, Random Forest takes the average, and for categories, it uses the majority vote, making the predictions more accurate and reliable.

6 This method is called bootstrapping, a technique where multiple subsets of data are created by sampling with replacement.

7 Several test runs were carried out to choose the number of iterations and the number of variables to be included in the final model. The selected values were the ones that resulted in the least out-of-bag error. The result of this exercise is shown in Appendix B.1.

8 Measures how well a model's predictions match the actual outcomes by calculating the difference or "error" between these predictions and the true values. The model's goal is to minimize this error. The smaller the error, the better it performs.

MAIN FINDINGS

VARIABLE SELECTION

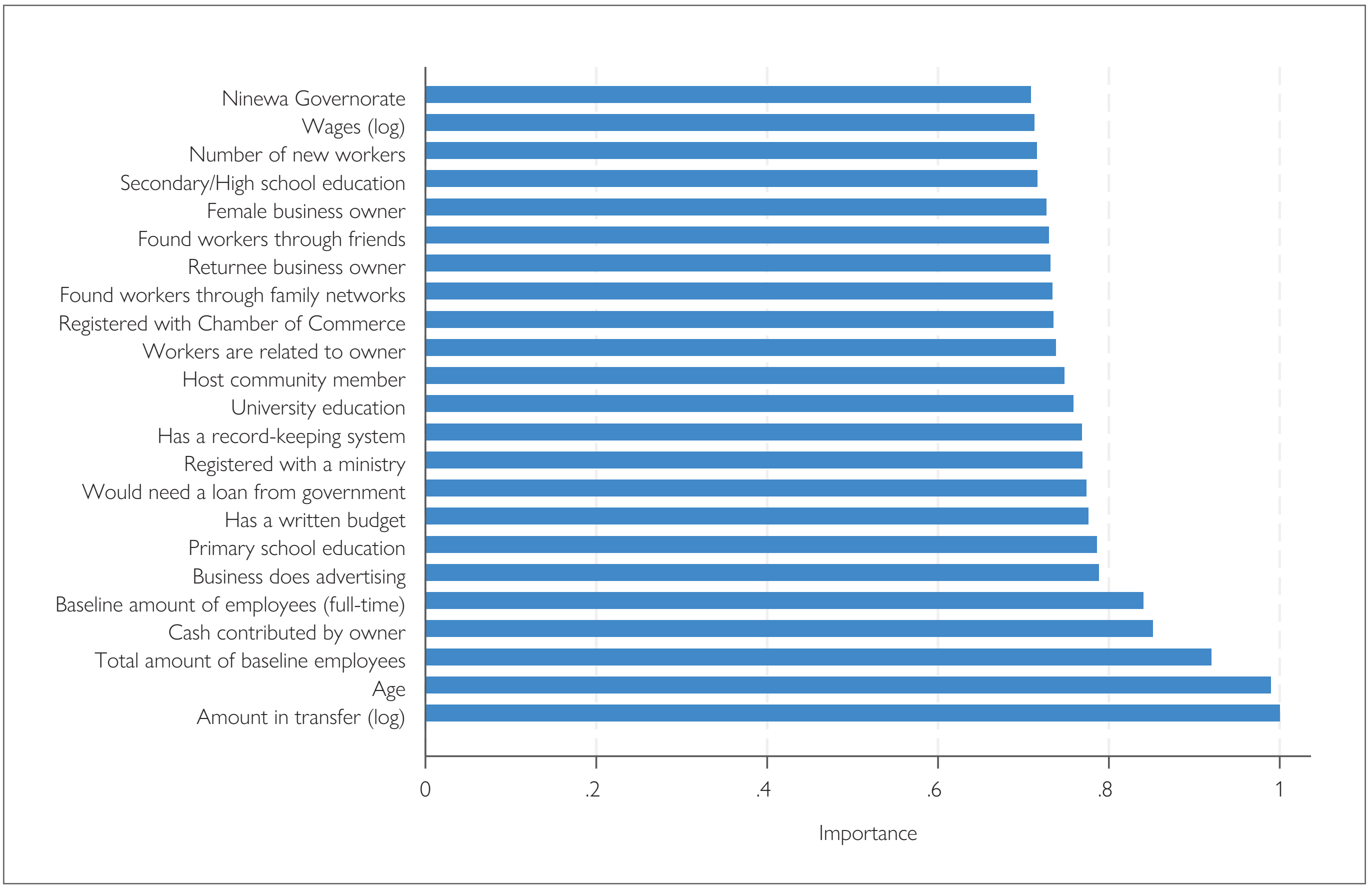
The first step is independently estimating two Random Forest models for the two different binary outcomes: (i) positive changes in profit in the best month of the year and (ii) reaching or exceeding the job creation commitment made before baseline, both by endline. Figure 1 shows the importance of each baseline characteristic in predicting the binary outcomes at endline. The model defines importance as the difference in prediction accuracy (change in the objective function) before and after including the variable in the model, normalized over the maximum score (the most critical variable has 100% importance). The importance score on its own does not convey any information about the direction of the relationship. For variables with a high importance score, we therefore show the Accumulated Local Effect (ALE) as a measure of the association between different levels of a baseline characteristic and the predicted outcome.[9]

Increase in profits of 12 months. The size of the awarded EDF grant (in absolute terms) was the most critical variable to predict profit increases between the baseline and endline (Figure 1, Panel A). Business size is also informative about endline outcomes, as the total number of employees at baseline is 91 per cent importance, and the number of full-time employees at baseline is 84 per cent importance. Panel B of Figure 1 shows the direction of the ALE for variables with the most importance.[10] Receiving smaller grants and having fewer employees is associated with a lower probability of increased profit by endline.

The Random Forest model also chose formality and business development indicators as relevant features for predicting profit, including being registered. The different methods through which workers are recruited also have high importance levels, as well as some social and demographic characteristics of the business owners (Figure 1).

Figure 1: Results for increases in profit from the Random Forest model

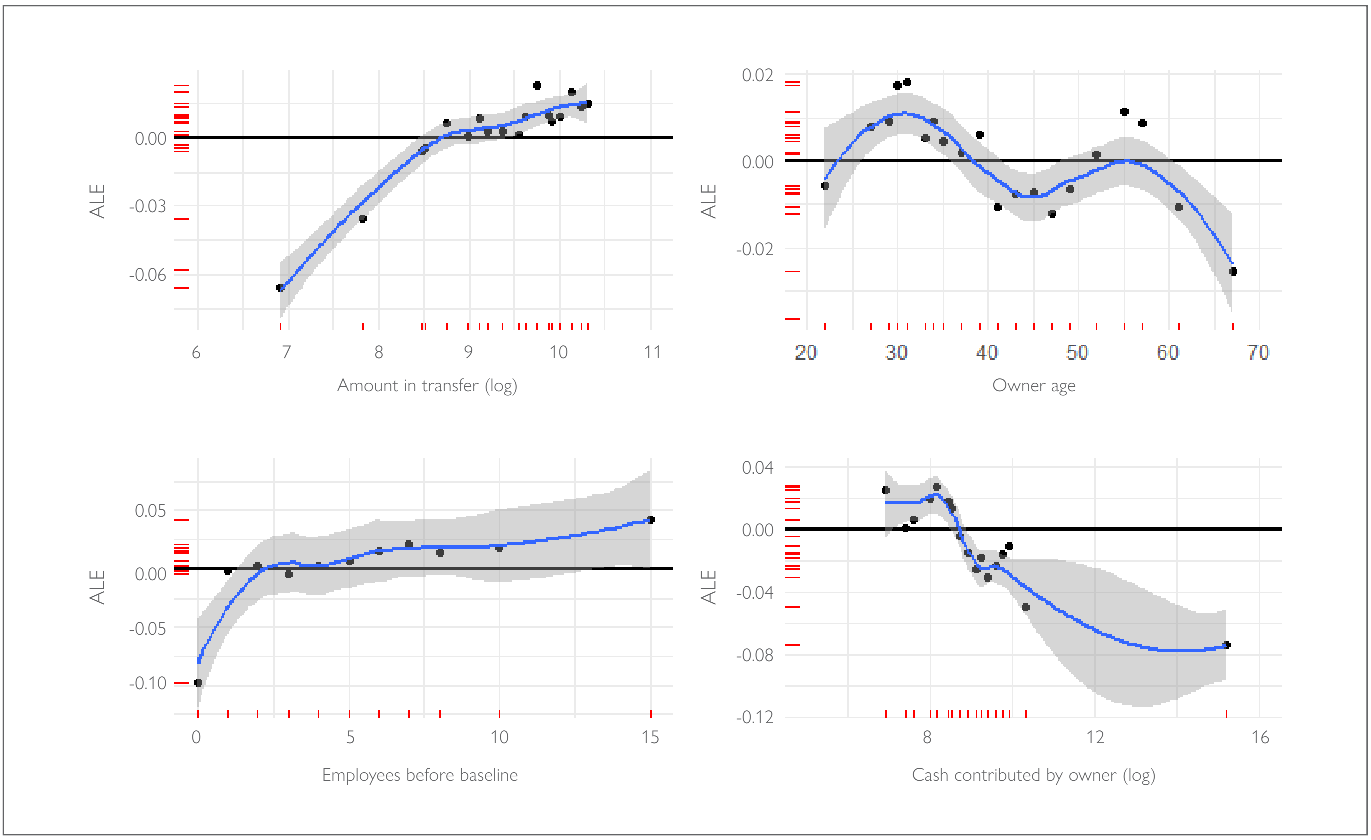
Panel A. Importance



9 ALE show how a feature influences a machine learning model's prediction by averaging local changes in predictions within small intervals of the feature, thus accounting for feature correlations (Molnar, 2019).

10 ALE shows the average change in the model's prediction as the feature changes while keeping other features constant.

Panel B. Accumulated Local Effect



Note: Importance is defined as the difference in prediction accuracy (change in the objective function) before and after including the variable in the model, normalized over the maximum score (the most critical variable always has 100% importance). The graphs display variables with values of importance over 0.70. An ALE shows the average change in the model's prediction as the feature changes while keeping other features constant. The model is run on two thirds of the database observations, as the remaining 33 per cent are left as a testing sample; thus, the graphs show the results for 1,085 observations.

Achieving job creation goals in 12 months. According to the Random Forest model, the business owner's age was the most critical variable in predicting the successful delivery of the firm's job creation goals (100%) (Figure 2, Panel A). The ALE plot for owner's age (Figure 2, Panel B) shows that being between 32 and 45 years old is positively associated with achieving the hiring commitment set in the business plan. Variables related to the size of the business plan also played an important role in predicting endline outcomes, with the amount of cash contributed by the owner having 69 per cent importance and the approved EDF transfer having 66 per cent. The fit lines in the ALE plots for these two variables move in the opposite direction. High grant amounts, above USD 18,000, are associated with a lower likelihood of reaching the hiring commitment, and so are low owner contributions.[11]

Meanwhile, high values of the owner's financial contribution to the business plan are positively associated with meeting the job creation goal. Baseline firm characteristics were the second most crucial group of predictors, in particular profit (profit in the best month of the year with 87% importance and profit in the last month with 85% in the baseline) and registration with a ministry (80% importance). According to the ALE (Figure 2, Panel B), larger profit values at baseline are associated with a lower likelihood of reaching the hiring commitment at endline.[12] Indicators of business formality that made up the list of significant variables for the model's prediction of success in their job creation objectives include having a written budget (80% importance), a record-keeping system (77%), doing advertising (79%), being registered with the Chamber of Commerce (74%) and contracts with employees (75%).

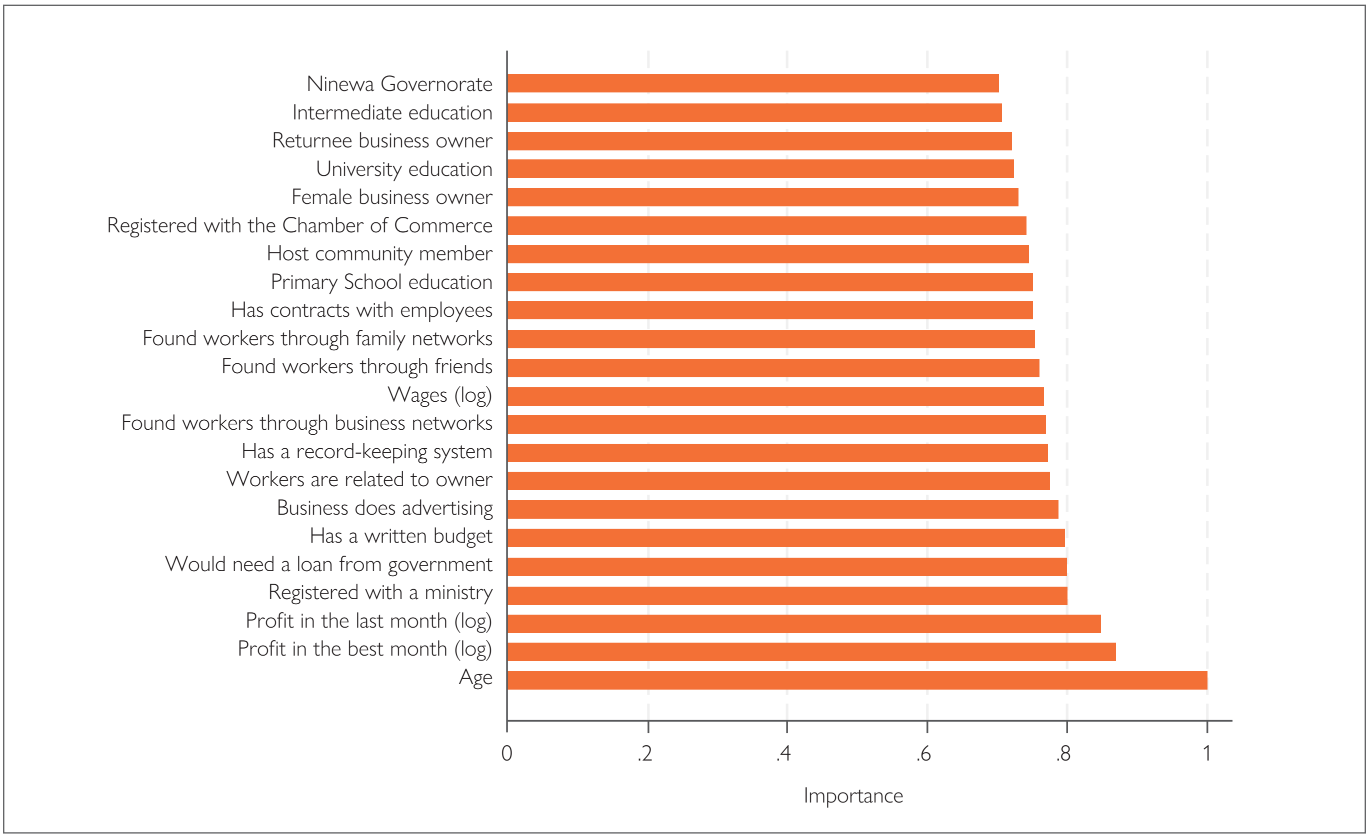
Recruitment channels for new workers were also important for this outcome variable, particularly when facilitated through friends and business networks. Additionally, demographic factors such as being female and a member of the host community were relevant as well.

11 While it is not possible to narrow down the reasons for these associations based on the current analysis, it is important to note that job creation targets are tailored to each business and set following negotiations between the business owners and EDF staff. The correlation between higher value grants and failure to reach the hiring commitment, therefore, does not necessarily mean lower performance in absolute terms. Instead, it could reflect unrealistic expectations or challenges in estimating financially viable objectives for larger enterprises. The finding that low owner contributions are associated with a lower probability of success suggests that having skin in the game may have a positive influence on the performance of granted business owners, a hypothesis that IOM Iraq is currently investigating in a separate study.

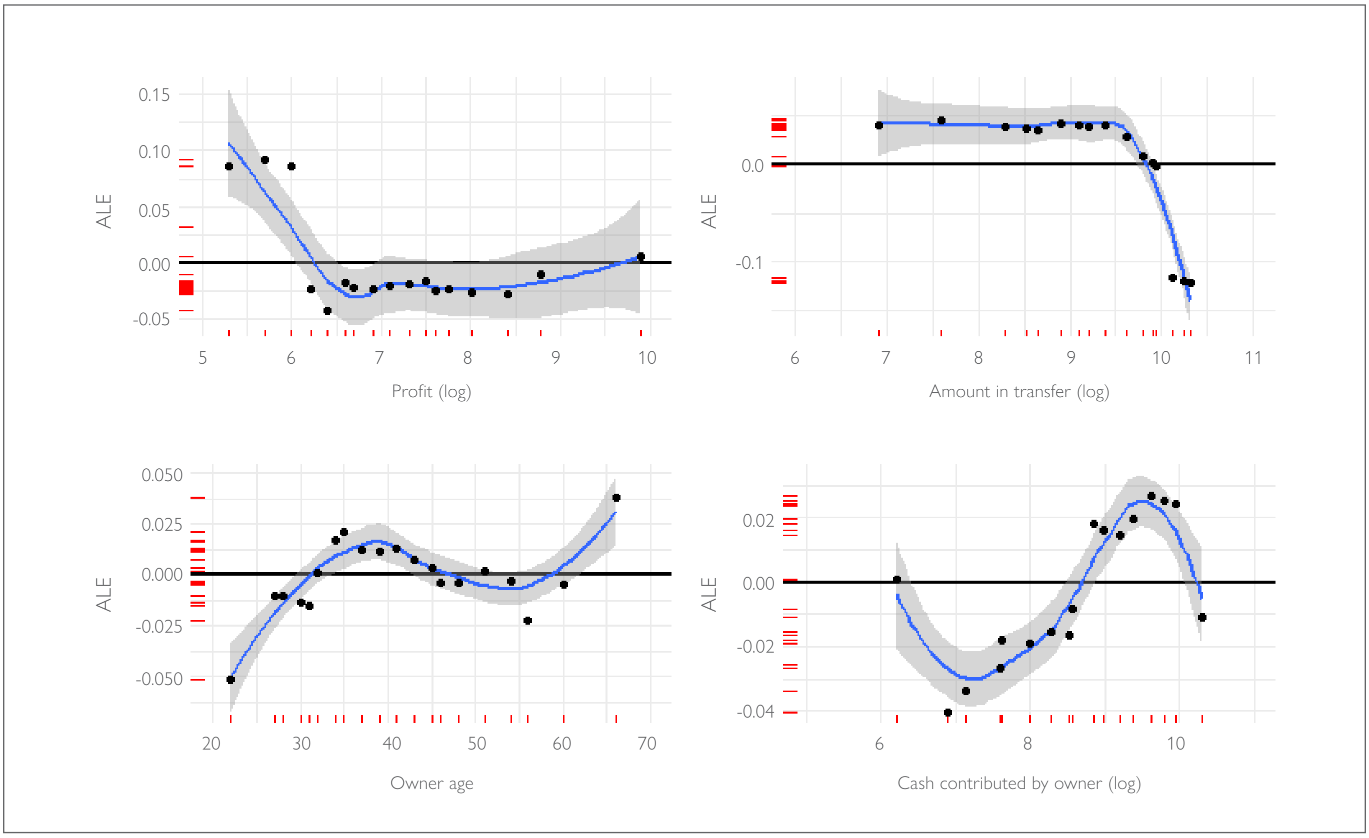
12 A plausible interpretation of this finding is that firms with higher profits at baseline may already be operating efficiently with capital-intensive processes, which reduces their need to hire more staff even as they grow. It is a good reminder that profit does not always translate to labour demand, especially for more advanced or optimized businesses.

Figure 2. Results for reaching or exceeding hiring commitment from the Random Forest model

Panel A. Importance



Panel B. Accumulated Local Effect (ALE)



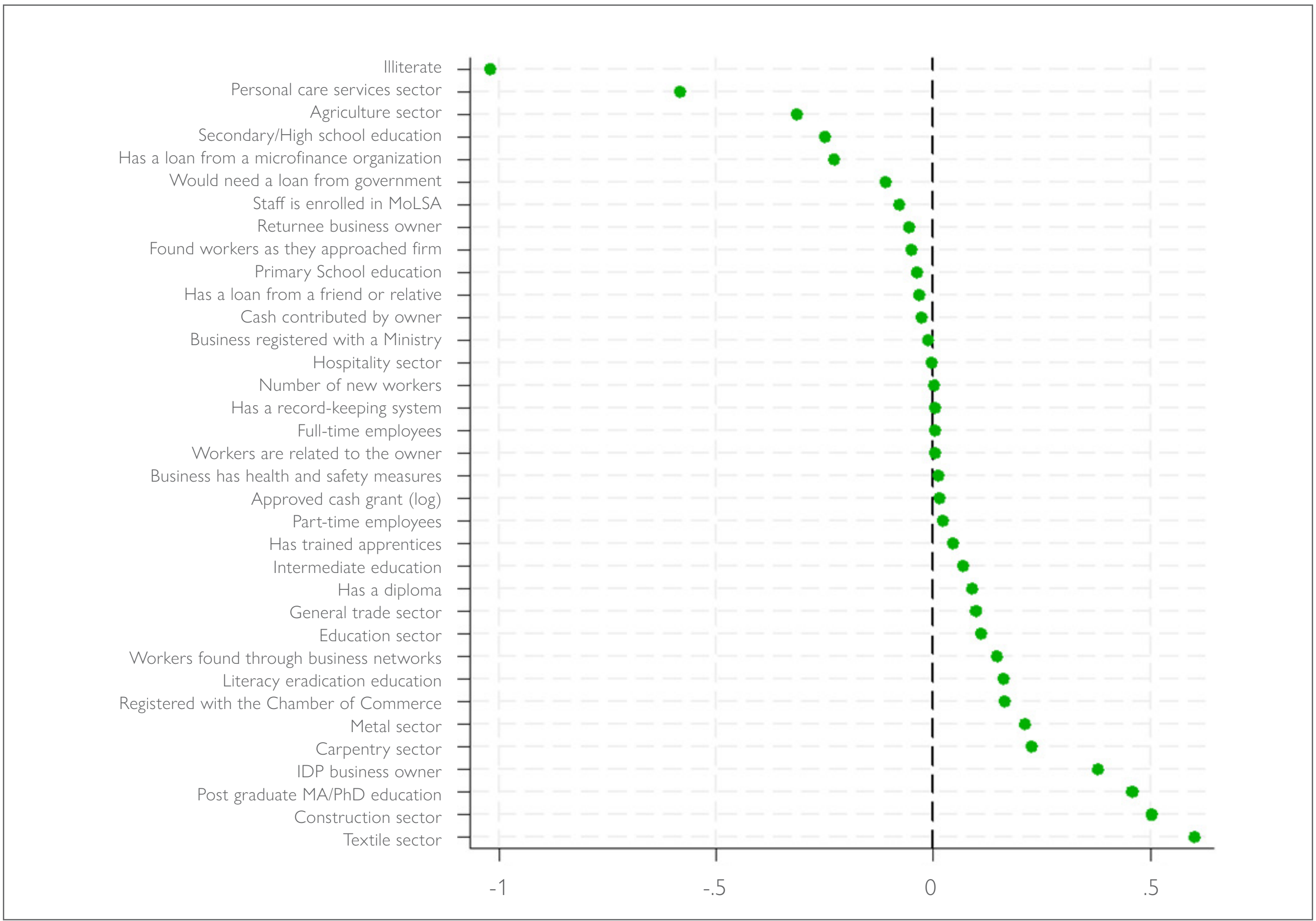
Note: Importance is defined as the difference in prediction accuracy (change in the objective function) before and after including the variable in the model, normalized over the maximum score (the most critical variable always has 100% importance). The graphs display variables with values of importance over 0.70. An ALE shows the average change in the model's prediction as the feature changes while keeping other features constant. The model is run on two thirds of the database observations, as the remaining 33 per cent are left as a testing sample, thus, the graphs show the results for 1,085 observations.

RESULTS COMPARISON FROM RANDOM FOREST AND ELASTIC NET MODELS

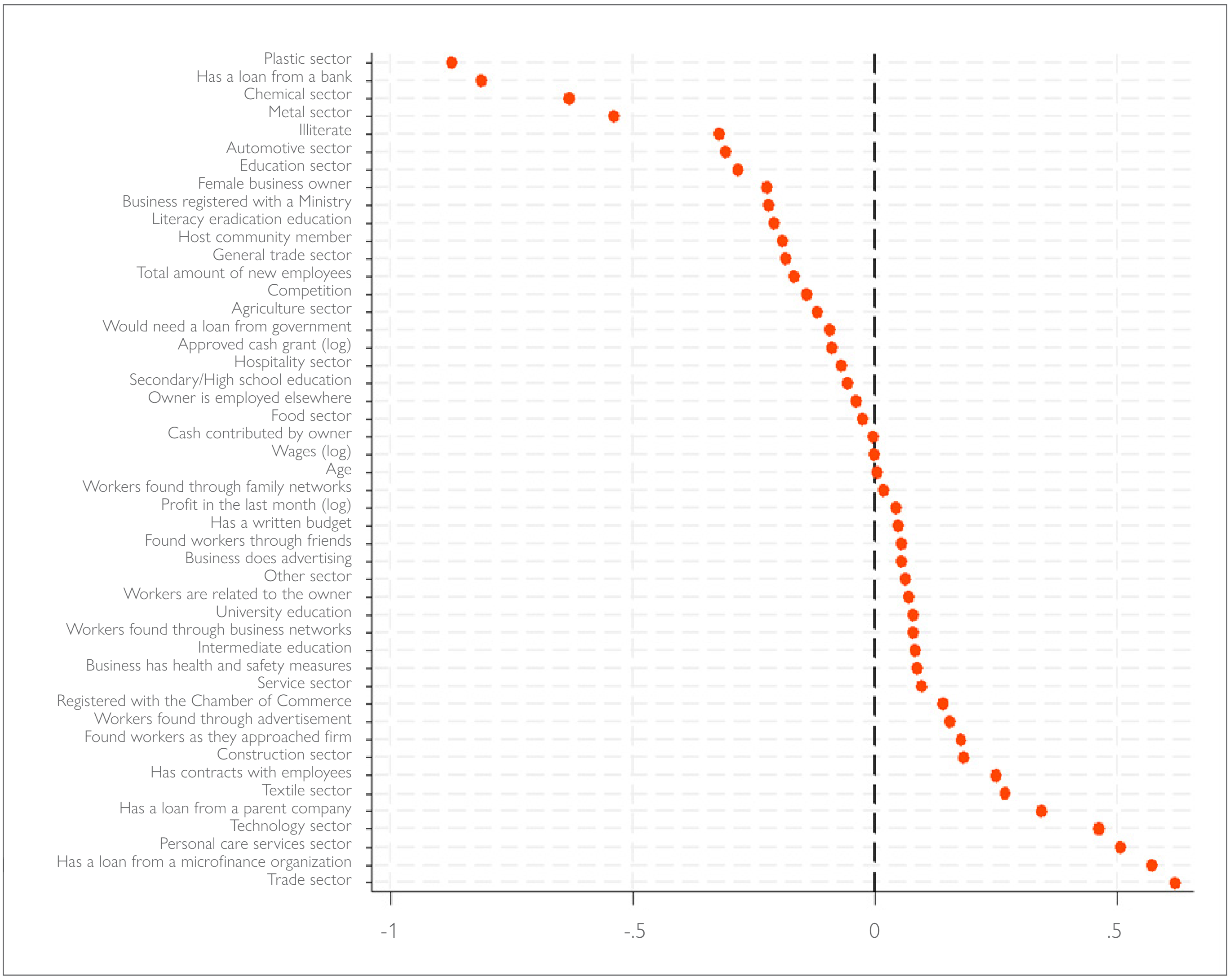
This section compares the selection of variables from the Random Forest to the Elastic Net Model for robustness. When predicting increases in business profit and achievement of the job creation goal, the models reach different conclusions regarding relevant characteristics. For increases in profit, Elastic Net gives high coefficients to sector and demographic variables, including post-graduate education and IDP status (both with positive coefficients; Figure 3). At the same time, Random Forest prioritizes the attributes of the cash transfer and the business' size. Formality indicators were considered relevant predictors for both models in this outcome variable. Elastic Net gave positive coefficients to registration with the Chamber of Commerce, which had more than 70 per cent importance for Random Forest. For the hiring commitment, Elastic Net chose sector binary variables, some debt characteristics (having a loan from a microfinance organization, parent company, or bank), and formality indicators (having contracts with employees and being registered with a Ministry) (Figure 3, Panel B). In demographic terms, all models picked at least one migration group as a relevant factor. Three out of four models regarded being a host community member as a significant predictor of job creation and profit increase. Three out of four models also report female business owners as a negative factor in predicting success 12 months after receiving the EDF grant.

Figure 3. Results from the Elastic Net model

Panel A: Increase in profit (best month of the year)



Panel B: Reaching or exceeding the hiring commitment



Note: The figure in Panel A shows elastic net coefficients for the binary outcome of increases in profit in the best month of the year between baseline and endline. For display purposes, this graph doesn't include coefficients related to geographic factors (governorates). The figure in Panel B shows elastic net coefficients for the binary outcome of reaching or exceeding the hiring commitment made at the baseline. For display purposes, this graph doesn't include coefficients related to geographic factors (governorates).

Table 2 shows the ranking and coefficients for the five most important variables according to the Random Forest model. As explained above, the models reached different conclusions regarding the most relevant variables for both outcomes. This is most likely explained by the difference in the predictive power of the models shown in Figure 4, with random forest performing significantly better than Elastic Net, likely as a result of its ability to better model complex, non-linear relationships.

Table 2. Comparison of Random Forest and Elastic Net

Factor	Random Forest		Elastic Net	
	Rank	Importance	Rank	Coefficient
Profit				
Amount in cash transfer (log)	1	100%	39	0.014
Age	2	98%	-	-
Employes before baseline	3	91%	-	-
Cash contributed by owner (log)	4	87%	37	-0.027
Full-time employees	5	84%	43	0.005
Job creation by endline				
Age	1	100%	55	0.004
Profit in the best month (log)	2	87%	-	-
Profit in the last month (log)	3	85%	50	0.044
Registered with a ministry	4	80%	22	-0.22
Would need a loan from the government	5	80%	37	-0.094

Note: Ranking of importance and coefficient size of the top five factors according to the Random Forest model. The coefficients from Elastic Net are organized according to their absolute value. Cells with no information on the Elastic Net panel correspond to variables that were excluded from the model in the regularization process.

PREDICTION PERFORMANCE

As the models were estimated for two binary outcomes that signal business success, one of the relevant results is the accuracy of their predictions. The models predict success or failure in terms of increases in profit and number of workers, and the accuracy describes the percentage of businesses that were accurately classified. In order to prevent overfitting, we test prediction accuracy out-of-sample using one third of the dataset as a test set, while training the models with the remaining two thirds of the data. The results can therefore be interpreted as the ability of the models to accurately predict endline outcomes with baseline data of a new sample of businesses with which it was not trained.

Prediction accuracy is influenced by a number of factors including, but not limited to: the type of statistical model, the size of the training dataset, use of appropriate predictor variables as inputs in the model, high-quality measurement of the data and the underlying randomness in the outcome variable.

Similar studies seeking to predict high-growth firms using a random forest model have found a wide variation in accuracy. For instance, Weinblat (2018) achieved a 39 per cent accuracy level with only 10 per cent of the data used for training on a database of 179.970 firms, while Lukita et al. (2023) reached 90 per cent accuracy with a sample of 370 firms, using 80 per cent of their data for training.

As shown in Table 3, in most cases, the Random Forest model correctly predicts which EDF businesses will reach their jobs creation target or achieve an increase in profits after 12 months. Conversely, our Elastic Net model has lower predictive power. In the testing set (543 observations), Random Forest correctly predicted success in both outcomes around 83 per cent of the time, while Elastic Net could predict correctly in about 60 per cent of cases.

The Random Forest approach also performs better when analysing other metrics of model performance. Sensitivity and specificity (true positives and true negatives, respectively) tell us how many SMEs were correctly predicted to succeed or fail for each outcome. If the models were used to screen EDF applications, high specificity would signal that fewer resources are wasted on businesses with a high likelihood of failure, and high sensitivity would signal that we are less likely to miss promising companies. Random Forest has values above 80 per cent for both outcomes, while Elastic Net performs significantly worse in terms of specificity. Random Forest also achieves lower percentages of false negatives and false positives.

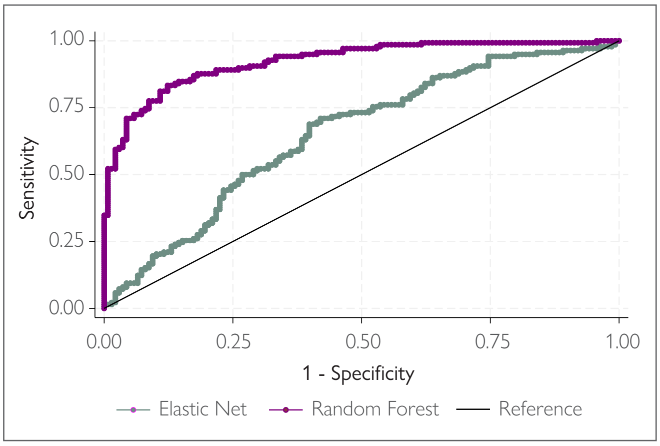
Table 3. Performance metrics

Performance Metric	Random Forest	Elastic Net
Dependent variable: Increase in profit		
Accuracy	84%	57%
True positives (TPR) (sensitivity)	86%	74%
True negatives (FPR) (specificity)	82%	37%
Ratio of false positives to true positives	18%	72%
Ratio of false negatives to true positives	17%	34%
Success predicted (% of SMEs)	54%	69%
False negatives (% of SMEs)	8%	14%
False positives (% of SMEs)	8%	29%
Dependent variable: Achieve hiring commitment		
Accuracy	83%	67%
TPR (sensitivity)	84%	67%
FPR (specificity)	81%	67%
Ratio of false positives to true positives	22%	49%
Ratio of false negatives to true positives	19%	50%
Success predicted (% of SMEs)	51%	50%
False negatives (% of SMEs)	8%	17%
False positives (% of SMEs)	9%	16%

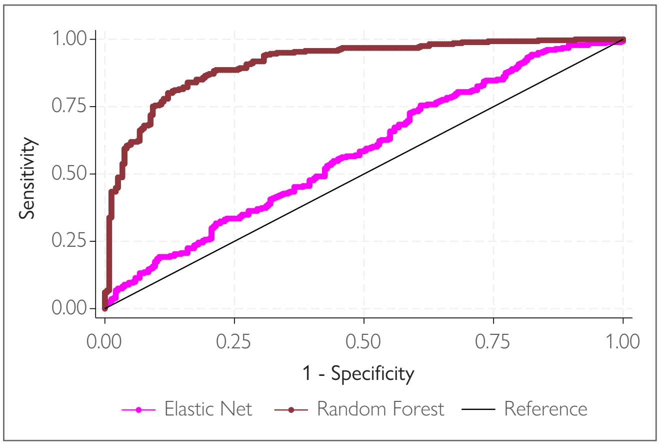
Note: Predictions were run on 33.3 per cent of the sample, not used to train the model, so values were calculated for 543 observations. The out-of-bag error for profit in the random forest was 0.135, and for the hiring commitment, 0.136.

Figure 4. Receiver Operating Characteristic

Panel A. Reaching or exceeding hiring commitment



Panel B. Increases in profit



Note: The ROC shows the trade-off between sensitivity and specificity for each model. The diagonal line indicates a model that mimics a random guess for classifying. Thus, curves above the reference perform better than random chance.

The difference in performance metrics between Random Forest and Elastic Net is shown in Figure 4 by the Receiver Operating Characteristic (ROC) graph. This plot illustrates the diagnostic ability of a binary classification model by showing the trade-off between a true positive rate and a false positive rate across various threshold settings. The diagonal line from (0,0) to (1,1) represents random guessing.[13] A model that performs no better than random chance would produce an ROC curve along this line. A model with good classification performance will push the ROC curve toward the top left corner of the graph (where the True Positive Rate (TPR) is high and False Positive Rate (FPR) is low). The closer the curve is to this corner, the better the model is. Figure 4 shows that, for each outcome, the Random Forest model performs significantly better than the Elastic Net and a random classifier. The 67 per cent and 57 per cent of accurately predicted outcomes by Elastic Net resemble a random choice.

The Area Under the ROC Curve (AUC) is a single number summarizing the model's performance. A perfect model has an AUC of 1.0, and a random classifier has an AUC of 0.5. Random Forest displays very high AUC values in our exercise, with 0.91 for both outcomes. Meanwhile, the Elastic Net variant has an AUC of 0.58 for-profit and 0.69 for the hiring commitment. With these values, the Elastic Net model is only marginally better than a random guess, while the Random Forest model shows very high explanatory power.[14]

13 If the ROC curve is below the diagonal, the model performs worse than random guessing.

14 These metrics align with what the deviance ratio of the Elastic Net model displays. The deviance ratio is a measure used to evaluate the performance of a model, like the R-squared in linear regression. It quantifies how much of the variation in the data is explained by the model. A deviance ratio close to 1 indicates that the model explains most of the variability in the data, meaning it fits well. A value close to 0 suggests the model has little explanatory power compared to a simple baseline model that assumes no predictors (just the intercept). For both outcomes, the deviance ratio in the Elastic Net case does not surpass 6 per cent.

DEMOGRAPHIC HETEROGENEITY

In this section, we analyse how the geographic location and demographic characteristics of participating business owners affect business success predictions. This analysis is important to assess whether specific groups may be penalized by the model, ensuring its ethical use to inform applicant screening. Additional analysis can be found in Appendix C, which presents the Average Local Effect for each of these variables as estimated by the Random Forest model.[15]

In general terms, the model may not be as accurate for subgroups that have few units in the sample. The testing sample, for which predicted values were estimated, consists of 81 per cent male and 20 per cent female business owners. Similarly, the sample comprises 61 per cent host community members, 35 per cent returnees and only 4 per cent IDPs. The governorate with the largest number of observations is Ninewa with 25 per cent of observations, followed by Basrah with 15 per cent and Kirkuk with 14 per cent.

ACROSS GOVERNORATES

The largest imbalances in average predicted success probability and in the rate of correct predictions are visible across governorates. Baghdad, being the country's capital, is an interesting case to illustrate the tradeoffs facing programmes such as EDF. When deciding where to target resources, policymakers may consider different factors including the likelihood of success according to different target outcomes, the accuracy of these predictions, and the underlying levels of need. EDF businesses in Baghdad have the second largest predicted probability of success in increasing profit by the endline and about average probability of success in meeting the job creation target. At the same time, Baghdad has the lowest poverty rate in the country, suggesting a lower need for recovery aid (Sharma et al., 2015; Omar, 2016).

On the other hand, the three governorates in the Kurdistan region have relatively low average probabilities of success, ranging between 40 per cent and 50 per cent (Figure 5, Panel A). In recent years, this region has been characterized by high average production growth (8% annual increase of GDP) and low poverty levels compared to the rest of the country (Sharma et al., 2015; SIDA, 2022), but also by one of the largest IDP populations in Iraq, estimated at 211,000 individuals in January 2025 (IOM DTM, 2025) Compared to other governorates, EDF businesses in Dohuk have a relatively low average probability of success in increasing profit (44%). Once again, the example highlights that the probability of success among screened businesses is only one among many metrics' decision-makers may want to consider. It is also important to note that model predictions for some governorates, such as Dohuk, may be less reliable due to smaller sample sizes, which can affect the accuracy of estimated success probabilities for these subgroups.

Differences in the model's predictive power associated with sample size are seen in other governorates, as geographic areas with the lower proportion of correct predictions are also the ones with the largest number of observations (Figure 5, Panel B). For example, Ninewa has one of the lowest proportions of correct predictions (77%), one of the lowest average probabilities of success (48%) and the largest sample (1,339 observations). This governorate was also picked as an important variable by the Random Forest model. When zooming into the probability distribution for this governorate, we find that the low average comes from a large variation in the model predictions, not a concentration of estimations around the mean. A possible interpretation of this finding is that, as the programme expands to reach a larger pool of businesses in a given area, the more obvious winners are exhausted, and it becomes harder to distinguish between more and less promising businesses.

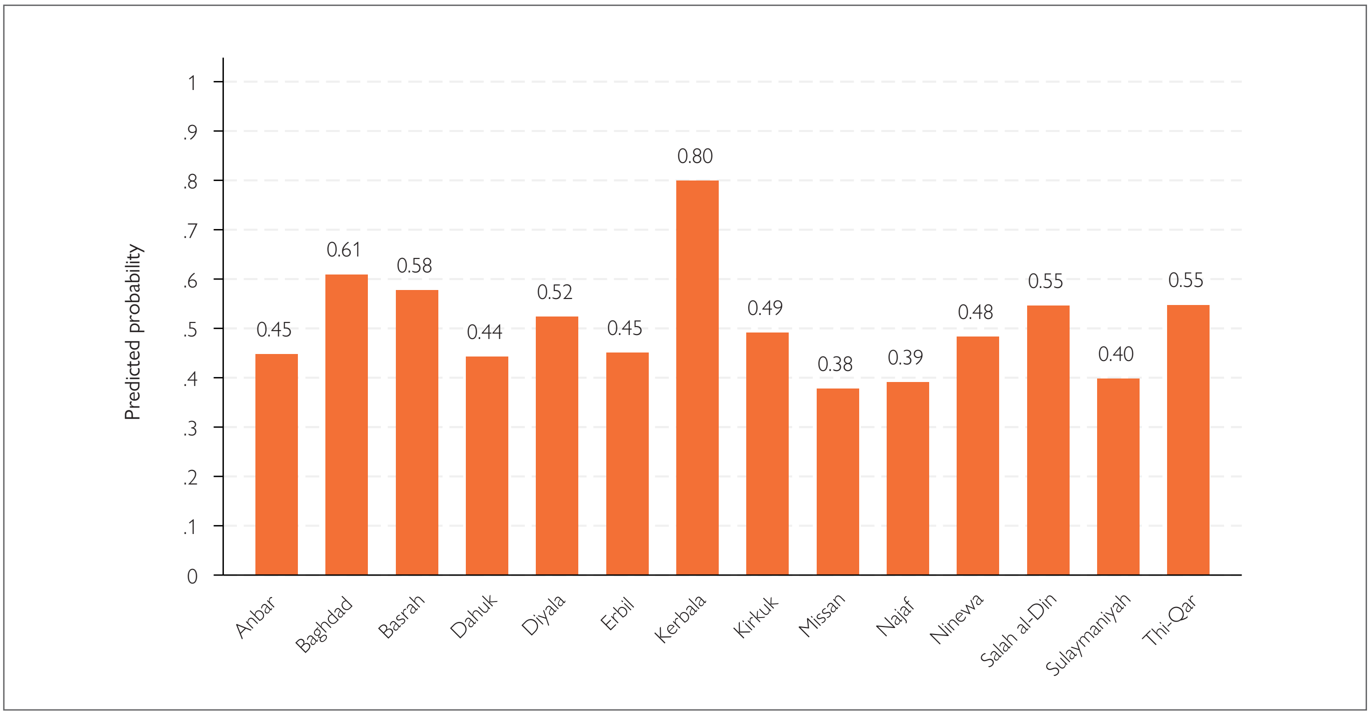
The southern region of Iraq has been characterized by underdevelopment and a lack of livelihood opportunities; these issues are commonly reported as a top social grievance in Basra, Thi-Qar, and Missan (IOM, 2023; UNDP, 2022). The poverty headcount rate in Missan ranges from 21 to 72 per cent, and in Thi-Qar, it is 37.6 per cent (World Bank, 2015). Missan and Najaf show the lowest average probabilities of success in the sample, with 38 and 39 per cent on average, as well as 80 and 75 per cent of correct predictions, respectively. However, other southern governorates show promising results, including Basrah and Thi-Qar, which have average success probabilities of 58 and 55 per cent, respectively, and the model correctly predicted 79 and 89 per cent of SMEs.

Furthermore, when using increases in profit as a dependent variable, we observe that businesses in Kerbala have, on average, higher predicted probabilities of success. In this sense, it is important to keep in mind that Kerbala is one of the governorates with the fewest observations (27), so the results for larger samples like Baghdad (400) and Basrah (678) may be more reliable. In governorates where low predicted success overlaps with larger gaps in baseline economic and business indicators, additional interventions may be appropriate to level the playing field.

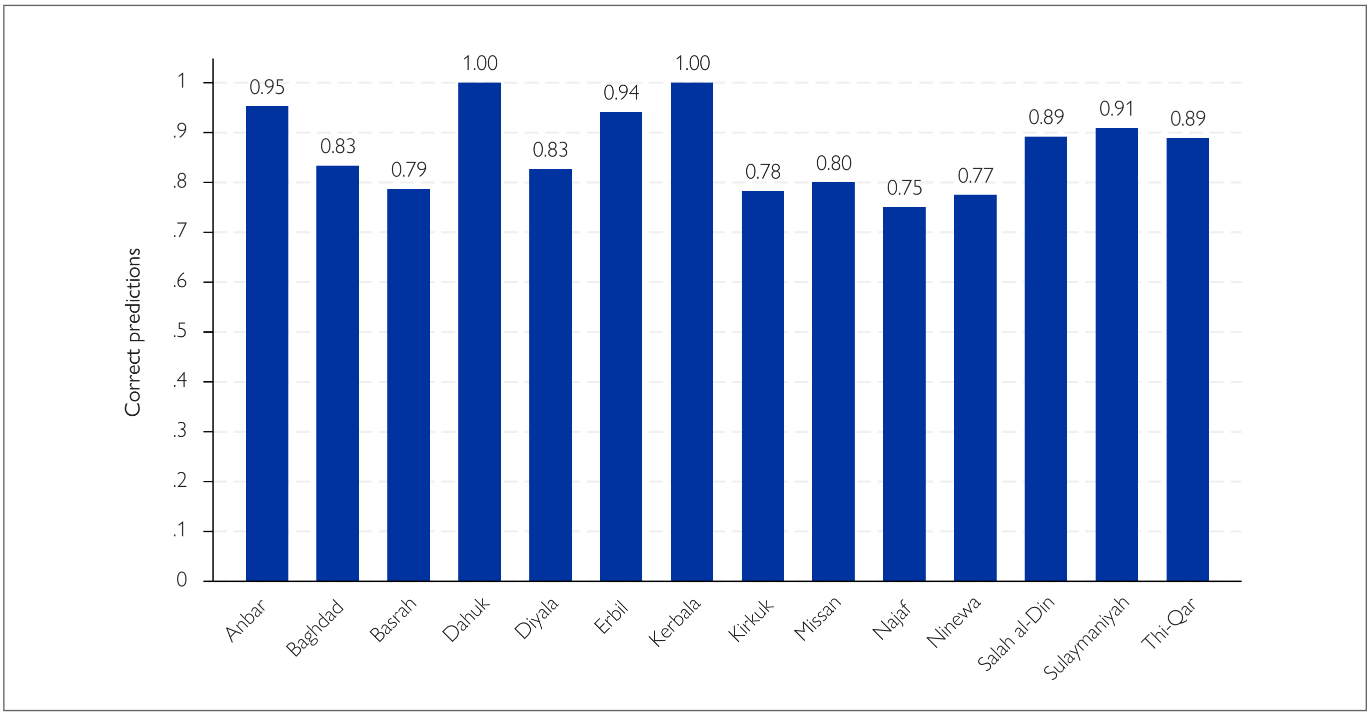
15 Appendix C shows a detailed analysis of the heterogeneous impacts of geographical location, economic sector and demographic factors on the predicted success of EDF programme participants, measured by profit increases and achievement of hiring commitments. Key findings include: (1) Businesses in Ninewa Governorate showed significantly higher probabilities of success, while those in Dahuk faced lower profit probabilities. (2) Construction and manufacturing sectors demonstrated higher success rates, while agriculture showed negative impacts. (3) Female business owners and host community members were associated with lower probabilities of success, while IDPs showed positive impacts, particularly in profit growth. The ALE methodology was used to analyse these heterogeneities, showing the average change in model prediction as each feature changes, holding others constant. However, it is important to note that the distribution of the sample across these categories, particularly demographic groups, and the low magnitude of the coefficients may impact the robustness of these findings and warrant further investigation.

Figure 5. Probability of increases in profit by governorates

Panel A. Average estimated probability of success



Panel B. Proportion of correct predictions by governorate

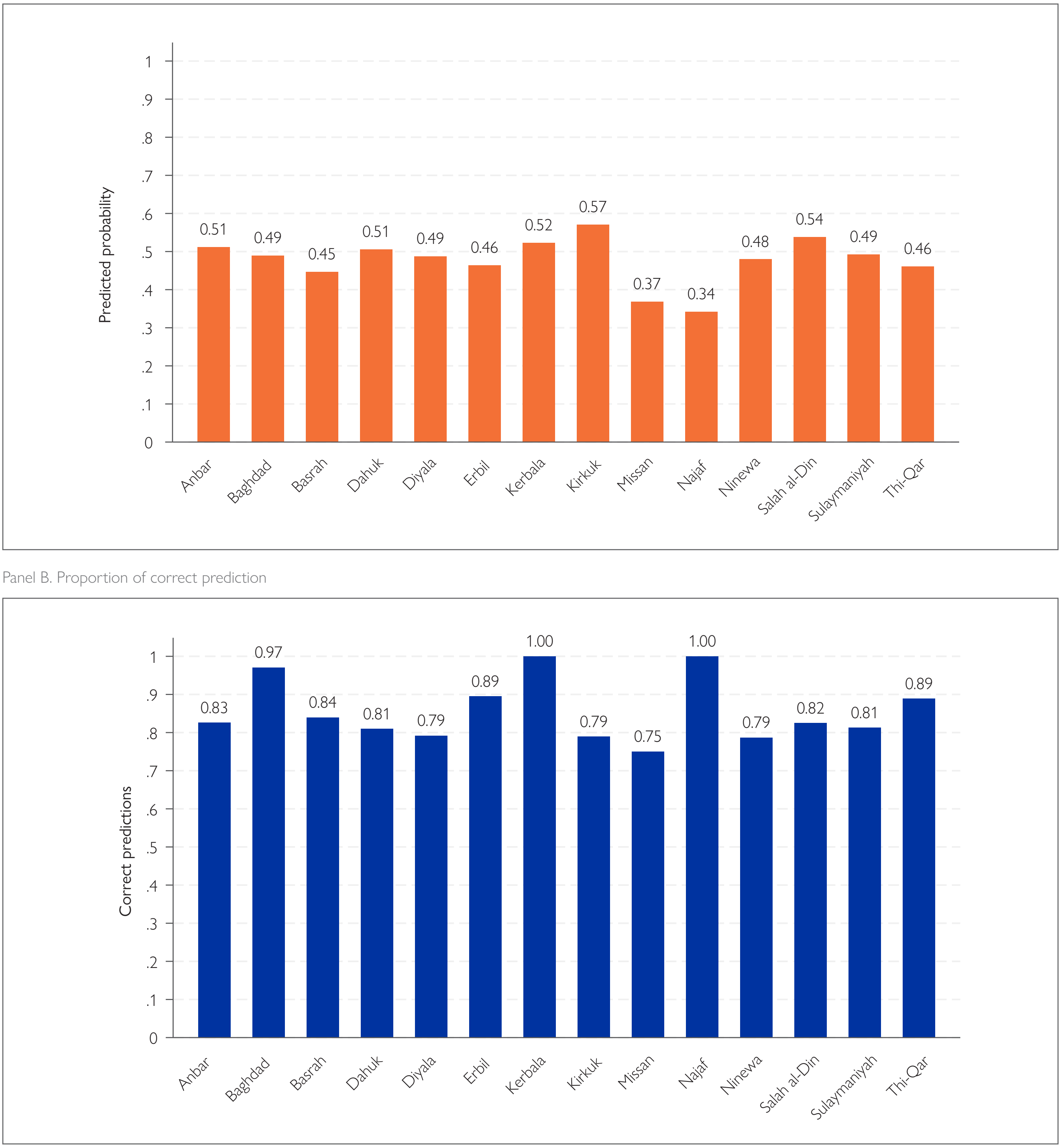


Note: Panel A shows the average probability of success in terms of increasing SME profit, as estimated by the random forest model, by governorates. Panel B shows the proportion of SMEs for which the outcome was correctly predicted by the model, otherwise called accuracy, also by governorate.

Gaps in success predictions are less extreme when using the achievement of the hiring commitment set at baseline as a dependent variable, but some of the observed trends remain. Missan and Najaf, where the model performs adequately (80 and 74% of correct predictions), also display the lowest success probabilities (38 and 39%, respectively; Figure 6). Nonetheless, when it comes to job creation, northern governorates outside the Kurdistan Region of Iraq (KRI) show promising results. Kirkuk and Salah al-Din are the governorates with the highest average probabilities of success (57 and 54%, respectively). Within the KRI, Erbil, Sulaymaniyah and Dahuk do not stand out from other governorates in their SMEs' probability of job creation, as they stand around the average.

Figure 6. Probability of achieving the hiring commitment by governorates

Panel A. Average estimated probability of success



Panel B. Proportion of correct prediction

Note: Panel A shows the average probability of success in terms of achieving the hiring commitment made at the baseline, as estimated by the random forest model, by governorates. Panel B shows the proportion of SMEs for which the outcome was correctly predicted by the model, otherwise called accuracy, also by governorate.

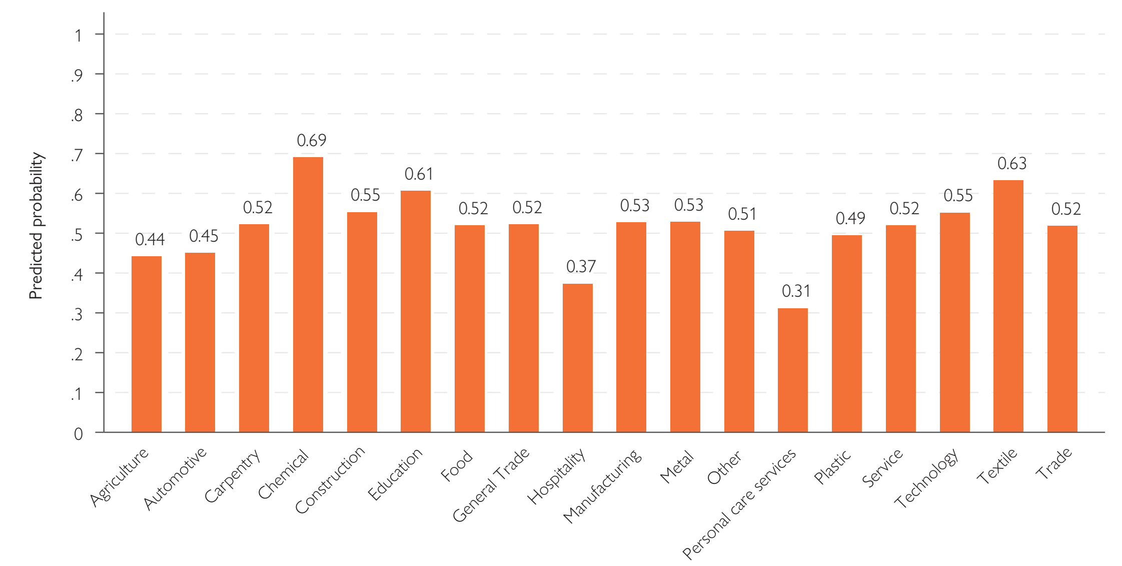
ACROSS SECTORS

The economic sector in which the SME operates can be a cause of concern for differing business conditions that lead to gaps in the probability of success. In line with findings from other studies conducted by IOM (2025), we see soft signs of a tradeoff between increases in profit and job creation for some sectors. For example, manufacturing, the largest sector in the sample, shows the highest probability of success in achieving the hiring commitment (55%, Figure 8, Panel A) and a relatively average probability of increased profit (53%, Figure 7, Panel A), signalling strong potential for SMEs in this sector. In manufacturing, the accuracy of the model for reaching the hiring commitment and having an increase in income is 79 per cent and 82 per cent respectively (Figure 8, Panel B and Figure 7, Panel B).[16] However, agriculture, the second-largest sector, shows the third-lowest average probability of an increase in profit (44%), and the second-lowest probability of reaching the hiring commitment at baseline (35%, with an accuracy of 80%).[17]

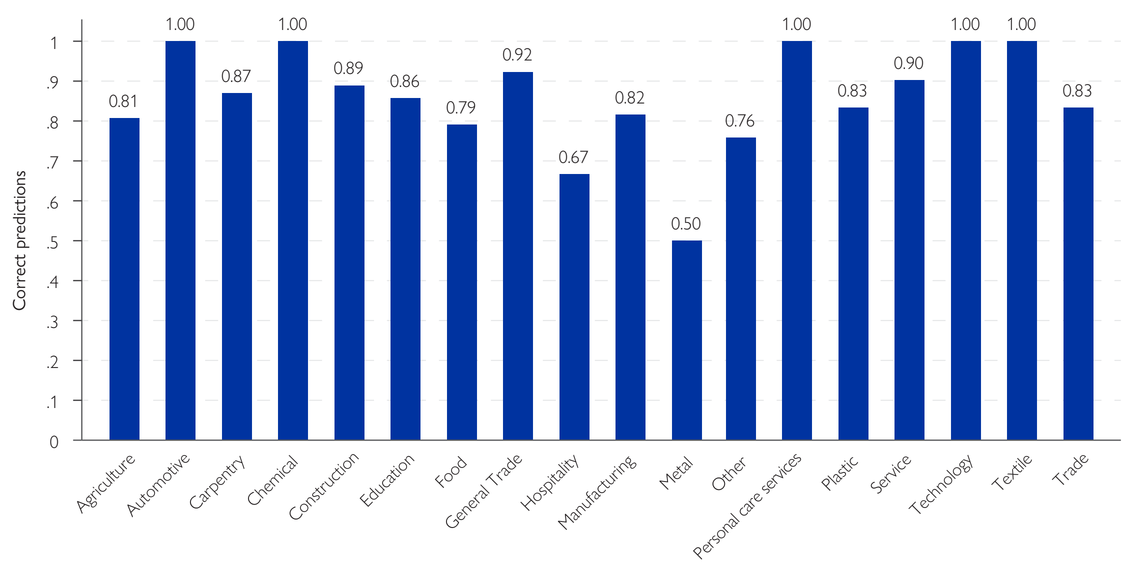
The lowest probabilities of success in terms of increased profit were given to the hospitality (37%) and personal care services (31%) sectors. The hospitality sector also has the fourth-lowest probability of reaching the hiring commitment (45%).

Figure 7. Probability of increases in profit by economic sector

Panel A. Average estimated probability of success



Panel B. Proportion of correct predictions



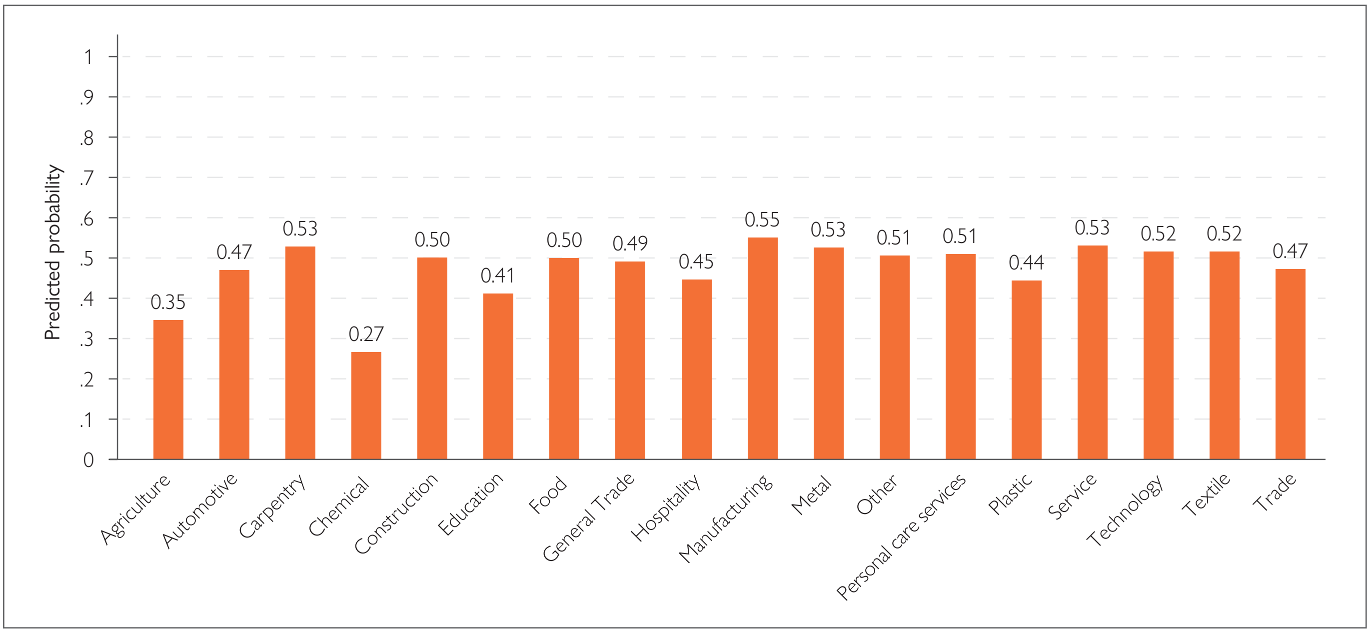
Note: Panel A shows the average probability of success in terms of increasing profit in the best month of the year, as estimated by the random forest model, by economic sectors. Panel B shows the proportion of SMEs for which the outcome was correctly predicted by the model, otherwise called accuracy, also by sectors.

16 The metal sector has the lowest accuracy for increasing profit (50%) and the second-lowest in hiring commitment (75%). The lowest accuracy in hiring commitment is hospitality (67%).

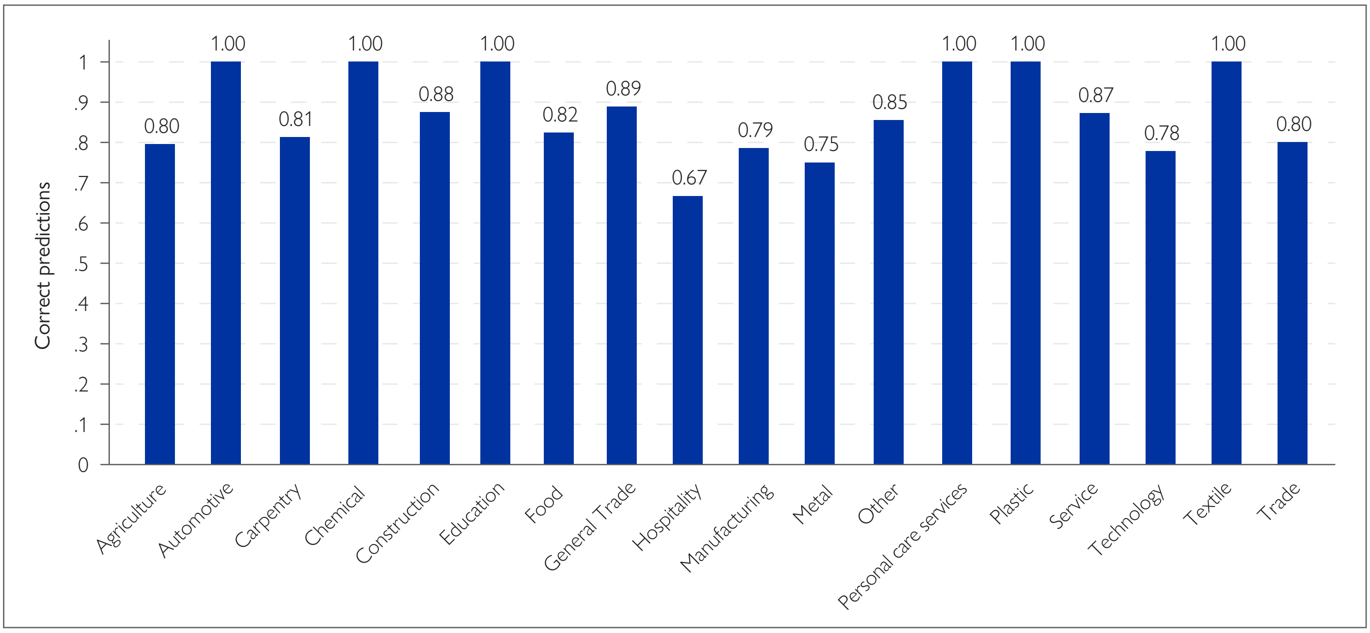
17 Agriculture is the most important livelihood source in Iraq. According to the Food and Agriculture Organization of the United Nations (FAO), about a third of the population lives in rural areas, making them dependent on agriculture-related activities (FAO, 2016).

Figure 8. Probability of achieving the hiring commitment by economic sector

Panel A. Average estimated probability of success



Panel B. Proportion of correct predictions



Note: Panel A shows the average probability of success in terms of achieving the hiring commitment made at the baseline, as estimated by the random forest model, by economic sectors. Panel B shows the proportion of SMEs for which the outcome was correctly predicted by the model, otherwise called accuracy, also by sectors.

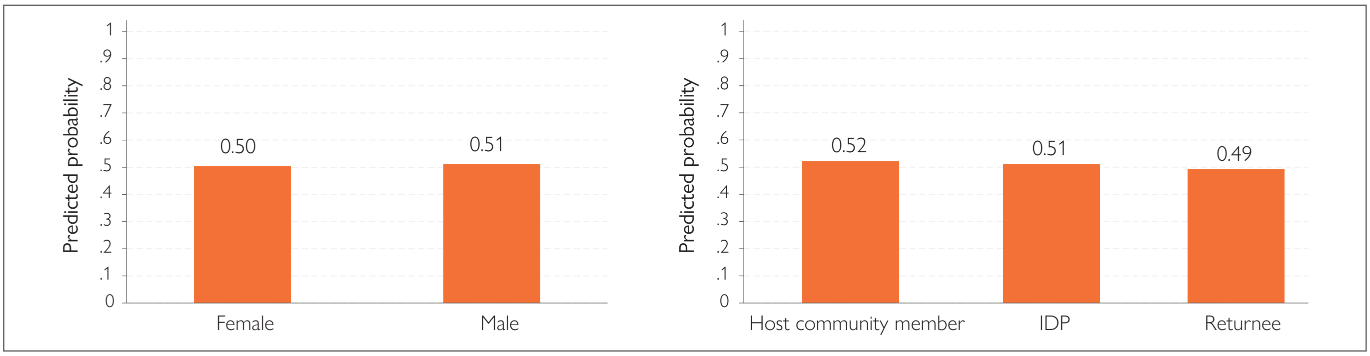
ACROSS GENDER AND MIGRATION STATUS

The average predictions and accuracy made by the Random Forest model do not show a broad difference by gender or migration status. The probability of an increase in profit for women is 50 per cent, and for men it is 51 per cent. Similarly, by migration status, host community members had a probability of 52 per cent reporting an increase in profit, IDPs 51 per cent, and returnees 49 per cent (Figure 9, Panel A). Furthermore, the probability of reaching the hiring commitment for women and men is 49 per cent, 48 per cent for host community members, 46 per cent for IDPs and 51 per cent for returnees. The accuracy of the gender model and the migration status model is above 78 per cent.[18] In interpreting these findings, it is important to highlight that selection effects are likely to be present: those who applied and received EDF grants represent relatively advantaged individuals within each group, rather than the population of female or displaced entrepreneurs at large.

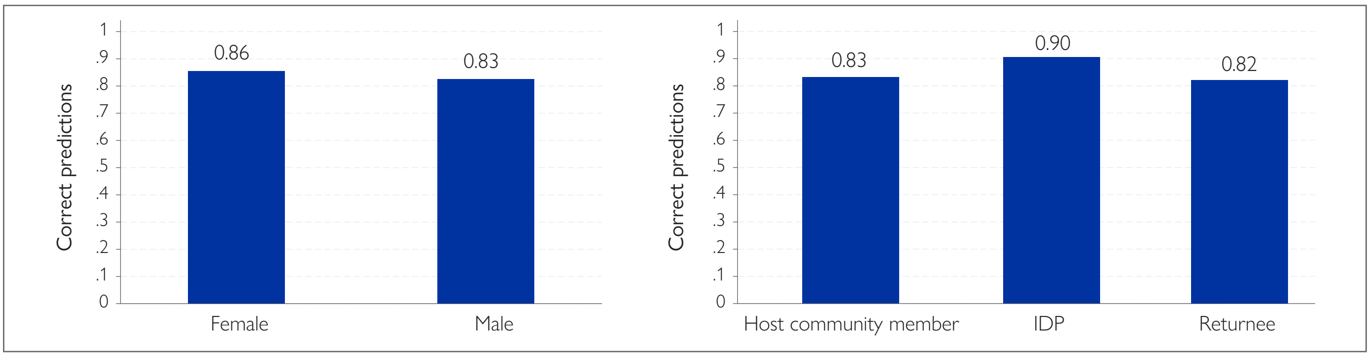
18 Appendix C shows similar results for the ALE of gender and displacement history. By keeping other factors constant, ALEs clean the coefficients of variation in other confounding variables (governorates, economic sector, age, profit or size, among others).

Figure 9. Probability of increased profit by gender and migration status

Panel A. Average estimated probability of success



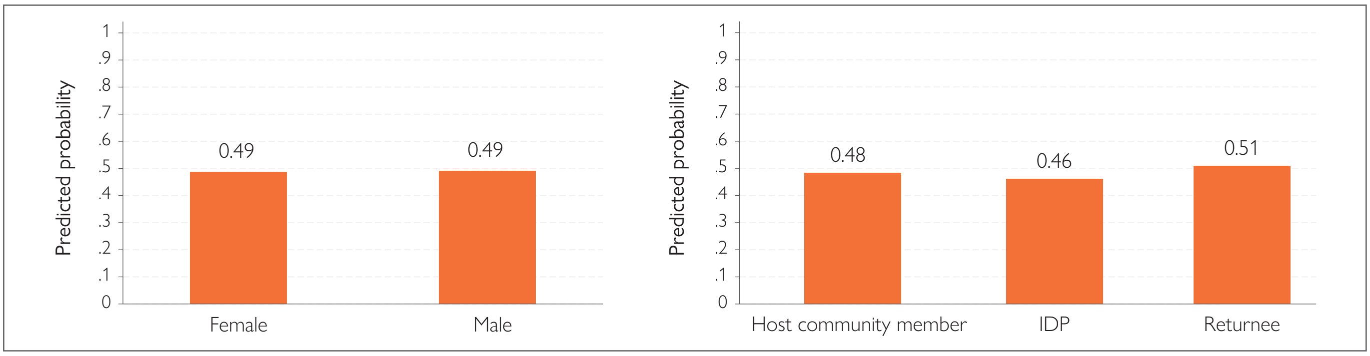
Panel B. Proportion of correct predictions



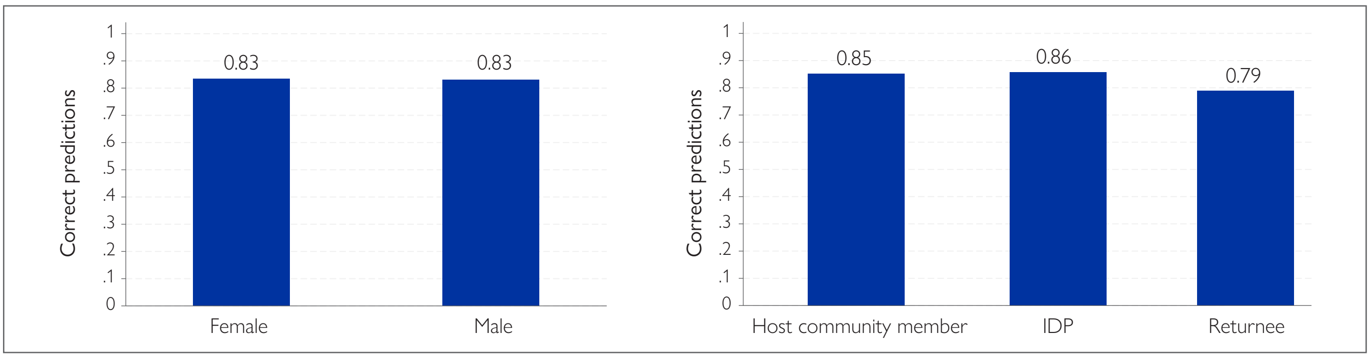
Note: Panel A shows the average probability of success in terms of increasing profit in the best month of the year, as estimated by the random forest model, by demographic characteristics of the business owner (gender and migration status). Panel B shows the proportion of SMEs for which the outcome was correctly predicted by the model, otherwise called accuracy, also by gender and migration status.

Figure 10. Probability of achieving the hiring commitment by gender and migration status

Panel A. Average estimated probability of success



Panel B. Proportion of correct predictions



Note: Panel A shows the average probability of success in terms of achieving the hiring commitment made at the baseline, as estimated by the random forest model, by demographic characteristics of the business owner (gender and migration status). Panel B shows the proportion of SMEs for which the outcome was correctly predicted by the model, otherwise called accuracy, also by gender and migration status.

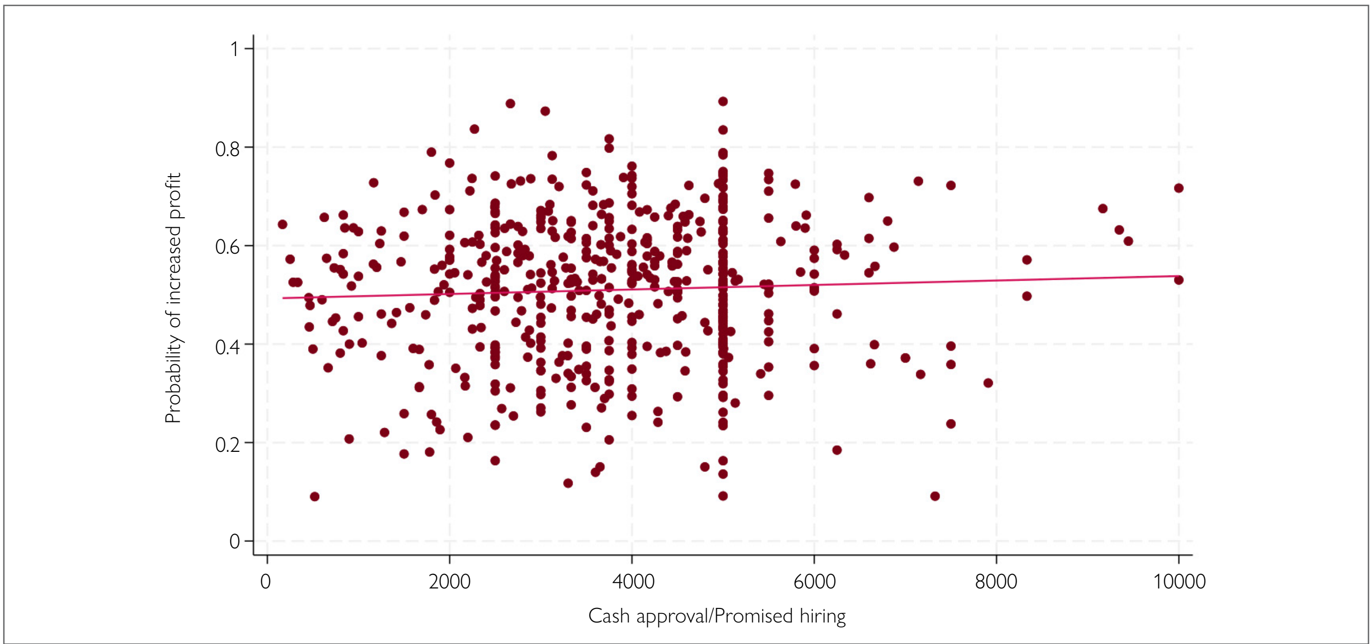
COMPARISON OF MODEL-BASED PREDICTIONS AND DECISION-MAKING HEURISTICS

This section assesses how simple decision-making heuristics compare with model-based predictions of success. As highlighted in the previous section, an effective screening process should consider businesses' likelihood of success, social impact, operational efficiency and other objectives. Understanding the trade-offs between these objectives is therefore crucial to inform decision-making.

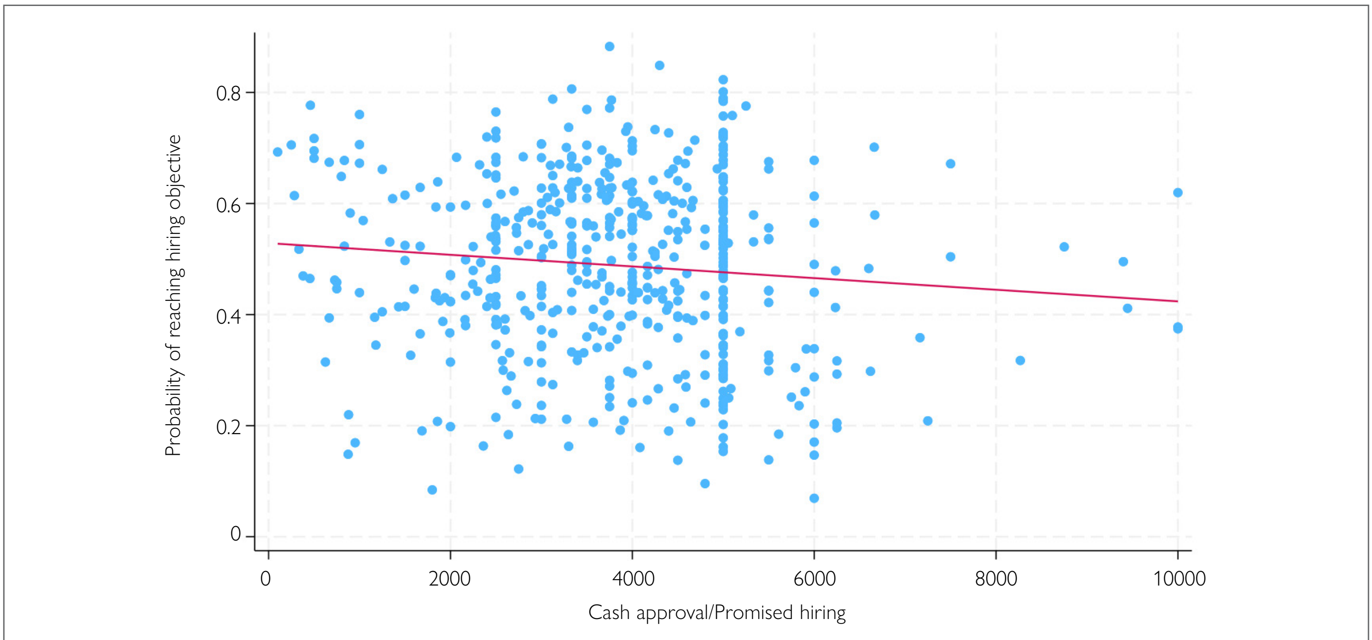
IOM's cost per job is a key EDF selection metric, calculated by dividing the grant amount by the number of committed hires (the sample average was USD 3,700). Figure 11, Panel A, shows a relatively slight positive trend between the probability of an increase in profit for an SME and the cost per job. Figure 11, Panel B shows a negative trend between the likelihood of achieving hiring commitment and IOM's cost per job. This result implies that businesses that are creating jobs at a lower cost for IOM are more likely to succeed at job creation.[19]

Figure 11. SME's Outcomes and IOM funding

Panel A. Achieving an increase in income and IOM's cost per job (IOM finding / promised hiring)



Panel B. Hiring commitment success and IOM's cost per job (IOM finding / promised hiring)



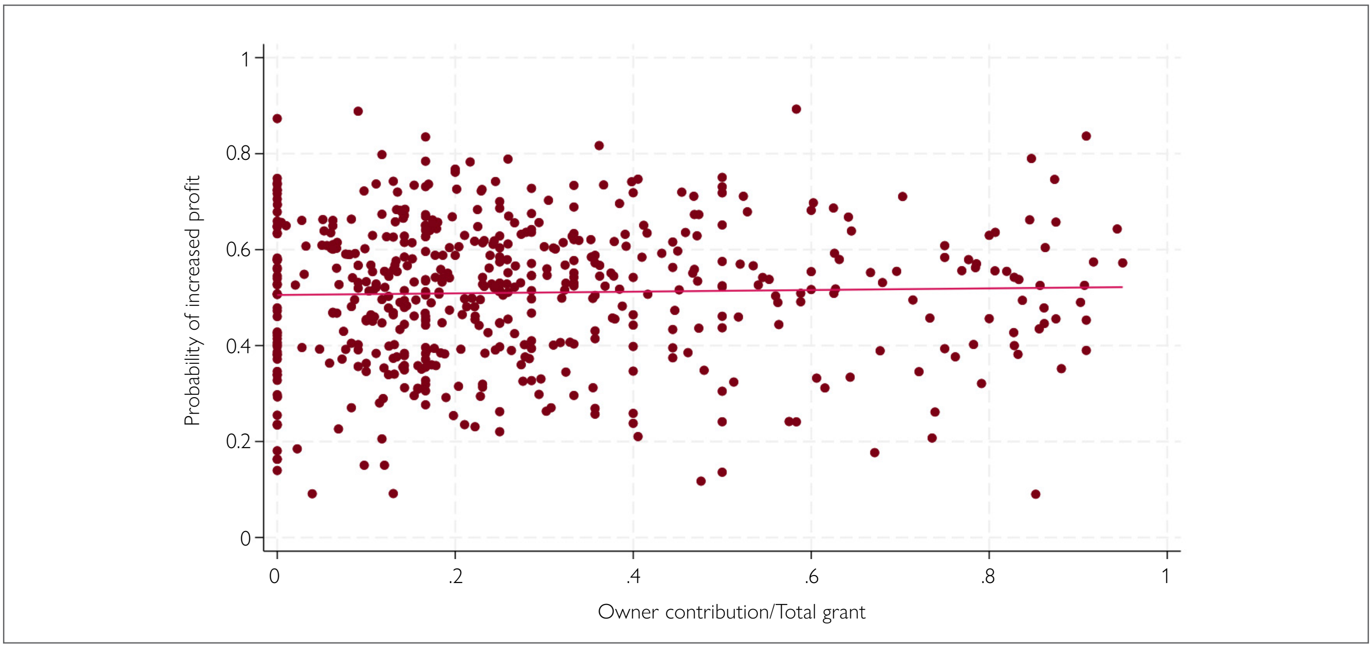
Note: Cost per job is calculated as the ratio between the cash approved for transfer by IOM and the hiring objective set before the baseline, shown in the X-axis of Panels A and B.

19 The disaggregated relationship between the cash investment (either by IOM or by the business owner), set hiring commitments and probability of success in job creation can be seen in Appendix D. Figures D.1 and D.2 disclose that, besides the role of IOM and business owner contribution, attainable hiring commitments are also correlated to increasing probability of creating jobs.

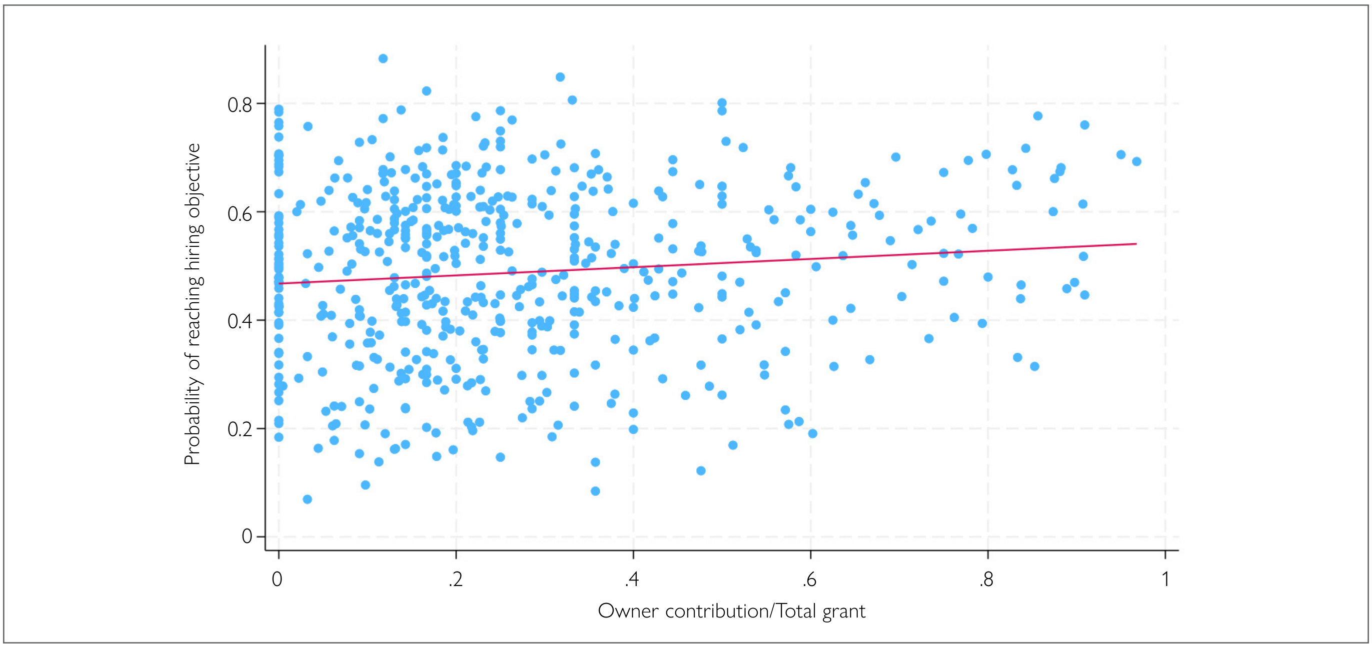
Looking at the SMEs' contribution, Figure 12, Panel A shows that the probability of increasing income and the share of the total grant contributed by the SMEs' owners are close to zero, showing no relation between the variables. However, Figure 12, Panel B shows that the SME's contribution is positively correlated to hiring commitment success, implying that a larger investment by SME beneficiaries is associated with a higher likelihood of success at job creation. The higher the SME owner's contribution, the greater the probability of reaching the hiring target, suggesting that greater personal investment is linked to better job creation outcomes.

Figure 12. SME's outcomes and contributions

Panel A. Achieving an increase in income and SME's cost per job (SME's contribution/ Total grant)



Panel B. Hiring commitment success and SME's cost per job (SME's contribution/ Total grant)



Note: The ratio of money contributed by the owner to the total amount of the grant is shown in the X-axis of Panels A and B. Success probabilities result from random forest predictions, which were calculated for 543 businesses.

CONCLUSION

This study sought to assess the feasibility of using data-driven machine learning models to predict business success among EDF grantees. The report focuses on two measures of business success: (i) increases in profit in the best month of the year, and (ii) reaching or exceeding the hiring commitment made by the business owner, both measured 12 months after award of the grants.

A Random Forest model accurately predicted these outcomes in around 80 per cent of cases, proving that a statistical model based on self-reported survey data can, despite its limitations, be a powerful tool for predicting the trajectory of selected businesses. The study highlights the potential value of integrating automated scoring systems powered by machine learning into the current EDF screening process, while ensuring an ethical, humane and transparent selection process. By using data-driven models that reflect the diversity of business profiles, the programme could better identify high-potential applicants that may be overlooked by more traditional screening tools. Such models can also help identify sectors, demographic groups and geographical areas facing structural barriers that require complementary forms of support.

Moreover, the findings suggest that the size and conditions applied to EDF grants play a decisive role in business outcomes. The amount of funding approved and the size of the contribution by the business owner are major factors influencing profit growth among recipients and the achievement of job creation targets, indicating that IOM's decisions have a direct impact on success rates. This suggests additional applications for machine learning models that could optimize grant conditions for businesses according to their characteristics.

The findings from the Random Forest model suggest that predicting business success requires flexible approaches capable of capturing the complexity of economic behavior. For example, profit is identified as an important predictor in the Random Forest model, which contributes significantly to how the model differentiates between businesses with higher and lower chances of success. However, the relationship is not linear. The model predicts a lower likelihood of success at lower profit levels, suggesting that businesses starting with minimal earnings face a higher risk of failure, regardless of whether their profit improves later. Similarly, the analysis shows that the likelihood of business success varies with the business owner's age, with the highest predicted outcomes concentrated among individuals between approximately 30 and 45 years old. Outside this range, the probability of success tends to decline, suggesting that younger and older entrepreneurs may face additional challenges. These findings underscore the value of data-driven models that can account for non-linear relationships and individual variation, offering a more accurate and equitable basis for identifying high-potential businesses.

Further research should explore broader and more inclusive indicators of business success. Relying solely on profit growth and job creation within a 12-month horizon may overlook firms that generate long-term value or contribute meaningfully to social outcomes. Expanding the definition of success to include factors such as business sustainability, female and youth employment, and community impact would help identify a wider range of businesses that are worth supporting through investment and programme attention.

APPENDIX

A. SELECTION OF VARIABLES IN THE BASELINE TO PREDICT CONTINUOUS VARIABLES IN THE ENDLINE

This section uses Elastic Net to calculate the variables from the baseline that predicted profit in the best month of last year and the number of employees in the endline. The variables from the baseline are chosen according to EDF program guidelines and the relevant literature (e.g., McKenzie, 2017; Fafchamps and Woodruff, 2017; McKenzie and Sansone, 2019; Wang and Guedes, 2024; Yoo et al., 2023).[20] The Elastic Net model picks the relevant characteristics and returns a list of variables with explanatory power for the variation of the dependent variable and their respective coefficients.

For the profit variable in the best month of the year, the Elastic Net model chose 37 variables, including specific governorates and different business characteristics. Figure 1, Panel A displays the coefficients for Elastic Net. Some demographic variables have significant coefficients for profit in the best month: being an IDP, a female and having primary school education, with adverse effects of over 5, 21 and 16 per cent respectively.[21] In financial terms, businesses with loans from friends or relatives have approximately 24 per cent lower predicted profit, while borrowing from a parent company has a positive effect (8%).

Furthermore, entrepreneurs with family members as workers have lower predicted profits (6% less). Hiring through business networks and advertisement both have positive coefficients for profit (4% and 22%, respectively). The Elastic Net also chose indicators of formality and have a positive coefficient.[22] Bigger businesses, measured through the number of current full-time employees and training of apprentices in the baseline, have higher predicted profits 12 months later. Higher wages were also associated with more significant profits in the best month of the year. The amount of cash contributed for the grant also has a positive predictive effect on profit.

In geographic terms, businesses in Babylon, Dahuk, Anbar and Erbil governorates are less prone to gaining more significant profits. Meanwhile, Baghdad, Basrah, Missan, Salah al-Din, Kerbala and Thi-Qar have positive coefficients.

When job creation (through the number of employees by endline) is the outcome variable, the Elastic Net model chooses 37 variables, including 11 governorate dummies (Figure 1, Panel B). The most significant negative coefficient is related to having a loan from a microfinance organization. Some demographic variables also have negative coefficients, including being a female (71% less), having primary school education (11% less) and being a host community member (5% less). Employing elsewhere and paying higher wages are also negatively correlated to hiring employees by endline (25% less and 7% less, respectively). IDPs were predicted to have more employees by the end of the cycle (88%).

Hiring conditions are some of the most critical variables, and those who hire employees through advertisement and business networks are predicted to double the size of their business. Those who hire through friends or family networks were also expected to increase their workforce significantly. Entrepreneurs with university and post-graduate diplomas had a positive coefficient for workers at the endline (56% and 30%). Variables from the baseline, such as profit and formality, were positively associated with the number of employees at the endline.

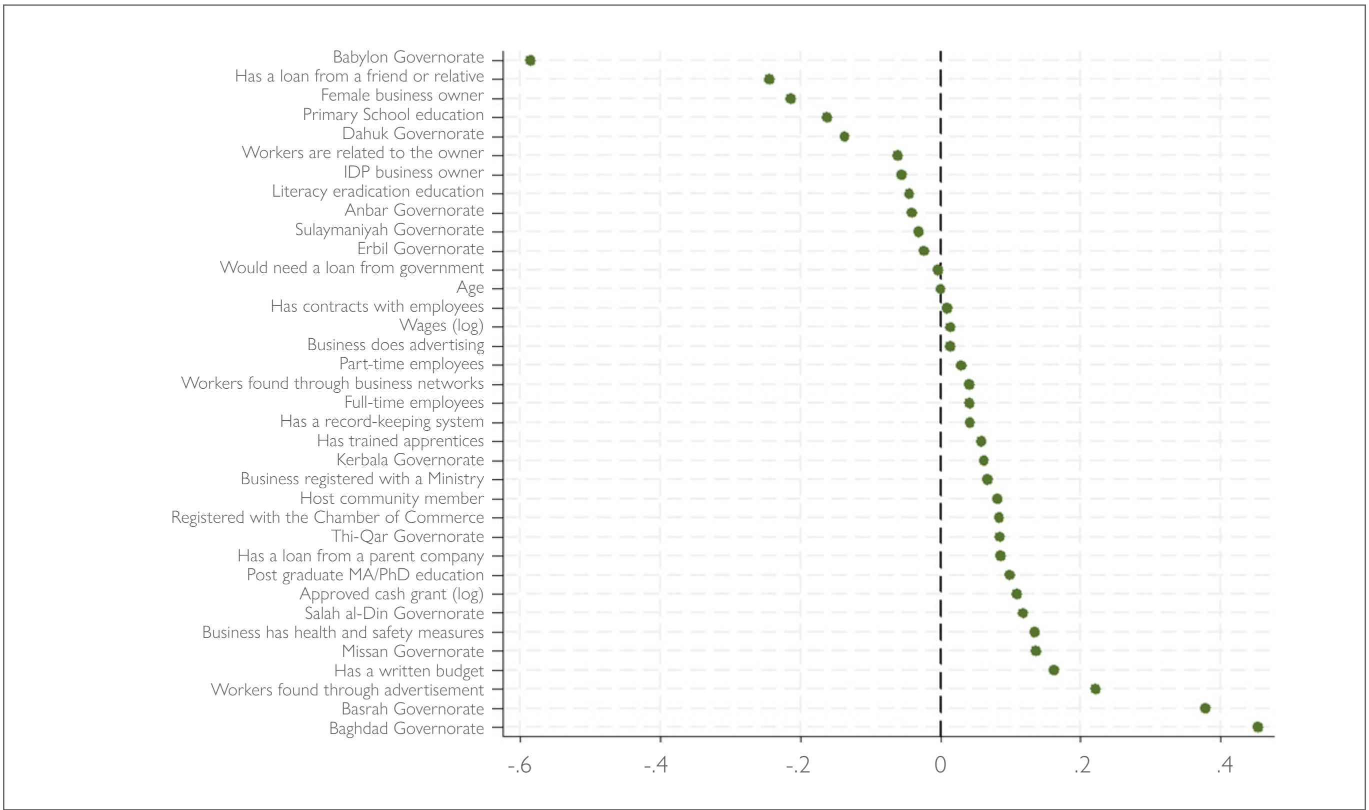
20 The variables from the baseline are the number of employees, business registration with the government, use of advertising, bookkeeping practices, new investments in the past year, need for financing, use of contracts with employees, wages, relationship to the community, anticipated years in business and geographical variables (district and governorate).

21 Being a host community member and having post-graduate education increases profit by 8 and 10 per cent, respectively

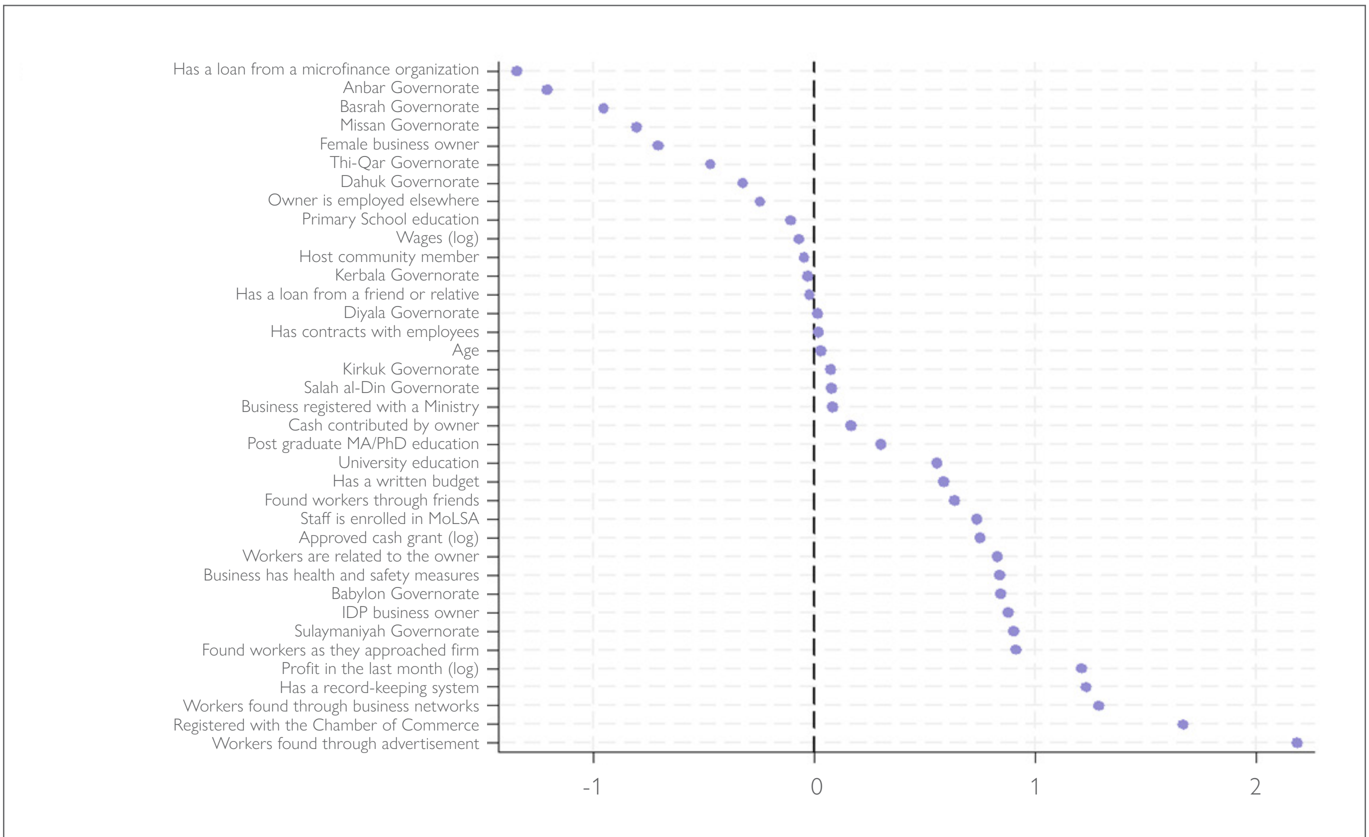
22 These include having a record-keeping system, a written budget, health and safety measures, staff enrolled in the social security system, and registration with the Chamber of Commerce.

Figure A.1. Variables chosen by Elastic Net

Panel A: Profit in the best month at the endline



Panel B: Number of employees at the endline

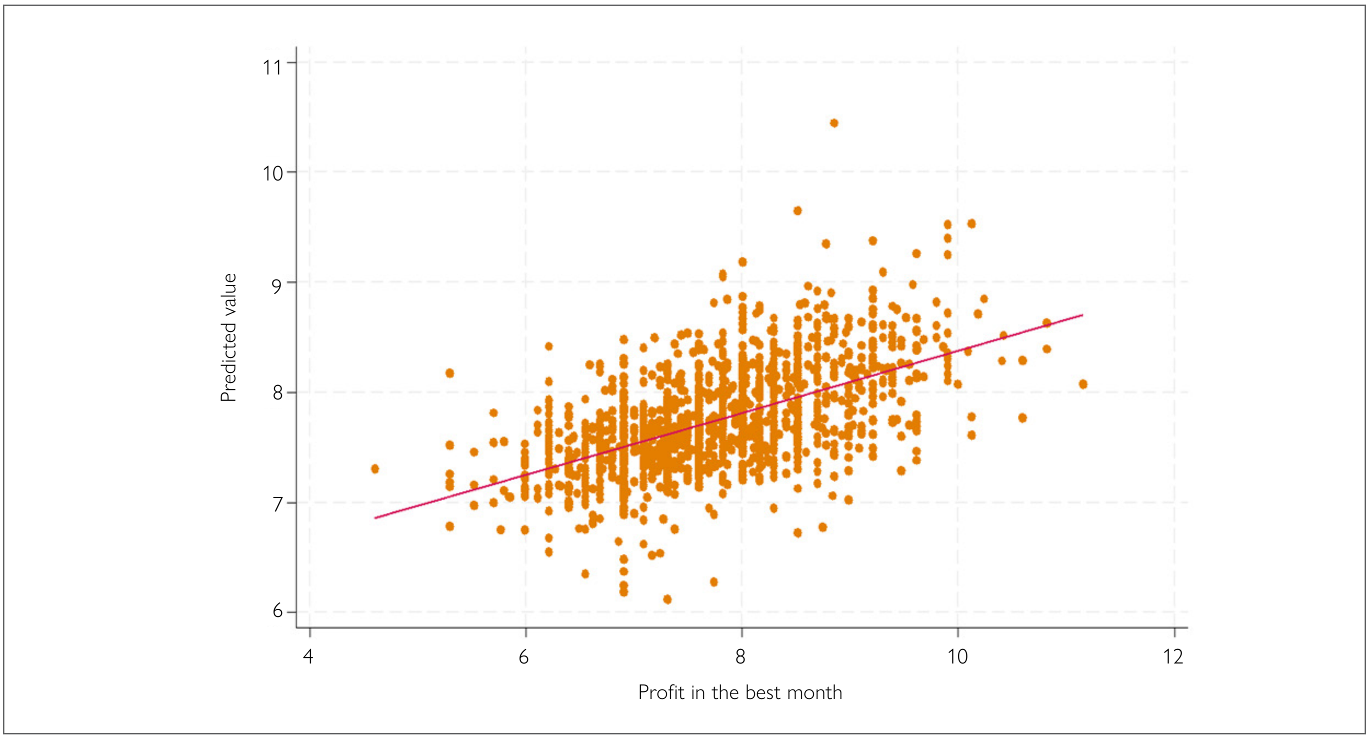


Note: Penalized coefficients estimated by Elastic Net. The regression includes answers to the survey at the baseline stage for 1,628 business owners. The dependent variable was the logarithm of profit in the best month of last year in the endline round.

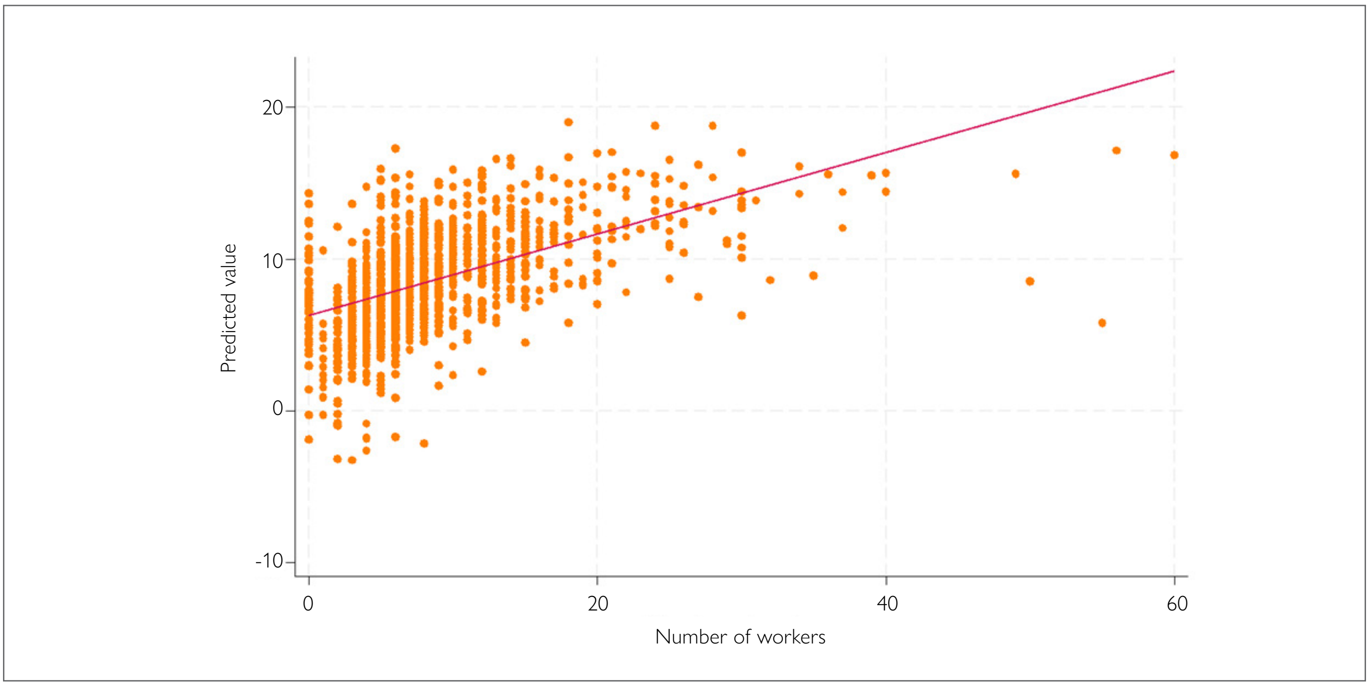
The Elastic Net model estimated with the baseline data was used to predict job creation and profit in the endline data.[23] Panel A of Figure A.1 shows a scatter plot of predictions for profit in the best month, and Panel B shows the same plot for the number of workers. Overall, the model's job creation predictions were less accurate than predicted values for profit. As shown in the figure, predicted values underestimated actual values, as business owners hired more employees than their baseline figures would have led to believe. At baseline, the average business had hired 0.5 employees in the previous six months, which increased to three employees by midline and decreased to one by endline.

Figure A.2 Predicted and observed values for the endline stage by Elastic Net model

Panel A. Profit in the best month of the year



Panel B. Number of workers

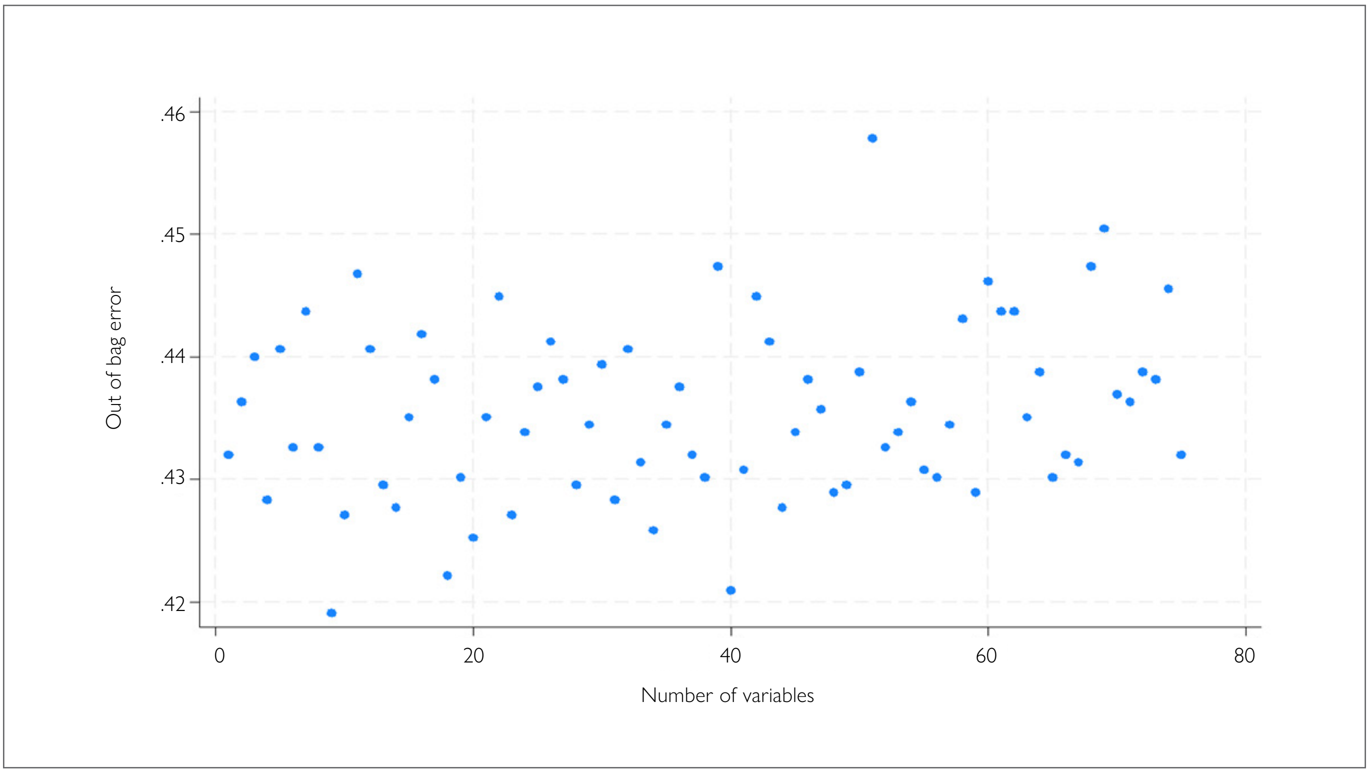


Note: Baseline data were used to train both models, and the data for both outcome variables was taken at the endline stage. Using the model results, the graph displays predicted values for endline profit and number of workers. In the profit model, values correlate to observed values by 0.56 and predicted values correlate to observed values by 0.54 for the number of new workers. The red line represents fitted values of predicted and observed profit.

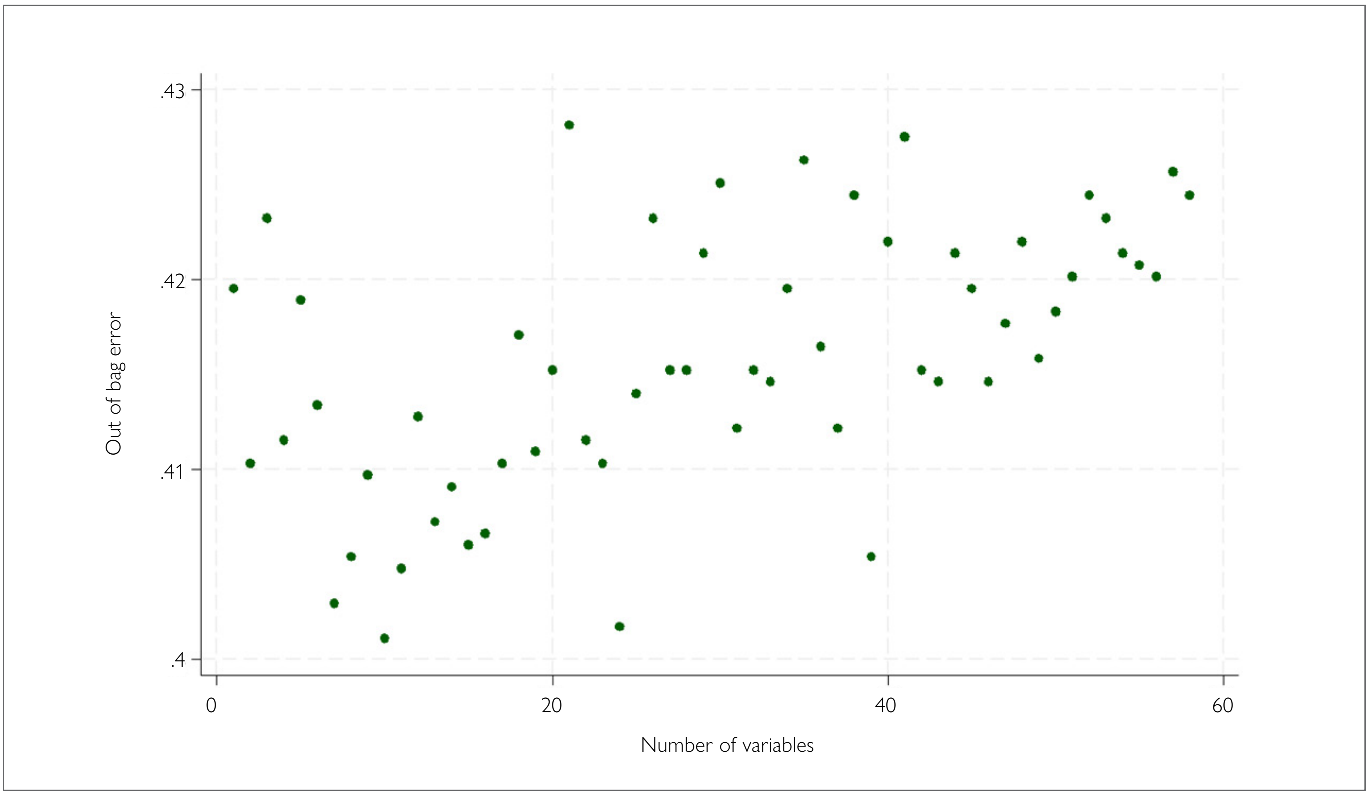
23 The model had an R-squared coefficient of 0.31 when predicting profit at endline, predicted values correlate to observed values by 0.56. The R-squared for the number of workers is 0.29 when predicting endline, and predicted values correlate to observed values by 0.54. The R-squared represents the percentage of the variation that the independent variables can explain. The latter signals that the chosen variables and estimated coefficients have a crucial explanatory power for the profit of EDF businesses.

Figure A.3 Evaluation of the optimal number of variables to be included in the Random Forest model

Panel A. Increases in profit in the best month of last year as dependent variable



Panel B. Reaching the hiring commitment as the dependent variable

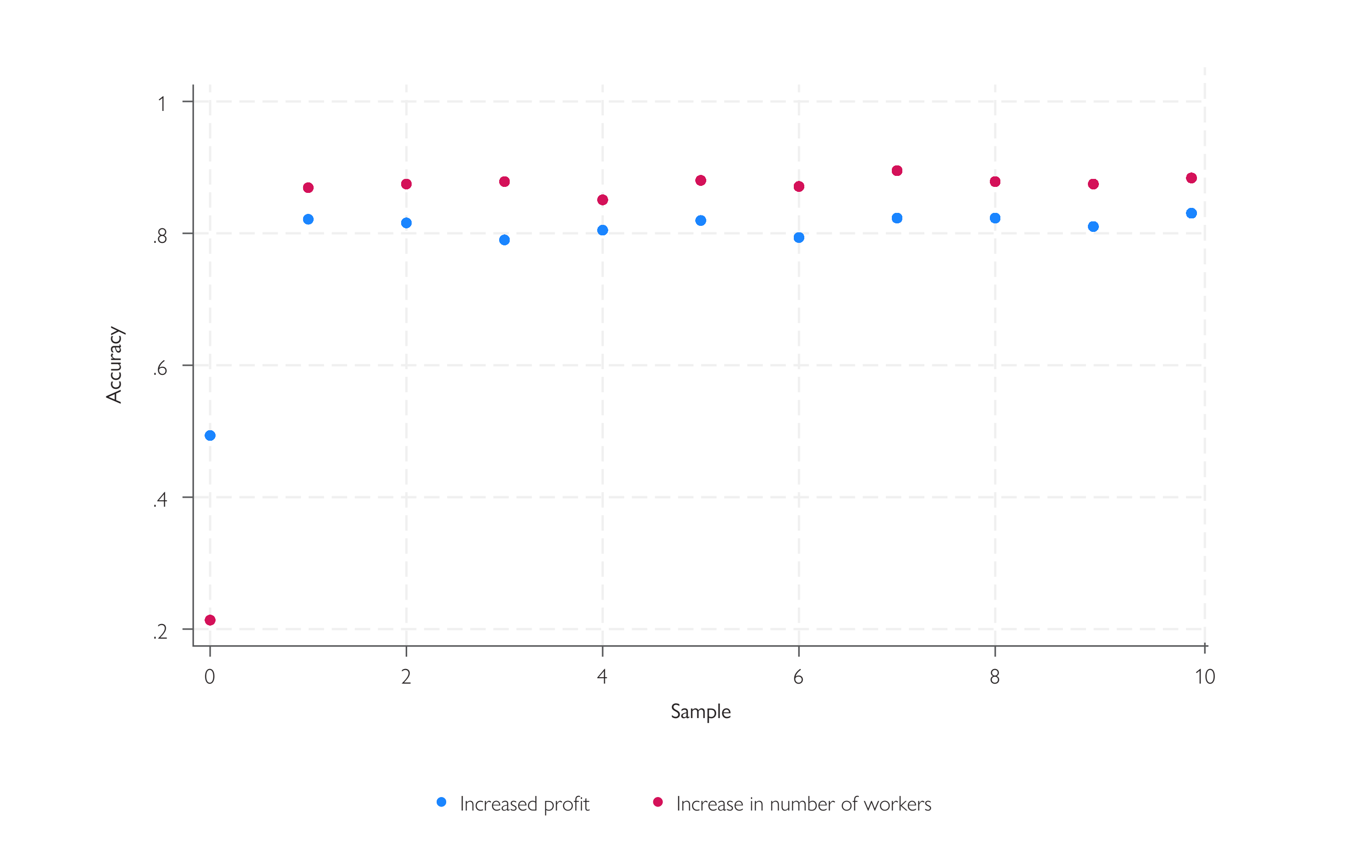


Note: Results for out-of-bag error under different values of variables to be chosen for a Random Forest model. The number of iterations was also evaluated for each regression, resulting in an optimum of 405 for increases in profit and 470 for the number of workers. The out-of-bag error is defined as the prediction error when testing the model out of the sample with which it was trained.

B. PLACEBO TESTS OF MODEL PERFORMANCE

To evaluate the Random Forest models, this report tested different groups or samples randomly selected from the baseline data to predict an increase in profit and the number of workers between the baseline and the endline. This exercise allows us to conclude that the predictions of the Random Forest models are similar even when trained with different baseline data sets. The same samples were used for random outcomes mimicking the chosen dependent variables (increased profit and achievement of the hiring objective). This placebo test shows us that the model's chosen characteristics are relevant for predicting profit and job creation, not just any random variable. Figure B.1 shows the accuracy levels when estimating the model with different samples, and a random outcome variables.[24] The model shows low accuracy levels for predicting a random outcome, and 80% accuracy when predicting increased profit and achieving hiring objectives through ten different samples, highlighting the methodology's robustness. Other studies with similar procedures have shown 80% and above accuracy levels with similar proportions of training-testing samples (Lukita et al., 2023; Weinblat, 2018).

Figure B.1. Accuracy of Random Forest on robustness tests



Note: The Random Forest model was trained and tested ten times. Each time, a different random sample of 70% of the baseline observations was used to train the model, and the remaining 30 per cent was used to test the accuracy of predictions. In the first test, the sample was kept the same as the original model, but the two outcomes were randomly generated with the same mean and standard deviation as increases in profit and increases in the number of workers.

Number of variables

24 The random outcome mimics the original variable's mean and standard deviation distribution.

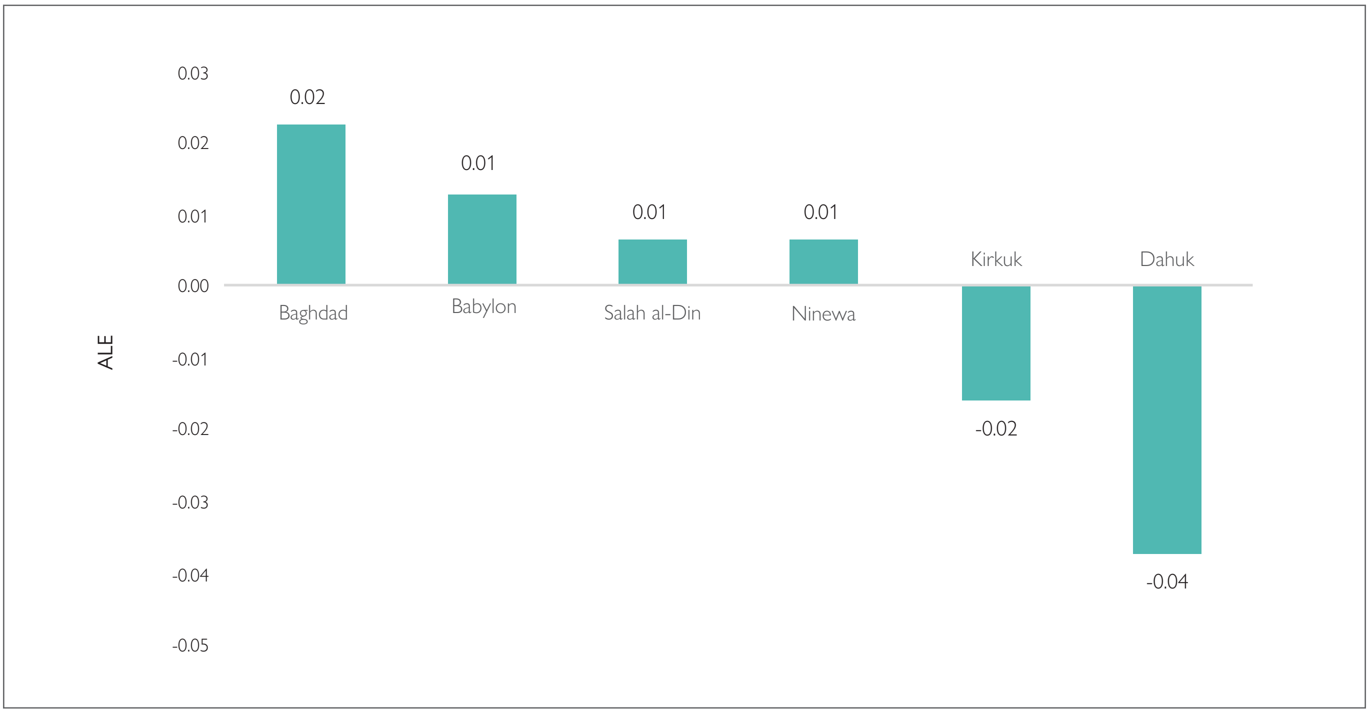
C. SUBGROUP ANALYSIS

This section further explores EDF program participants' differing probabilities of business success. Here heterogeneity is analyzed through the ALE[25] of geographical location, economic sector and demographic characteristics of gender and migration status.

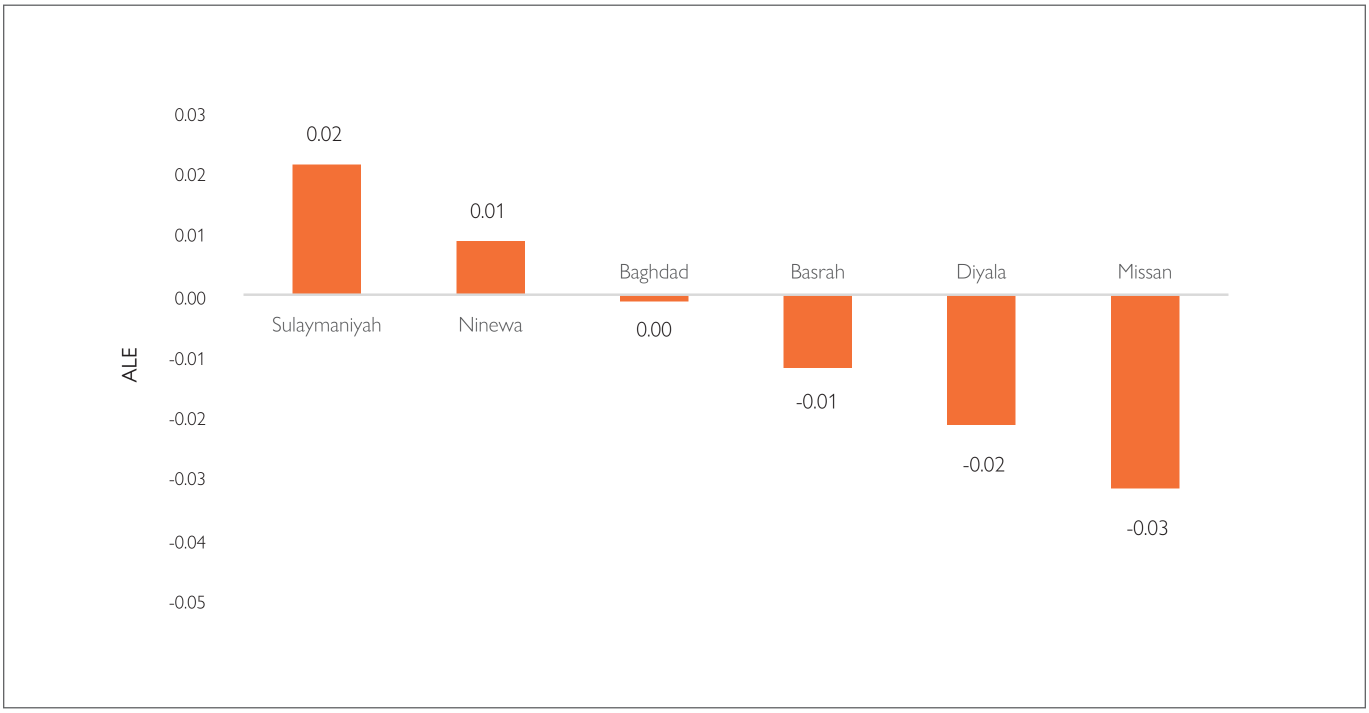
Geographical heterogeneity

Figure C.1. Accumulated Local Effect by governorates

Panel A. Increases in profit



Panel B. Reach or exceed hiring commitment



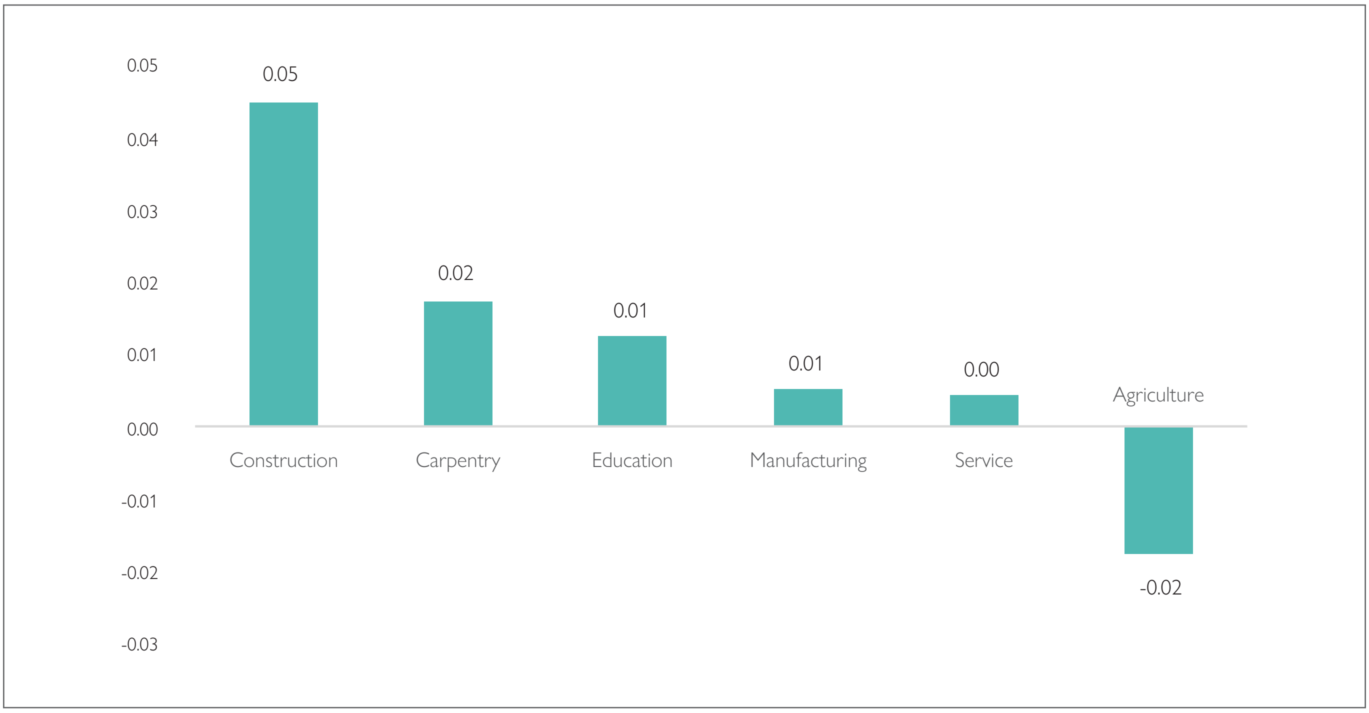
Note: An ALE shows the average change in the model's prediction as the feature changes while keeping other features constant. The regressors shown in both panels are binary variables, the bar shows the effect of the variable when it takes the value of 1. The plot shows the values within each group with the highest importance.

25 An ALE shows the average change in the model's prediction as the feature changes while keeping other features constant.

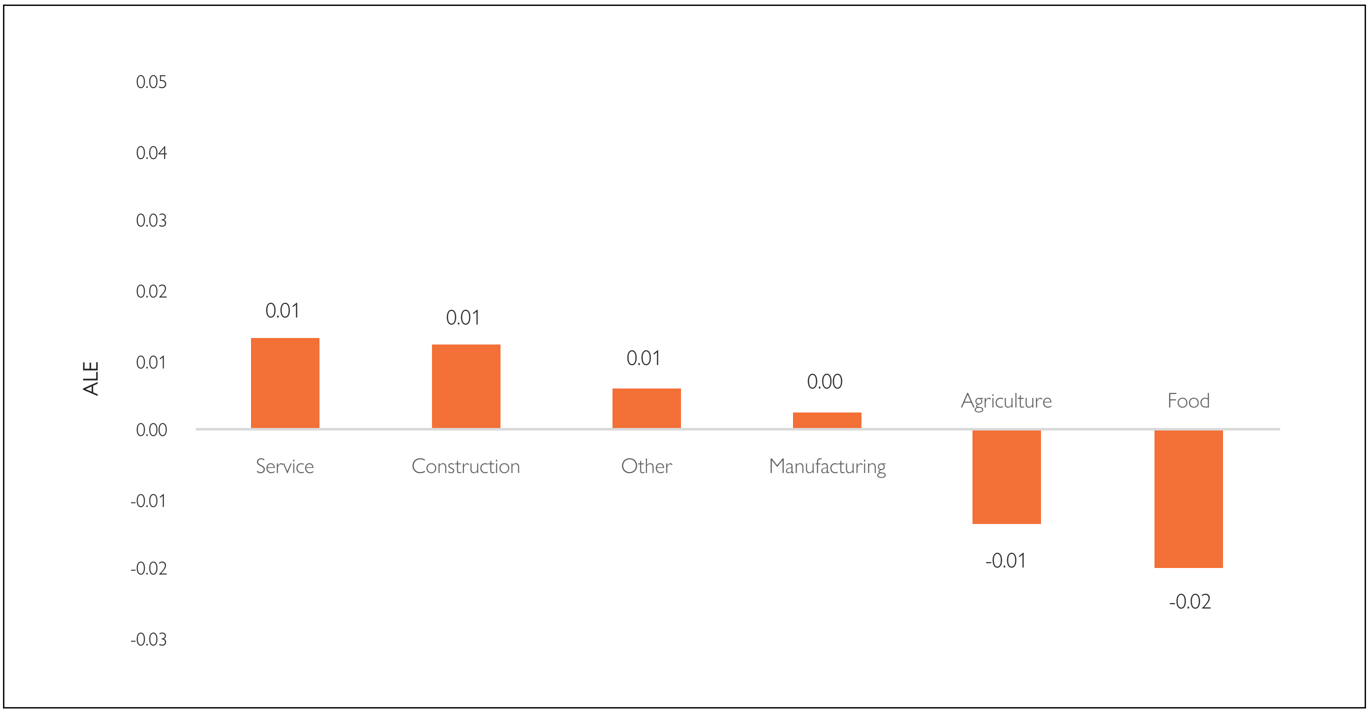
Heterogeneity by economic sector

Figure C.2. Accumulated Local Effect by sectors

Panel A. Increases in profit



Panel B. Reach or exceed hiring commitment

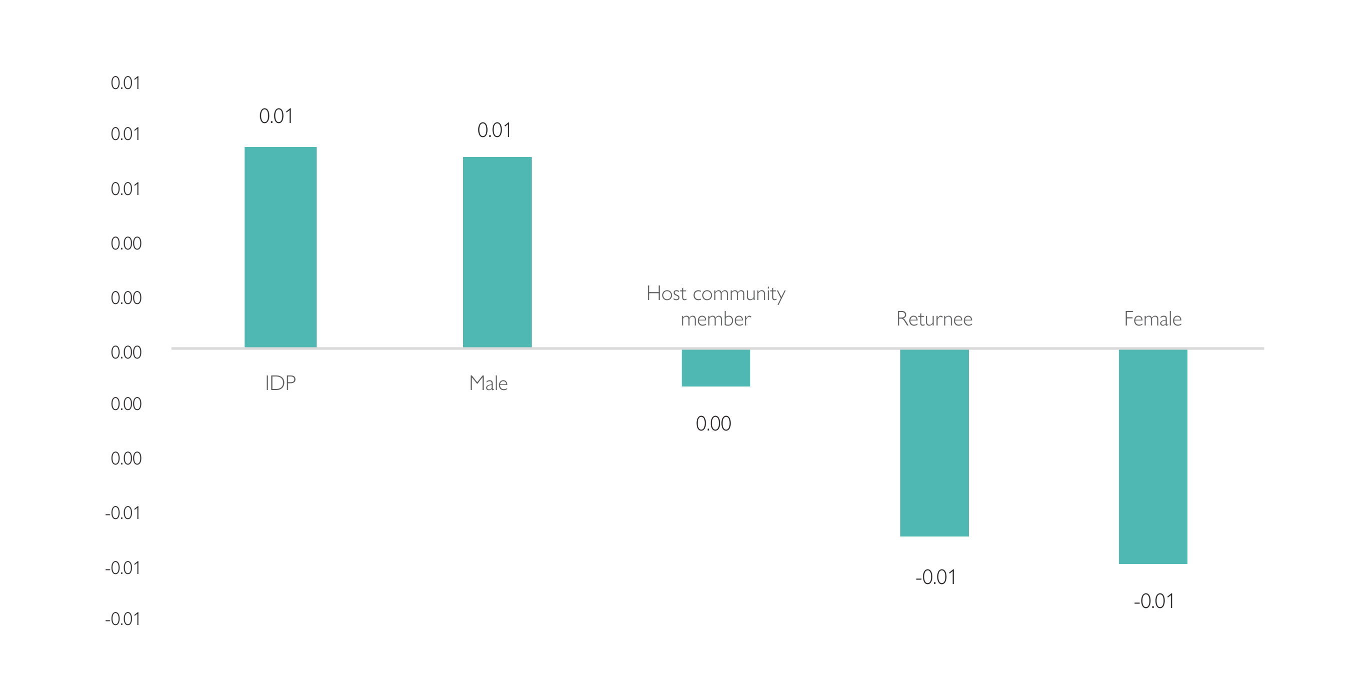


Note: An ALE shows the average change in the model's prediction as the feature changes while keeping other features constant. The regressors shown in both panels are binary variables, the bar shows the effect of the variable when it takes the value of 1. The plot shows the values within each group with the highest importance.

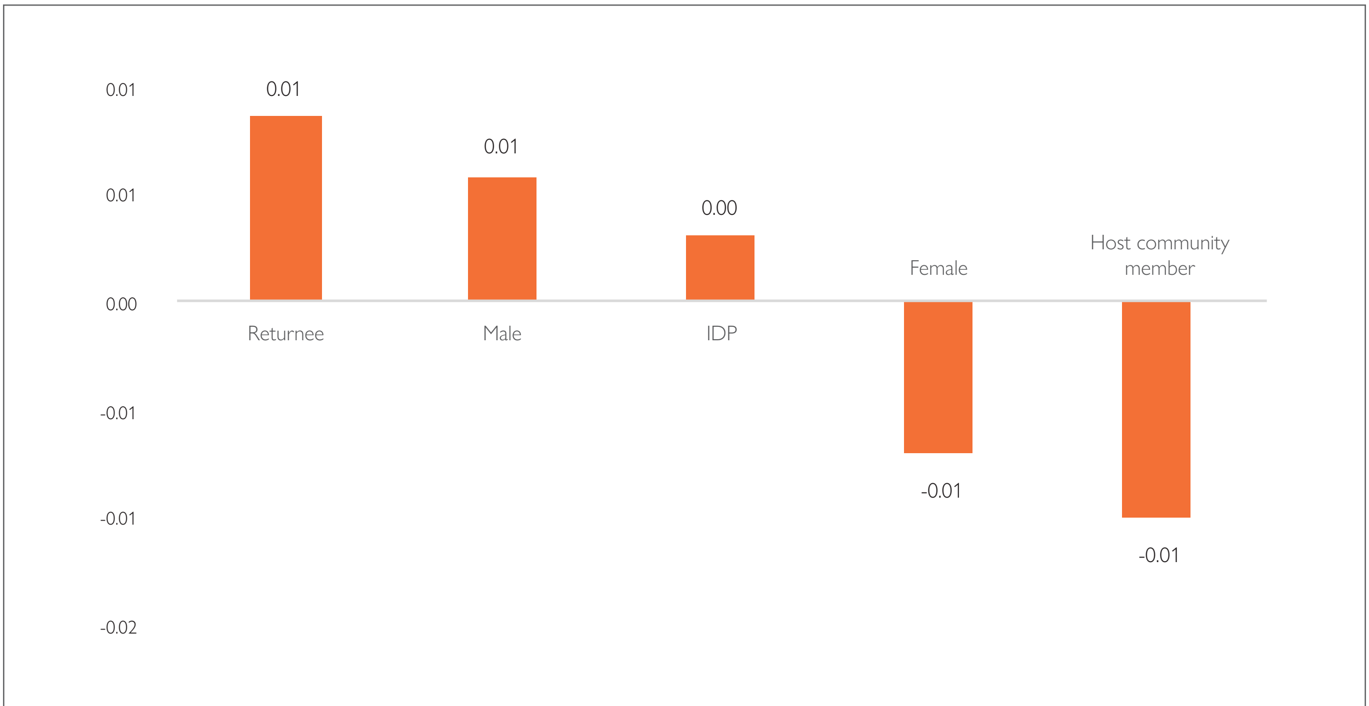
Gender and migration status

Figure C.3. ALE by demographic factors

Panel A. Increases in profit



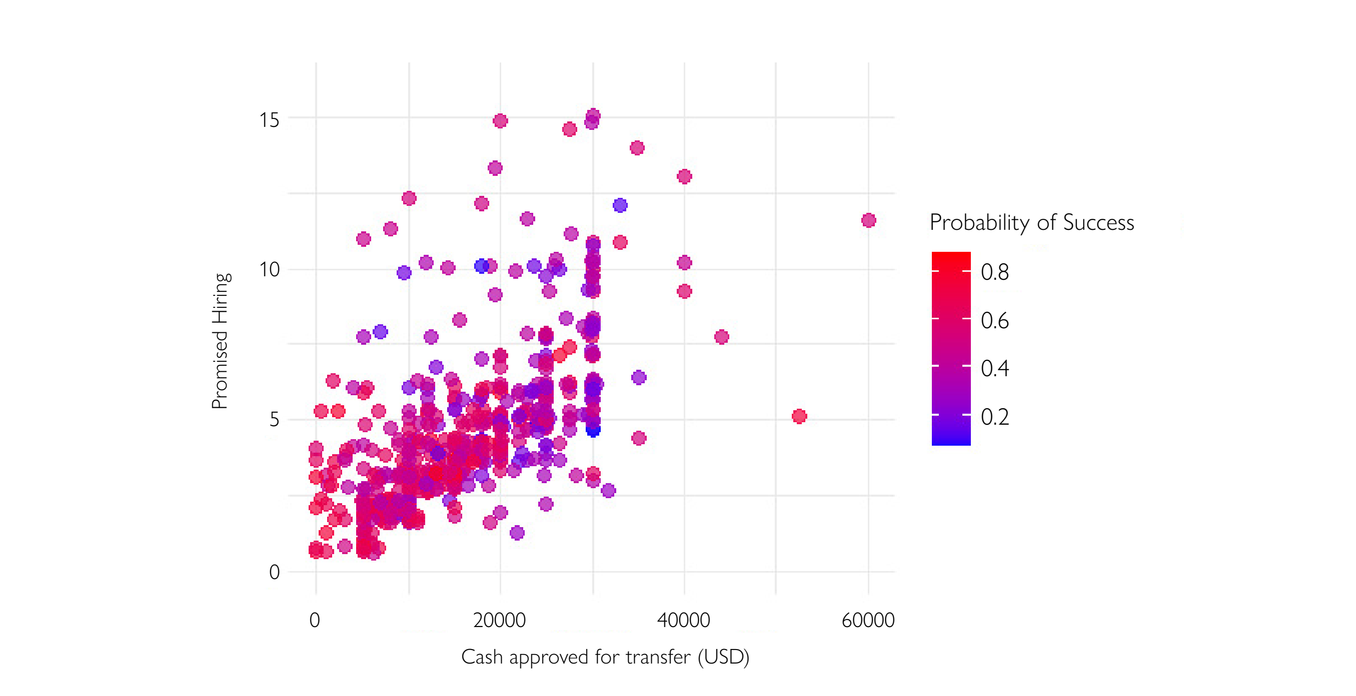
Panel B. Reach or exceed hiring commitment



Note: An ALE shows the average change in the model's prediction as the feature changes while keeping other features constant. The regressors shown in both panels are binary variables, the bar shows the effect of the variable when it takes the value of 1.

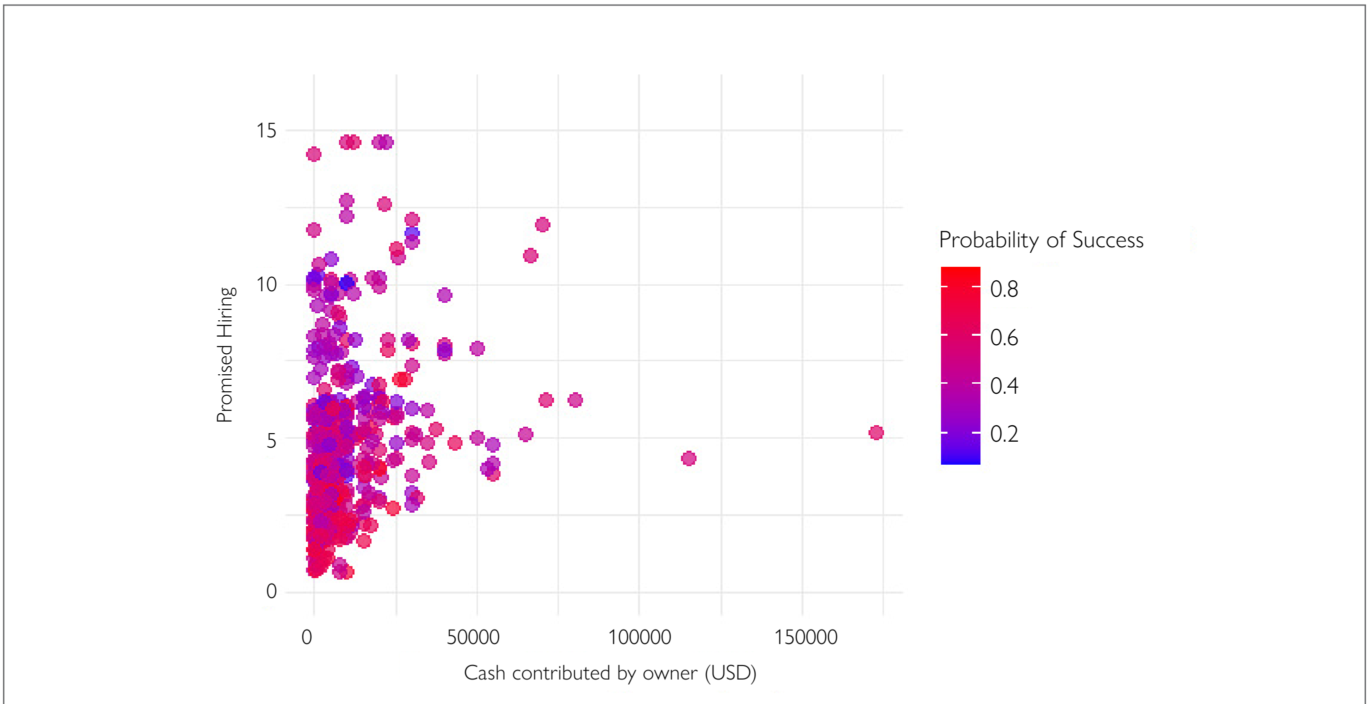
D. SOURCES OF FUNDING AND COMMITMENTS

Figure D.1. Cash transfer amount vs. hiring commitment success



Note: This scatter plot shows the relationship between transfer amount (in logarithm), hiring commitment, and success probability as calculated for the testing sample (543 businesses).

Figure D.2. Contributed amount vs. hiring commitment success



Note: This scatter plot shows the relationship between the cash contributed by the business owner (in logarithm), hiring commitment and success probability as calculated for the testing sample (543 businesses).

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