Disagreement between Human and Machine Predictions

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We document how professional analysts' predictions of firm exits disagree with machine-based predictions. First, on average, human predictions underperform machine predictions. Second, nonetheless, the relative performance of human to machine predictions improves for firms with less observable information, possibly due to the unstructured information used only in human predictions. Specifically, under the environment where the number of exit firms are much smaller than that of non-exit firms, the reduction of type I error achieved by reallocating prediction tasks for those opaque firms from machines to humans leads to better prediction performance.

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I. Introduction

Prediction is an important task in both private business and public policy. Recent advances in prediction techniques, such as machine learning, have helped make the conduct of prediction tasks more reliable than those dependent upon human judgment and classical parametric models. The practical application of these new prediction techniques has been the focus of recent academic, policy, and business discussions (Varian 2014; Mullainathan and Spiess 2017; Athey 2019). The successful application of these techniques has already been reported in a number of fields, including labor markets (Chalfin et al. 2016), public services (Kleinberg et al. 2018; Bazzi et al. 2019; Lin et al. 2020), medical services (Patel et al. 2019; Mei et al. 2020), and the financial industry (Agrawal et al. 2018).

The growing employment of these powerful prediction techniques naturally raises the question of the ways in which machine predictions disagree with and outperform human predictions. This question is particularly relevant given the number of recent studies which argue that technological advances will lead either to the replacement of human labor with machines in certain types of jobs (e.g., Frey and Osborne 2017) or to the reallocation of human resources to other types of jobs (e.g., Autor et al. 2003; Acemoglu and Autor 2011; Acemoglu and Restrepo 2018). Understanding the ways in which machines outperform humans in prediction, we can identify those cases in which human predictions outperform machine predictions. While this has started to be examined in, for example, the field of medical studies (e.g., Raghu et al. 2019), it has not yet been investigated in the context of social science.

The goal of this paper is to document, in the context of firm exits, the patterns of disagreement between human predictions and machine-based predictions and their relative prediction performance. First, following the literature in medical studies, we test the relative performance of predictions based on machine learning techniques and those based on human judgment for the two modes of firm exits, i.e., corporate default and voluntary closure. Second, we document the systematic patterns of disagreements between human and machine predictions for those events. The disagreement between them is measured with the relative prediction performance of human and machine. Thus, we can see not only whether human and machine disagree but also, more importantly, the ways in which they disagree. Suppose a firm actually does default ex-post. Ex-ante human and machine predictions could differ. As reported by Kleinberg et al. (2018) in the context of judicial bail decisions, it is highly likely that machine predictions will on average outperform human predictions. Nonetheless, the relative performance of human predictions may be better in specific circumstances, such as default predictions for informationally opaque firms. Given this conjecture, we document the relative performance of human and machine predictions conditional on the characteristics of their prediction targets. Third, after confirming the characteristics (esp., opaqueness of the firms) systematically correlated with the relative performance of human predictions compared with machine predictions, we implement a set of counterfactual exercises reallocating prediction instances for firms with specific characteristics from machine to human and see how overall prediction performance varies.

To the best of our knowledge, this article is the first to explicitly study the systematic patterns of disagreement between human and machine predictions in the context of social science, and to use these systematic patterns to improve overall prediction performance.[1] We take advantage of our access to a huge volume of firm-level high-dimension panel data collected by one of the largest Japanese credit reporting agencies, together with the prediction results of professional analysts

[1] Anderson et al. (2017) report, in the domain of chess, that human decision tends to be wrong for more difficult instance. Their study shares the motivation with ours in the sense that both characterize the determinants of the performance of human decisions. The difference is that we compare human predictions not only with the ground truth (i.e., exits which we observe ex-post), which is done in Anderson et al. (2017), but also with machine predictions.

working for the company and detailed individual attributes of those analysts. These comprehensive datasets provide us with an ideal research ground where we can construct a machine-based prediction model, compare its predictions with human predictions, and document how they disagree and perform.

The empirical findings are summarized as follows. First, the average performance in predicting firm exits is better for machines than humans, in line with the results reported by existing studies in other fields (e.g., Kleinberg et al. 2018). Second, nonetheless, the relative performance of human predictions to those of machines improves as the availability of information on firm characteristics declines. This could be the case when human predictions effectively employ unstructured information associated with prediction instances. This kind of unstructured information has been referred to as "soft information" (e.g., Liberti and Petersen 2019). Examples of soft information include workers' skill levels, the CEO's management ability, the prospects of future product development, and so on. It is difficult to record all of this highly qualitative information as structured (i.e., "hard") information in, for example, firms' financial statements or other documents. To verify this conjecture, we compare the human predictions recorded in our dataset not only with machine predictions but also with the part of the human predictions solely correlated with structured information.[2] As the latter "structured" human predictions do not rely on unstructured information, the comparison between the original and the structured human predictions tells us to what extent unstructured information has been used in human predictions. Similar to the comparison between the original human predictions and machine predictions, we find that the performance of human predictions relative to that of "structured" human predictions improves as the availability of information on firm characteristics

[2] The similar attempt for replicating human decisions has been done in the context of, for example, chess (e.g., McIlroy-Young et al. 2020).

declines. We also separately regress the performance of human and machine predictions on various characteristics and confirm that the negative marginal impacts associated with low availability of information is more sizable for machine predictions than for human predictions.

Given the empirical finding that the availability of observable information is a key driver in the disagreement between human and machine predictions and their relative performance, we implement a set of counterfactual exercises that reallocate prediction instances from machine to professional analysts, depending on how much information is available for each firm. As the "improvement" in relative performance of human predictions along with the change in specific firm characteristics does not necessarily mean that the "level" of conditional performance of human predictions is higher than that of machine predictions, these counterfactual exercises are useful to confirm whether there could be any cases in which humans outperform machines.

Using the number of available variables for each firm, which is orthogonalized to other firm characteristics such as firm size, past growth trend, and industry fixed-effects, we classify firms into five categories ranging from firms with smallest information, small information, average information, large information, and largest information. For most of the cases except for firms with smallest information, machine predictions outperform human predictions in terms of both type I and type II errors, which leads to better prediction performance of machines. Nonetheless, we also find that reallocating prediction tasks for firms with smallest information from machine to human leads to a sizable reduction in type I error. To illustrate, for firms with smallest information, the number of actually non-exit firms predicted as "exit" by machine but "non-exit" by human is larger than the number of actually non-exit firms predicted as "non-exit" by machine but "exit" by human. Thus, reallocating prediction tasks for those firms from machines to humans reduces the number of false-positives, and the type I error becomes smaller. We should note, however, that the reallocation of the prediction tasks for these firms is also accompanied by a larger type II error; i.e., the number of actually exit firms predicted as "exit" by machine but "non-exit" by human is larger than the number of actually exit firms predicted as "non-exit" by machine but "exit" by human. Thus, reallocating prediction tasks from machine to human also reduces the number of true-positives, and type II errors increase. As the number of exit firms are much smaller than that of non-exit firms in the case of firm exits, the reduction of type I error achieved by reallocating prediction tasks for those opaque firms from machines to humans overwhelms the increase in type II error. This is the mechanics in which the relative performance of human predictions to that of machine predictions improves as the availability of information on firm characteristics declines.

These results jointly suggest the usefulness of powerful machine-based prediction techniques for practical purposes and highlight a subtle feature of human prediction in the context of exit prediction. Overall, most of the prediction work for firm exits can be assigned to machines. Nonetheless, under specific circumstances, such as when prediction targets are informationally opaque due to less available information and the user of the prediction results is more concerned about type I error than type II error due to, for example, the imbalance between the numbers of exit and non-exit firms, then there is still room for human predictions to outperform machine predictions.

The rest of the paper proceeds as follows. Section II presents the theoretical underpinning of our empirical study, which follows Raghu et al. (2019). Section III explains our empirical methodology and a brief account of the institutional background related to the prediction of firm exits. Section IV gives details of the data used for our study. Section V presents and discusses the empirical results. Section VI concludes.

II. Conceptual Framework

In this section, we present the conceptual framework representing the disagreement between human and machine predictions and their relative performance. Suppose there is a prediction instance f for a specific outcome. In the present paper, we set predictions for firms' default and voluntary closure as our prediction instance f. The instance f is accompanied by a set of attributes. It consists of, for example, the number of available information associated with the firms. The instance f has the actual outcome $a(f)$, which we refer to as a ground truth. This ground truth will be revealed ex-post when we observe whether the firm defaults or not within specific periods of time. For the instance f, a prediction machine has its own prediction denoted by $m(f)$. Similarly, a professional analyst i with a set of individual attributes has its own prediction for the instance f. We name this analyst's prediction $h(f,i)$. Using these items, first, we can define the prediction error $\Theta(f)$ of the machine prediction for an instance f as follows:

(1) $$\Theta(f) = L(a(f), m(f)).$$

Second, we can define the prediction error $\Omega(f,i)$ of the human prediction for an instance f by an analyst i as follows:

(2) $$\Omega(f,i) = L(a(f), h(f,i)).$$

Suppose we have a set of prediction instances U. What we ultimately want to solve is an allocation problem of U to machine (i.e., S) or analysts (i.e., T). Such an optimization problem can be formulated as follows:

(3) $$\min_{S,T} \sum_{f\in S} \Theta(f) + \sum_{f\in T} \Omega(f,i) \text{ s.t. } S \cup T = U; S \cap T = \emptyset.$$

This is a problem called "an algorithmic triage" in Raghu et al. (2019). Solving this problem, we obtain the best assignment (S^*, T^*) as a function of (f, i). This optimal assignment function tells us whether we should assign a specific prediction instance f to the prediction machine or to an analyst i. In this paper, we specifically aim at identifying $\Theta(f)$ and $\Omega(f, i)$ so that we can understand the sources of the disagreement and further solve the algorithmic triage problem as a counterfactual exercise.

For this purpose, we define an additional function $Proxy_{f,i}$ as follows:

(4) $$Proxy_{f,i} = \Omega(f, i) - \Theta(f).$$

As $\Theta(f)$ and $\Omega(f, i)$ denote the prediction errors of the machine and the analyst, the relative performance of the human prediction becomes higher as $Proxy_{f,i}$ becomes smaller. As we explicitly demonstrate in the following sections, this $Proxy_{f,i}$ accounts not only for the disagreement between human and machine predictions but also for their relative performance.

While the current setup suffices to study the systematic disagreement between human and machine predictions, further decomposition of $\Omega(f, i)$ into those correlated with structured information and the rest of the components is useful for understanding the source of the disagreement between human and machine predictions. Let $\Omega_h(f)$ account for the error component of the human prediction correlated with structured observable attributes of the instance f. Using this decomposition, we can define another measure for disagreement between the human prediction and the "structured" human prediction which relies solely on hard information.

(5) $$Proxy'_{f,i} = \Omega(f, i) - \Omega_h(f).$$

Suppose $Proxy'_{f,i}$ becomes smaller as the change in an attribute of the instance f (e.g., the amount of available information decreases). This means the relative performance of the human prediction to the human prediction relying on the observable (i.e., structured) information becomes higher due to the change in the attribute. In the current illustration representing the amount of available information, this suggests that, as the volume of structured information becomes smaller, the room for analysts to effectively employ unstructured information for prediction becomes larger. This comparison between human predictions and "structured" human predictions highlights the source for human predictions to surpass machine predictions, with the latter (i.e., machine predictions) relying only on structured information.

III. Empirical Strategies

This section presents, first, how we construct a machine learning-based prediction model for firm dynamics. Then, we explain how to identify the determinants of disagreement and the relative performance of human and machine predictions.

A. Machine Prediction

To obtain machine prediction, we construct a standard machine learning method. Our particular problem of predicting relatively rare firm exit events (which occur with a low probability) falls into the class of "imbalanced label prediction" tasks. Following the literature, we apply a weighted random forest, a minority-class oversampling method.[3] Random forest models aggregate many individual decision tree models, each trained on a randomly selected sample from the training data. Particularly for predicting rare events, Chen et al. (2004) develop an extension of

[3] We also use other machine learning techniques such as LASSO and extreme gradient boost to construct prediction models and confirm the robustness of our results. All the results are in the appendix.

the random forest, called a weighted random forest. Intuitively, the method weighs data corresponding to a minority event (e.g., a firm exit) much more heavily than that corresponding to a majority event (e.g., non-exit).

In our baseline exercise, we train models with the realization of outcome variables from the end of year $t-1$ to the end of year t using the information available over the periods from year $t-3$ to $t-1$, and conduct out-of-sample predictions of the realization of outcome variables from the end of year t to the end of year $t+1$ using the information available over the periods from year $t-2$ to t.

We utilize the Receiver Operating Characteristic (ROC) curve to evaluate the predictive performance of the model. To implement the prediction task of a binary exit outcome, we need a specific threshold. When a predicted score surpasses the threshold, a positive binary outcome is indicated. For a given trained model, the ROC curve plots the true and false positive rates corresponding to the varying of this threshold value. Without any predictors (i.e., random guess), the curve should trace the 45-degree line, and curves closer to the top-left corner are desirable (maximize true positive rate and minimize false positive rate). With this motivation, it is conventional to also summarize the ROC curve by the area under the curve (AUC).

B. Human Prediction

In this section, we explain how to obtain human prediction. After introducing our measure for human prediction, we discuss how to justify the measure and an alternative approach we use.

"fscore".—Credit reporting agencies examine and predict firm exits as these firm-level outcomes are of great interest to business entities and government sectors. Examples of such credit reporting agencies include Dunn and Bradstreet in the US,

Experian in European countries, and Tokyo Shoko Research (TSR) in Japan.[4] In addition to providing structured information such as financial statements to their clients, credit reporting companies typically calculate and publish a credit rating score, which we call as "*fscore*" in the present paper, to summarize the overall performance of a firm. This score is typically constructed from both observable (i.e., structured) information on firm characteristics, and from the contents of in-depth interviews on owner characteristics, reputation, growth opportunity, and so on (i.e., unstructured information). The score is constructed by a professional analyst and assigned to each firm in each year. As in financial institutions such as banks, each analyst is evaluated by the prediction performance of this $fscore$ and thus has a reasonable incentive to produce good predictions.

These credit reporting agencies typically rely on their own (often confidential) algorithm to construct the scores. While a part of the score systematically depends on structured information collected by those agencies, a large part of the score reflects professional analysts' subjective evaluation of the targeted firm. To illustrate, a score given by TSR (max: 100 points) is the summation of (i) the ability of the owner (max: 20 points) based on business attitude, experience, and asset condition, (ii) the growth possibility (max: 25 points) based on past sales growth, growth of profit, and characteristics of the products, (iii) stability (max: 45 points) based on firm age, stated-capital, financial statement information, room for collateral provision, and real and financial transaction relationships, and (iv) reputation (max 10 points) based on the level of disclosure and overall reputation. Most of these items are rarely recorded as structured information but largely as unstructured information such as analysts' subjective evaluation of those firms.

[4] TSR is one of the largest credit reporting agencies in Japan and operates in the areas of credit research, publishing, and database distribution. The central product of TSR is unsolicited-basis company reports representing the performance of each targeted firm. TSR sells them to a variety of clients including banks, securities houses, non-financial enterprises, and governmental organizations. A typical credit report consists of more than ten pages and includes firms' basic characteristics and financial statement information. The clients of TSR purchase the reports for various reasons such as evaluating the credit worthiness of client firms, screening on transaction partners, and understanding the overall market environment.

Given this institutional background, we use the *fscore* assigned by TSR as the output of human predictions.

We use this score and the ex-post record of exit to run a weighted Probit estimation having the exit indicator on the left hand-side and only $fscore$ on the right hand-side of the estimated equation. Through this, we transform $fscore$ taking the value of 0-100 to the score associated with the occurrence of the firm exit and use it as the result of human prediction.[5]

Can we really use fscore as human prediction?—There could be several immediate concerns over using the *fscore* as the output of human predictions. First, this score might also be constructed by some machine algorithms. If this is the case, the comparison between *fscore* and machine predictions could not account for the differences between human and machine predictions, being merely a comparison of two algorithms. While the *fscore* used in the present study reflects professional analysts' subjective evaluation of targeted firms and largely employs both the structured and unstructured information, we also try to separate out the analysts' predictions correlated with structured information from the original *fscore* as explained below. Using this framework, we can explicitly study the difference between predictions based on structured information and those based on unstructured information, the latter of which can be handled only by human analysts.

Second, machine predictions can take into full account higher dimensions of information than human analysts can do. When this is the case, the comparison between *fscore* and machine prediction might account only for the difference between the two different datasets used by human and machine. While we think the

[5] We should note that due to the weighting procedure aiming at a minority-class oversampling, the output obtained by WRF and this Probit estimation is not exactly the exit probability in the data. It would be rather the probability of exits in the balanced sample consisting of equal numbers of exits and non-exits. Given there is no problem for us to use these probabilities as far as the machine outputs are constructed in the comparable way, we use them in the following empirical analyses. We also construct a ranking based on the output obtained by WRF and the Probit estimation, and use the ranking for our empirical analysis.

ability to handle different volumes of information itself is one aspect of the difference between humans and machines and thus worth examining, we also try to compare human and machine predictions on an equal footing in terms of the volume of structured information.

Third, the target of predictions might not be exactly the same for machine predictions and human predictions. This issue is called as omitted payoff bias in the literature (Chalfin et al. 2016). As we will detail in the next section, we construct machine learning-based prediction models explicitly targeting one of the two modes of firm exits (i.e., default and voluntary closure), while the *fscore* summarizes the overall performance of a firm. Although the *fscore* is typically used in credit risk management and thus largely accounts for the prospects of firm exits, it is better to have human predictions more directly connected to firm exits.[6] For this purpose, we employ not only the overall firm performance score but also the sub-scores corresponding to the financial stability of firms as human predictions.

Apart from these concerns over using the *fscore* as the output of human predictions, we should also bear in mind the external validity of the results. Disagreements between human and machine predictions may be important in other situations, such as the comparison between machine and investors who put more emphasis on the "upside" of a firm's performance rather than the downside. To address these concerns, we implement the same set of analyses for firms' sales growth and assess the robustness of our results regarding firm exits.

Structured human prediction.—As already noted, *fscore* is likely to account for both structured and unstructured information. While it is still informative to compare the original *fscore* with the machine score, we also extract the component

[6] TSR guidelines provide the following categorization of *fscore* ranges: (a) caution required (scores 29 and under), (b) medium caution required (scores between 30 and 49), (c) little caution required (scores between 50 and 64), (d) no specific concern (scores between 65 and 79), and (e) no concern at all (scores 80 and above).

of *fscore* associated only with such unstructured information. For this purpose, we construct a machine learning-based prediction model for *fscore* by using the same right hand-side variables as we use to construct the machine prediction model. Such a "structured" *fscore* accounts only for the part of *fscore* correlated with the structured information. Using this predicted score and the actual record of exit to run a weighted Probit estimation, we transform the "structured" *fscore* to the probability associated with the occurrence of the firm exits.

C. Measurement of "disagreement"

We measure the disagreement between human and machine predictions for a specific exit mode of firm f in year t. We standardize the machine scores of exits, *fscore*, and "structured" *fscore* as mean zero and standard deviation is one. By using these standardized scores for machine (ML), analyst (H), and "structured" human (*SH*) denoted by $Outcome$, we compute a variable $Proxy$ for a triplet of firm (f), analyst (i), and time (t), which is conceptualized in the previous section, as the following definition:

(6)
$$Proxy_{f,i,t} = Outcome^{ML}_{f,t} - Outcome^{H}_{f,i,t} \text{ for exit firms,}$$
$$= Outcome^{H}_{f,i,t} - Outcome^{ML}_{f,t} \text{ for non-exit firms,}$$

(7)
$$Proxy'_{f,i,t} = Outcome^{SH}_{f,t} - Outcome^{H}_{f,i,t} \text{ for exit firms,}$$
$$= Outcome^{H}_{f,i,t} - Outcome^{SH}_{f,t} \text{ for non-exit firms.}$$

Due to the way we compute $Proxy$, this measure of the disagreement becomes larger when the machine or "structured" human produces better predictions than the human does.

We should also note that, in our data detailed in the next section, these predictions and the ex-post outcomes accounting for firm exits are all observable. In this sense, our analysis does not suffer from the selective label problem that some of the ex-post outcomes cannot be observed due to selection (Lakkaraju et al. 2017).

D. Identifying the determinants of "disagreement"

Once a measurement of $Proxy$ is obtained, we can estimate the relationship between $Proxy$ and various explanatory variables consisting of informational opaqueness of firms ($\boldsymbol{O}_{f,t}$), firm attributes ($\boldsymbol{F}_{f,t}$), analyst attributes ($\boldsymbol{I}_{i,t}$), and team attributes ($\boldsymbol{Z}_{i,t}$) as well as various configurations of fixed-effects ($\boldsymbol{\eta}_{f,i,t}$):

(8) $Proxy_{f,i,t} = G\left(\boldsymbol{O}_{f,t}, \boldsymbol{F}_{f,t}, \boldsymbol{I}_{i,t}, \boldsymbol{Z}_{i,t}\right) + \boldsymbol{\eta}_{f,i,t} + \varepsilon_{f,i,t}$ for $t = 2013, \cdots, 2016$.

In the baseline estimation, we employ a firm-level fixed-effect, analyst-level fixed-effect, and year-level fixed-effect for $\boldsymbol{\eta}_{f,i,t}$, while alternative configurations of fixed-effects are also employed for the robustness check.

IV. Data

In this section, we will give details of the data used in our empirical analysis. All the data is obtained from TSR through the joint research agreement between Hitotsubashi University and TSR. We use the multiple datasets detailed below to construct a machine-based prediction model for firm exits, estimating the determinants of $Proxy_{f,i,t}$, and implement counterfactual exercises.

A. Firm-level panel data

One of our main data sources is an annual-frequency panel of Japanese firm data from t=2010 to 2016, providing information on firms' financial statements and basic details such as industry classification, company owner characteristics, precise geographic location, firm age, etc. This year identifier t accounts for the timing of data collection and means that the data labeled year t consists of the data extracted as of the end of December of the year t from the data server owned by TSR. Given a large portion of Japanese firms use an accounting period up to the end of March, the file labeled t =2012, for example, consists of a large amount of firm information corresponding to the accounting period up to the end of March 2012. The original data covers around three million firms in each year. We use the data covering around one million firms, which provide the information we need for our empirical analysis. According to the Japanese Small and Medium Size Enterprises Agency, there are around three- to four-million active companies in Japan. The TSR data accounts for around one-third of that firm population. One point of note is that the sample selection is tilted toward some specific industries, such as construction companies.

These firm-level panel data are accompanied by three types of relational information regarding real and financial partners. First, this information contains a list of up to 10 lender banks. Second, the information also covers firm-to-firm trade. It lists up to 48 customer and supplier firms for each company. In addition to the list of each target firm's trade partners, we also use the trade relationship reported by those trade partners. As there are many trade relationships not reported by the targeted firms but only by their trade partners, this operation significantly extends the list of trade partners. Third, the data also contain the list of shareholders.

B. Prediction instances

We consider the two firm exit outcomes to be predicted over the one-year ahead window: firm default and voluntary closure. The explanatory variables and outcome variable used in constructing a machine-based prediction model are defined for separate time intervals; explanatory variables from 2010 to 2012 to predict the outcome defined over the one-year window from the end of 2012 to the end of 2013, explanatory variables from 2011 to 2013 to predict the outcome from the end of 2013 to the end of 2014, and so on. The latest data are the explanatory variables from 2014 to 2016, used to predict the outcome from the end of 2016 to the end of 2017.[7]

We measure firm exits in the two modes (i.e., default and voluntary closure) if firms exited from the market for these reasons as reported by TSR over the one-year window. Then, we separately prepare two dummy variables that take 1 if firms exit through either default or voluntary closure.

C. Firm attributes

To construct a machine-based prediction model of firm exits, we use the following six categories of firm attributes: Firms' basic characteristics (***firm own***), firms' detailed financial statement information (***financial statement***), geography and industry-related variables (***geo/ind***), firm-bank borrowing relationship variables (***bank***), supply chain network variables (***network***), and shareholder-subsidiary shareholding relationship variables (***shareholder***). All the variables categorized in each group are summarized in appendix.

We set up the two prediction models for each one of the exit modes using these six groups of firm attributes together with the differenced and double-differenced variables of those variables. We create a set of dummy variables to deal with missing variables, taking the value of one if the corresponding variable is missing for a firm and zero otherwise. When a missing variable dummy takes one, we fill in zero to the original missing record.

[7] The configuration of the data is as follows: Training - (i) outcome from 2012-2013 using 2010-2012, (ii) outcome from 2013-2014 using 2011-2013, (iii) outcome from 2014-2015 using 2012-2014, (iv) outcome from 2015-2016 using 2013-2015 while Prediction - (i) outcome from 2013-2014 using 2011-2013, (ii) outcome from 2014-2015 using 2012-2014, (iii) outcome from 2015-2016 using 2013-2015, (iv) outcome from 2016-2017 using 2014-2016. Each number corresponds to the case of test and train.

D. Potential determinants of disagreement

To estimate the determinants of the disagreement between human and machine predictions, we set up the following three groups of variables, i.e., the number of available information, firm attributes, and analyst/team attributes.

Number of available variables.—As the most important potential determinant in our analysis, which is denoted by $\boldsymbol{O}_{f,t}$, we employ the number of variables available (#(*available variables*)) for each firm in the dataset. This number accounts for the opaqueness of firms. When this number is small, both humans and machines can use only a limited number of structured information. As humans can also employ soft information, the estimated coefficient associated with #(*available variables*) show how effectively human predictions use such soft information.

Firm attributes.—We use a subset of variables we used for constructing machine prediction model as the potential determinants, which we denoted as $\boldsymbol{F}_f$. The list consists of the logarithm of firm sales, its difference, the listed status dummy variable, the number of industries the targeted firms operate in. We employ this list of variables as they are less prone to missing data.[8] In addition to these variables, we also use the information relating to the task priority of each firm (*priority*) inside the credit reporting agency, which is denoted by a number with a larger number corresponding to a higher priority. The dataset includes the firm-level panel data of *fscore*, which we explained in the previous section. The number is computed as the sum of the four sub-scores representing the ability of the owner, growth possibility,

[8] Note that the existence of missing data in specific variables can be taken care of by introducing dummy variables account for the missing in the non-parametric model such as random forest we use for constructing prediction model. Contrary to this, the parametric model such as the panel estimation used for identifying the determinants of the disagreement cannot take care of the missing variables well.

stability, and reputation. In the following empirical analysis, we use both the *fscore* and the decomposition of each component.

Analyst/Team attiributes.—We also use the attributes $\boldsymbol{I}_i$ of the analysts. To measure $\boldsymbol{I}_i$, at each data point, we use the attributes of the analysts working for TSR as stored in the anonymized background information associated with the company's analysts. As analysts enter and exit the pool of TSR employees, the data is unbalanced panel data. This dataset is accompanied by a table listing the firms assigned to each analyst at each data point, which we use to relate analysts to firms. The dataset allows us to identify the list of assigned firms in each year and the tenure years of each analyst. The former information allows us to calculate the number of firms assigned to each analyst and any previous exposure of an analyst to other firms in the industry of the targeted firms, which can be interpreted as the industry expertise of the analyst.

The dataset also allows us to measure the characteristics associated with the team each analyst belongs to, which is denoted by $\boldsymbol{Z}_{i,t}$. First, we measure the size of the team by counting the number of analysts in each department. Second, we measure the average tenure years of all members of the team. Third, we measure the average number of firms assigned to the analysts in the team. Fourth, we also measure the average industry expertise of all the analysts in each team.

We should note that this analyst and team information is endogenous as the assignment of analysts to teams and to targeted firms is not random. Thus, we treat these variables simply as control variables in the regression of the determinants for $Proxy_{f,i,t}$ and do not intend to establish any causal relation between these variables and $Proxy_{f,i,t}$.

Table 1 summarizes the variables used to estimate the determinants of the disagreement between human and machine predictions, together with the *fscore*, structured *fscore*, and $Proxy_{f,i,t}$.

Table 1: Summary statistics

Variable	Definition	#samples	min.	25%tile	median	mean	75%tile	max	sd
Disagreement									
$Proxy_{f,i,t}$	Relative performance of machine predictions for firm *f*. The larger (smaller) value means that machine (analyst *i*) can predict outcome better.	3,983,158	-5.066	-0.95	-0.09	0.00	0.89	5.62	1.29
$structured\ fscore_{f,t}$	Firm *f*'s hypothetical *fscore* considered as analysts could use only hard information for predictions. It is calculated as a replication of *fscore* by machine prediction method.	3,983,158	19.300	43.27	46.19	46.82	49.66	80.95	5.26
Number of available variables									
$\#(available\ variables)_{f,t}$	The number of firm *f*'s hard information available for predictions.	3,983,158	10	38.00	80.00	91.02	132.00	276	60.42
Firm Characteristics									
$\log(sales_{f,t})$	The logarithm of firm *f*'s gross sales.	3,983,158	0.000	10.29	11.29	11.37	12.41	23.92	1.86
$\log(sales_{f,t})-\log(sales_{f,t-1})$	Log change in firm *f*'s gross sales.	3,983,158	-14.230	-0.06	0.00	0.01	0.07	12.73	0.36
$\#(industry)_{f,t}$	The number of industry codes which are assigned to firm *f*. It takes values from 1 to 3.	3,983,158	1	1.00	2.00	1.92	3.00	3	0.85
$priority_{f,t}$	Firm *f*'s relative importance for analysts.	3,810,937	0	0.00	2.00	14.76	8.00	41,290	75.80
$fscore_{f,t}$	A score that summarizes an overall performance of firm *f* provided by TSR. It takes values from 0 to 100.	3,983,158	0	43.00	46.00	46.82	50.00	88	5.91
Analyst Characteristics									
$\#(tenure\ years)_{i,t}$	Analyst *i*'s length of serveice.	3,503,183	0.003	3.59	8.05	10.51	15.38	43.620	8.67
$\#(assigned\ companies)_{i,t}$	The number of companies for which analyst *i* is responsible to make *fscore*.	3,810,987	1	610	939	1,516	1,862	11,570	1,684.70
$industry\ experience_{f,i,t}$	The number of companies (1) having the same industry codes as firm *f*, and (2) having been responsible for analyst *i* to make *fscore* for recent 3 years.	3,810,987	1	27.00	85.00	263.60	271.00	6,241	515.25
Team Characteristics									
$\#(team\ members)_{i,t}$	The number of colleagues belonging to the same division as analyst *i*.	3,495,647	0	8.00	13.00	15.02	20.00	119	9.70
Average $\#(tenure\ years)_{i,t}$	Average length of service across team members including analyst *i*.	3,466,648	0.504	7.50	9.76	10.35	12.72	37.19	4.18
Average $industry\ experience_{f,i,t}$	Average industry experience across team members including analyst *i*.	3,466,648	0	25.67	60.33	117.60	162.30	883.00	136.57
Average $\#(assigned\ companies)_{i,t}$	Average number of assigned companies across the team members including analyst *i*.	3,466,648	1	920.20	1,230.00	1,407.00	1,877.00	3,543	679.30

V. Empirical Results

In this section, first, we compare the performance of machine-based predictions and human predictions. Then, we identify how the disagreement between those predictions varies with changes in the characteristics of the targeted companies. After confirming that there could be room for human predictions to outperform machine predictions, we implement counterfactual exercises.

A. Prediction performance

The following four panels in Table 2 show the AUCs and standard errors of the five prediction models for the years 2013 to 2016. The first and second rows show the performance of human predictions and machine predictions, respectively. The third row is for the structured human predictions. The fourth and fifth rows show the performances of machine predictions with different sets of independent variables. The fourth row is the case where we add *fscore* to the list of independent variables used to construct a machine prediction model. The fifth row corresponds to the case where we use only a small set of independent variables to construct a machine prediction model.[9] Using a smaller set of independent variables to construct a machine-based prediction model allows us to compare human and machine predictions on an equal footing in terms of the volume of structured information.

[9] As the smaller set of variables, we employ all the ***firm own*** variables except for dividend-related variables, ***financial statement*** variables representing total assets, profit, and EBITDA, all the ***bank*** variables, ***network*** variables representing only customers and suppliers with direct links, and ***shareholder*** variables in direct shareholding relations.

Table 2: AUC

Test data: t = 2013

Model	default	voluntary closure
Human	0.634 (0.0049)	0.719 (0.0030)
Machine	0.793 (0.0041)	0.828 (0.0024)
Structured human	0.617 (0.0046)	0.749 (0.0027)
Machine & *fscore*	0.807 (0.0040)	0.829 (0.0023)
Machine with small information	0.777 (0.0044)	0.829 (0.0024)

Test data: t = 2014

Model	default	voluntary closure
Human	0.639 (0.0052)	0.729 (0.0031)
Machine	0.780 (0.0045)	0.828 (0.0024)
Structured human	0.622 (0.0049)	0.757 (0.0028)
Machine & *fscore*	0.794 (0.0043)	0.830 (0.0024)
Machine with small information	0.765 (0.0048)	0.829 (0.0024)

Test data: t = 2015

Model	default	voluntary closure
Human	0.653 (0.0055)	0.737 (0.0031)
Machine	0.786 (0.0045)	0.833 (0.0024)
Structured human	0.638 (0.0052)	0.766 (0.0028)
Machine & *fscore*	0.799 (0.0044)	0.835 (0.0024)
Machine with small information	0.768 (0.0050)	0.834 (0.0025)

Test data: t = 2016

Model	default	voluntary closure
Human	0.663 (0.0053)	0.748 (0.0031)
Machine	0.773 (0.0045)	0.841 (0.0025)
Structured human	0.648 (0.0050)	0.776 (0.0027)
Machine & *fscore*	0.789 (0.0044)	0.843 (0.0025)
Machine with small information	0.758 (0.0049)	0.843 (0.0024)

Note: Each number represents AUC and the number in the parentheses is its standard error.

First, we can immediately notice that the AUC of machine predictions (the second row) is significantly higher than that of human predictions (the first row) given the size of standard errors of those AUCs. This is the case even when we employ a smaller set of independent variables to make a machine prediction model (the fifth row). Thus, human predictions underperform machine predictions on average.

Second, in the case of default prediction, human predictions outperform those of structured human (the first and third rows). We also find that *fscore* makes an additional contribution to the overall performance of the machine predictions (the second and fourth rows). These results contrast with the findings of Kleinberg et al. (2018). In their empirical analysis of judicial bail decisions, they show that the structured human does a better job of identifying risky criminals than the judge's prediction. They claim that the "psychologist's view," where humans tend to make noisy predictions, outdoes the "economist's view" where humans can use soft information to make a better prediction. Our result suggests that, at least in our setup for default predictions, the economist's view should be more reliable. One point to note is that, as for predictions of voluntary closure, the structured human does a better job than the human prediction does, which is consistent with the psychologist's view.[10]

B. Determinants of disagreement

Table 3 summarizes the results of the panel estimation associated with default and voluntary closure. All the coefficients are shown in the percent point (i.e., the estimated coefficients times 100).

[10] In the appendix, we examine the recall and precision measures for machine, human, and structured human predictions over different thresholds for prediction.

Table 3: Baseline estimation

	default				voluntary closure			
	Machine vs. Human		*SH vs. Human*		*Machine vs. Human*		*SH vs. Human*	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Number of available variables								
#(*available variables*) $_{f,t}$	0.566	0.001 ***	0.041	0.000 ***	0.485	0.001 ***	0.031	0.000 ***
Firm characteristics								
log(*sales* $_{f,t}$)	-18.545	0.127 ***	3.987	0.028 ***	-8.511	0.111 ***	5.036	0.030 ***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	13.015	0.097 ***	-0.618	0.022 ***	5.205	0.086 ***	-0.521	0.023 ***
listed $_{f,t}$	-2.105	2.758	0.605	0.621	-18.931	2.429 ***	-6.351	0.662 ***
#(*industry*) $_{f,t}$	-3.009	0.159 ***	-0.084	0.036 **	0.097	0.140	-0.129	0.038 ***
priority $_{f,t}$	0.001	0.000 **	0.000	0.000 ***	0.002	0.000 ***	-0.000	0.000 **
Analyst characterstics								
#(*assigned companies*) $_{i,t}$	-0.001	0.000 ***	-0.000	0.000 ***	-0.001	0.000 ***	-0.000	0.000 ***
industry experience $_{f,i,t}$	-0.004	0.000 ***	0.000	0.000 ***	-0.001	0.000 ***	0.001	0.000 ***
Team characteristics								
#(team members) $_{i,t}$	0.081	0.012 ***	-0.001	0.003	0.106	0.010 ***	-0.001	0.003
Average #(*tenure years*) $_{i,t}$	0.136	0.016 ***	-0.008	0.004 **	-0.008	0.014	-0.006	0.004
Average industry experience $_{f,i,t}$	0.014	0.001 ***	0.000	0.000	0.001	0.001	0.000	0.000
Average #(*assigned companies*) $_{i,t}$	-0.001	0.000 ***	-0.000	0.000 ***	-0.002	0.000 ***	-0.000	0.000 ***
Constant	152.997	1.512 ***	-49.111	0.340 ***	54.692	1.331 ***	-59.965	0.363 ***
Firm fixed-effect	yes		yes		yes		yes	
Analyst fixed-effect	yes		yes		yes		yes	
Year fixed-effect	yes		yes		yes		yes	
#(obs)	3,238,817		3,238,817		3,238,817		3,238,817	
F	14,314.100		3,591.740		12,417.240		3,908.300	
Adj. R-squared	0.879		0.789		0.831		0.777	
Within R-squared	0.071		0.019		0.062		0.020	

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Regardless of whether we use default or voluntary closure as the prediction target, we find that the relative prediction performance of human to machine becomes better for firms with less observable information for their attributes (i.e., lower values for #(*available variables*)). Thus, for firms with less observable information, the relative performance of human predictions to machine predictions improves.

Why do analysts perform better in the case of opaque firms with smaller amounts of observable information? One conjecture is that analysts are using unstructured information, which, by definition, cannot be used in machine predictions. To confirm this conjecture, we also run the panel regression for $Proxy'_{f,i,t}$, which is defined by replacing $Outcome_{f,t}^{ML}$ with $Outcome_{f,i,t}^{SH}$. This regression characterizes under what conditions human predictions outperform those of the structured human. The obtained results show the similar pattern in Table 3, i.e., relative prediction power of human predictions compared with structured human becomes higher as the amount of available information becomes smaller.[11]

We also regress separately the performance of human and machine predictions on the same set of characteristics. From the estimation results (reported in the appendix), we confirm that the negative marginal impact associated with lower availability of information is greater for machine predictions than for human predictions. This could be the case when human predictions effectively use unstructured information to make predictions.

To check the robustness of the results and address the concerns we raised in the previous section, first, we employ alternative methods of measuring the disagreement between human and machine predictions. As detailed above, we are using the ex-post record of firm exits to obtain the probabilities of exit implied by *fscore* and "structured" *fscore*. As the transformation of *fscore* to the probability is simply a monotonic transformation and does not change the order of the score, it does not affect the comparison of human and machine predictions. Nonetheless, in reality, such an ex-post record of exit used in calibrating *fscore* to probability is not attainable in the process of human predictions. Thus, we also construct a set of rankings based on the machine prediction, *fscore*, and "structured" *fscore*. In this ranking of prediction outcomes, we do not need to refer to the ex-post default records. Second, we also define a dummy variable taking the value of one if $Proxy_{f,i,t}$ is positive and zero otherwise. We use this dummy variable and run a linear probability model with the abovementioned fixed effects and conditional

[11] We can also find that the marginal impact of available information on the relative performance of human predictions to that of structured humans is much smaller than that for human vs. machine. This means that the sensitivity of the structured human predictions with respect to the level of available information is much smaller than that of machine.

logit model with firm-level fixed effects. We also set 1 to 10 variables depending on the level of $Proxy_{f,i,t}$ and run ordered-logit estimation without fixed effects. Third, we replace analyst-level fixed effect with analyst-year-level fixed effect so that we can take complete account of analyst-level unobservable factors varying over time. Fourth, we employ one of the sub-scores of *fscore*, which represents the "stability" of a firm, instead of the total *fscore*, so that the target of human predictions becomes plausibly more comparable to that of machine predictions. Fifth, instead of weighted random forest, we employ LASSO or extreme gradient boost for producing machine predictions. All the results are shown in the appendix and are consistent with the results in Table 3.

C. Counterfactual exercises

Can we use the empirical findings presented in the previous section to improve overall prediction performance for firm exits? Given the performance of humans relative to machines improves for more opaque firms with smaller amounts of observable information, it is natural to assign firms with smaller observable information to humans and firms with larger information to machines.

Based on this conjecture, we split the sample into five subsamples according to the number of observable variables. We aim at setting up multiple groups for which the relative performance of human to machine differs. To construct subgroups purely tied to the number of observable variables, we regress #(available variables) to a firm's sales, growth, and industry classification, all of which are significant in the estimation of $Proxy_{f,i,t}$, and take out the residual. Then, we use this residual to sort the firms and construct five subsamples so that we can set up five groups of firms depending on the level of #(available variables) orthogonal to other firm attributes.

In each subsample, we evaluate the performances of human and machine predictions. By comparing, for example, the number of false negatives based on machine predictions (M) to those based on human predictions (H) for the same set of firms, we can describe what happens to the prediction performance for the subsample by reallocating prediction tasks from machine to human.

Table 4: Reallocation of prediction instances

(a) Firms actually do *NOT* exit ex-post

	Prediction for default			*Prediction for voluntary closure*		
	M = default H = not default (1)	M = not default H = default (2)	(2)/(1)	M = closure H = not closure (1)	M = not closure H = closure (2)	(2)/(1)
~20 %tile	49,117	23,068	0.47	25,206	19,453	0.77
20~40 %tile	36,094	54,446	1.51	28,326	23,667	0.84
40~60 %tile	37,362	46,368	1.24	28,370	28,134	0.99
60~80 %tile	33,409	39,218	1.17	20,249	30,962	1.53
80 %tile~	11,652	30,608	2.63	8,026	34,406	4.29

(b) Firms actually do exit ex-post

	Prediction for default			*Prediction for voluntary closure*		
	M = default H = not default (3)	M = not default H = default (4)	(3)/(4)	M = closure H = not closure (3)	M = not closure H = closure (4)	(3)/(4)
~20 %tile	88	21	4.19	140	51	2.75
20~40 %tile	82	40	2.05	195	42	4.64
40~60 %tile	86	37	2.32	231	43	5.37
60~80 %tile	74	37	2.00	174	54	3.22
80 %tile~	38	27	1.41	72	45	1.60

Note: M and H denote the predictions of machine and human, respectively.

The two panels in Table 4 summarize the number of false positive, false negative, true positive, and true negative cases for the five subsamples. We treat the top 30% of firms in terms of the prediction score as the firms predicted to exit.[12]

For example, the columns marked (1) in panel (a), show the number of false-positives for machine predictions and true-negatives for human predictions, as these columns show the number of firms that do *not* exit ex-post. Conversely, the columns marked (2) in panel (a) show the number of true-negatives for machine predictions and false-positives for human predictions for firms that do not exit ex-post. Panel (b) in Table 4 summarizes the number in the same manner but for the firms that actually *do* exit ex-post.

[12] For robustness check, we vary this prediction threshold (i.e., the top 30% in this baseline exercise) from the top 50% to the top 20% and confirm the results do not change.

Comparing the numbers in each column, we can see how type I and type II errors vary depending on whether prediction instances are allocated to machine or human. In six out of the ten rows in Panel (a), the number in columns marked (1) is smaller than that in (2), while in Panel (b), all the numbers in the columns marked (3) are larger than those in (4).

First, this means that type II error is always smaller in machine predictions than human predictions, regardless of the level of available information. Even for the firms with smallest information, human predictions cannot outperform machine predictions. Second, in the case of the firms with smallest information however (i.e., the first raw labeled as "~20%tile"), it is still possible to reduce the number of false-positives, and thus reduce type I error, by reallocating the default prediction instances from machine to human (i.e., the number of false-positives is reduced from 49,117 to 23,068). In the case of voluntary closure, we can also achieve smaller type I error for firms with the smallest, small, and average information (i.e., the first, second, and third raws labeled "~20%tile", "20~40%tile", and "40~60%tile") by reallocating the default prediction instances from machine to human.

We should note, nonetheless, that such a reallocation of prediction tasks is accompanied by larger type II error, as shown above. The numbers in columns (3) are always larger than that in (4), which suggests that reallocating the prediction instances from machine to human always increases the number of false negatives. As one interesting result, we can also find that, in the case of default predictions, the ratio tends to be larger as we move from the subsample with smallest information to that with largest. This pattern is inconsistent with the positive coefficient obtained in our estimation for $Proxy_{f,i,t}$. This is the case simply because, in our data, the number of exits is much smaller than that of non-exits. In other words, the relative performance of human predictions to machine predictions with respect to the level of available information is driven by human predictions correctly predicting non-exit firms.

These results reconfirm the usefulness of machine-based prediction techniques in the context of exit predictions. There is however room for human predictions to outperform machine predictions under specific circumstances, such as when the prediction targets are opaque due to less available information or when the user of the prediction results is more concerned with type I error than type II due to, for example, the imbalance between the numbers of exit and non-exit firms.

D. Growth prediction

We have so far focused on exit predictions. What happens if we focus on the upside of firm dynamics instead? We repeat the same analyses by considering firm growth as the target of our predictions. We define growth in sales for a firm as a sales growth rate of one standard deviation higher than the industry average defined in two-digits over the one-year window used to measure the outcome. Then, we prepare a dummy variable that takes 1 if firms experience a growth rate higher than these criteria.

As predictions for upside events are the mirror image of downside predictions, we conjecture that while overall prediction performance is still higher for machine prediction than human, and the relative performance of human predictions also becomes higher when the available information is smaller as we have described, the source of this better performance is not from lower type I error but from lower type II error. In other words, analysts correctly predict non-growth for actual non-growth firms based on smaller information. As presented in the appendix, this is indeed the case.

VI. Conclusion

We examine empirically the relative performance of machine-based and human subjective predictions for firm exits. Using a huge volume of firm-level high-dimension panel data, we find that human predictions are not as accurate as machine predictions on average. As for predicting the exits of firms with less observable information, nonetheless, the relative performance of human predictions improves.

As one important point to note when using machine predictions in practice, Luca et al. (2016) claim that machine predictions cannot ensure automated decision making as it is necessary to take into account the various dimensions of the problems under consideration. The present paper provides an evidence that it is also necessary to take into account the conditions under which a prediction is to be assigned to machine. Our findings cast light on the circumstances and the extent to which tasks should be allocated either to machine or to human.

Future extensions of the present study may benefit from the inclusion of additional explanatory variables as regressors for $Proxy$. A large-sized aggregate-level shock, such as a market downturn or a natural disaster, could have an impact on the marginal effect of each determinant of $Proxy$. Understanding potentially relevant shocks is useful in considering how we should allocate prediction tasks to machines and humans under specific circumstances. Such an additional analysis will help us to understand both the nature of human error and how humans and machines can work together to provide accurate predictions.

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Appendix A

The list of variables we use for constructing machine learning-based prediction model is as follows:

Firm-own characteristics (*firm own*): As variables representing firms' own characteristics, we use firm size measured by the logarithm of sales and the change in sales from the previous period, profit-to-sales ratio and any change from the previous period, the status of dividend payments (paid or not) and any change from the previous period, whether the firm is listed or not, the number of employees, the logarithm of stated capital, and dummy variables representing industry classification (note: multiple industry codes are recorded). We also use firm age, owner age, and the number of establishments.

Firms' financial statement information (*financial statement*): We set up a number of financial variables used in the literature as variables representing firms' detailed financial statement information.[13]

Industry and geographical information (*geo/ind*): We set up the following two groups of variables as variables representing the industry and area to which the firms belong. First, we construct the variables measuring the average sales growth of firms located in the same city as the targeted firms. Second, we compute the average sales growth of firms belonging to the same industry classified in the 2-digit level.

[13] The list of "***financial statement***" variables consists of the following items: Logarithm of total assets, cash-to-total assets ratio, liquid assets-to-total assets ratio, tangible assets-to-total assets ratio, receivables turn-over, inventory turn-over, total liability-to-total assets ratio, liquid liability-to-total assets ratio, bond-to-total liability ratio, bank borrowing-to-total liability ratio, bank short borrowing-to-total bank borrowing ratio, payables turn-over, interest coverage ratio, liquid assets-to-liquid liability ratio, fixed compliance ratio, fixed ratio, working capital turn-over, gross profit-to-sales ratio, operating profit-to-sales ratio, ordinary profit-to-sales ratio, net profit before tax-to-sales ratio, logarithm of EBITDA, logarithm of EBITDA-to-sales ratio, special income-to-sales ratio, special expenses-to-sales ratio, and labor productivity.

Lender banks information (*bank*): As variables representing firms' borrowing relationships with lender banks, we construct a dummy variable to represent a change in main lenders (i.e., top lender bank) or in the number of lender banks.

Supply-chain linkage information (*network*): We construct the following two groups of variables to represent the supply chain network. First, we compute widely used network metrics for each firm by using the supply chain network information. The metrics consist of degree centrality; eigenvector centrality; egonet eigenvalue; co-transaction; and the number of transaction partners, both direct (i.e., customers and suppliers) and indirect (i.e., suppliers' suppliers, customers' suppliers, etc.). Second, we construct a number of variables representing the characteristics of transaction partners. To summarize this information, we employ the average, maximum, minimum and the sum of *fscore* associated with each transaction partner. Note that while the network metrics cover both direct and indirect transaction partners, the transaction partners' characteristics only cover direct transaction partners.

Shareholder linkage information (*shareholder*): We set up similar variables to those for supply chain network as predictors for shareholder information.

Appendix B

Here we list the tables and figures referred to in the main body of the paper for the robustness check. First, we show an alternative way to compare the prediction power of machine, human, and the "structured" human (Figure A1). We can confirm that machine predictions outperform human predictions on average. Regarding the comparison between human predictions and those of the structured human, human predictions are more precise in the case of default predictions, while the structured human is better in terms of recall in the case of voluntary closure. Second, instead of estimating the determinants of $Proxy_{f,i,t}$, we estimate separately the determinants of $Proxy^{m}_{f,t}$ and $Proxy^{h}_{f,i,t}$, which are defined as below, representing the prediction performance of machine and human, respectively. Comparing the estimated coefficients associated with the independent variables, we can see how the respective prediction powers of machine and human vary according to the change in determinants (Table A1).

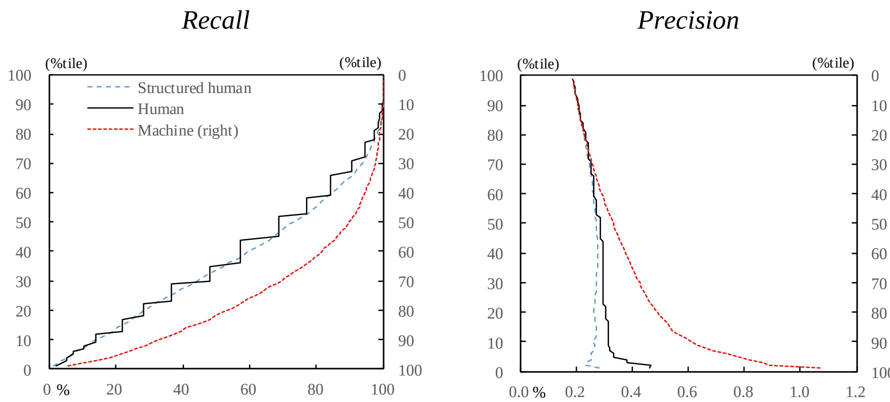
(A1) $$Proxy^{m}_{f,t} = Outcome^{ML}_{f,t} - 1 \text{ for exit firms,}$$
$$= 1 - Outcome^{ML}_{f,t} \text{ for non-exit firms,}$$

(A2) $$Proxy^{h}_{f,i,t} = Outcome^{H}_{f,i,t} - 1 \text{ for exit firms,}$$
$$= 1 - Outcome^{H}_{f,i,t} \text{ for non-exit firms.}$$

Third, we construct a set of rankings based on the machine prediction, *fscore*, and "structured" *fscore* and repeat the same estimation for the disagreement (Table A2). Fourth, we also define a dummy variable taking the value of one if $Proxy_{f,i,t}$ is positive and zero otherwise and run a linear probability model and conditional logit model (Table A3). We also set 1 to 10 variables, depending on the level of $Proxy_{f,i,t}$, and run an ordered-logit estimation (Table A4). Fifth, we replace analyst-level fixed effect with analyst-year-level fixed effect (Table A5). Sixth, we employ one of the sub-scores of *fscore*, which represents the “stability” of each firm, instead of the total *fscore*, so that the target of human predictions becomes plausibly more comparable to that of machine predictions (Table A6). Seventh, we summarize the results of the proxy estimation and counterfactual exercise representing firm growth (Table A7). Eighth, we repeat the AUC estimation and proxy estimation based on the two alternative methods (i.e., LASSO and extreme gradient boost) (Table A8, A9). All the results are consistent with the ones we presented in the main body of the present paper.

Figure A1: Recall and precision measures over different thresholds

Default (test year: *t*=2016)



Voluntary closure (test year: *t*=2016)

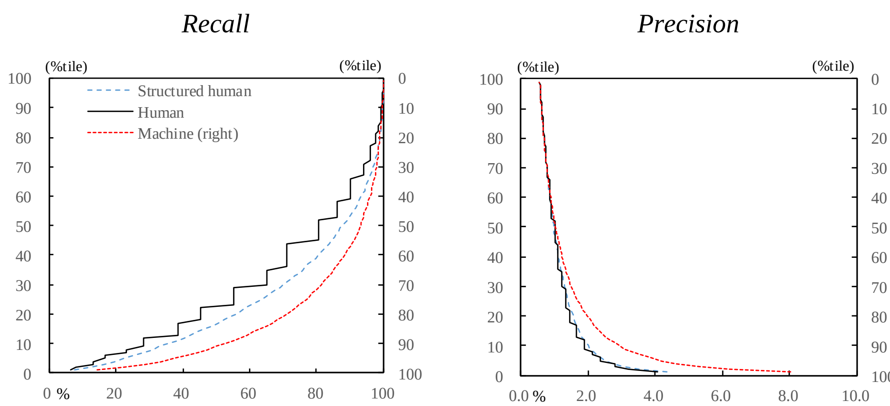


Table A1: Prediction performance of machine and human

	default				*voluntary closure*			
	Machine		***Human***		***Machine***		***Human***	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
umber of available variables								
#(*available variables*) $_{f,t}$	0.102	0.000 ***	0.008	0.000 ***	0.118	0.000 ***	0.012	0.000 ***
irm characteristics								
log(*sales* $_{f,t}$)	2.318	0.020 ***	5.024	0.014 ***	6.461	0.021 ***	7.493	0.021 ***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	1.701	0.015 ***	-0.440	0.011 ***	0.231	0.017 ***	-0.760	0.016 ***
listed $_{f,t}$	2.477	0.443 ***	2.621	0.303 ***	-1.838	0.481 ***	2.168	0.467 ***
#(*industry*) $_{f,t}$	-0.502	0.025 ***	0.099	0.017 ***	0.244	0.027 ***	0.202	0.027 ***
priority $_{f,t}$			0.000	0.000 *			0.000	0.000 *
nalyst characterstics								
#(*assigned companies*) $_{i,t}$			0.000	0.000 ***			0.000	0.000 ***
industry experience $_{f,i,t}$			-0.000	0.000 ***			-0.000	0.000 ***
eam characteristics								
#(team members) $_{i,t}$			0.002	0.001			-0.005	0.002 **
Average #(*tenure years*) $_{i,t}$			0.014	0.002 ***			0.016	0.003 ***
Average industry experience $_{f,i,t}$			-0.000	0.000 **			0.000	0.000
Average #(*assigned companies*) $_{i,t}$			0.000	0.000 ***			0.000	0.000 ***
onstant	29.191	0.226 ***	-4.012	0.166 ***	-19.798	0.245 ***	-28.631	0.256 ***
irm fixed-effect	yes		yes		yes		yes	
nalyst fixed-effect	yes		yes		yes		yes	
ear fixed-effect	yes		yes		yes		yes	
(obs)	3,756,803		3,238,817		3,756,803		3,238,817	
	53,485.400		15,304.020		78,182.190		14,025.710	
dj R-squared	0.815		0.897		0.876		0.866	
'ithin R-squared	0.092		0.075		0.129		0.069	

Table A2: Rank-based disagreement estimation

	Machine vs. Human					
	default			***voluntary closure***		
	Coef.	S.E.		Coef.	S.E.	
Number of available variables						
#(*available variables*) $_{f,t}$	1,607.929	4.271	***	1,527.788	3.784	***
Firm characteristics						
log(*sales* $_{f,t}$)	-58,115.530	374.526	***	-25,088.000	331.840	***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	37,273.310	287.922	***	16,041.170	255.107	***
listed $_{f,t}$	27,956.380	8,164.855	***	-34,210.110	7,234.288	***
#(*industry*) $_{f,t}$	-8,595.519	471.108	***	620.723	417.415	
priority $_{f,t}$	5.258	1.144	***	8.109	1.013	***
Analyst characterstics						
#(*assigned companies*) $_{i,t}$	-1.894	0.313	***	-3.357	0.277	***
industry experience $_{f,i,t}$	-11.528	0.604	***	-6.217	0.535	***
Team characteristics						
#(team members) $_{i,t}$	268.315	34.572	***	346.771	30.632	***
Average #(*tenure years*) $_{i,t}$	384.545	48.371	***	-63.242	42.858	
Average industry experience $_{f,i,t}$	39.630	2.346	***	-2.152	2.079	
Average #(*assigned companies*)	-2.936	0.437	***	-5.742	0.387	***
Constant	470,115.500	4,475.366	***	125,805.500	3,965.298	***
Firm fixed-effect	yes			yes		
Analyst fixed-effect	yes			yes		
Year fixed-effect	yes			yes		
#(obs)	3,238,817			3,238,817		
F	13,426.970			13,873.310		
Adj. R-squared	0.876			0.820		
Within R-squared	0.067			0.069		

Table A3: Dummy variable measure for disagreement

(1) Linear probability model

	Machine vs. Human					
	default			***voluntary closure***		
	Coef.	S.E.		Coef.	S.E.	
Number of available variables						
#(*available variables*) $_{f,t}$	0.157	0.001	***	0.265	0.001	***
Firm characteristics						
log(*sales* $_{f,t}$)	-5.664	0.076	***	-3.578	0.085	***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	4.064	0.059	***	2.315	0.065	***
listed $_{f,t}$	2.856	1.664	*	-7.332	1.849	***
#(*industry*) $_{f,t}$	-1.350	0.096	***	0.042	0.107	
priority $_{f,t}$	0.001	0.000	***	0.002	0.000	***
Analyst characterstics						
#(*assigned companies*) $_{i,t}$	-0.000	0.000		-0.001	0.000	***
industry experience $_{f,i,t}$	-0.001	0.000	***	-0.000	0.000	**
Team characteristics						
#(team members) $_{i,t}$	0.041	0.007	***	0.041	0.008	***
Average #(*tenure years*) $_{i,t}$	0.005	0.010		0.005	0.011	
Average industry experience $_{f,i,t}$	0.006	0.000	***	0.000	0.001	
Average #(*assigned companies*) $_{i,t}$	-0.001	0.000	***	-0.001	0.000	***
Constant	93.738	0.912	***	59.737	1.014	***
Firm fixed-effect	yes			yes		
Analyst fixed-effect	yes			yes		
Year fixed-effect	yes			yes		
#(obs)	3,238,817			3,238,817		
F	3,135.790			6,343.690		
Adj. R-squared	0.721			0.659		
Within R-squared	0.016			0.033		

(2) Conditional logit model

	Machine vs. Human					
	default			***voluntary closure***		
	Coef.	S.E.		Coef.	S.E.	
Number of available variables						
#(*available variables*) $_{f,t}$	1.942	0.013	***	2.587	0.012	***
Firm characteristics						
log(*sales* $_{f,t}$)	-87.264	1.207	***	-42.894	1.011	***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	65.887	0.962	***	28.807	0.783	***
listed $_{f,t}$	45.617	25.010	*	-82.705	20.077	***
#(*industry*) $_{f,t}$	-20.860	1.326	***	-6.271	1.235	***
priority $_{f,t}$	0.095	0.014	***	0.072	0.008	***
Analyst characterstics						
#(*assigned companies*) $_{i,t}$	0.000	0.001		0.000	0.000	
industry experience $_{f,i,t}$	0.006	0.001	***	-0.002	0.001	*
Team characteristics						
#(team members) $_{i,t}$	0.425	0.071	***	0.409	0.065	***
Average #(*tenure years*) $_{i,t}$	-0.241	0.114	**	-0.067	0.104	
Average industry experience $_{f,i,t}$	0.022	0.006	***	-0.104	0.005	***
Average #(*assigned companies*) $_{i,t}$	-0.003	0.001	***	-0.002	0.001	**
Constant						
Firm fixed-effect	yes			yes		
Analyst fixed-effect	no			no		
Year fixed-effect	no			no		
#(obs)	736,498			922,303		
Log-likelihood	-259,176.670			-315,385.000		
χ-squared	30,953.570			57,174.730		

Table A4: Ordered logit estimation

	Machine vs. Human			
	default		***voluntary closure***	
	Coef.	S.E.	Coef.	S.E.
umber of available variables				
#(*available variables*) $_{f,t}$	1.214	0.005 ***	2.262	0.005 ***
irm characteristics				
log(*sales* $_{f,t}$)	-171.686	0.244 ***	-22.596	0.210 ***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	103.072	0.390 ***	26.065	0.366 ***
listed $_{f,t}$	542.157	6.472 ***	-103.528	5.877 ***
#(*industry*) $_{f,t}$	-48.697	0.389 ***	-1.500	0.385 ***
priority $_{f,t}$	0.086	0.003 ***	0.010	0.002 ***
nalyst characterstics				
#(*assigned companies*) $_{i,t}$	0.001	0.000 ***	-0.001	0.000 ***
industry experience $_{f,i,t}$	0.047	0.001 ***	0.032	0.001 ***
eam characteristics				
#(team members) $_{i,t}$	2.314	0.028 ***	2.805	0.028 ***
Average #(*tenure years*) $_{i,t}$	-0.375	0.049 ***	-0.498	0.049 ***
Average industry experience $_{f,i,t}$	0.255	0.002 ***	0.297	0.002 ***
Average #(*assigned companies*) $_{i,t}$	-0.030	0.000 ***	-0.041	0.000 ***
onstant				
irm fixed-effect	no		no	
nalyst fixed-effect	no		no	
ear fixed-effect	no		no	
(obs)	3,466,611		3,466,611	
og-likelihood	-6,008,220.100		-6,508,573.100	
-squared	621,072.400		253,758.480	

Table A5: Alternative fixed-effects specification

	Machine vs. Human					
	default			*voluntary closure*		
	Coef.	S.E.		Coef.	S.E.	
Number of available variables						
#(*available variables*) $_{f,t}$	0.571	0.001	***	0.482	0.001	***
Firm characteristics						
log(*sales* $_{f,t}$)	-19.063	0.125	***	-8.293	0.111	***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	13.213	0.096	***	5.074	0.085	***
listed $_{f,t}$	-4.449	2.732		-19.247	2.412	***
#(*industry*) $_{f,t}$	-3.538	0.158	***	0.002	0.140	
priority $_{f,t}$	0.000	0.000		0.002	0.000	***
Analyst characterstics						
#(*assigned companies*) $_{i,t}$						
industry experience $_{f,i,t}$	0.001	0.000	***	0.000	0.000	
Team characteristics						
#(team members) $_{i,t}$						
Average #(*tenure years*) $_{i,t}$						
Average industry experience $_{f,i,t}$	0.017	0.001	***	0.000	0.001	
Average #(*assigned companies*) $_{i,t}$						
Constant	157.847	1.465	***	49.298	1.293	***
Firm fixed-effect	yes			yes		
Analyst-Year fixed-effect	yes			yes		
Year fixed-effect	yes			yes		
#(obs)	3,238,266			3,238,266		
F	22,197.050			18,409.250		
Adj. R-squared	0.882			0.834		
Within R-squared	0.073			0.061		

Table A6: Using sub-score as human predictions

	default				*voluntary closure*			
	Machine vs. Human		***SH vs. Human***		***Machine vs. Human***		***SH vs. Human***	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Number of available variables								
#(*available variables*) $_{f,t}$	0.637	0.002 ***	0.018	0.000 ***	0.519	0.002 ***	0.018	0.000 ***
Firm characteristics								
log(*sales* $_{f,t}$)	5.178	0.191 ***	3.120	0.044 ***	13.864	0.166 ***	3.240	0.044 ***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	17.783	0.142 ***	-2.203	0.033 ***	13.444	0.123 ***	-2.283	0.033 ***
listed $_{f,t}$	8.962	3.434 ***	4.606	0.787 ***	-9.880	2.974 ***	4.304	0.787 ***
#(*industry*) $_{f,t}$	-2.132	0.227 ***	0.090	0.052 *	1.092	0.197 ***	0.086	0.052 *
priority $_{f,t}$	0.000	0.000	0.000	0.000	0.001	0.000 **	-0.000	0.000
Analyst characterstics								
#(*assigned companies*) $_{i,t}$	-0.002	0.000 ***	0.000	0.000 ***	0.000	0.000 **	0.001	0.000 ***
industry experience $_{f,i,t}$	-0.003	0.000 ***	0.001	0.000 ***	0.002	0.000 ***	0.001	0.000 ***
Team characteristics								
#(team members) $_{i,t}$	0.028	0.019	-0.017	0.004 ***	0.026	0.017	-0.018	0.004 ***
Average #(*tenure years*) $_{i,t}$	0.080	0.026 ***	-0.046	0.006 ***	-0.078	0.022 ***	-0.047	0.006 ***
Average industry experience $_{f,i,t}$	0.026	0.001 ***	-0.002	0.000 ***	-0.005	0.001 ***	-0.002	0.000 ***
Average #(*assigned companies*) $_{i,t}$	0.001	0.000 ***	0.000	0.000 **	-0.001	0.000 ***	0.000	0.000
Constant	-132.004	2.359 ***	-38.266	0.540 ***	-212.930	2.044 ***	-39.522	0.540 ***
Firm fixed-effect	yes		yes		yes		yes	
Analyst fixed-effect	yes		yes		yes		yes	
Year fixed-effect	yes		yes		yes		yes	
#(obs)	2,199,518		2,199,518		2,199,518		2,199,518	
F	10,515.140		719.200		11,101.810		752.040	
Adj. R-squared	0.825		0.712		0.830		0.718	
Within R-squared	0.081		0.006		0.085		0.006	

Table A7: Growth prediction

(1) $Proxy$ estimation

	Machine vs. Human			***SH vs. Human***		
	Coef.	S.E.		Coef.	S.E.	
Number of available variables						
#(*available variables*) $_{f,t}$	0.196	0.003	***	0.037	0.000	***
Firm characteristics						
log(*sales* $_{f,t}$)	-50.833	0.229	***	-0.166	0.039	***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	14.032	0.174	***	-0.439	0.030	***
listed $_{f,t}$	-24.028	4.837	***	3.056	0.830	***
#(*industry*) $_{f,t}$	-1.239	0.281	***	0.036	0.048	
priority $_{f,t}$	0.005	0.001	***	0.000	0.000	
Analyst characterstics						
#(*assigned companies*) $_{i,t}$	-0.000	0.000		-0.000	0.000	***
industry experience $_{f,i,t}$	0.003	0.000	***	0.000	0.000	***
Team characteristics						
#(team members) $_{i,t}$	-0.167	0.021	***	-0.008	0.004	**
Average #(*tenure years*) $_{i,t}$	-0.357	0.029	***	-0.014	0.005	***
Average industry experience $_{f,i,t}$	-0.017	0.001	***	0.000	0.000	
Average #(*assigned companies*) $_{i,t}$	0.001	0.000	***	-0.000	0.000	***
Constant	574.761	2.737	***	-0.627	0.470	
Firm fixed-effect	yes			yes		
Analyst fixed-effect	yes			yes		
Year fixed-effect	yes			yes		
#(obs)	3,037,588			3,037,588		
F	4,799.540			650.920		
Adj. R-squared	0.590			0.639		
Within R-squared	0.026			0.004		

(2) Counterfactual exercise

(a) Firms that actually do not grow ex-post (b) Firms that actually grow ex-post

	M = growth H = not growth (1)	M = not growth H = growth (2)	(2)/(1)	M = growth H = not growth (3)	M = not growth H = growth (4)	(3)/(4)
~20 %tile	12,799	30,678	2.40	1765	791	2.23
20~40 %tile	15,822	38,401	2.43	2170	978	2.22
40~60 %tile	18,513	31,610	1.71	2660	883	3.01
60~80 %tile	25,171	22,727	0.90	3599	760	4.74
80 %tile~	34,835	11,263	0.32	5308	401	13.24

Table A8: AUCs of alternative prediction models for default

Test data: t = 2013

Model	LASSO	XGBoost
Human	0.634 (0.0049)	
Machine	0.783 (0.0042)	0.807 (0.0039)
Structured human	0.529 (0.0047)	0.598 (0.0046)
Machine & *fscore*	0.806 (0.0040)	0.823 (0.0037)
Machine with small information	0.746 (0.0046)	0.783 (0.0043)

Test data: t = 2014

Model	LASSO	XGBoost
Human	0.639 (0.0052)	
Machine	0.774 (0.0047)	0.787 (0.0044)
Structured human	0.537 (0.0051)	0.558 (0.0096)
Machine & *fscore*	0.798 (0.0044)	0.815 (0.0042)
Machine with small information	0.740 (0.0051)	0.768 (0.0049)

Test data: t = 2015

Model	LASSO	XGBoost
Human	0.653 (0.0055)	
Machine	0.774 (0.0049)	0.804 (0.0044)
Structured human	0.547 (0.0053)	0.500 (0.0115)
Machine & *fscore*	0.804 (0.0046)	0.818 (0.0044)
Machine with small information	0.735 (0.0054)	0.772 (0.0050)

Test data: t = 2016

Model	LASSO	XGBoost
Human	0.663 (0.0053)	
Machine	0.779 (0.0049)	0.786 (0.0046)
Structured human	0.563 (0.0054)	0.516 (0.0111)
Machine & *fscore*	0.803 (0.0046)	0.810 (0.0045)
Machine with small information	0.738 (0.0054)	0.767 (0.0049)

Note: Each number represents AUC and the number in the parentheses is its standard error.

Table A9: Proxy estimation based on alternative prediction models

(1) LASSO

	Machine vs. Human			***SH vs. Human***		
	Coef.	S.E.		Coef.	S.E.	
Number of available variables						
#(*available variables*) $_{f,t}$	0.495	0.002	***	0.150	0.001	***
Firm characteristics						
log(*sales* $_{f,t}$)	-12.859	0.146	***	10.266	0.082	***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	17.666	0.113	***	-1.179	0.063	***
listed $_{f,t}$	59.775	3.193	***	4.973	1.792	***
#(*industry*) $_{f,t}$	-4.934	0.184	***	-0.769	0.103	***
priority $_{f,t}$	0.007	0.000	***	0.001	0.000	***
Analyst characterstics						
#(*assigned companies*) $_{i,t}$	-0.001	0.000	***	-0.001	0.000	***
industry experience $_{f,i,t}$	-0.001	0.000	***	-0.000	0.000	
Team characteristics						
#(team members) $_{i,t}$	0.112	0.014	***	0.009	0.008	
Average #(*tenure years*) $_{i,t}$	0.123	0.019	***	0.016	0.011	
Average industry experience $_{f,i,t}$	0.009	0.001	***	-0.005	0.001	***
Average #(*assigned companies*) $_{i,t}$	-0.001	0.000	***	-0.001	0.000	***
Constant	97.460	1.750	***	######	0.982	***
Firm fixed-effect	yes			yes		
Analyst fixed-effect	yes			yes		
Year fixed-effect	yes			yes		
#(obs)	3,238,817			3,238,817		
F	9,181.380			4,103.740		
Adj. R-squared	0.841			0.832		
Within R-squared	0.047			0.021		

(2) Extreme gradient boost

	Machine vs. Human			***SH vs. Human***		
	Coef.	S.E.		Coef.	S.E.	
Number of available variables						
#(*available variables*) $_{f,t}$	0.449	0.003	***	0.075	0.004	***
Firm characteristics						
log(*sales* $_{f,t}$)	0.298	0.264		2.947	0.348	***
log(*sales* $_{f,t}$) - log(*sales* $_{f,t-1}$)	12.878	0.203	***	-0.930	0.268	***
listed $_{f,t}$	-5.342	5.763		-24.407	7.592	***
#(*industry*) $_{f,t}$	-3.276	0.333	***	-5.364	0.438	***
priority $_{f,t}$	-0.051	0.001	***	-0.123	0.001	***
Analyst characterstics						
#(*assigned companies*) $_{i,t}$	0.002	0.000	***	-0.001	0.000	**
industry experience $_{f,i,t}$	-0.008	0.000	***	0.010	0.001	***
Team characteristics						
#(team members) $_{i,t}$	0.768	0.024	***	0.392	0.032	***
Average #(*tenure years*) $_{i,t}$	0.508	0.034	***	0.139	0.045	***
Average industry experience $_{f,i,t}$	-0.035	0.002	***	-0.020	0.002	***
Average #(*assigned companies*) $_{i,t}$	-0.005	0.000	***	-0.006	0.000	***
Constant	-52.916	3.159	***	-27.909	4.161	***
Firm fixed-effect	yes			yes		
Analyst fixed-effect	yes			yes		
Year fixed-effect	yes			yes		
#(obs)	3,238,817			3,238,817		
F	2,886.910			1,230.400		
Adj. R-squared	0.506			-0.042		
Within R-squared	0.015			0.007		