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Forecasting recoveries in debt collection: Debt collectors and information production

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Abstract

Recent theoretical work suggests that debt collection agencies play an important role in gathering and processing debtor information. We study a comprehensive data set with information provided by original creditors and information gathered in third-party debt collection. In line with the theoretical results, the initial information is sparse and the gathered information is essential for better-informed predictions.

KEYWORDS

debt collection, loss given default, recovery rate

JEL CLASSIFICATION

G3; G21; G22; G29

1 | INTRODUCTION

The management of accounts receivable and accounts payable plays a vital role in the balance sheets of many producers of goods and services. It is common practice in many industries (e.g. insurance, telecommunications, and mail order services) to commission specialized collection

We are deeply indebted to Seghorn AG for providing the data set and kindly giving a wide range of advice on the debt collection industry that enabled this study. We thank John Doukas and an anonymous referee for valuable input and suggestions. We are further grateful to the participants and discussants of the HypoVereinsbank Seminar 2017 in Bochum, Germany; the German Operations Research Society Financial Management and Financial Institutions Workshop 2017 in Magdeburg, Germany; the European Conference on Data Analysis 2017 in Wroclaw, Poland; the 35th Annual Conference of the French Finance Association in Paris, France; the 2018 Annual Meetings of the European Financial Management Association in Milan, Italy; and Christopher Jung, Antonio Della Bina, Henning Cordes, Jörn Debener, Judith Schneider, and other members of the Finance Center Münster for their valuable comments, which helped improve this study.

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agencies to collect distressed receivables. Similarly, banks tend to resort to collection agencies in difficult cases (Thomas, Matuszyk, & Moore, 2012). According to industry studies, collection firms managed a total of €60 billion of receivables in Germany at the end of 2015 (Bülow, 2016) and over \$792 billion in the United States at the end of 2016 (Ernst & Young, 2017).

Surprisingly, little is known about how collection agencies manage accounts successfully. There is, in particular, little knowledge about what factors drive collection recoveries. Thomas et al. (2012) and Han & Jang (2013) have studied these factors for bank loans, Beck, Grunert, Neus, and Walter (2017) have studied them for other goods and services, and Hoehstoetter, Nazemi, Rachev, and Bozic (2012) have examined the choice of prediction models. To the best of our knowledge, these are the only results in this field.

A collection agency can use information from different sources to predict collection recoveries. One important distinction is between the information original creditors provide and the information debt collection agencies gather themselves.¹ Earlier empirical work, such as that of Hoehstoetter et al. (2012), Thomas et al. (2012), and Beck et al. (2017), mainly focuses on initially available information. Thomas et al. (2012) and Beck et al. (2017) find this information to be sparse.

Interestingly, recent theoretical work, such as that of Drozd & Serrano-Padial (2017), suggests that debt collection plays an important role in gathering and processing debtor information. Fedaseyeu & Hunt (2018) place stronger emphasis on reputational issues but note that debt collection agencies in particular gain information on a customer's willingness to pay. There is no empirical evidence on the importance of information production in debt collection agencies to date.

Given these considerations, the main purpose of this study is to examine how valuable information gathered in third-party debt collection is for collection recovery prediction. We make three important contributions to the literature. First, we study predictive characteristics with a large proprietary data set of more than 300,000 distressed claims in a field where there is no publicly available data and almost no academic literature to date. This allows our study to complement the few earlier works on the drivers of collection recovery. Second, we explicitly apply methods of calculating variable importance to the predictive characteristics. We thus show that the initially provided information is not only sparse but also insufficient for making precise predictions. Third—and this is our most important contribution—debt collection agencies make use of a much more valuable set of information that is gathered from external sources, repeated contact with the debtor, investigations into a debtor's financial situation, and experience with a debtor in general.

The remainder of this paper is structured as follows. In Section 2, we briefly review the available literature on debt collection agencies. Section 3 introduces our data set and descriptive statistics. Section 4 presents the research design and the regression results. Section 5 describes our various robustness checks. Section 6 concludes.

2 | RELATED LITERATURE

There is generally little theoretical and empirical work on the debt collection industry. Beck et al. (2017) study predictive characteristics of collection on a German debt collection data set. They find the average level of collection to be around 65%, with a strong bimodal shape. Thomas et al. (2012) study the differences between in-house and third-party collection claims on loans issued in the

¹We refer to the original creditor's collection process as in-house collection and to the later debt collector's process as third-party collection. We use the term debtor when referring to the individual or company that is overdue on one or more claims. The initial holder of the claim is referred to as the original creditor or business partner.

United Kingdom. They identify three main differences: there is less debtor and contract information in third-party debt collection, the claims are older, and the quality of claims is lower. They further identify several characteristics as being predictive in the two cases. Our own results make use of and extend these findings. Hoechstoeetter et al. (2012) study the choice of prediction methods with an enormous German data set of several million claims from nine different industries. Their results further show that mean recovery levels vary tremendously across industries. We extend this literature by providing more evidence on the drivers of debt collection recovery.

Thomas et al. (2012) and Beck et al. (2017) highlight that debtor and contract information provided by the initial creditor is sparse. These studies further consider the sparsity of information to be a typical aspect of the debt collection business, which is in line with the data of Hoechstoeetter et al. (2012). Building on these important insights, we study how valuable additionally gathered information is for recovery prediction.

Makuch, Dodge, Ecker, Granfors, and Hahn (1992), Chin & Kotak (2006), and Miller et al. (2012) further document considerable improvements in the profitability of debt collection firms and departments through the introduction of operational innovations. These methods partly rely on debtor and contract characteristics for making optimal workout process decisions. Identifying the key drivers of recoveries is essential in implementing these operational improvements. Han & Jang (2013) further document that choices of workout actions in the collection process for Korean loans explain recovery success better than individual characteristics.

One central paper underlying our argument is that of Drozd & Serrano-Padial (2017), who argue that a crucial factor in the expansion of consumer credit in recent decades is improved information processing in the debt collection industry through the use of information technology. This improved information processing allows greater effort to be focused on debtors, who are then more likely to pay. The enhanced efficiency of debt collection has allowed for an expansion of consumer credit, while the risk of consumer credit in terms of charge-off rates has increased over this period. This argument is important, since it implies that debt collection agencies are critical in information production and processing. Fedaseyeu & Hunt (2018) argue that debt collection agencies are important since they can use harsher debt collection actions than original creditors; however, the authors note that debt collection agencies, in particular, produce information on a debtor's willingness to pay. Our results shed more light on the question of whether debt collection agencies play a role in information production and processing, and we evaluate how important this role is in terms of increased prediction accuracy.

Drozd & Serrano-Padial (2017) further show that debt collection has a positive influence on credit supply. Several studies point in a similar direction. Fedaseyeu (2015) reports that more restrictive debt collection state laws in the United States have had a negative impact on the availability of collection services and, via this channel, on the credit supply. Fonseca, Strair, and Zafar (2017) support these findings and, in addition, discover that this affects borrowers with worse creditworthiness in particular. Better-informed regulation of the debt collection industry is, therefore, beneficial to users of goods and services.

3 | DATA DESCRIPTION

3.1 | Debt collection data set

Our data set is provided by Seghorn AG, a large German debt collection agency that mainly offers collection services in the insurance, banking, and mail order industries. The data consist of insurance receivables, claims the original creditors transferred on a commission basis. This

means that the collection agency receives compensation for the collection service, while the debtor payments and the claim itself remain in the possession of the initial holder.² The collection agency further guarantees a minimum average collection rate to the claim holder. This minimum average collection rate is contractually agreed with the original creditor.³

There are two different types of receivables in our data. The first and main type is missed premium payments. Over 98% of our data are in this category. The second category is recourse receivables. Recourse receivables result from insurance events where the insurance company makes payments but considers the insurance customer or a third party to be liable for these payments. Regarding premium payments, insurance companies can choose to withdraw from a contract (new contracts) or cancel a contract within a certain period (ongoing contracts). However, debt collection is regarded as a way to maintain the customer base in a trade-off between retaining existing customers and investing in marketing to gain new customers. In cases involving payments, the insurance contract can just be continued. In the opposite case, the insurance company can terminate the contract later. The minimum collection rate offered by the debt collection agency is further used by the insurance companies in pricing and accounting insurance contracts.

The data set contains three subsamples from different insurers, A, B, and C. Samples A and B result from the same insurance product, while sample C results from a different one. Since the samples were each transferred by different insurance companies, they were independent of each other before the transfer to the collection agency. The collection agency received the claims over the years 2012–2014 on a regular basis, and all of these claims involve debtors located in Germany. Debt collection processes usually consist of written reminders and phone calls, and then possibly legal action. The collection efforts of the original creditors are limited to written reminders and possibly telephone calls.

Regarding data cleansing, 250 claims missing exposure data or smaller than €5 and 10 accounts missing gender information were removed. A total of 22 customer ages under 15 were set to missing. The data set used in the analysis contains 182,880 claims from sample A, 16,623 claims from sample B, and 126,615 claims from sample C.

Our data set contains a comprehensive body of contract and debtor characteristics that were provided by the collection agency. We further collect spatial and macroeconomic information from the following sources:⁴ unemployment rates from the Federal Employment Agency (*Bundesagentur für Arbeit*); postal codes (*Postleitzahl*) matched to counties (*Landkreis*) and independent cities (*kreisfreie Stadt*) from OpenGeoDB; and the geographic coordinates of the postal code areas from OpenGeoDB.

3.2 | Construction of the dependent variable

The data contain the monthly collection payments for each individual account, starting from the date of transfer to the collection agency. Following Dermine & de Carvalho (2006) and Gürtler & Hibbeln (2013), we analyze payments over a standardized payment period. Accordingly, only accounts that have been in debt collection for this minimum number of months are considered. This approach aims to ensure consistency across

²The collection agency can charge the compensation to the debtor. Third-party debt collection is a legal service under the German Legal Services Act (*Rechtsdienstleistungsgesetz*). The size of the compensation for this debt collection service must comply with the Lawyers' Compensation Act (*Rechtsanwaltsvergütungsgesetz*).

³The minimum average collection rate agreement alone could provide incentive to focus more effort on large accounts. The compensation for the collection service is an incentive to work out all claims, where the expected payments cover at least the claim itself and possible variable workout costs.

⁴The regional characteristics were collected by the authors. These are, therefore, not necessarily the characteristics used by the collection agency.

claims.⁵ We use a standardized fixed period of around 4 years. The exact number of months and the level of collection are not explicitly stated here, by request of the collection agency.

The collection rate is then calculated by dividing the sum of monthly payments for an account i over a period t by the account's exposure at the time of transfer $t = 0$, as follows:

$$CR_{i,t} = \frac{\sum_{j=1}^t \text{Payment}_{i,j}}{\text{Initial exposure}_{i,t=0}}. \quad (1)$$

As a common step, workout expenses and collection fees paid by the debtor to the collection agency do not enter the calculation. Debtor payments first service the initial claim; fees and possible late payment interest imposed by the collection agency are serviced last and are accounted for separately.

Table 1 presents the distribution of cumulative collections for each account over the repayment horizons for all three samples. The distribution has strong concentrations at the boundaries of full or no payment. This is similar to the strong bimodal distribution of collection recoveries found by Beck et al. (2017). Less than 6% of all accounts lie strictly between 0 and 1.

3.3 | Initially provided information

The sample contains a comprehensive set of independent variables. Table 2 presents descriptive statistics and definitions for the explanatory characteristics. We highlight additional important information in this section and Section 3.4. Table 2 indicates whether a variable belongs to the initial information or subsequently obtained information.

The exposure (*EXP*) is the amount in euros that is due when the debt collection agency receives the claim. The age of the debtor (*AGE*) is the debtor age at that time. The dummy for insolvent accounts (*INS.acqu*) indicates whether the account was insolvent before the transfer to the debt collection agency. As Beck et al. (2017) note, the corporate dummy (*FIRM*) indicates whether a debtor has the legal form of a corporation. An individual debtor can therefore be a private person, a private company, or a partnership. The telephone contact dummy (*TEL*) indicates whether known telephone contact details are available. The variable *PREMIUM* indicates whether a claim results from a missed premium payment. The remaining cases are recourse receivables. The age of the account (*AGE.ACC*) is calculated as the difference between the beginning of the contract period and the time of transfer to the collection agency. In the case of samples A and B, the insurance product generally requires an insurance fee payment before the beginning of the contract period; therefore, the claims were in arrears when the payment was not received by the beginning of the insurance period. In sample C, fee payments were generally acceptable shortly after the beginning of the insurance period, but the payments were expected to arrive at least shortly after the beginning of the insurance period. A claim from sample C is, therefore, considered to have been in arrears when the payment was not received shortly after the beginning of the insurance term.

⁵Accounts that are more recent will tend to have lower collection rates, on average, because there are fewer payment months. Moreover, the use of only closed accounts would introduce a bias, because successful accounts are closed by definition, whereas unsuccessful accounts can remain open over several years.

TABLE 1 Distribution of the collection rate for boundary and non-boundary cases

This table reports the fraction of accounts that yield a cumulative partial, full, or no payment. Full payments and non-payments are combined to conceal the specific level of recovery.

Interval		Sample		
		A	B	C
Full or no payment	($CR = 0$ and $CR = 1$)	0.944	0.977	0.959
Partial payment	($0 < CR < 1$)	0.056	0.023	0.041

3.4 | Accumulated information

We collect four groups of accumulated information: spatial information, external credit assessments, customer relationship information, and information on financial and nonfinancial assets.

There are multiple reasons why regions can differ in their collection rate of collection of *spatial information* (for a discussion on regional scoring, see Fernandes & Artes, 2016). These include a higher proportion of steady jobs, stronger sources of income, differences in debt enforcement institutions, as well as cultural factors that influence the willingness to service debt. We include three proxies for the quality of an area. The first two are calculated as the mean collection rate over the accounts in a county/city ($CR.c$) and in a postal code area ($CR.p$). The mean is calculated over all other debtors, except the one in question. For postal code areas with fewer than 10 accounts of other debtors, the value is replaced by the mean in the closest postal code area with at least 10 accounts to ensure reliable numbers. These proxies allow for taking several sources of differences between regions into account. The mean collection rate by postal code area allows for a granular consideration of spatial differences. We further include the unemployment rate ($UNEMPL.c$) published by the Federal Employment Agency at the county level. This metric is particularly addressed in the measurement of spatial differences in available sources of income. Beck et al. (2017) consider the unemployment rate at the federal state level and find it to be negatively related to the collection rate. Similarly, Bellotti & Crook (2012) distinguish between council/poor housing, suburban/wealthy, rural, and other areas and find these categories to be predictive of loss given default in consumer finance. We therefore expect the mean collection rates at the county and postal code levels to be positively related to the collection rate and the unemployment rate to be negatively related to collection rates.

Credit scores ($SCORE.num$) are a very important source of *external credit assessments*. Drozd & Serrano-Padial (2017) list the easier provision of credit scores as one factor in how information technology has made debt collection processes more efficient in recent decades. Dierkes, Erner, Langer, and Norden (2013) study the importance of credit scores in assessing the default probability of small firms and find them to be essential.

The credit scores that we use are obtained from Schufa, a large supplier of individual and corporate credit assessments in Germany. According to self-reported numbers, Schufa maintains data on more than 65 million individuals and more than 5 million firms. The score mainly relies on information regarding ongoing and past loans, bank accounts, mobile phone contracts, and so on. Both the existence of these contracts and whether there were missed or delayed payments are part of the score. The providers of services mentioned transfer this information to Schufa. This score is similar to that outlined for Creditreform by Dierkes et al. (2013). Where applicable, relevant public credit information published by authorities, such

TABLE 2 Summary statistics

This table reports summary statistics for the numerical variables in the collection samples in its first three sections. The variables *CR.OTHER*, *CR.c*, and *CR.p* are listed separately in the fourth section to conceal the specific level of recovery. The final section reports the relative frequencies of the true values for the dichotomous variables. ‘Initial’ indicates whether a characteristic is provided by the initial creditor.

Numerical characteristics	Initial	Sample A							
		N	Mean	St. Dev.	Min	25 Pctl.	Median	75 Pctl.	Max
<i>EXP</i> : Exposure level handed over to debt collection	Yes	182,880	200.996	762.768	6.41	61.25	99.31	185.46	>100,000
<i>AGE</i> : Age of the debtor	Yes	172,118	44.927	12.798	15	35	45	53	110
<i>AGE.ACC</i> : Time in in-house collection	Yes	182,698	145.112	93.378	-21	87	120	170	4,456
<i>UNEMPL.c</i> : County unemployment rate	No	182,880	7.226	2.970	1.1	5	6.6	9.2	18.5
<i>SCORE.num</i> : Numerical credit score	No	49,472	8.599	3.618	1	6	9	12	13
	Initial	Sample B							
		N	Mean	St. Dev.	Min	25 Pctl.	Median	75 Pctl.	Max
<i>EXP</i> : Exposure level handed over to debt collection	Yes	16,623	173.578	298.542	5	57.81	98.58	197.55	>15,000
<i>AGE</i> : Age of the debtor	Yes	6,979	45.309	13.279	18	35	45	54	96
<i>AGE.ACC</i> : Time in in-house collection	Yes	10,501	131.809	62.911	35	105	108	144	1,904
<i>UNEMPL.c</i> : County unemployment rate	No	16,623	6.872	2.912	1.1	4.5	6.5	8.8	16.5
<i>SCORE.num</i> : Numerical credit score	No	0	-	-	-	-	-	-	-
	Initial	Sample C							
		N	Mean	St. Dev.	Min	25 Pctl.	Median	75 Pctl.	Max
<i>EXP</i> : Exposure level handed over to debt collection	Yes	126,015	352.285	828.646	5	39.765	114.1	330.17	>50,000
<i>AGE</i> : Age of the debtor	Yes	116,174	42.376	12.441	15	32	41	51	101
<i>AGE.ACC</i> : Time in in-house collection	Yes	102,449	170.367	212.956	-146	66	106	234	7,879
<i>UNEMPL.c</i> : County unemployment rate	No	126,015	7.333	3.177	1.1	4.7	7	9.8	18.5
<i>SCORE.num</i> : Numerical credit score	No	76,498	8.504	4.030	1	5	9	12	13

	Initial	Sample A N	Sample B N	Sample C N
<i>CR.OTHER</i> : Mean coll. rate on other accounts	No	113,588	1809	34,267
<i>CR.c</i> : Mean coll. rate in the same county	No	182,880	16,623	126,015

(Continues)

TABLE 2 (Continued)

	Initial	Sample A <i>N</i>	Sample B <i>N</i>	Sample C <i>N</i>
<i>CR.p</i> : Mean coll. rate in the same postal code area	No	182,880	16,623	126,015

Dichotomous characteristics	Initial	Sample A True	Sample B True	Sample C True
<i>INS.acqu</i> : Insolvency before third-party collection	Yes	0.019	0.020	0.049
<i>FIRM</i> : Legal form of a corporation	Yes	0.046	0.069	0.060
<i>MALE</i> : Male debtor	Yes	0.647	0.658	0.642
<i>TEL</i> : Telephone contact details available	Yes	0.624	0.419	0.396
<i>PREMIUM</i> : Premium payment	Yes	0.992	1.000	0.981
<i>INS.proc</i> : Insolvency in third-party collection	No	0.023	0.017	0.035
<i>TITLE</i> : Legally enforceable claim	No	0.386	0.259	0.388
<i>FIN.STATUS</i> : Financial status information	No	0.046	0.154	0.064

as insolvencies, further affects the score; however, soft public information, such as information obtained from social media, is not taken into account. Spatial information is only used in cases where no other information is available (0.03% of scored entities and individuals). Data such as profession, income, property, marital status, and nationality are not reported to Schufa and are not part of the scores.⁶

As a comparison, the characteristics the Fair Isaac Corporation (FICO) uses in scoring consist of the following information:⁷ 35% payment history and missed or delayed payments, including insolvencies, and so on; 30% the amount still owed; 15% the length of the credit history; 10% the mix of credit products; and 10% the extent of recently obtained new credit. Since the Schufa score is also mainly calculated from information on existing contracts and delays on these contracts, these scores are comparable to the FICO scores in the USA.

The credit bureau score is obtained by the debt collection agency in cases of insufficient payment after written reminders and telephone calls. The score is obtained to decide whether legal actions are considered promising. The score is not obtained earlier, since obtaining it is costly. Obtaining the score is therefore indicative of a collection process in which the initial collection actions did not result in sufficient payments, and is therefore associated with lower collection rates. We discuss this point and the implications for our estimated coefficients in detail in Section 4.2.3. For sample B, the credit score was not obtained because of an agreement with the original creditor; therefore, this sample contains no credit bureau scores. The reported credit score is the last obtained. In cases with multiple accounts, it is therefore possible that the score was obtained in the most recent collection process. We discuss this point in the robustness checks in Section 5. Furthermore, some of the information in the score could already be captured in the insolvency dummies, the dummy for enforceable claims, and, arguably, a

⁶Details on the information that is considered in the scores are available at <https://www.schufa.de>.

⁷For the score's composition and more detailed descriptions of the individual components, see <https://www.myfico.com>.

dummy for single accounts, since (multiple) delays in payments will likely be reflected in the score. We discuss this point in the robustness checks also in Section 5.

The score levels range from A, which is the best score, to M, which is the worst. We use this score as a numerical variable by setting scores of A equal to 1, scores of B to 2, and so on. We generally expect better scores to coincide with higher collection rates and the scores to have a strong impact on prediction quality.

Debt collection agencies further obtain information on debtors and their willingness to pay over the course of a *customer relationship* within one debt collection process or over processes with multiple claims. This can lead to a better understanding of how to effectively communicate with a customer or the extent of payments to expect. We add two variables that proxy for this. The first is a dummy indicating whether the debtor only has one account in collections or multiple accounts (*SINGL.ACC*); the second is the average collection rate over all accounts of the same debtor, except the one in question (*CR.OTHER*). The variables are calculated in sample, in the sense that they are calculated over observations within our data set.⁸

There are reasonable arguments that predict the single account dummy to be positively related to the collection rate, such as that of Thomas et al. (2012), or negatively related, such as for Beck et al. (2017); therefore, we do not expect a specific relation. We do expect, however, a strong positive coefficient for the collection rate on other accounts. A dummy for insolvencies during the debt collection process (*INS.proc*) also provides more information over time. We include this variable and expect a negative relation to the debt collection rate. Overall, when customer relationship information is influential, it should greatly increase the prediction quality.

An important characteristic in deciding how to proceed with difficult cases is *financial status information*. Over the course of a debt collection process, a debt collection agency learns whether a debtor possesses any financial or nonfinancial assets. This is important information in determining agreements to settle the claim. In cases in which a court declares a debt legally enforceable (we add *TITLE* as a dummy for these cases), there is a formal process for obtaining financial status information.⁹ We add a dummy for cases in which this process is applied (*FIN.STATUS*). The financial status information is obtained from a bailiff, which is costly.¹⁰ The bailiff sets an appointment with the debtor to list all of the debtor's financial and nonfinancial assets. The debtor is obliged to disclose this information correctly. In cases of payment, the debtor bears the costs of the bailiff; in cases without payment, the debt collection agency will not be compensated for the costs. Financial status information is therefore mostly obtained for larger exposures.¹¹

The overall effect of obtaining financial status information can be ambiguous, since there will be several unsuccessful collection actions before the financial status is obtained. Therefore, obtaining financial status information indicates a difficult debt collection process. This can result in claims where the financial status information is weaker than in the overall sample. However, since the financial status information removes the debtor's incentives to withhold payment, the effect should be at least strongly positive, in comparison to accounts that are in collections for an equally long time.

⁸The value of this information could, therefore, be even greater when calculating these measures out of sample for more data.

⁹There are two ways that the debt can become legally enforceable. In the first case, the creditor can request a judicial reminder to pay from a court (legal dunning proceedings). If the creditor does not dispute this reminder, the claim becomes enforceable. The second alternative is to sue the debtor. A creditor can sue the debtor directly without legal dunning proceedings. These steps are similar to those in the USA. Atradius (2018) provides a concise overview of legal debt collection actions in different countries.

¹⁰A similar process for obtaining financial status information exists in the USA. Instead of a bailiff, an attorney provides the financial status. The debtor is also obliged to disclose all information on financial status. See Atradius (2018) for more details.

¹¹We discuss the implications of this in Section 4.2.5.

In summary, we look at four types of additionally gathered information. Among the *spatial characteristics*, we expect regions with higher collection rates on other debtors and lower unemployment rates to be predictive of higher collection rates. *Credit bureau scores* contain important information regarding payments that are still expected. Considering *customer relationship information*, when debt collection agencies have multiple accounts, we expect the collection success for other accounts to be predictive of the collection rate. *Financial status information* is valuable information in cases where there are insufficient payments, even after several collection actions. Especially compared to other similarly difficult cases, financial status information should provide a better picture of how to effectively recover a claim, which should result in higher collection rates.

4 | ANALYSIS

4.1 | Empirical model and research design

We aim to compare the value of information gathered in third-party debt collection with that of the information provided by original creditors. We examine first whether the extent of the initially disclosed information is low. We thus also contrast our findings with those of previous studies, to extend the small amount of knowledge on the drivers of collection recovery. Only the initial information enters this step. In the second step, we analyze the information that the debt collection agency gathers, that is, we use the spatial information, credit score, customer relationship information, and financial status information.

Our empirical modeling analysis uses the fractional regression model of Papke & Wooldridge (1996), a common approach in modeling the recovery rate of bank loans (Dermine & de Carvalho, 2006; Ingermann, Hesse, Bélorgey, & Pfungsten, 2016). Furthermore, Beck et al. (2017) use this approach to model collection rates. All of the tables report standard errors clustered at the year times postal code level. The coefficients are calculated as conditional marginal effect, which is the change in the outcome of the collection rate for a change of one standard deviation for continuous variables and a change of one unit for dichotomous variables. The marginal effects are calculated at their median for the continuous variables, and at zero for the dichotomous variables. To retain as much of the data as possible, we replace the missing variable values with the variable mean and add a dummy for missing variable values for *AGE*, *AGE.ACC*, *SCORE.num*, and *CR.OTHER* (the dummy for missing *CR.OTHER* values is *SINGL.ACC*).¹²

We measure whether characteristics are the main or important drivers of recoveries in three different ways. First, we assess whether a characteristic has a statistically significant effect in the regression model, as outlined above. If this is the case, we determine whether the marginal effects indicate a large effect on the collection rate. As a third criterion, we assess the change in the adjusted R^2 value resulting from the inclusion or exclusion of certain variables. In defining what relevant changes are in this setting, we refer to results from the recovery rate literature that predicts collection rates in a methodologically similar manner. Bellotti & Crook (2012) report adjusted values between 10.5% and 11.1% in a linear regression on a comprehensive set of debtor, contract, spatial, and macroeconomic characteristics; Gürtler & Hibbeln (2013) report values between 4.4% and 18.9%; Loterman, Brown, Martens, Mues, and Baesens (2012) examine six different loan data sets and find R^2 values between 1.2% and 44.12%. The R^2 value is

¹²As an alternative approach, we conduct our analysis excluding accounts with missing variable values (see Section 5). The results remain qualitatively unchanged.

considerably higher in studies that include information on collateral—up to 76.9% for Ingermann et al. (2016) or up to 61% for Qi & Yang (2009). Given that the values not including collateral are often low, predicting the recovery rate is considered a difficult problem. An improvement of several percentage points represents an important contribution.

One important aspect of our study is that we can compare results on different data sets that were independently managed before being handed over to third-party debt collection. This allows us to examine in detail whether the results can be generalized over different portfolios. We therefore conduct our analysis on the three samples individually to exploit this important characteristic.

4.2 | Regression results

4.2.1 | Initially disclosed information

Table 3 presents the regression results for the baseline model with the initially disclosed information. Most of the variables have a consistent relation with the collection rate over all three samples, which applies to the firm dummy, the dummy for insolvencies before third-party debt collection, the telephone contact details, and the dummy for missed premium payments. The level of the exposure is not significant in all of the three samples, but the sign is consistent. The coefficients are less consistent for customer age, the age of the account, and the male customer dummy.

The exposure (*EXP*) has negative coefficients for all three samples. The coefficient is significant in samples A and C; for sample A, an increase of one standard deviation in exposure results in a 2.7 percentage point lower expected collection rate, and in sample C, the collection rate decreases greatly, by 12.6 percentage points. This may appear large, but, given that the standard deviation of the exposure is relatively high compared to the mean values, this effect seems more relevant to particularly high exposures. Table 4 reports the change in the adjusted R^2 value when removing exposure from the three full models in Table 5, which is less than one percentage point in samples A and B. The influence on prediction quality is higher in sample C, with a change of 1.46 percentage points, which is quite considerable, at least in sample C. The negative coefficients are in line with the results of Hoehstoetter et al. (2012) on collection recoveries and of Thomas et al. (2012). Interestingly, Beck et al. (2017) find a positive relation, arguing that this is due to incentives leading to a greater focus on large exposures. Our rationale is that larger exposures are more difficult to repay.

The firm dummy (*FIRM*) has a negative significant coefficient in all three samples. The effect in terms of the coefficients is considerable, since firms have collection rates that are 5.2, 11.3, and 10.8 percentage points lower, respectively. This result is in contrast to that of Beck et al. (2017), who find a positive relation with recoveries. Hoehstoetter et al. (2012) find inconsistent results.¹³ The influence on the adjusted R^2 value is small for all three samples (see Table 4).

The availability of telephone contact information (*TEL*) has a large positive relation with the collection rate, with an effect of around 28.7, 23.8, and 21.9 percentage points, respectively, in samples A to C. The strong effect is further supported by the change in the adjusted R^2 value (see Table 4). This result is in line with those of Hoehstoetter et al. (2012) and Thomas et al. (2012), who find lower recoveries for worse contact information. This could be due to easier contact with debtors or better-maintained contact information being a signal of debtor quality.

Debtors who are insolvent before the transfer (*INS.acqu*) consistently have a far lower collection rate, which is intuitive and expected. The age of the account (*AGE.ACC*) is significantly negative in samples A and B, but positive in some models of sample C (see Table 5). The relation in

¹³We analyze individuals and firms collectively, in line with these studies. Robustness checks find similar driving characteristics for both groups (see Section 5).

TABLE 3 Regression results: Initially disclosed information

This table reports the fractional regression results for samples A to C. For each sample, the results are presented including only the information initially provided to the collection agency. Standard errors are clustered at the year times postal code level, and are reported in parentheses. The coefficients are calculated as the conditional marginal effects, which are given by the change in the outcome of the collection rate for a change of one standard deviation for continuous variables and a change of one unit for dichotomous variables. The marginal effects are calculated at their median for the continuous variables and at zero for the dichotomous variables. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

	Dependent variable: Collection rate		
	Sample A	Sample B	Sample C
<i>EXP</i>	-0.027*** (0.003)	-0.007 (0.005)	-0.126*** (0.003)
<i>AGE</i>	0.016*** (0.002)	-0.014*** (0.004)	-0.006*** (0.001)
<i>AGE.NA</i>	-0.008 (0.013)	0.058*** (0.011)	0.045*** (0.008)
<i>MALE</i>	-0.003 (0.004)	-0.020** (0.009)	0.006** (0.002)
<i>FIRM</i>	-0.052*** (0.016)	-0.113*** (0.017)	-0.108*** (0.011)
<i>INS.acqu</i>	-0.370*** (0.009)	-0.386*** (0.021)	-0.096*** (0.005)
<i>TEL</i>	0.287*** (0.003)	0.238*** (0.011)	0.219*** (0.002)
<i>AGE.ACC</i>	-0.091*** (0.002)	-0.045*** (0.007)	0.014*** (0.002)
<i>AGE.ACC.NA</i>	-0.267*** (0.046)	-0.063*** (0.007)	-0.008*** (0.003)
<i>PREMIUM</i>	0.149*** (0.020)		0.083*** (0.013)
Adj. R^2	0.114	0.094	0.141
χ^2	10,242.51	999.67	10,624.10
χ^2 Prob.	0.000	0.000	0.000
Observations	182,880	16,623	126,015

this sample is therefore unclear, which is supported by the change in the adjusted R^2 values (see Table 4). Beck et al. (2017) argue that an older account is indicative of worse debtor quality, since more time in in-house collection leaves less recovery for the third-party. This finding is in line with the empirical results of Beck et al. (2017). When controlling for more characteristics, our numbers support this argument. The coefficient for missed premium payment claims (*PREMIUM*) is significantly positive for samples A and C, where there are two types of claims. The importance of the variable in Table 4 is low in both samples.

TABLE 4 Changes in the adjusted R^2 values when removing individual characteristics

This table reports the change in the adjusted R^2 values when excluding individual characteristics from the full models corresponding to Table 5. The first section of the table lists the baseline adjusted R^2 values in the first row and the change in the adjusted R^2 values when excluding the respective variable in the rows below. The second section of the table first states the baseline adjusted R^2 values for a full model for accounts with non-missing credit scores. The second value in this section indicates the extent to which the adjusted R^2 values of this model fall when the score is excluded. The third section reports the numbers for enforceable claims and for excluding the financial status information from this model.

	Sample		
	A	B	C
Full model:			
Baseline R^2	0.4262	0.1834	0.3201
Excluded variable (ΔR^2):			
<i>EXP</i>	-0.0003	-0.0000	-0.0146
<i>AGE</i>	-0.0008	-0.0011	-0.0018
<i>MALE</i>	-0.0000	-0.0002	-0.0010
<i>FIRM</i>	-0.0001	-0.0037	-0.0001
<i>INS.acqu</i>	-0.0069	-0.0356	-0.0017
<i>TEL</i>	-0.0132	-0.0263	-0.0479
<i>AGE.ACC</i>	-0.0033	-0.0049	0.0000
<i>PREMIUM</i>	0.0000		0.0000
<i>CR.c</i>	-0.0002	0.0000	-0.0002
<i>UNEMPL.c</i>	-0.0001	-0.0011	-0.0004
<i>CR.p</i>	-0.0006	-0.0001	-0.0001
<i>SCORE.num</i>	-0.0279		-0.0512
<i>INS.proc</i>	-0.0177	-0.0414	-0.0076
<i>CR.OTHER</i>	-0.1205	-0.0145	-0.0591
<i>TITLE</i>	-0.0247	-0.0154	-0.0032
<i>FIN.STATUS</i>	-0.0000	-0.0001	-0.0010
Full model, non-missing <i>SCORE.num</i> :			
Baseline R^2	0.3984		0.3733
Excluded variable (ΔR^2):			
<i>SCORE.num</i>	-0.0444		-0.0884
Full model, <i>TITLE</i> :			
Baseline R^2	0.3921	0.1077	0.3358
Excluded variable (ΔR^2):			
<i>FIN.STATUS</i>	-0.0000	-0.0004	-0.0013

The age of the customer and the male dummy have less consistent or nonsignificant coefficients over the three samples; however, the coefficient of the age variable (*AGE*) becomes significantly negative in all three samples when controlling for more information (see Table 5). It appears that older debtors tend to be less likely to pay. The dummy for male debtors (*MALE*) is mostly significant; however, the signs are inconsistent, and there does not seem to be a clear and consistent relation with the collection rate. There is little influence on the adjusted R^2 for both variables (see Table 4).¹⁴

¹⁴The results for the age, gender dummy, and firm dummy variables must be considered with caution, because firms do not have age or gender values and are much less likely to have credit scores, which could induce multicollinearities. However, the results remain qualitatively unchanged when estimating results for

TABLE 5 Regression results: Stepwise addition of gathered characteristics

This table reports the fractional regression results for samples A to C. For each sample, the results are presented for the stepwise inclusion of information gathered after the beginning of the third-party collection process, namely, spatial characteristics (1), credit bureau scores (2), customer relationship information (3), and financial status information (4). Standard errors are clustered at the year times postal code level, and are reported in parentheses. The coefficients are calculated as the conditional marginal effects, which are given by the change in the outcome of the collection rate for a change of one standard deviation for continuous variables and a change of one unit for dichotomous variables. The marginal effects are calculated at their median for the continuous variables and at zero for the dichotomous variables. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

		Dependent variable: Collection rate											
		Sample A				Sample B				Sample C			
		(1)	(2)	(3)	(4)	(1 and 2)	(3)	(4)	(1)	(2)	(3)	(4)	
<i>EXP</i>		-0.029*** (0.003)	-0.032*** (0.003)	-0.030*** (0.003)	-0.016*** (0.002)	-0.007 (0.005)	-0.001 (0.001)	0.0004 (0.001)	-0.126*** (0.003)	-0.100*** (0.003)	-0.063*** (0.002)	-0.080*** (0.002)	
<i>AGE</i>		0.013*** (0.002)	0.002 (0.002)	-0.006*** (0.002)	-0.010*** (0.001)	-0.014*** (0.004)	-0.005*** (0.001)	-0.005*** (0.001)	-0.007*** (0.001)	-0.014*** (0.001)	-0.010*** (0.001)	-0.014*** (0.001)	
<i>AGE.NA</i>		-0.007 (0.013)	-0.117*** (0.012)	-0.077*** (0.011)	-0.063*** (0.007)	0.058*** (0.011)	0.009*** (0.003)	0.004 (0.002)	0.046*** (0.008)	-0.016** (0.008)	-0.014*** (0.005)	-0.021*** (0.007)	
<i>MALE</i>		-0.004 (0.004)	0.022*** (0.003)	0.014*** (0.003)	0.006** (0.002)	-0.021** (0.009)	-0.006** (0.003)	-0.004* (0.002)	0.005** (0.002)	0.031*** (0.002)	0.020*** (0.001)	0.026*** (0.002)	
<i>FIRM</i>		-0.048*** (0.016)	-0.026* (0.015)	-0.029** (0.013)	-0.035*** (0.009)	-0.112*** (0.017)	-0.025*** (0.005)	-0.027*** (0.004)	-0.108*** (0.011)	-0.083*** (0.010)	-0.022*** (0.006)	-0.033*** (0.008)	
<i>INS.acqu</i>		-0.368*** (0.009)	-0.352*** (0.009)	-0.314*** (0.010)	-0.230*** (0.007)	-0.383*** (0.021)	-0.112*** (0.006)	-0.103*** (0.005)	-0.097*** (0.005)	-0.035*** (0.005)	-0.036*** (0.003)	-0.059*** (0.005)	
<i>TEL</i>		0.284*** (0.003)	0.209*** (0.003)	0.174*** (0.003)	0.103*** (0.002)	0.235*** (0.011)	0.063*** (0.003)	0.045*** (0.003)	0.220*** (0.002)	0.183*** (0.002)	0.115*** (0.002)	0.160*** (0.002)	
<i>AGE.ACC</i>		-0.089*** (0.002)	-0.069*** (0.002)	-0.060*** (0.002)	-0.027*** (0.001)	-0.045*** (0.007)	-0.012*** (0.002)	-0.008*** (0.001)	0.013*** (0.002)	0.003* (0.002)	0.001 (0.001)	0.0004 (0.001)	
<i>AGE.ACC.NA</i>		-0.265*** (0.047)	-0.252*** (0.045)	-0.222*** (0.047)	-0.097*** (0.029)	-0.060*** (0.007)	-0.017*** (0.002)	-0.006*** (0.002)	-0.006** (0.003)	0.0005 (0.003)	-0.001 (0.002)	0.002 (0.002)	
<i>PREMIUM</i>		0.149*** (0.020)	0.058*** (0.019)	0.042** (0.020)	-0.0003 (0.012)				0.079*** (0.012)	0.021* (0.011)	0.012* (0.007)	-0.017 (0.010)	

(Continues)

TABLE 5 (Continued)

	Dependent variable: Collection rate											
	Sample A			Sample B			Sample C					
	(1)	(2)	(3)	(4)	(1 and 2)	(3)	(4)	(1)	(2)	(3)	(4)	
<i>CR.c</i>	0.025*** (0.002)	0.021*** (0.002)	0.016*** (0.002)	0.010*** (0.001)	0.005 (0.004)	0.001 (0.001)	0.001 (0.001)	0.015*** (0.001)	0.011*** (0.001)	0.005*** (0.001)	0.007*** (0.001)	
<i>UNEMPL.c</i>	-0.011*** (0.002)	-0.008*** (0.002)	-0.007*** (0.002)	-0.005*** (0.001)	-0.014*** (0.004)	-0.004*** (0.001)	-0.004*** (0.001)	-0.006*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.009*** (0.001)	
<i>CR.p</i>	0.033*** (0.002)	0.027*** (0.002)	0.019*** (0.002)	0.012*** (0.001)	0.002 (0.004)	0.0003 (0.001)	-0.0002 (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.003*** (0.001)	0.004*** (0.001)	
<i>SCORE.num</i>	-0.102*** (0.002)	-0.084*** (0.002)	-0.053*** (0.001)	-0.053*** (0.001)				-0.117*** (0.001)	-0.117*** (0.001)	-0.069*** (0.001)	-0.087*** (0.001)	
<i>SCORE.num.NA</i>	0.316*** (0.004)	0.267*** (0.004)	0.097*** (0.003)	0.097*** (0.003)				0.116*** (0.002)	0.116*** (0.002)	0.067*** (0.002)	0.075*** (0.002)	
<i>INS.proc</i>	-0.563*** (0.011)	-0.563*** (0.011)	-0.350*** (0.007)	-0.350*** (0.007)				-0.154*** (0.009)	-0.127*** (0.007)	-0.138*** (0.005)	-0.188*** (0.006)	
<i>SINGL.ACC</i>	-0.239*** (0.003)	-0.239*** (0.003)	-0.152*** (0.002)	-0.152*** (0.002)				-0.075*** (0.007)	-0.054*** (0.005)	0.085*** (0.002)	0.115*** (0.003)	
<i>CR.OTHER</i>	0.253*** (0.002)	0.253*** (0.002)	0.157*** (0.001)	0.157*** (0.001)				0.019*** (0.001)	0.014*** (0.001)	0.062*** (0.001)	0.085*** (0.001)	
<i>TITLE</i>			-0.158*** (0.003)	-0.158*** (0.003)				-0.041*** (0.003)	-0.041*** (0.003)		-0.059*** (0.003)	
<i>FIN.STATUS</i>			-0.008* (0.005)	-0.008* (0.005)				0.002 (0.003)	0.002 (0.003)		0.063*** (0.004)	
Adj. R ²	0.123	0.242	0.401	0.426	0.095	0.156	0.183	0.144	0.248	0.317	0.32	
χ ²	11,003.46	18,634.63	34,461.32	36,089.69	1,011.27	1,441.63	1,810.45	10,918.27	19,003.04	22,800.39	23,158.96	
χ ² Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
Observations	182,880	182,880	182,880	182,880	16,623	16,623	16,623	126,015	126,015	126,015	126,015	

The overall adjusted R^2 values of the models built on the initially disclosed set of information are between 9.4% and 14.1%. Using the results of Loterman et al. (2012), who report values of up to 44.12%, or of Qi & Yang (2009), who find values of up to 61%, as a benchmark, we find these values to be rather low. In summarizing the individual coefficients, we can confirm a positive relation with better contact information and a negative relation with the firm dummy. Some predictive characteristics seem to be unreliable, such as the gender dummy. When taking more characteristics into account, we find that older debtors and claims that remained longer in in-house collection have lower collection rates. Larger exposures tend to be related to lower collection rates as well. Most of the initially provided variables individually tend to contribute little to the prediction quality. The overall adjusted R^2 value including only the initially available information is also moderate.

4.2.2 | Spatial characteristics

The results, including the spatial characteristics, are stated in the first column of the three sections of Table 5. All three characteristics are significant in samples A and C, and the unemployment rate (*UNEMPL.c*) is significant in sample B.¹⁵ In line with the idea of regional scoring, the mean collection rates in the county and the postal code area have a positive coefficient. The unemployment rate, as a measure presumed negatively related to the income of the local population, has negative coefficients. The coefficients indicate a change in the dependent variable of between 0.3 and 3.3 percentage points for a standard deviation change in the spatial characteristic. Assessing the individual influence on the adjusted R^2 values in Table 4, we find all three variables are rather weak, and the overall improvement in the prediction quality is relevant but fairly moderate. The increases in the adjusted R^2 values are 0.9, 0.1, and 0.3 percentage points in samples A to C, respectively.

Since we analyze characteristics down to the level of the postal code area, the prediction quality could improve beyond the values outlined here when building even finer-grained spatial scores. More data seem to further improve the value of spatial scores, as reflected by the increase in prediction quality from samples B and C to A.

4.2.3 | External credit assessment

The credit bureau score (*SCORE.num*) is added in the second column of Table 5. A credit score that is one standard deviation worse decreases the collection rate by 10.2 percentage points in sample A; and by 11.7 percentage points in sample C. Considering that even the worst scores appear regularly and that the score has a wide range of values, this variation in the collection rate is considerable.¹⁶ The dummy for missing scores has a significant positive coefficient in samples A and C. This result is consistent with a collection process that was difficult before the score was obtained.

individuals and firms separately (see Section 5). Furthermore, the dummy for firms remains significantly negative when we exclude age, gender, and credit scores (results not tabulated here, but available on request).

¹⁵The mean collection rates in the county (*CR.c*) and in a postal code area (*CR.p*) individually become significant when the two other variables are removed, but are nonsignificant when they are controlled for (results not tabulated here, but available on request).

¹⁶When including dummies for the credit score levels to replace the numerical score variable, we find it noteworthy that the dummy coefficients are strictly monotonic over all score levels in both samples A and C. (These additional regression results are not tabulated here, but are available on request.) This finding further points to the strong discriminatory power of the credit score.

The strong relation of the score to the collection rate is further emphasized by the overall increase in the adjusted R^2 value in Table 5 from column (1) to column (2). The values increase by 11.9 percentage points in sample A and by 10.4 percentage points in sample C, which is sizable, especially considering the general level of the adjusted R^2 values.

Obtaining the credit bureau score does, in a sense, already provide some information on the pace of the collection process that is *ex post* knowledge and not available in a prediction context. Therefore, we additionally calculate the change in the adjusted R^2 values from removing the credit bureau score from a model estimated only on accounts with a credit bureau score. These results are reported in Table 4. The adjusted R^2 values are, overall, lower in this subset in sample A (39.9%) and higher in this subset in sample C (37.3%). In sample A, the change in the adjusted R^2 value when excluding the score is about half as high compared to the values including accounts with no score, indicating that the lack of a score contains information on the pace of the collection process. The difference is, however, still considerable. In sample C, the change in the adjusted R^2 values is smaller but remains of a similar magnitude compared to the earlier results, which is in line with more unconditionally obtained credit scores.

4.2.4 | Experience with the customer

The third column of Table 5 includes the outcomes of other collection processes with the debtor (*CR.OTHER*), as well as information on insolvencies during the respective collection process (*INS.proc*). The mean collection rate on the other accounts (*CR.OTHER*) has a significantly positive coefficient over all three samples. Given an increase of one standard deviation, the collection rate increases by 25.3, 1.9, and 6.2 percentage points, respectively; the effect is particularly strong in sample A. Including the dummy for debtors becoming insolvent during the third-party collection process decreases the collection rate significantly, by 56.3, 15.4, and 13.8 percentage points, respectively, in samples A to C.

From the second to the third columns of Table 5, the adjusted R^2 value increases by 15.9, 6.1, and 6.9 percentage points in samples A to C, respectively. In the larger samples, the majority of this increase results from payments on other accounts. The influence on the adjusted R^2 value of the dummy for insolvencies during the collection process in Table 4 is 1.8, 4.1, and 0.8 percentage points, respectively.

4.2.5 | Financial status information

Financial status is very important information in collection cases that are particularly difficult. The dummy for accounts where this information (*FIN.STATUS*) is obtained is added in the fourth column of Table 5. Since financial status could only be obtained when there is already a court order to pay, there is a dummy for this (*TITLE*), as well as a control.

The dummy for the court order to pay has a strong negative and significant coefficient in all three samples, particularly in sample A. The level of importance is also rather high when considering Table 4. The coefficient of the financial status dummy is significantly positive and considerable in sample C, slightly negative in sample A, and nonsignificant in sample B. The overall influence on the adjusted R^2 values in Table 4 is also relatively low in all three samples. However, the results do not capture the entire impact of the financial status information when comparing cases with such information to the overall sample.

Therefore, we apply a matching procedure pairing all financial status information accounts with a similar account without financial status information that was in the third-party debt

collection process for a similar amount of time without being fully paid. We match on exposure and the credit score, since the exposure plays a role in the decision to obtain the financial status information, and we want to control for differences in solvability. The exposure is matched using a Mahalanobis metric, and the credit score is matched exactly. Table 6

presents the matching results.¹⁷ The lower part of the table lists the means of the exposure and the credit score. The results show that the financial status information sample and the matched sample are statistically similar in terms of exposure, using *t*-tests. The credit score is matched exactly. The number of pairs indicates a match for almost all the cases with financial status information (8.500, 2.574, and 8.053, respectively). The top row of the table lists the group means of the collection rate. The differences in mean are considerable in all three samples, but they are particularly large in sample B.

To obtain a proxy for variable importance in terms of R^2 , we calculate a regression model that includes the full list of variables from Table 5 after combining the set of the accounts with financial status information and related matches. When excluding the financial status dummy, we find R^2 decreases by 5, 11, and 2.7 percentage points, respectively.¹⁸

In summing up the results, we find a quite noteworthy change from the initial adjusted R^2 values to the values including the characteristics gathered after the time of transfer. The overall increases sum to 31.2, 8.9, and 17.9 percentage points for samples A to C, respectively. In samples A and C, the increase exceeds the initial adjusted R^2 values, and in sample B the increase is at about the same magnitude as the initial level. We infer that a major part of the quality of predictions relies on information that needs to be gathered later rather than the information provided initially. The value of the initially provided information is moderate compared to the R^2 values typically stated in recovery rate studies. The R^2 values of the full model, including all gathered information, are considerable compared to the typical values stated in these studies. Assessing the characteristics provided initially, we find a negative effect for exposure level and, possibly, the age of the account. The availability of telephone contact details is positively related to the collection rate, and older customers and firms tend to have lower collection rates. Among the gathered information, better spatial areas and accounts with other successful collection processes have higher collection rates. The collection rate is much lower for worse credit scores. Financial status information is very important in collecting from difficult debtors.

5 | ROBUSTNESS CHECKS

In this section, we present several robustness checks. We estimate the results for shorter standardized fixed payment periods. We then estimate the results when excluding missing variable values, cases with hard negative credit information, and multiple accounts. In a last step, we examine whether there are differences between individual and corporate debtors.

In Section 3.2 we calculate the collection rate over a uniform payment period of about 4 years. This period is chosen to estimate the results on a uniform and, in particular, long payment period to assess the results on ultimate collection recoveries (Hoechstetter et al., 2012, discuss the choice of payment periods but use shorter periods compared to ours). However, to show that our results are not dependent on this specific choice of payment period,

¹⁷We produced several alternative specifications, including the full list of variables from Table 5 and several subsets of it. The results are of similar magnitude. These specifications are available on request.

¹⁸These results are available from the authors on request.

we replicate the results from Section 4.2 using two different payment periods. These periods are, respectively, half as long and a quarter as long as the main payment period (see Figure IA.1 and Table IA.1 in the online supporting materials; further results for other payment horizons are available on request). These additional analyses also make the results more comparable with those of potential studies using shorter debt collection processes.

Looking at the results, we see a small number of coefficients become nonsignificant. The premium payment dummy further becomes significantly negative. The financial status information has a consistent negative coefficient in the shortest payment period, which is reasonable, since this action is applied at later stages of the debt collection process. This is reflected in the fact that the coefficients become less negative or positive in the longer of the two short collection periods. The other results remain qualitatively unchanged.¹⁹

The data set contains many accounts with missing characteristics. This is a typical feature in debt collection, due to the information provided by the in-house collection department. We treat these cases by including dummies for missing values and setting the missing values to the variable mean. To make doubly sure this approach does not affect the results, we fit the regression models by only including complete accounts (Table IA.2 in the online supporting materials). The results remain qualitatively unchanged.

In the three samples, some debtors are linked to multiple accounts. This could be problematic, for example, in the case of the credit score, since we only observe the latest score and the score could have changed from one requested in an earlier case to one requested later. Therefore, we further estimate the results from Section 4.2 by only including accounts of one-time debtors. This is done by excluding all accounts in which the debt collection agency has at least one other case with the same debtor in the database. Table IA.2 in the online supporting materials presents these results. The results remain qualitatively unchanged. The coefficient for the credit score is more negative than in the case including multiple accounts in sample C, and remains similar in sample A. When excluding the credit score from this sample, we find the adjusted R^2 values decrease by 5.9 and 6.1 percentage points, respectively.

Credit scores can further contain publicly available information that is also included in other independent variables; this applies to insolvencies and enforceable claims. Therefore, we estimate one full model by excluding cases with publicly available negative credit information, as well as cases with multiple accounts. The results are presented in Table IA.3 in the online supporting materials. The coefficients of the credit score decrease but remain of considerable magnitude. When excluding the credit score from this sample, we find the adjusted R^2 values decrease by 3.1 and 4.2 percentage points, respectively. The importance of the credit score variable is therefore still strong.

Our samples contain both individual and corporate debtors. Since it can be argued that these groups could be driven by different factors, we estimate the regression models from Section 4.2 for both groups separately. The results are presented in Table IA.4 in the online supporting materials. For the individual debtors, who account for the majority of cases, all of the results remain qualitatively unchanged. For the corporate debtors, the exposure becomes nonsignificant in sample A and positive in sample B. One could hypothesize that the specific exposure amount is less informative for corporations, which can differ greatly in size. The spatial characteristics also lose

¹⁹When assessing Figure IA.1 in the online supporting materials, it is interesting to further note that the mean collection rate depends on the length of the collection process. According to statements by practitioners, knowledge on what recovery to ultimately expect is an important asset for collection agencies, gained through experience with many cases and portfolios. This knowledge is usually not available to original creditors.

significance, and the coefficient for financial status is also less consistent. However, conducting similar matching as in Section 4.2.5, we find the results to be qualitatively unchanged.²⁰

6 | CONCLUSION

Delegating the collection of distressed receivables to debt collection agencies is common practice in many industries, but, surprisingly, very little is known about the successful management of receivables in third-party debt collection. Furthermore, earlier work has mainly studied information provided at the beginning of debt collection processes. Recent theory suggests that producing additional information is an important function of the debt collection industry. This work therefore studies how valuable information gathered in third-party debt collection is for predictions of collection rates.

We make the following three important contributions to the literature. First, we collect and study a large proprietary debt collection data set that allows us to complement the few earlier works on the drivers of collection recoveries. Second, using variable importance methods, we empirically support the notion that the information usually provided by the initial creditor plays a limited role in explaining the variation in collection rates. And third, using our extensive set of variables, we show that the information that is gathered in third-party debt collection plays a crucial role in making predictions more reliable. This finding supports the theoretical argument that debt collection agencies perform a function of producing information. Our results therefore empirically complement the theoretical picture of debt collectors who are active in information production. Our results are important for a better understanding as well as better regulation and management of the debt collection industry.

REFERENCES

- Atradius (2018). International debt collections handbook. Amsterdam, The Netherlands. Available at: <https://atradiuscollections.com/global/reports/global-international-debt-collections-handbook.html>
- Beck, T., Grunert, J., Neus, W., & Walter, A. (2017). What determines collection rates of debt collection agencies? *Financial Review*, 52(2), 259–279.
- Bellotti, T., & Crook, J. (2012). Loss given default models incorporating macroeconomic variables for credit cards. *International Journal of Forecasting*, 28(1), 171–182.
- Bülow, S. (2016). Update Branchenstudie Inkasso: Neue Zahlen, Daten und Fakten über das Forderungsmanagement. *Zeitschrift für das Forderungsmanagement*, 2(3), 223–226.
- Chin, A. G., & Kotak, H. (2006). Improving debt collection processes using rule-based decision engines: A case study of Capital One. *International Journal of Information Management*, 26(1), 81–88.
- Dermine, J., & de Carvalho, C. N. (2006). Bank loan losses-given-default: A case study. *Journal of Banking & Finance*, 30(4), 1219–1243.
- Dierkes, M., Erner, C., Langer, T., & Norden, L. (2013). Business credit information sharing and default risk of private firms. *Journal of Banking & Finance*, 37(8), 2867–2878.
- Droz, L. A., & Serrano-Padial, R. (2017). Modeling the revolving revolution: The debt collection channel. *American Economic Review*, 107(3), 897–930.
- Ernst & Young. (2017). The impact of third-party debt collection on the US national and state economies in 2016. Technical report. Available at: <https://www.acainternational.org/assets/ernst-young/ey-2017-aca-state-of-the-industry-report-final-5.pdf>

²⁰The differences in means are significant, and the exact values are 0.106, 0.1, and 0.148, respectively. These results are available on request.

- Fedaseyeu, V. (2015). *Debt collection agencies and the supply of consumer credit* (Working Paper No. 15-23). Philadelphia: Federal Reserve Bank of Philadelphia.
- Fedaseyeu, V., & Hunt, R. M. (2018). *The economics of debt collection: Enforcement of consumer credit contracts* (Working Paper No. 18-4). FRB of Philadelphia.
- Fernandes, G. B., & Artes, R. (2016). Spatial dependence in credit risk and its improvement in credit scoring. *European Journal of Operational Research*, 249(2), 517–524.
- Fonseca, J., Strair, K., & Zafar, B. (2017). *Access to credit and financial health: Evaluating the impact of debt collection* (Staff Report No. 814). New York: Federal Reserve Bank of New York.
- Gürtler, M., & Hibbeln, M. (2013). Improvements in loss given default forecasts for bank loans. *Journal of Banking & Finance*, 37(7), 2354–2366.
- Han, C., & Jang, Y. (2013). Effects of debt collection practices on loss given default. *Journal of Banking & Finance*, 37(1), 21–31.
- Hochstetter, M., Nazemi, A., Rachev, S. T., & Bozic, C. (2012). *Recovery rate modelling of non-performing consumer credit using data mining algorithms* (RMI Working Paper No. 12/09). Singapore: National University of Singapore Risk Management Institute.
- Ingermann, P.-H., Hesse, F., BÉlorgey, C., & Pflingsten, A. (2016). The recovery rate for retail and commercial customers in Germany: A look at collateral and its adjusted market values. *Business Research*, 9(2), 179–228.
- Loterman, G., Brown, I., Martens, D., Mues, C., & Baesens, B. (2012). Benchmarking regression algorithms for loss given default modeling. *International Journal of Forecasting*, 28(1), 161–170.
- Makuch, W. M., Dodge, J. L., Ecker, J. G., Granfors, D. C., & Hahn, G. J. (1992). Managing consumer credit delinquency in the US economy: A multi-billion dollar management science application. *Interfaces*, 22(1), 90–109.
- Miller, G., Weatherwax, M., Gardinier, T., Abe, N., Melville, P., Pendus, C., & Cooley, B. (2012). Tax collections optimization for New York State. *Interfaces*, 42(1), 74–84.
- Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*, 11(6), 619–632.
- Qi, M., & Yang, X. (2009). Loss given default of high loan-to-value residential mortgages. *Journal of Banking & Finance*, 33(5), 788–799.
- Thomas, L. C., Matuszyk, A., & Moore, A. (2012). Comparing debt characteristics and LGD models for different collections policies. *International Journal of Forecasting*, 28(1), 196–203.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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