

On the Rise of FinTechs: Credit Scoring Using Digital Footprints

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We analyze the information content of a digital footprint—that is, information that users leave online simply by accessing or registering on a Web site—for predicting consumer default. We show that even simple, easily accessible variables from a digital footprint match the information content of credit bureau scores. A digital footprint complements rather than substitutes for credit bureau information and affects access to credit and reduces default rates. We discuss the implications for financial intermediaries' business models, access to credit for the unbanked, and the behavior of consumers, firms, and regulators in the digital sphere. (*JEL* G20, G21, G29)

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The growth of the internet leaves a trace of simple, easily accessible information about almost every user worldwide, a trace we refer to as a “digital footprint.” Even without writing text about oneself, uploading financial information, or providing friendship or social network data, the simple act of accessing or registering on a Web page leaves behind valuable information. As a simple example, every Web site can effortlessly track whether a customer is using an iOS or an Android device, or track whether a customer comes to the Web site via a search engine or a click on a paid ad. In this paper, we seek to understand whether the digital footprint helps augment information traditionally considered to be important for default prediction and whether it can be used for the prediction of consumer payment behavior and defaults.

Understanding the informativeness of digital footprints for consumer lending is significantly important. A key reason for the existence of financial intermediaries is their superior ability to access and process information relevant for screening and monitoring of borrowers.¹ If digital footprints yield significant information about predicting defaults, then FinTechs firms—with their superior ability to access and process digital footprints—can threaten the information advantage of financial intermediaries and thereby challenge financial intermediaries’ business models.²

We analyze the importance of simple, easily accessible digital footprint variables for default prediction using a comprehensive and unique data set covering approximately 250,000 purchases from an E-commerce company located in Germany. Judging the creditworthiness of its customers is important because goods are shipped first and paid for later. The use of digital footprints in similar settings is growing around the world.³ Our data set contains ten digital footprint variables that are easily accessible for any firm operating in the digital sphere (examples include the device type, the operating system, and the e-mail provider). In addition to these digital footprint variables, our data set also contains a credit score from a private credit bureau. We are therefore able to assess the discriminatory ability of the digital footprint variables both separately, vis-à-vis the credit bureau score, and jointly with the credit bureau score.

Our results suggest that even the simple, easily accessible variables from the digital footprint proxy for income, character, and reputation and are

¹ See, in particular, Diamond (1984), Boot (1999), and Boot and Thakor (2000) for an overview of the role of banks in overcoming information asymmetries and Berger et al. (2005) for empirical evidence.

² On the competition between FinTech lenders and traditional financial intermediaries, see, for example, Chen, Wu, and Yang (2019), Fuster et al. (2019), Tang (2019), Vallée and Zeng (2019), and De Roure, Pelizzon, and Thakor (2018). A digital footprint also can be used by financial intermediaries themselves, but, to the extent that it proxies for current relationship-specific information, it reduces the gap between traditional banks and those firms more prone to technology innovation.

³ The appendix offers anecdotal examples of firms that use the digital footprint both for lending decisions and in insurance markets.

highly valuable for default prediction. For example, the difference in default rates between customers using iOS (Apple) and Android (e.g., Samsung) is equivalent to the difference in default rates between a median credit score and the 80th percentile of the credit bureau score. Bertrand and Kamenica (2017) document that owning an iOS device is one of the best predictors for being in the top quartile of the income distribution. Our results are therefore consistent with the device type being an easily accessible proxy for otherwise difficult to collect income data.

Variables that proxy for character and reputation are also significantly related to future payment behavior. For example, customers coming from a price comparison Web site are almost half as likely to default as customers being directed to the Web site by search engine ads, consistent with marketing research documenting the importance of personality traits for impulse shopping.⁴ Belenzon, Chatterji, and Daley (2017) and Guzman and Stern (2016) have documented an “eponymous entrepreneurs effect,” implying that whether a firm is named after their founders matters for subsequent performance. Consistent with their results, customers having their names in the e-mail address are 30% less likely to default, equivalent to the differences in default rates between a median credit bureau score and the 70th percentile of the credit bureau score.

We provide a more formal analysis of the discriminatory power of digital footprint variables by constructing receiver operating characteristics and determining the area under the curve (AUC). The AUC ranges from 50% (pure random prediction) to 100% (perfect prediction) and it is a simple and widely used metric for judging the discriminatory power of credit scores.⁵ The AUC corresponds to the probability of correctly identifying the good case if faced with one random good and one random bad case (Hanley and McNeil 1982). Following Iyer et al. (2016), an AUC of 60% is generally considered desirable in information-scarce environments, whereas AUCs of 70% or greater are the goal in information-rich environments. The AUC using the credit bureau score alone is 68.3% in our data set. This is strikingly similar to the 66.6% AUC using the credit bureau score alone documented in a consumer loan sample of a large German bank (Berg, Puri, and Rocholl 2017).⁶

Interestingly, the information content of a model that uses only the digital footprint variables equals or exceeds the information content of a model that only uses the credit bureau score: the AUC of the model using digital footprint variables is 69.6%, 1.3 percentage points (PP) higher than the AUC of the model using only the credit bureau score (68.3%). This finding is remarkable, because

⁴ See, for example, Rook (1987), Wells, Parboteeah, and Valacich (2011), and Turkylmaz, Erdem, and Uslu (2015).

⁵ See, for example, Stein (2007), Altman, Sabato, and Wilson (2010), Iyer et al. (2016), and Vallée and Zeng (2019).

⁶ It is higher than the AUC from U.S. peer-to-peer lending data using the credit bureau score only (Iyer et al. 2016). Note that the German credit bureau may use some information that U.S. bureaus are legally prohibited from using under the Equal Credit Opportunity Act. Examples include gender, age, and current and previous addresses.

our data set only contains digital footprint variables that are easily accessible for any firm conducting business in the digital sphere. The AUC of the combined model (credit bureau score and digital footprint) is 73.6%, an improvement of 5.3 PP over the model using the credit bureau score only. This suggests that the digital footprint complements credit bureau information. The improvement of 5.3 PP is similar to the 5.7 PP improvement in a U.S. peer-to-peer lending data set from access to a large set of borrower financial information and nonstandard information, and it is also sizeable relative to the improvement by 8.8 PP–11.9 PP from using bank-internal relationship-specific information documented in two German consumer loan data sets.⁷

Our results are robust to a large set of **robustness tests**. In particular, we show that digital footprint variables are not simply proxies for time or region fixed effects (measured via 2-digit ZIP codes), age, or gender, and results are robust to various default definitions and sample splits and hold out-of-sample as well. Furthermore, we show that digital footprints today can forecast future changes in the credit bureau score, thereby providing indirect evidence that the predictive power of digital footprints is not limited to short-term loans originated online, but that digital footprints matter for predicting creditworthiness for more traditional loan products as well.

We proceed by discussing the key economic outcomes and implications of our findings. First, we **decompose the explanatory power of the digital footprint into each of the individual variables**. We document that not a single variable dominates, but almost all the variables significantly contribute to the predictive power of the digital footprint. For some of the variables, we know from related literature that they correlate with financial characteristics (e.g., the use of iOS vs. Android), whereas other characteristics (e.g., the time of purchase or clicking on a paid ad) are more difficult to relate to financial characteristics. Given the nature of our data set, we are not able to precisely disentangle the extent to which digital footprints proxy for financial characteristic versus characteristics traditionally viewed as soft information. Future research might look at the relation between digital footprints and bank-internal relationship-specific information in more detail, in particular also to analyze whether the type of information contained in the digital footprint supersedes or substitutes for relationship-specific soft information.

Second, we document that default rates drop significantly after the introduction of the digital footprint, thereby highlighting the economic benefit to the E-commerce firm of using the digital footprint. The proportion of customers having access to credit remains roughly the same, but the composition of those having access to credit changes: customers with a good

⁷ See Iyer et al. (2016) for the study using U.S. peer-to-peer lending data. Nonstandard information used in this study include the listing text, group and friend endorsements, and borrower choice variables, such as listing duration and listing category. See Berg, Puri, and Rocholl (2017) and Puri, Rocholl, and Steffen (2017) for the studies using German consumer loan data.

digital footprint and a low credit bureau score gain access to credit while customers with a medium credit bureau score and a poor digital footprint lose access to credit.

Third, we show that digital footprints work equally well for unscorable as for scorable customers. This result holds in the context of a developed economy, so any extrapolation to a developing market setting is subject to external validity concerns. With this caveat in mind, our findings provide suggestive evidence that digital footprints can have the potential to boost financial inclusion for the 2 billion adults worldwide that lack access to credit.

Fourth and finally, we discuss implications of our findings for the behavior of consumers, firms and regulators. Consumers might plausibly change their behavior if digital footprints are widely used for lending decisions (Lucas 1976). While some of the digital footprint variables are clearly costly to manipulate or require a customer to change her intrinsic habits, others can be manipulated more easily. We argue that digital footprints warrant an in-depth discussion *in particular if* the Lucas critique applies: if the use of digital footprints leads people to change their behavior, then digital footprints cause people to behave differently than they would have otherwise. Such a behavior clearly affects people's everyday lives, in particular with the increasing digitization of people's lives. Regulators are likely to watch closely whether digital footprints violate individuals' privacy rights, as well as to analyze to what extent digital footprints proxy for variables that are legally prohibited to be used in lending decisions.

Prior papers have highlighted the role of relationship-specific information for lending as well as the informativeness of nontraditional data sources.⁸ Our paper differs from the prior literature in that the information we are looking at is provided simply by accessing or registering on a Web site and, therefore, stands out for their ease of collection. The processing and interpretation of these variables does not require human ingenuity, effort on the side of the applicant (such as uploading financial information or inputting a text description about oneself), or the availability of friendship or social network data. Our results imply that barriers to entry in financial intermediation might be lower in a digital world, and the digital footprint can be used to process applications faster than traditional lenders (see Fuster et al. 2019 for an analysis of process time of FinTech lenders versus traditional lenders). A credit score based on the digital footprint should therefore serve as a benchmark for other models that use more elaborate sources of information that might be either more costly to collect or only accessible to a selected group of intermediaries.

⁸ See Mester, Nakamura, and Renault (2007), Norden and Weber (2010), and Puri, Rocholl, and Steffen (2017) for relationship-specific information. Nontraditional data sources analyzed in the literature include soft information in peer-to-peer lending (Iyer et al. 2016), friendships and social networks (Hildebrandt, Puri, and Rocholl 2017; Lin, Prabhala, and Viswanathan 2013), text-based analysis of applicants listings (Gao, Lin, and Sias 2017; Dorfleitner et al. 2016; Netzer, Lemaire, and Herzenstein 2018), and signaling and screening via contract terms (reserve interest rates in Kawai, Onishi, and Uetake 2016; maturity choice in Hertzberg, Liberman, and Paravisini 2016).

1. Institutional Setup, Descriptive Statistics, and the Digital Footprint

1.1 Institutional setup

We access data about 270,399 purchases from an E-commerce company selling furniture in Germany (similar to “Wayfair” in the United States) between October 2015 and December 2016. Before purchasing an item, a customer needs to register using his or her name, address, and e-mail. Judging the creditworthiness of its customers is important, because goods are shipped first and invoiced for later.⁹ After the purchase, the items are sent to the customer together with an invoice. The customer has 14 days to pay the invoice. If the customer does not pay on time, three reminders (one per e-mail, a second by e-mail, and a third by letter) are sent out. A customer who does not pay after three reminders is in default, and the claim is transferred to a debt collection agency, on average 3.5 months from the order date. The claims in our data set are therefore akin to a short-term consumer loan.

The company uses a digital footprint (discussed in detail further below) as well as information from two private credit bureaus to decide whether customers have a sufficient creditworthiness. The first credit bureau provides basic information, such as whether the customer exists and whether the customer is currently in or has been recently in bankruptcy. This score is used to screen out customers with fraudulent data as well as customers with clearly negative information.¹⁰ The second credit bureau score draws on credit history data from various banks (credit card debt and loans outstanding, past payment behavior, number of bank accounts and credit cards), sociodemographic data, and payment behavior data sourced from retail sales firms, telecommunication companies, and utilities. This credit bureau score is requested for purchases exceeding EUR 100, and we consequently restrict our data set to purchases for which the company requested a credit bureau score.¹¹ We label those customers for whom a credit bureau score from this second credit bureau exists “scorable customers.” The digital footprint and the credit bureau scores are only used to determine whether a customer can pay by invoice, they do not affect the price of the item purchased.¹²

⁹ Customers can choose to pay upfront instead of paying after shipment of the products. Customers paying upfront are not included in our data set. Paying after shipment, so-called “deferred payment,” is by far the dominant payment type: more than 80% of customers choose to pay after shipment if this method is offered to a customer. Furthermore, if payment via invoice is offered, then 85% of the customers will purchase the items. If payment via invoice is not offered, only 45% of the customers will purchase the items. These numbers are descriptive in nature and therefore have to be interpreted with care; however, they provide suggestive evidence of the importance of payment via invoice in this environment.

¹⁰ The firm switched the credit bureau that provides this basic information in July 2016. Results are very similar for pre-July 2016 and post-July 2016.

¹¹ The company requests the credit bureau score if the customer’s shopping cart amount exceeds EUR 100, even when the customer ultimately purchases a smaller amount.

¹² This implies that differences in default rates observed in our study cannot be due to differences in interest rates/prices charged to high- versus low-creditworthiness customers. For technological and regulatory reasons,

The E-commerce company has been using a digital footprint together with the credit bureau score from October 19, 2015 onward to decide whether to allow a customer to purchase via invoice (i.e., whether or not to grant a loan). Our sample period in the main analysis runs from October 19, 2015 to December 31, 2016; that is, a digital footprint has been used throughout our entire sample period. The firm jointly uses the credit bureau score together with the digital footprint: if the predicted default rate is above 10%, then customers are not allowed to purchase via invoice. The 10% threshold is based on the firm's gross margins. The firm cannot make the prices of its products dependent on the creditworthiness of a customer. This implies that it is unprofitable for the firm to allow a customer to buy via invoice if the predicted default rate exceeds the product margin.

Restricting our data set to orders exceeding EUR 100 and excluding customers with a very low creditworthiness has the benefit of making our data set more comparable to a typical credit card, bank loan or peer-to-peer lending data set. It also implies that the discriminatory power of the variables in our data set is likely to be larger in a sample of the whole population compared to a sample that is selected based on creditworthiness. In particular, we might therefore underestimate the scoring improvement coming from the digital footprint.

1.2 Descriptive statistics

Our data set comprises 270,399 purchases between October 2015 and December 2016. The credit bureau score is available for 254,819 observations (94% of the sample) and unavailable for 15,580 observations (6% of the sample). Nonexistence is due to customers being unscorable, that is, not having a sufficient credit history that would allow the credit bureau to calculate a credit score. In the following and throughout the entire paper, we distinguish between scorable and unscorable borrowers, that is, those with and without a credit bureau score.¹³ As shown in Figure 1A, the purchases are roughly distributed even over time with slight increases in orders during October and November, as is typical for the winter season. Table 1 provides descriptive statistics for both subsamples, and Table A1 defines all variables.

In the sample with credit bureau scores, the average purchase volume is EUR 318 (approximately USD 350), and the mean customer age is 45.06 years. On average, 0.9% of customers default on their payment. Our default definition comprises claims that have been transferred to a debt collection

the E-commerce firm assesses credit risk only *after* a customer has put items in her basket, when prices already have been revealed to the customer and thus cannot be price differentiated based on the creditworthiness of the customer.

¹³ Note that the information from the first credit bureau that provides basic information exists for all customers (both scorable and unscorable) in our data set.

Table 1
Descriptive statistics

<i>A. Customers with credit bureau score</i>							
Variable	Unit	N	Mean	SD	P25	Median	P75
Order and customer							
Order amount	Euro	254,819	317.75	317.10	119.99	218.90	399.98
Gender	Dummy (0=male, 1=female)	254,819	0.66	0.47	0	1	1
Age ^a	Number	254,613	45.06	13.31	34	45	54
Credit bureau score	Number (0=worst, 100=best)	254,819	98.11	2.05	97.58	98.86	99.41
Payment behavior							
Default	Dummy (0/1)	254,819	0.009	0.096	0	0	0
<i>B. Customers without credit bureau score</i>							
Variable	Unit	N	Mean	Std.	P25	Median	P75
Order and customer							
Order amount	Euro	15,580	324.57	319.22	119.99	221.60	399.99
Gender	Dummy (0=male, 1=female)	15,580	0.70	0.46	0	1	1
Age ^a	Number	555	38.20	10.46	30	35	46
Credit bureau score	Number (0=worst, 100=best)	15,580	na	na	na	na	na
Payment behavior							
Default	Dummy (0/1)	15,580	0.025	0.156	0	0	0

This table presents summary statistics for the whole sample. The sample period ranges from October 19, 2015 to December 2016. Panel A provides descriptive statistics for customers with credit bureau score. Panel B provides descriptive statistics for customers without credit bureau score. For variable definitions, see Table A1.

Missing information on age indicates that the credit bureau does not have information about a customer's age. Observations with nonmissing age in panel B are cases in which the credit bureau has information about the age of the customer, but not enough information to provide a credit score. na, not available.

^aBased on information from the credit bureau.

agency.¹⁴ The credit bureau score ranges from 0 (worst) to 100 (best). Scores are highly skewed, with 99% of the observations ranging between 90 and 100. The average credit bureau score is 98.11, the median is 98.86. Figure 1 provides the distribution of credit bureau scores, together with (smoothed) default rates and standard error bands (± 2 standard errors). The average credit bureau score of 98.11 corresponds to a default rate of approximately 1%, and default rates grow exponentially when credit bureau scores decrease, with a credit bureau of 95 corresponding to a 2% default rate and a credit bureau of 90 corresponding to a 5% default rate. Standard errors are generally higher for lower credit bureau scores (due to the smaller number of observations), but do not exceed 0.25% even for a credit bureau score as low as 90. Note that default rates are not annualized but constitute default rates over a shorter window of approximately 3.5 months.

Descriptive statistics for the sample without credit bureau score are similar with respect to order amount and gender, with age being somewhat lower (consistent with the idea that it takes time to build up a credit history) and default rates being significantly higher (2.5%).

¹⁴ The average time between the order date and the date a claim is transferred to the debt collection agency is 103 days in our sample, that is, approximately 3.5 months.

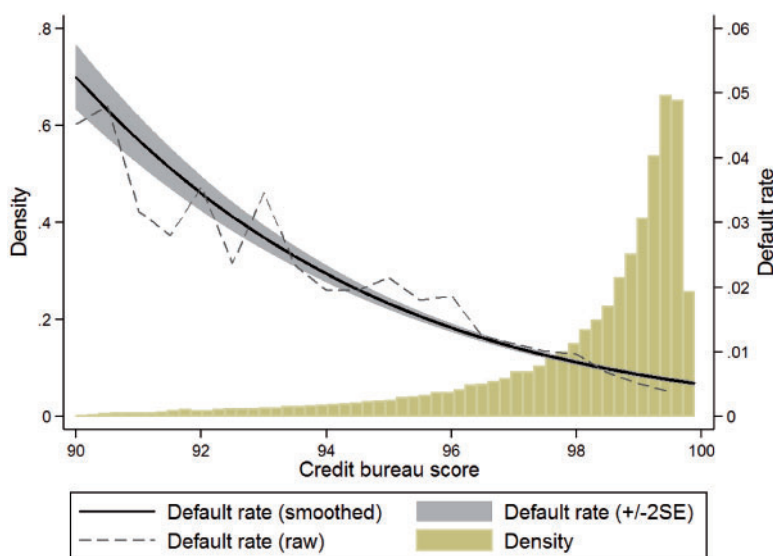


Figure 1
Credit bureau score distribution and default rates

This figure shows the distribution of the credit bureau score and the raw and smoothed default rates as a function of the credit bureau score. *Default(0/1)* is equal to one if the claim has been transferred to a debt collection agency. The smoothed default rates have been determined using a logistic regression and a second-order polynomial of the credit bureau score. The gray-shaded area represents a 2 standard error band around the smoothed default rates using the Delta method. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

1.3 Representativeness of data set

Our data set is largely representative of the geographic distribution of the German population overall. As can be seen from Figure A1, panel B, the share of observations in our sample closely follows the population share for all sixteen German states. Furthermore, the mean customer age is 45.06 years, comparable both to the mean age of 43.77 in the German population and to the mean age of 45.24 reported by Berg, Puri, and Rocholl (2017) in a sample of more than 200,000 consumer loans at a large German private bank. Our sample is restricted to customers of legal age (18 years and older) and less than 5% of the customers are older than 70. The age distribution in our sample therefore resembles the age distribution of the German population aged 18–70: the interquartile range of the German population aged 18–70 ranges from 31–56, compared to an interquartile range of 34–54 in our sample.

The average default rate in our sample is 1.0% (0.9% for scorable customers, 2.5% for unscorable customers). As discussed above, these default rates constitute default rates over a window of approximately 4 months, implying a scaled-up annualized default rate of 3.0%. Table A2 offers a comparison of our default rate to those from other studies. Berg, Puri, and Rocholl (2017) report an average default rate of 2.5% in a sample of more than 200,000

consumer loans at a large German private bank; the major German credit bureau reports an average default rate of 2.4% (2015) and 2.2% (2016) in a sample of more than 17 million consumer loans, and the two largest German banks report probability of default estimates of 1.5% (Deutsche Bank) and 2.0% (Commerzbank) across their entire retail lending portfolio. Default rates reported by Puri, Rocholl, and Steffen (2017) in a sample of German savings banks are somewhat lower. Taken together, this evidence suggests that default rates in our sample are largely representative of a typical consumer loan sample in Germany. Charge-off rates on consumer loans in the United States across all commercial banks as reported by the Federal Reserve were approximately 2% in 2015/2016, implying a comparable default rate to our sample. Default rates reported in some U.S. peer-to-peer lending studies are higher (up to 10% per annum). However, the studies with the highest default rates were conducted using loans originated in 2007/2008 at the height of the financial crisis. More recent studies report default rates that are comparable to our default rates on an annualized basis (e.g., Hertzberg, Liberman, and Paravisini (2016) report a 4.2% annualized default rate in a sample of Lending Club loans originated in 2012/2013).

1.4 Digital footprint

In addition to the credit bureau score described above, the company collects a “digital footprint” for each customer. All digital footprint variables are simple, easily accessible variables that every firm operating in the digital sphere can collect at almost no cost. Table A1 lists all digital footprint variables.

The digital footprint comprises easily accessible pieces of information known to proxy for the economic status of a person, for instance, the device type (desktop, tablet, mobile) and operating system (e.g., Windows, iOS, Android). As documented by Bertrand and Kamenica (2017), owning an iOS device is one of the best predictors for being in the top quartile of the income distribution. Furthermore, the distinct features of most commonly used e-mail providers in Germany (e.g., Gmx, Web, T-Online, Gmail, Yahoo, or Hotmail) also allow us to infer information about the customer’s economic status. Gmx, Web, and T-online are common e-mail hosts in Germany which are partly or fully paid. In particular, T-online is a large internet service provider and is known to serve a more affluent clientele, given that it offers internet, telephone, and television plans and in-person customer support. A customer obtains a T-online e-mail address only if she purchased a T-online package. Yahoo and Hotmail, in contrast, are fully free and mostly outdated services. Thus, based on these simple variables, the digital footprint provides easily accessible proxies of a person’s economic status absent of private information and difficult-to-collect income data.

Second, the digital footprint provides simple variables known to proxy for character, such as the channel through which the customer has visited the homepage of the firm. Examples for the channel include paid clicks (mainly

through paid ads on Google or by being retargeted by ads on other Web sites according to preferences revealed by prior searches), direct (a customer directly entering the URL of the E-commerce company in her browser), affiliate (customers coming from an affiliate site that links to the E-commerce company's Web page, such as a price comparison site), and organic (a customer coming via the nonpaid results list of a search engine). Information about a person's character (such as her self-control) is also reasonably assumed to be revealed by the time of day at which the customer makes the purchase (for instance, we find that customers purchasing between noon and 6 p.m. are approximately half as likely to default as customers purchasing from midnight to 6 a.m.).

Finally, corporate research documents that firms being named after their owners have a superior performance. This so-called "eponymous effect" is mainly driven via a reputation channel (Belenzon, Chatterji, and Daley 2017). We find it reasonable to extend this finding to the choice of e-mail addresses. A testable prediction from this prior literature is that eponymous customers—those who include their first and/or last names in their e-mail address—are less likely to default. In contrast to eponymous customers, those arguably less concerned with including their name but instead include numbers or type errors in their e-mail address default more frequently. The digital footprint provides this type of simple information that can serve as a proxy for reputation in the form of four dummies: whether the last and/or first name is part of the e-mail address, whether the e-mail address contains a number, whether the e-mail contains an error, and whether the customer types either the name or the shipping address using lowercase on the homepage.¹⁵

Note that some of the variables discussed above are likely to proxy for several characteristics. For example, iOS devices are a predictor of economic status (Bertrand and Kamenica 2017) and might also proxy for character (e.g., status-seeking users might be more likely to buy an iOS device). It is not our target to point to exactly one single channel that can explain why digital footprints variables can predict default. Rather we want to highlight existing research that provides guidance as to why we can expect these variables to matter for default prediction.

2. Empirical Results

2.1 Univariate results

Table 2 provides univariate results for the sample of customers with credit bureau scores.

As expected, the credit bureau score clearly exhibits discriminatory ability: the default rate in the lowest credit score quintile is 2.12%, more than twice the

¹⁵ Kreditech is an example of a German company already using simple typography variables, such as the lack of capital letters, to evaluate credit risk and detect possible fraud and online impersonations (see BBVA 2017).

Table 2**Credit bureau score, digital footprint variables, and default rates (scorable customers)**

Variable	Value	Observations	Proportion (%)	Default rate (%)	t-test against baseline
Credit bureau score (by quintile)	All	254,819	100	0.94	
	Q1 - lowest	50,980	20	2.12	Baseline
	Q2	50,949	20	1.02***	(-14.17)
	Q3	50,991	20	0.68***	(-19.51)
	Q4	51,181	20	0.47***	(-23.37)
	Q5 - highest	50,718	20	0.39***	(-24.89)
Device	All	254,819	100	0.94	
	Desktop	145,879	57	0.74	Baseline
	Tablet	45,575	18	0.91***	(3.62)
	Mobile	26,808	11	2.14***	(21.84)
	Do-not-track setting	36,557	14	0.88***	(2.90)
Operating system	All	254,819	100	0.94	
	Windows	124,605	49	0.74	Baseline
	iOS	41,478	16	1.07***	(6.35)
	Android	29,089	11	1.79***	(16.64)
	Macintosh	21,163	8	0.69	(-0.79)
	Other	1,927	1	1.09*	(1.74)
	Do-not-track setting	36,557	14	0.88***	(2.66)
E-mail host	All	254,819	100	0.94	
	Gmx (partly paid)	58,609	23	0.82	Baseline
	Web (partly paid)	54,867	22	0.86	(0.70)
	T-Online (affluent customers)	30,279	12	0.51***	(-5.32)
	Gmail (free)	27,845	11	1.25***	(6.02)
	Yahoo (free, older service)	11,923	5	1.96***	(11.33)
	Hotmail (free, older service)	10,241	4	1.45***	(6.11)
	Other	61,055	24	0.90	(1.38)
Channel	All	254,819	100	0.94	
	Paid	111,399	44	1.11	Baseline
	Direct	45,183	18	0.84***	(-4.78)
	Affiliate	24,770	10	0.64***	(-6.68)
	Organic	18,295	7	0.86***	(-3.00)
	Other	18,615	7	0.69***	(-5.24)
	Do-not-track setting	36,557	14	0.88***	(-3.69)
Checkout time	All	254,819	100	0.94	
	Evening (6 p.m.-midnight)	108,549	43	0.85	Baseline
	Night (midnight-6 a.m.)	6,913	3	1.97***	(9.49)
	Morning (6 a.m.-noon)	46,601	18	1.09***	(4.55)
	Afternoon (noon-6 p.m.)	92,756	36	0.89	(0.91)
Do-not-track setting	All	254,819	100	0.94	
	No	218,262	86	0.94	Baseline
	Yes	36,557	14	0.88	(-1.12)
Name in e-mail	All	254,819	100	0.94	
	No	71,017	28	1.24	Baseline
	Yes	183,802	72	0.82***	(-9.99)
Number in e-mail	All	254,819	100	0.94	
	No	213,649	84	0.84	Baseline
	Yes	41,170	16	1.41***	(10.95)
Is lowercase	All	254,819	100	0.94	
	No	235,569	92	0.84	Baseline
	Yes	19,250	8	2.14***	(18.07)
E-mail error	All	254,819	100	0.94	
	No	251,319	99	0.88	Baseline
	Yes	3,500	1	5.09***	(25.71)

This table provides default rates by credit bureau score quintile and default rates by category of each of the digital footprint variables. The sample is based on scorable customers, that is, the set of customers for which a credit bureau score is available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

average default rate of 0.94% and 5 times the default rate in the highest credit score quintile (0.39%).¹⁶

Interestingly, the univariate results indicate discriminatory ability for the digital footprint variables as well. The digital footprint variables that proxy for income and wealth reveal significant differences in payment behavior. For example, orders from mobile phones (default rate 2.14%) are 3 times as likely to default as orders from desktops (default rate 0.74%) and two-and-a-half times as likely to default as orders from tablets (default rate 0.91%). Orders from the Android operating systems (default rate 1.79%) are almost twice as likely to default as orders from iOS systems (1.07%), consistent with the idea that consumers purchasing an iPhone are usually more affluent than consumers purchasing other smartphones. As expected, customers from a premium internet service (T-online, a service that mainly sells to affluent customers at higher prices but with better service) are significantly less likely to default (0.51% vs. the unconditional average of 0.94%). Customers from shrinking platforms like Hotmail (an old Microsoft service) and Yahoo exhibit default rates of 1.45% and 1.96%, almost twice the unconditional average.

Information on character is also significantly related to default rates. Customers arriving on the homepage through paid ads (either clicking on paid Google ads or being retargeted after prior Google searches) exhibit the largest default rate (1.11%). One possible interpretation is that ads, in particular ads that are shown multiple times on various Web sites to a customer, seduce customers to buy products they potentially cannot afford. Customers being targeted via affiliate links, for example, price comparison sites, and customers directly entering the URL of the E-commerce company in their browser exhibit lower-than-average default rates (0.64% and 0.84%). Finally, customers ordering during the night have a default rate of 1.97%, approximately twice the unconditional average.

Only a few customers make typos while inputting their e-mail addresses (roughly 1% of all orders), but these customers are much more likely to default (5.09% vs. the unconditional mean of 0.94%). Customers with numbers in their e-mail addresses default more frequently, which is plausible given that fraud cases also have a higher incidence of numbers in their e-mail address.¹⁷ Customers who use only lowercase when typing their name and shipping address are more than twice as likely to default as those writing names

¹⁶ Using credit bureau scores from Lending Club over the same period we find that the default rate only increases by a factor of 2.5 from the highest to the lowest credit bureau score quintile, suggesting our credit bureau score has more discriminatory power than the credit bureau score in the Lending Club data set, a fact we will confirm later using AUCs.

¹⁷ Approximately 10%–15% of defaults are identified as fraud cases. Compared to nonfraud defaults, fraud cases have a higher incidence of numbers in their e-mail address. This is consistent with anecdotal evidence, suggesting that fraudsters create a large number of e-mail addresses and do so in a way that uses a string combined with consecutive numbers. We show in Column 3 of Table 6 that the results are robust to excluding cases of fraud. We also find that the digital footprint is predictive of the risk of fraud and has discriminatory power over the credit bureau score in predicting fraud. Results are available on request.

and addresses with first capital letters. Interestingly, we find that eponymous customers who use their first and/or last name in their e-mail address are less likely to default. Thus, information on reputation also shows significant power for predicting default rates. These findings are consistent with recent findings by Belenzon, Chatterji, and Daley (2017), who show that eponymous firms perform better, supporting the reputational explanation of their findings.

2.2 Measures of association between variables, combination of digital footprint variables

In the next step, we report measures of association between the credit bureau score, the digital footprint variables, and control variables (*Age*, *Gender*, *Order amount*, monthly date, and type of the purchase item), to assess whether the digital footprint variables are correlated with the credit bureau score and among each other, or whether they provide independent information. As most of the digital footprint variables are categorical variables, standard measures for ordinal variables (e.g., Pearson's correlation or Spearman rank correlation) are not feasible. We therefore report Cramér's V, which provides a measure of association between categorical variables that is bounded in the interval [0,1], with 0 denoting no association and 1 denoting perfect association. To allow calculation of Cramér's V, we transform the continuous variables (*Credit bureau score*, *Checkout time*, *Age*, and *Order amount*) into categories by forming quintiles by credit bureau score, age, and order amount, and categorizing the checkout time into morning, afternoon, evening, and night. Table 3 reports the results.

Interestingly, the Cramér's V between the credit bureau score and the digital footprint variables is economically small, with values ranging between 0.01 and 0.07. This suggests that digital footprint variables act as complements rather than substitutes for credit bureau scores, a claim we will analyze more formally below in a multivariate regression setup.

The association between the variables *Device type* and *Operating system* is high. This is not surprising, for example, most desktop computers run on Windows and most tablets on iOS or Android. To avoid multicollinearity, we therefore simply use the most frequent combinations from these two categories in our multivariate regressions below.¹⁸ All other combinations of digital footprint variables have a Cramér's V of less than 0.25. The low correlation of the additional control variables and the digital footprint suggests that the digital footprint also does not simply proxy for age, gender, the monthly date, loan amount, or type of the purchase item.

The fact that many of the digital footprint variables provide mutually independent information suggests that a combination of digital footprint variables is significantly more powerful in predicting default than single

¹⁸ The most-frequent combinations are Windows and Macintosh for desktop computers; Android and iOS for tablets; and Android and iOS for mobile phones. See Table A4 for descriptive statistics.

Table 3
Correlation/association between credit bureau score, digital footprint, and control variables (scorable customers)

	Credit bureau score	Device type	Operating system	E-mail host	Channel	Checkout time	Name in e-mail	Number in e-mail	Is lowercase	E-mail error	Age	Order amount	Item category	Month
Main variables														
Credit bureau score ^a	1.00***	0.07***	0.05***	0.07***	0.03***	0.03***	0.01***	0.07***	0.02***	0.00	0.20***	0.01***	0.05***	0.01***
Device type		1.00***	0.71*** ^b	0.07***	0.06*** ^b	0.04***	0.05***	0.06***	0.07***	0.01***	0.12***	0.03***	0.05***	0.06***
Operating system			1.00***	0.08***	0.06*** ^b	0.04***	0.06***	0.08***	0.06***	0.01***	0.10***	0.02***	0.04***	0.03***
E-mail host				1.00***	0.03***	0.03***	0.08***	0.18***	0.04***	0.06***	0.16***	0.02***	0.02***	0.01***
Channel					1.00***	0.02***	0.01***	0.02***	0.04***	0.02***	0.09***	0.04***	0.06***	0.13***
Checkout time ^a						1.00***	0.01***	0.01***	0.01***	0.01*	0.06***	0.01***	0.03***	0.02***
Name in e-mail							1.00***	0.22***	0.01***	0.02***	0.04***	0.01	0.03***	0.01
Number in e-mail								1.00***	0.02***	0.00**	0.06***	0.01***	0.04***	0.01***
Is lowercase									1.00***	0.03***	0.03***	0.02***	0.02***	0.02***
E-mail error										1.00***	0.03***	0.01**	0.01***	0.01*
Control variables														
Age ^a											1.00***	0.05***	0.11***	0.03***
Order amount ^a												1.00***	0.27***	0.02***
Item category													1.00***	0.11***
Month														1.00***

This table provides a measure of association, Cramér's V, between credit bureau score quintiles, the digital footprint, and additional control variables. Cramér's V measures the association between two categorical variables and is bounded between [0,1], with 0 denoting no association and 1 denoting perfect association. To allow calculation of Cramér's V, continuous variables have been transformed into categories by forming quintiles of the variables. Please note that most digital footprint variables are nominal categorical variables so that Pearson's correlation coefficient or Spearman's rank correlation cannot be determined. The sample is based on scorable customers, that is, the set of customers for which a credit bureau score is available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

^a Transformed into quintiles.

^b We exclude customers with a do-not-track setting, as the setting simultaneously applies to device, operating system, and channel information.

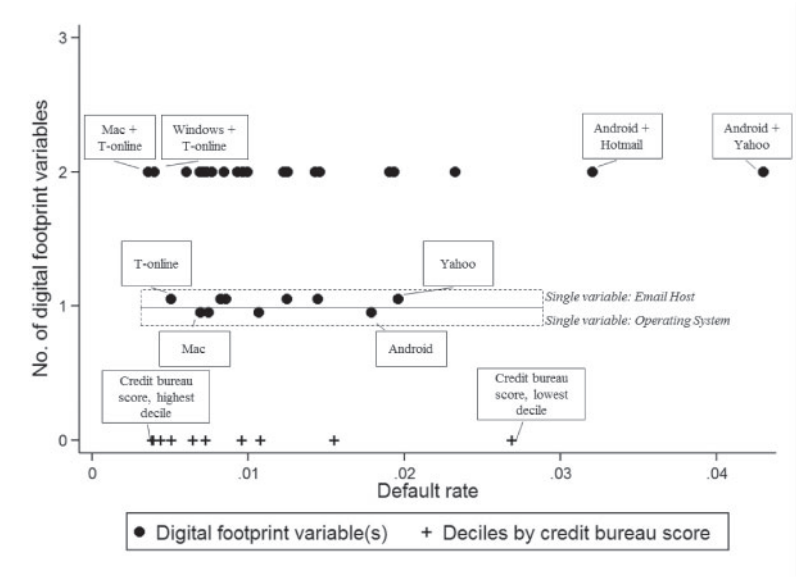


Figure 2
Default rates by combinations of digital footprint variables
This figure shows default rates for combinations of the variables *Operating system* and *E-mail host* for all combinations that contain at least 1,000 observations. The x-axis shows default rates, and the y-axis illustrates whether the respective dot comes from a single digital footprint variable (e.g., “Android users”) or whether it comes from a combination of digital footprint variables (e.g., “Android + Hotmail”). Default rates for credit bureau score deciles are provided as reference points along the row at the very bottom. The sample only includes customers with credit bureau scores. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

variables. Figure 2 illustrates this idea. The figure depicts default rates using the variables *Operating system* and *E-mail host* separately and in combination. The sample is restricted to customers with a credit bureau score.

Among the categories from these two variables, T-online users have the lowest default rate (0.51%), while Yahoo users have the highest default rate (1.96%). As a reference point, we list deciles by credit bureau score at the bottom of Figure 2. The default rate of T-online users of 0.51% is approximately equal to the default rate in the 7th decile of credit bureau scores, while the default rate of Yahoo users (1.96%) is between the 1st and 2nd decile of credit bureau scores. When combining information from both variables (*Operating system* and *E-mail host*), default rates are even more dispersed.¹⁹ We observe the lowest default rate for Mac-users with a T-online e-mail address. The default rate for this combination is 0.36%, which is lower than the average default rate in the 1st decile of credit bureau scores. On the other extreme, Android users with a Yahoo e-mail address have an average default rate of 4.30%, significantly higher

¹⁹ The following results are not driven by small sample sizes; that is, all categories reported in Figure 2 have at least 1,000 observations.

than the 2.69% default rate in the highest decile of credit bureau scores. These results suggest that even two simple variables from the digital footprint allow categorizing customers into default bins that match or exceed the variation in default rates from credit bureau deciles.

2.3 Multivariate results: Digital footprint and default

Table 4 provides multivariate regression results of a default dummy on the credit bureau score and digital footprint variables. We use a logistic regression and report the AUC for every specification. The AUC is a simple and widely used metric for judging the discriminatory power of credit scores (see, e.g., Stein 2007; Altman, Sabato, and Wilson 2010; Iyer et al. 2016). The AUC ranges from 50% (purely random prediction) to 100% (perfect prediction). Following Iyer et al. (2016), an AUC of 60% is generally considered desirable in information-scarce environments, whereas AUCs of 70% or greater are the goal in information-rich environments. We also plot the receiver operating characteristic, which is used to calculate the AUC in Figure 3.

The AUC corresponds to the probability of correctly identifying the good case if faced with one random good and one random bad case. Note that customers with a low creditworthiness are excluded from buying via invoice. Intuitively, this should make it more difficult to discriminate between good and bad cases, because the customers with the worst creditworthiness are not part of our sample. Thus, the AUC in our sample should be lower than the AUC in the sample of the entire population, both when using the credit bureau score and when using the digital footprint for predicting default. At the same time, the exclusion of low creditworthiness customers makes our AUC more comparable to a typical credit card, bank loan or peer-to-peer lending data set where low creditworthiness customers are usually also excluded from accessing credit.

Column 1 of Table 4 reports results using the (continuous) credit bureau score as an independent variable. As expected and consistent with Figure 1, the credit bureau score is a highly significant predictor of default, with higher credit scores being associated with lower default rates. The AUC using only the credit bureau score is 68.3% and is significantly different from chance (AUC of 50%). This result is comparable to the 66.6% AUC using the credit bureau score alone documented in a consumer loan sample of a large German bank (Berg, Puri, and Rocholl 2017) and the 66.5% AUC using the credit bureau score alone in a loan sample of 296 German savings banks (Puri, Rocholl, and Steffen 2017). This result is higher than the AUC of 62.5% reported by Iyer et al. (2016) in a U.S. peer-to-peer lending data set using the Experian credit score only and the AUC of 59.8% we compute for comparison using credit bureau scores for Lending Club loans. This suggests that the credit bureau score provided to us by a German credit bureau clearly possesses discriminatory power and we use the AUC of 68.3% as a benchmark for the digital footprint variables in the following.

Table 4
Default regressions (scorable customers)

Variables	(1) Credit bureau bureau score		(2) Digital footprint		(3) Credit bureau score & digital footprint		(4) Credit bureau score & digital footprint, further controls	
	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
Credit bureau score	-0.17***	(-7.89)			-0.15***	(-6.67)	-0.14***	(-5.90)
Device type & operating system ^a								
Desktop/Windows			Baseline		Baseline		Baseline	
Desktop/Macintosh			-0.07	(-0.53)	-0.13	(-1.03)	-0.19	(-1.52)
Tablet/Android			0.29***	(3.19)	0.29***	(3.06)	0.33***	(3.44)
Tablet/iOS			0.08	(1.05)	0.08	(0.97)	0.07	(0.89)
Mobile/Android			1.05***	(17.25)	0.95***	(15.34)	1.01***	(16.13)
Mobile/iOS			0.72***	(9.07)	0.57***	(6.73)	0.61***	(7.26)
E-mail Host ^a								
Gmx (partly paid)			Baseline		Baseline		Baseline	
Web (partly paid)			0.00	(0.00)	-0.02	(-0.22)	-0.01	(-0.08)
T-Online (affluent customers)			-0.40***	(-3.90)	-0.35***	(-3.35)	-0.27**	(-2.47)
Gmail (free)			0.34***	(3.81)	0.29***	(3.09)	0.27***	(2.86)
Yahoo (free, older service)			0.75***	(9.19)	0.72***	(8.98)	0.70***	(8.28)
Hotmail (free, older service)			0.35***	(3.70)	0.28***	(2.72)	0.25**	(2.32)
Channel								
Paid			Baseline		Baseline		Baseline	
Affiliate			-0.49***	(-5.35)	-0.54***	(-5.58)	-0.61***	(-6.31)
Direct			-0.27***	(-4.25)	-0.28***	(-4.44)	-0.26***	(-4.30)
Organic			-0.15*	(-1.79)	-0.15*	(-1.74)	-0.15*	(-1.82)
Other			-0.47***	(-4.50)	-0.48***	(-4.36)	-0.39***	(-3.43)
Checkout time								
Evening (6 p.m.-midnight)			Baseline		Baseline		Baseline	
Morning (6 a.m.-noon)			0.28***	(4.50)	0.28***	(4.60)	0.29***	(4.75)
Afternoon (noon-6 p.m.)			0.08	(1.42)	0.08	(1.47)	0.10*	(1.92)
Night (midnight-6 a.m.)			0.79***	(7.73)	0.75***	(7.09)	0.72***	(6.68)
Do-not-track setting			-0.02	(-0.25)	-0.07	(-0.91)	-0.09	(-1.19)
Name in e-mail			-0.28***	(-5.67)	-0.29***	(-5.70)	-0.29***	(-5.59)
Number in e-mail			0.26***	(4.50)	0.23***	(3.91)	0.22***	(3.85)
Is lowercase			0.76***	(13.10)	0.74***	(13.20)	0.74***	(13.24)
E-mail error			1.66***	(20.00)	1.67***	(20.36)	1.70***	(20.37)
Constant	12.42***	(5.76)	-4.92***	(-62.87)	9.97***	(4.48)	9.04***	(4.06)
Control for Age, Gender, Item category, Loan amount, and month and region fixed effects	No		No		No		Yes	
Observations	254,819		254,819		254,819		254,613	
Pseudo R²	.0244		.0524		.0717		.0921	
AUC	0.683		0.696		0.736		0.762	
(SE)	(0.006)		(0.006)		(0.005)		(0.005)	
Difference to AUC=50%	0.183***		0.196***		0.236***		0.262***	
Difference AUC to (1)			0.013*		0.053***		0.080***	

We estimate default rate regressions where the dependent variable (*Default(0/1)*) is equal to one if the claim has been transferred to a debt collection agency. Column 1 provides results using the credit bureau score as the independent variable; Column 2 provides results using the digital footprint variables as independent variables; Column 3 uses both the credit bureau score and the digital footprint variables as independent variables; and Column 4 adds additional controls (*Age, Gender, Loan amount, Item type*) and month and region fixed effects. All models are estimated using a logistic regression model. Standard errors are adjusted for 97 clusters by 2-digit ZIP codes. The sample is based on scorable customers, that is, the set of customers for which a credit bureau score is available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

We only report coefficients for the 6 largest e-mail providers even though we use the largest eighteen categories in the regression (all e-mail providers with at least 1,000 observations). Using only the six reported e-mail hosts does not significantly affect the results.

^a We omit the coefficients for the rare combinations that contain other operating systems, see Table A5 for descriptive statistics.

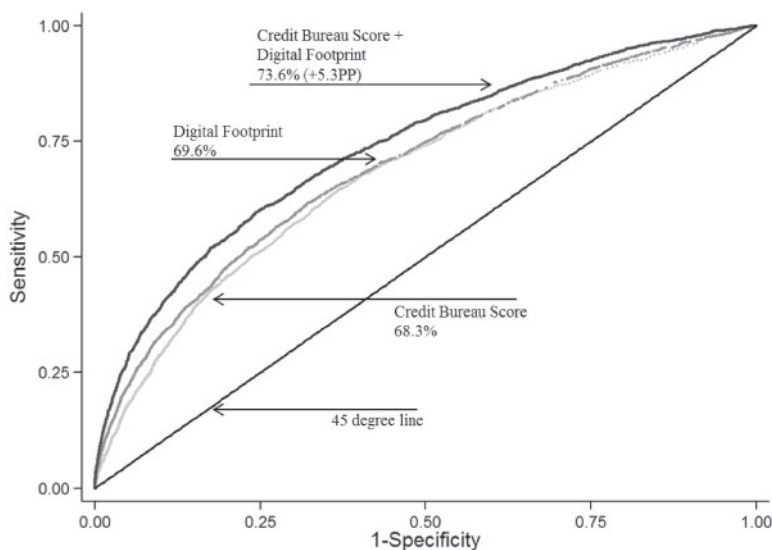


Figure 3
AUC for scorable customers for various model specifications

This figure illustrates the discriminatory power of three different model specifications by providing the receiver operating characteristics curve (ROC curve) and the area under curve (AUC). The ROC curves are estimated using a logit regression of the default dummy on the credit bureau score (light gray), the digital footprint (gray), and both the credit bureau score and a digital footprint (dark gray). The sample only includes customers with credit bureau scores. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

Column 2 reports results for the digital footprint; Column 3 uses both the credit bureau score and the digital footprint variables; and Column 4 adds month and region fixed effects and controls for age, gender, the loan amount, and purchase item category.²⁰ Standard errors are clustered at the 2-digit ZIP code level in all specifications. For categorical variables, all coefficients need to be interpreted relative to the baseline level. We always choose the most popular category in a variable as the baseline level. We report AUCs in the bottom rows of Table 4 and test for differences in AUCs using the methodology by DeLong, DeLong, and Clarke-Pearson (1988).

Interestingly, digital footprint variables have an AUC of 69.6%, which is higher than the AUC of the credit bureau score.²¹ These results suggest that even simple, easily accessible variables from the digital footprint are as useful

²⁰ The E-commerce company classifies purchase items into 16 categories, with customers most frequently buying from the following categories: “lamps” (13% of purchases), “bedroom” (12% of purchases), and “living room” (12% of purchases). The remaining categories (small furniture, garden, dining, pillows, home textiles, baby, office, household, children & youth, bathroom, carpets & flooring, boutique, kitchen) are roughly evenly distributed.

²¹ Note that in Table 4 we report only the 6 largest categories for e-mail providers even though we use the largest 18 categories in the regression (all e-mail providers with at least 1,000 observations). In a regression using only the 6 reported e-mail hosts, the AUC of the digital footprint decreases by 0.9 PP, still being higher than the AUC using credit bureau score alone.

in predicting defaults as the credit bureau score. We focus on the economic and statistical significance of the variables in Column 2 in the following discussion.

The variables *E-mail error*, *Mobile/Android*, and the *Night* dummy have the highest economic significance. The variable *E-mail error* is a simple dummy variable that is equal to one in only a few cases, and thus allows categorizing a small portion of customers as being high risk. Customers with an E-mail Error have an odds ratio of defaulting which is $\exp(1.66)=5.25$ times higher than customers without an E-mail Error. Given that default rates are rather small, default probabilities p and odds ratios ($p/(1-p)$) are very similar, implying that customers with an E-mail Error default approximately 5.25 times more frequently than customers without E-mail Error.

Android users default more frequently than the baseline category, consistent with the univariate results and consistent with the fact that consumers purchasing an iPhone are usually more affluent than consumers purchasing other smartphones. Customers purchasing at night (midnight-6am) also default more frequently than customers purchasing at other times of the day, suggesting that purchases made during a time when many people might be asleep are fundamentally different from daytime purchases.

In Column 3 of Table 4, we complement the digital footprint variables with the credit bureau score. Both the coefficient on the credit bureau score and the coefficients on the digital footprint variables barely change compared to Columns 1 and 2. This suggests that the digital footprint variables complement rather than substitute for the information content of the credit bureau score. As a consequence, the AUC of the combined model using both the digital footprint variables and the credit bureau score (73.6%) is significantly higher than the AUC of each of the stand-alone models (68.3% for the credit bureau score and 69.6% for the digital footprint variables).²²

In Column 4 of Table 4, we add time and region fixed effects and control for age, gender, the loan amount, and the category of the purchased item. Results remain almost unchanged, suggesting that neither the credit bureau score nor the digital footprint act as simple proxies for different regions, different subperiods, or different age, gender, or purchase item characteristics. While older people are expectedly less likely to default, consistent with the idea that it takes time to build up a credit history, coefficients for the credit bureau score and the digital footprint remain very similar.²³ Only the coefficient for users of the premium service T-online, which is known to serve more affluent and older customers,

²² Please note that AUCs generated by two independent variables cannot be simply summed, because the AUC of an uninformative variable is already 50%.

²³ The coefficient on $\text{Log}(\text{age})$ in Column 4 of Table 4 is -0.22 (significant at the 10% level) and the coefficient on $\text{log}(\text{loan amount})$ is -0.20 (significant at the 1% level), suggesting that a doubling in age or loan volume reduces defaults by approximately one-fifth. The gender dummy enters with an insignificant coefficient, implying no effect of gender on the probability of default.

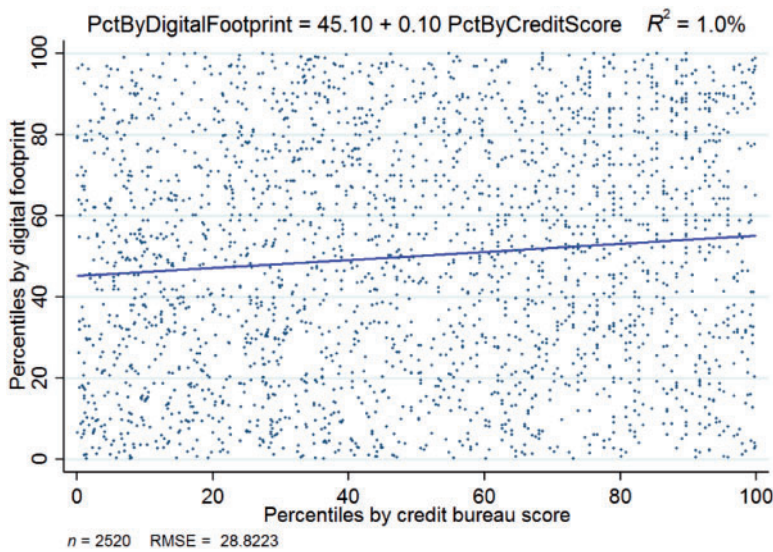


Figure 4
Correlation between digital footprint and credit bureau score (scorable customers)

This figure illustrates the correlation between the credit bureau score and the digital footprint. The x-axis shows percentiles by credit bureau score. The y-axis shows percentiles by the digital footprint. The digital footprint is estimated using the results from Column 2 of Table 4 and multiplied by minus 1 to ensure the same ordering as the credit bureau score (high value = low default probability). The sample only includes customers with credit bureau score and is based on a 1% random sample in order to be able to visualize the results. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

decreases slightly in economic significance (from -0.35 in Column 3 to -0.27 in Column 4).²⁴

Figure 4 provides a more detailed look at the correlation between the credit bureau score and the digital footprint. Using the results from Column 2 of Table 4, we construct a default prediction using only the digital footprint variables for each observation in our sample. For each observation, Figure 4 then depicts the percentile using the credit bureau score as well as the percentile using the digital footprint score. As an example, if a customer has a very good credit bureau score (=low default probability) and a very low default probability by the digital footprint as well, then it would end up in the upper right-hand corner of Figure 4. A customer with a low credit bureau score (=high default probability) and a very high default probability by the digital footprint as well would end up in the lower left-hand corner. Observations where credit score and digital footprint have opposing predictions end up in the upper left-hand corner or the lower right-hand corner. Figure 4 clearly shows that the correlation between

²⁴ Clustering by 3-digit ZIP codes, age, or week rather than 2-digit ZIP codes does not materially change significance levels for any of the variables in all specifications.

credit bureau score and digital footprint is very low (R^2 of 1.0%, implying a correlation of approximately 10%). These results confirm our prior observation that the digital footprint acts as a complement, rather than a substitute, of the credit bureau score.

2.4 Out-of-sample tests

Table 4 was estimated in-sample which may overstate discriminatory power due to overfitting. We therefore provide both out-of-sample and out-of-sample/out-of-time tests. For the out-of-sample tests, we use $N \times 2$ -fold cross-validation. $N \times 2$ -fold cross-validation is a common method to evaluate out-of-sample performance of an estimator (see, e.g., Dietterich (1998) for a general discussion of cross-validation techniques). We thereby randomly divide the full sample into half samples A and B, estimate a predictive logistic regression using sample A, and use the coefficients to create predicted values for the observations in sample B. We then estimate a predictive regression using sample B and use the coefficients to create predicted values for observations in sample A. Finally, we determine the AUC for the full sample of observations, using all predicted values estimated out-of-sample. We repeat this procedure $N=100$ times and report the mean out-of-sample AUCs in Column 2 of Table 5. For the out-of-sample/out-of-time tests, we split the sample in three roughly equally-sized time periods (October 2015–February 2016, March 2016–July 2016, and August 2016–December 2016). The first subperiod is used to estimate the model; the second subperiod is not utilized, to reflect the fact that it takes time to observe the default/no-default outcome; and the third subperiod is used to determine the AUC. The out-of-sample/out-of-time test allows us to judge whether parameters determined at the beginning of our sample period still provide a valid estimate at the end of our sample period.

Table 5 provides the results. The out-of-sample AUC is less than 1 PP lower than the in-sample AUC for all specifications apart from the fixed effects regression. In the fixed effects specification, out-of-sample AUCs are 2.8 PP lower than in-sample AUCs. This is not surprising given that overfitting is in particular an issue when many explanatory variables are used. AUCs for the fixed effects regressions are of little relevance for our paper as the fixed effects regressions serve the sole purpose of showing that neither the credit bureau score nor the digital footprint variables are simple proxies for any of the control variables or fixed effects.

Column 3 of Table 5 provides results for the out-of-sample/out-of-time (OOS-OOT) tests. OOS-OOT tests would yield a different result if the relationship between the digital footprint and defaults is not stable over time, for example, because customers learn how to game the digital footprint. Reassuringly, the OOS-OOT AUC is very similar to both the in-sample and the out-of-sample AUC. In particular, there seems to be little

Table 5
Out-of-sample estimates

	(1) Baseline (in-sample)	(2) Out-of-sample	(3) Out-of-sample/out-of-time
AUC credit bureau score	0.683	0.681	0.691
N	254,819	254,819	74,543
AUC digital footprint	0.696	0.688	0.692
N	254,819	254,819	74,543
AUC credit bureau score + Digital footprint	0.736	0.728	0.739
N	254,819	254,819	74,543
AUC credit bureau score + Digital footprint, fixed effects	0.762	0.734	0.730
N	254,613	254,613	74,543

This table provides robustness tests out-of-sample for all main regression specifications. We report AUCs for scorable customers for the model specifications from Table 4. Column 1 reports the baseline results. Column 2 reports out-of-sample estimates of the AUC using Nx2-fold cross-validation. We thereby randomly divide the full sample into half samples A and B. We then estimate a predictive logistic regression using sample A and use the coefficients to create predicted values for observations in sample B. We also estimate a predictive regression using sample B and use the coefficients to create predicted values for observations in sample A. We then determine the AUC for the full sample of observations, using all predicted values estimated out-of-sample. The AUCs reported in Column 2 are the mean AUCs from 100 iterations. In Column 3, we provide out-of-sample/out-of-time estimates. We thereby split the sample in roughly three equally-sized time periods (October 2015–February 2016, March 2016–July 2016, and August 2016–December 2016). The first subperiod is used to estimate the model; the second subperiod is not utilized, to reflect the fact that it takes time to observe the default/no-default outcome; and the third subperiod is used to determine the AUC. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

evidence that the link between digital footprints and defaults changes quickly over time.²⁵

2.5 Alternative default definitions and sample splits

Table 6 provides various robustness tests. Panel A uses alternative default definitions, and panel B provides results for various sample splits. In all panels, we report the AUC for the credit bureau score, for the digital footprint, and for both.

Panel A, Column 2, uses an alternative default definition, namely default after efforts by the collection agency. The collection agency fully recovers approximately 40% of the claims, resulting in a reduced default rate after the collection agency process. The relative importance of credit bureau score versus digital footprint is almost unaffected and the AUC increases slightly. This seems intuitive, given that it is more difficult to predict customers who don’t pay in the first months, but pay at a later point in time, than to simply predict customers who won’t be able to pay at all. Nine percent of defaults by scorable customers are cases of fraud. Column 3 of panel A excludes fraud cases, showing that the predictive power of the digital footprint and its relatively better performance

²⁵ We also test for changes in each individual coefficient over time using the same three subperiods described above. Coefficients are rather stable over time with no consistent movements of coefficients in any direction for any of the digital footprint variables.

Table 6
Robustness tests (scorable customers)

<i>A. Default definition</i>	(1)	(2)	(3)	(4)
	Baseline (default = transfer to collection agency)	Default = Write-down	Exclude cases of fraud (9% of defaults)	Loss given default (R^2 reported)
AUC credit bureau score	0.683	0.692	0.681	0.013
AUC Digital footprint	0.696	0.723	0.691	0.062
AUC credit bureau score + digital footprint	0.736	0.757	0.730	0.069
N	254,819	254,819	254,604	2,384

<i>B. Sample splits</i>	(1)	(2)	(3)	(4)
	Small orders < EUR 218.91	Large orders ≥ EUR 218.91	Female	Male
AUC credit bureau score	0.688	0.678	0.689	0.670
AUC Digital footprint	0.711	0.689	0.697	0.700
AUC credit bureau score + digital footprint	0.749	0.729	0.743	0.724
N	127,410	127,409	168,374	86,445

This table provides robustness tests using alternative default definitions as well as various sample splits. Panel A provides results using alternative default definitions. Column 1 reports results using the standard default definition (default = transfer to debt collection agency); Column 2 provides a stricter default definition (default = no full repayment after attempts of debt collection agency). Column 3 excludes fraud cases. Column 4 uses only the sample of defaulted loans and uses the loss given default as the dependent variable. In Column 4 we report the R^2 instead of the AUC, as Column 4 is estimated using a linear regression model while all other models are estimated using a logistic regression. Panel B provides results for various sample splits. All models are estimated using a logistic regression model; apart from Column 4 in panel A, which is estimated using a linear regression model. The sample is based on scorable customers, that is, the set of customers for which a credit bureau score is available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

are not driven solely by fraud cases.²⁶ Column 4 of panel A reports results using the loss given default (measured as a percentage of the purchase value) as the dependent variable. Compared to the credit bureau score, the digital footprint is both economically and statistically a better predictor of loss given default. Therefore, a digital footprint not only helps to predict default but also helps to predict recovery rates for defaulted exposures. Panel B reports various subsample splits. Results are very similar for small and large orders (split at the median) as well as for female and male customers.

Overall, the robustness tests suggest that our key results from Table 4—digital footprints predict default as well or even better than the credit bureau score, and digital footprint and credit bureau score are complements rather than substitutes—is robust for different default definitions and various sample splits. This suggests even simple, easily accessible variables from the digital footprint are important for default prediction over and above the information content of credit bureau scores.

²⁶ We find that the digital footprint is predictive of the risk of fraud, and the digital footprint has discriminatory power over the credit bureau score in predicting fraud. Results are available on request.

2.6 External validity

The analysis presented so far provides evidence of the predictive power of the digital footprint for short term loans for products purchased online. A remaining concern is that the default behavior on short-term E-commerce loans is not representative of other loans, such as consumer or mortgage loans. In Section 2.3 we showed that our data set is largely representative of a typical German consumer loan sample in terms of age distribution, geographic distribution, as well as default rates. Table A3, which is also discussed in Section 2.3, further shows that the credit bureau score has very similar predictive power in our sample compared to consumer loan samples both at German savings banks and at German private banks.

In this section, we provide further evidence for the external validity of our setting. In particular, we test whether digital footprints today can forecast future changes in the credit bureau score. If a good digital footprint today predicts an increase in the credit bureau score in the future, then this is evidence that digital footprints matter for other loan products as well. We therefore run regressions of the form:

$$\Delta(CreditScore_{t+1}, CreditScore_t) = \beta_0 + \beta_1 \Delta(DF_t, CreditScore_t) + X + \varepsilon, \quad (1)$$

where $\Delta(CreditScore_{t+1}, CreditScore_t)$ is the change in credit bureau score between $t + 1$ and t , $\Delta(DF_t, CreditScore_t)$ is the difference between predicted default rates using the digital footprint variables (i.e., predicted values from Column 2 of Table 4) and predicted default rates using the credit bureau score (i.e., predicted values from Column 1 of Table 4), and X is a set of control variables. We winsorize both the dependent and the independent variable in Equation (1) at the 1% and 99% levels. A limitation of our data set is that the left-hand-side variable is available only for customers who are part of our original data set and have returned to the E-commerce company at least once up to March 2018.²⁷ For each observation in our original data set from Table 4, we check whether the customer returned to the platform and report the latest available credit bureau score for each customer. For returning customers, the E-commerce company only requests a new credit score if the existing credit score is older than 6 months, implying that the difference between t and $t + 1$ in Equation (1) is at least 181 days. The average (median) time between t and $t + 1$ in Equation (1) is 450 days (431 days), that is, a little over 1 year.²⁸

²⁷ The data set in Table 4 is limited to the period from October 2015 to December 2016, to allow for a subsequent observation of default rates and loss given defaults. For changes in credit bureau scores we expand the data set until March 2018. Please note that while the sample from Table 4 is limited to customers who pass the minimum creditworthiness condition (see Section 2.1), the subsequent credit bureau score is also available for returning customers who were denied buying via invoice upon returning because of a very low credit bureau score.

²⁸ Changes in credit bureau scores may plausibly affect customers' decision to return to the E-commerce company, but such a selection does not necessarily invalidate our regression design. For the estimate of β_1 in Equation (1),

Table 7 provides the regression results for Equation (1). Column 1 provides results without control variables. The coefficient on $\Delta(DF_t, CreditScore_t)$ is economically and statistically highly significant. The coefficient of -75.86 suggests that if the digital footprint default prediction is 1 PP higher than the credit bureau default prediction (e.g., the digital footprint predicts a 2% default probability, whereas the credit bureau score predicts a 1% default probability), then the credit bureau score decreases by 0.76 points in the future. Given that German credit bureau scores represent 1-year survival probabilities, this suggests that the credit bureau score adjusts 76% on its way toward the digital footprint. To ensure that our results are not driven by mean-reversion, we control for $CreditScore_t$ in Column 2. As expected, the coefficient decreases but remains both economically and statistically highly significant at -28.43. Controlling for month and region fixed effects barely changes the coefficient (Column 3 of Table 7). The effect is rather monotone across quintiles by $\Delta(DF_t, CreditScore_t)$, suggesting that effects are not driven only by particularly negative or particularly positive digital footprints. In Column 5 of Table 7 we analyze the predictive power of the digital footprint across the credit bureau score spectrum. We do so by constructing an indicator for the digital footprint being better than the credit bureau score and interacting this dummy with quintiles of the credit bureau score distribution. The baseline effect is clearly positive, showing that better digital footprints are on average associated with a future improvement in credit bureau scores. Furthermore, some evidence suggests that the predictive power is larger for lower credit bureau scores (see Table 7, Column 5).

Taken together, the evidence suggests that digital footprints today forecast subsequent changes in credit bureau scores. This result provides a window into the traditional banking world. As credit bureau scores are known to predict default rates for traditional loan products, our results point to the usefulness of digital footprints for traditional loan products as well.

3. Economic Outcomes and Implications

3.1 Economic mechanism

We have been careful so far not to take a stance on the economic mechanism that might explain our results. We do not have access to financial information of the customers in our sample, nor do we have access to bank-internal relationship specific information. Therefore, we cannot fully decompose the informativeness of the digital footprint into one part that proxies for financial characteristics and another part that proxies for what is traditionally viewed as

we rely on the assumption that the decision to return to the E-commerce platform is not related to both the difference $\Delta(DF_t, CreditScore_t)$ and the subsequent change in credit bureau scores. If, for example, customers whose creditworthiness using the digital footprint is better than their creditworthiness using the credit bureau score return only if their credit bureau score has increased, then the coefficient β_1 would be downward biased (and vice versa).

Table 7
Predicting changes in the credit bureau score with the digital footprint

Dependent variable	(1) $\Delta (\text{CreditScore}_{t+1}, \text{CreditScore}_t)$	(2) $\Delta (\text{CreditScore}_{t+1}, \text{CreditScore}_t)$	(3) $\Delta (\text{CreditScore}_{t+1}, \text{CreditScore}_t)$	(4) $\Delta (\text{CreditScore}_{t+1}, \text{CreditScore}_t)$	(5) $\Delta (\text{CreditScore}_{t+1}, \text{CreditScore}_t)$
$\Delta (\text{DigitalFootprint}_t, \text{CreditBureauScore}_t)$	-75.86*** (-11.86)	-28.43*** (-4.64)	-30.11*** (-5.05)		
Q1 (-100% to -0.49%)				0.40** (2.52)	
Q2 (-0.49% to -0.25%)				0.15* (1.75)	
Q3 (-0.25% to -0.05%)				baseline	
Q4 (-0.05% to +0.35%)				0.08 (0.91)	
Q5 (+0.35% to +100%)				-0.39*** (-3.04)	
DigitalFootprint-Better-Than-CreditBureauScore (0/1)					0.33**
DigitalFootprint-Better-Than-CreditBureauScore (0/1) x					(2.14)
LowCreditBureauScore					0.86** (2.36)
Q2					0.03 (0.13)
Q3					baseline -0.13 (-0.71)
Q4					0.00 (0.01)
HighCreditBureauScore		-0.43*** (-13.47)	-0.42*** (-13.28)	-0.42*** (-10.05)	FE for each credit score quintile absorbed
CreditBureauScore _t	0.37*** (8.75)	41.99*** (13.51)	absorbed	absorbed	Yes
Constant	No	No	Yes	Yes	Yes
Month & region fixed effects					
Observations	17,646	17,646	17,646	17,646	17,646
Adj. R ²	.028	.071	.081	.081	.074

This table provides a linear regression of changes in credit bureau scores on the difference between the default probability using the digital footprint and the default probability using the credit bureau score. The independent variable $\Delta(\text{DigitalFootprint}_t, \text{CreditScore}_t)$ measures the difference in predicted values of Column 2 of Table 4 and the predicted values of Column 1 of Table 4. The dependent variable $\Delta(\text{CreditScore}_{t+1}, \text{CreditScore}_t)$ measures the change in credit bureau score between (1) the credit bureau score as of the date of purchase from Table 4 and (2) the latest available credit bureau score up to March 2018. Two credit bureau scores at two different dates are only available when customers return to the E-commerce company at least once between October 2015 and March 2018. Column 2 adds the initial credit bureau score as a control variable; Column 3 adds month and region fixed effects; Column 4 displays results by quintile of $\Delta(\text{DigitalFootprint}_t, \text{CreditScore}_t)$; and Column 5 tests the predictive power of the digital footprint across credit score quintiles. The dependent variable and the continuous independent variables are winsorized at the 1% and 99% levels. For variable definitions, see Table A1.

Table 8
Marginal AUC for digital footprint variables and combinations of digital footprint variables

A. Individual digital footprint variables (dependent variable: default (0/1))

Variable	Stand-alone AUC (%)	Marginal AUC (PP)
Computer & operating system	59.03	+1.71***
E-mail host	59.78	+2.44***
E-mail Host: paid versus nonpaid dummy	53.80	+0.98***
E-mail Host: Variation within nonpaid e-mail hosts	57.82	+1.79***
Channel	54.95	+0.70***
Checkout time	53.56	+0.63***
Do not track setting	50.40	+0.14*
Name in e-mail	54.61	+0.30**
Number in e-mail	54.15	+0.19**
Is lowercase	54.91	+1.15***
E-mail error	53.08	+1.78***

B. Combinations of digital footprint variables (dependent variable: default (0/1))

Variables	Stand-alone AUC (%)	Marginal AUC (PP)
Potential proxy for income		
Potential proxy for income, financially costly to change (computer & operating system, e-mail host: paid vs. nonpaid dummy)	61.03	+2.20
Unlikely to be a proxy for income, not financially costly to change (nonpaid e-mail host, channel, checkout time, do not track setting, name in e-mail, number in e-mail, is lowercase, e-mail error)	67.35	+8.52
Impact on everyday behavior		
Requires one-time action only (computer & operating system, e-mail host, do not track setting, name in e-mail, number in e-mail)	64.92	+7.25
Requires thinking about how to behave during every individual purchase (channel, checkout time, is lowercase, e-mail error)	62.30	+4.63

This table provides AUCs for each digital footprint variable separately (panel A) and AUCs for selected combinations of digital footprint variables (panel B). The stand-alone AUC is the AUC using only the variable(s) listed in the column “Variable(s).” The marginal AUC of variable(s) *X* is defined as the AUC of the full model using all digital footprint variables minus the AUC of the model using all variables, except variable(s) *X*. All models are estimated using a logistic regression model using the default dummy as a dependent variable. The sample is based on scorable customers, that is, the set of customers for which a credit bureau score is available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

soft information. However, we can decompose the overall informational content of the digital footprint into each of the individual variables. Some of the digital footprint variables, we know from related literature, correlate with financial characteristics (e.g., the use of iOS vs. Android), whereas other characteristics (e.g., the time of purchase or clicking on a paid ad) are more difficult to relate to financial characteristics.²⁹

Panel A of Table 8 reports AUCs and marginal AUCs for each digital footprint variable separately. The marginal AUC of variable *X* is defined as the AUC of the full model using all digital footprint variables minus the AUC of the model using all variables except *X*. Not a single variable dominates the list:

²⁹ Bertrand and Kamenica (2017) document that owning an iOS device is one of the best predictors for being in the top quartile of the income distribution. See, for example, Rook (1987), Wells, Parboteeah, and Valacich (2011), and Turkeyilmaz, Erdem, and Uslu (2015) for the importance of personality traits in impulse shopping behavior.

Computer & Operating system, *E-mail host*, and *E-mail error* all have marginal AUCs above 1.5 PP and below 2.5 PP. The discriminatory power of the variable *E-mail host* is mainly driven by variation within nonpaid e-mail hosts, and less so by differences in default rates between paid and nonpaid e-mail hosts. The marginal impact of *Do not track setting*, *Name in E-mail*, and *Number in E-mail* is below 0.5 PP AUC. The variables *Channel*, *Checkout time*, and *Is lowercase* exhibit marginal AUCs between 0.5 PP and 1.5 PP.

Panel B of Table 8 provides AUCs and marginal AUCs for selected combinations of digital footprint variables. The first row of panel B categorizes digital footprint variables by their financial costs to switch from one to another. We hypothesize that those variables that are financially costly to change (such as buying an expensive device or switching to a paid e-mail host) are plausibly correlated with a customers' financial characteristics, such as income or wealth. On the other hand, changing the channel can be done at no financial cost, but might require self-discipline, such as always visiting price comparison sites or never clicking on paid ads. The variables that are less likely to be proxies for income have both a higher stand-alone AUC (67.35% vs. 61.03%) and a higher marginal AUC (+8.52 PP vs. +2.20 PP). This result is mostly driven by the fact that there are fewer variables that are likely to be proxies for income than variables that are unlikely to be proxies for income, and not by the fact that variables that are unlikely to be proxies for income have a higher AUC per variable compared to variables that are more likely to be proxies for income. Taken together, these results provide suggestive evidence that digital footprints contain information over and above purely financial characteristics.

In panel B of Table 8 we also group the digital footprint variables by their impact on everyday behavior. Some of the digital footprint variables are determined by a single action, potentially dating several months or years back. Examples include the choice of the e-mail address or a do-not-track setting. Other variables are determined during each purchase process anew, such as the decision to visit a price comparison site (channel), the checkout time, or making typos. We see that both variables determined by a single action and variables determined during each purchase process anew significantly contribute to the informativeness of the digital footprint.

Future research might look at the relation between digital footprints and financial characteristics in more detail, in particular also to analyze whether the type of information contained in the digital footprint supersedes or substitutes for relationship-specific soft information and for the value of human judgment in the loan granting process (Berg 2015). Some surveys suggest that loan applicants are unwilling to provide even very basic information, such as their bank account number or their credit card number when applying for a loan online.³⁰ Digital footprints clearly stand out for their ease of collection:

³⁰ Crosman (2017) reports that half of applicants say it is too much trouble typing in a bank account number when applying for a loan online via a smartphone.

applicants don't need to provide and verify income or bank account information, but these variables are simply collected by accessing or registering on a Web site. This provides a significant advantage for customer experience as well as cost savings, which is particularly important for the small volume/high quantity retail business.

3.2 Access to credit and default rates at the E-commerce firm

In the following, we analyze access to credit and default rates around the introduction of the digital footprint on October 19, 2015. This is important as it affects economic outcomes for both customers (access to credit) and the E-commerce firm (volume of transactions, default rate, and profitability).

Conceptually, using a better scoring model has an ambiguous effect on access to credit. The direction of the effect depends on whether or not lenders are willing to provide credit at the pooling price. More specifically, if the pooling price leads to Akerlof-type unraveling, then more information increases access to credit. If, however, the pooling price does not lead to unraveling, then more information can lead to lower access to credit.³¹

For the analysis on access to credit, we expand our data set to include all cases where a customer has proceeded with the purchase process to the point where payment options are presented to the customer. The data set thus includes both customers that have been offered payment by invoice and customers that have not been offered payment by invoice. In both cases, it includes customers who have completed the purchase and those who did not complete their purchase. The analysis of default rates continues to use the sample of customers who purchased via invoice, that is, the sample described in Sections 2.1 and 2.2.

We split the observations into two subsamples, largely representing purchases between EUR 100–1,100 and purchases above EUR 1,100. Sample 1 (“Score and Digital Footprint Added”) consists of purchases between EUR 100–1,100 where the customer was known to the first credit bureau.³² For this sample, the credit bureau score was not used for any purchases prior to October 19, 2015. The firm experimented with an almost 100% acceptance rate prior to October 19, 2015, and started using both the credit bureau score and the digital footprint after October 19, 2015. Sample 2 (“Digital Footprint Added”) consists of larger purchases (>EUR 1,100) and purchases where the customer was unknown to the first credit bureau. For these purchases, the credit bureau score was used

³¹ As an illustrative example, assume the E-commerce firm has access to a credit bureau score and the credit bureau score is either good (probability of default 5%) or bad (probability of default 15%). If the firm's margin is 16%, all customers have access to credit. Additional information via the digital footprint will push some of the customers with a bad credit bureau score beyond the 16% threshold, thus decreasing access to credit. If the firm's margin is 14%, only half of the customers have access to credit. Additional information via the digital footprint will push some of the customers with a bad credit score below the 14% threshold, thus increasing access to credit. See proposition 4 in Pagano and Japelli (1993) and panels A and B of figure 2 in Einav and Finkelstein (2011) for a detailed conceptual discussion.

³² The first credit bureau provides basic information, such as whether the customer exists and whether the customer is currently in or has been recently in bankruptcy (see Section 2.1 for a detailed description).

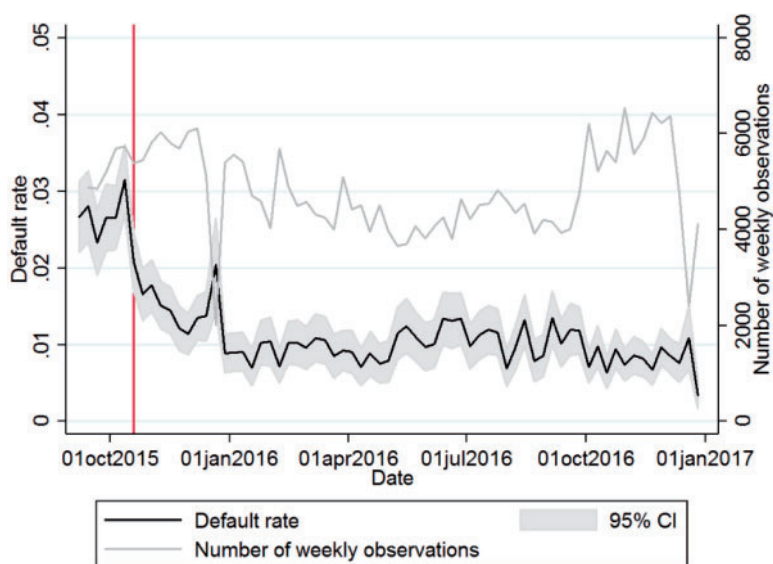


Figure 5
Default rates around the introduction of the digital footprint

This figure illustrates the development of default rates and number of observations around the introduction of the digital footprint. The vertical line indicates October 19, 2015, that is, the date of the introduction of digital footprints. The sample period ranges from September 2015 to December 2016. For variable definitions, see Table A1.

prior to October 19, 2015, and both the credit bureau score and the digital footprint were used after October 19, 2015. We exclude customers with repeat orders from both subsamples as they were always offered payment via invoice after October 19, 2015.³³

Figure 5 plots the development of default rates and access to credit around October 19, 2015. Default rates significantly drop by approximately 50% around October 19, 2015, whereas the number of purchases made via invoice remains unchanged. This figure suggests that using more information (adding the digital footprint for all observations and adding the credit bureau score for some of the observations) helped to significantly reduce default rates. It also highlights a reshuffling effect, as opposed to a simple explanation or contraction effect: customers with favorable digital footprints gain credit access while customers with unfavorable digital footprints lose credit access.

Table 9 breaks down the results by subsample. In panel A/sample 1 (“Score and Digital Footprint Added”), default rates drop from 2.54% to

³³ Note that customers were not aware of these thresholds. Using a McCrary density test, we also do not find evidence for more bunching just below these thresholds during the time periods when these thresholds were in place, see Figure A2.

Table 9

Development of default rates and access to credit around the introduction of the digital footprint
(Univariate results)

		Default rate (%)			Invoice offered (%)			Credit bureau score		
	N	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ
<i>A. Categories</i>										
Sample 1: ScoreAndDFAdded	33,896	2.54	1.19	−1.36***	96.65	90.05	−6.60***	na	98.26	na
Sample 2: DFAdded	10,807	3.62	2.33	−1.29***	39.00	40.11	1.11***	97.82	97.84	0.02
<i>B. Subcategories of “DFAdded”</i>										
DFAdded / High score	3,614	0.84	0.88	0.04	90.00	90.94	0.95	99.42	99.42	0.00
DFAdded / Medium score	4,023	1.82	2.14	0.33	85.21	87.72	2.50***	98.17	98.16	0.00
DFAdded / Low score	2,088	6.33	3.75	−2.57***	31.59	27.52	−4.07***	94.45	94.41	−0.04
DFAdded / Unscorable	1,082	11.65	6.44	−5.22***	10.14	9.59	−0.54	na	na	na

This table depicts default rates, the percentage of customers to which a loan is offered, as well as the average credit bureau score over a ± 6 -week window around the introduction of the digital footprint on October 19, 2015. Panel A depicts averages for two different categories: the category *ScoreAndDFAdded* consists of all observations where the October 19th rule change introduced both a credit bureau score and the digital footprint; the category *DFAdded* consists of all observations where the October 19th rule change introduced the digital footprint but a credit bureau score was requested both prior and after October 19, 2015. Panel B further splits the category *DFAdded* into subcategories *High score* (upper tercile of the credit bureau score distribution, $99.04 < \text{credit bureau score} \leq 100$), *Medium score* (middle tercile of the credit bureau score distribution, $96.67 < \text{credit bureau score} \leq 99.05$), *Low score* (lower tercile of the credit bureau score distribution, $0 \leq \text{credit bureau score} \leq 96.67$), and *Unscorable* (no credit bureau score available). The number of observations (*N*) in the second column refers to the number of observations for the default rate analysis. For variable definitions, see Table A1. na, not applicable.

1.19% (i.e., by 53%), whereas acceptance rates drop from 96.7% to 90.0%.³⁴ This drop in default rates is beneficial for the E-commerce firm.³⁵ Given that both the credit bureau score and the digital footprint were used after, but not prior, to October 19, 2015, it is impossible to separate the effect of the credit bureau score versus the effect of the digital footprint for this sample.

In panel A/sample 2 ("Digital Footprint Added"), default rates decrease significantly (from 3.62% to 2.33%, i.e., by 42%), whereas acceptance rates slightly increase from 39.0% to 40.1%. Again, a lower default rate, coupled with a higher acceptance rate, is clearly beneficial for the E-commerce firm. Panel B of Table 9 provides further details about sample 2. Customers with a credit bureau score in the highest tercile are not affected: default rates and acceptance rates do not change after the introduction of the digital footprint. This makes intuitive sense because digital footprints rarely make a difference for customers in the highest tercile by credit bureau score. Default rates decrease for customers with a low credit bureau score (from 6.33% to 3.75%, i.e., by 41%), whereas the average credit bureau score does not change (94.45 vs. 94.41; see last columns in panel B of Table 9). The digital footprint helps to accept applications with a

³⁴ In the sample "Score and Digital Footprint Added," we largely observe pooling before October 19, 2015. Before October 19, 2015, the E-commerce firm only rejected firms in this sample if the basic credit bureau had negative information (i.e., customer is currently in or recently has been in bankruptcy) or if there was evidence of fraud (e.g., numerous accounts from the same device).

³⁵ If we denote the net operating margin by x , then profits increase as long as $90.0\% \cdot (x - 1.19\%) > 96.7\% \cdot (x - 2.54\%) \Leftrightarrow (x < 20.15\%)$. That is, profits increase if operating margins are below 20% – which is clearly the case. This calculation is a back-of-the-envelope-calculation that abstracts from future profits from the customer relationship via repeat purchases and from customers switching to other payment types.

good digital footprint score that would not have been accepted solely based on the credit bureau score, and it rejects applications with a poor digital footprint score that would have been accepted solely based on the credit bureau score. Overall, this significantly improves the credit quality of the portfolio.

The E-commerce company accepted some of the unscorable customers based on a so-called “address score” prior to October 19, 2015. This address score is simply based on the area where someone lives, with applicants from areas with a good average creditworthiness getting better scores and applicants from areas with poor creditworthiness receiving worse scores. The address score thus allows some borrowers to get credit access without having an individual credit score. Note that the address score is available for all customers (because the E-commerce company knows the address of every customer). The default rate in this segment was very high (11.65%) prior to October 19, 2015. After October 19, 2015, when the firm starts using the digital footprint, acceptance rates remained steady at approximately 10%, but default rates dropped significantly (from 11.65% to 6.44%, i.e., by 45%). Thus, while the area where someone lives determined credit access prior to October 19, 2015, the digital footprint score resulted in access to credit in a way that is less discriminatory (in a sense that it does not solely depend on the address where a person lives). According to the firm, the default rate of 11.65% was not sustainable, these customers were only allowed to purchase via invoice because of a trial-and-error culture before October 19, 2015. The most plausible counterfactual without access to the digital footprint is therefore full credit rationing and no credit access for these customers.

Table 10 provides results for the default rate in a multivariate setup using a simple time series difference (default rates post- vs. pre-introduction of the digital footprint). We use a linear regression design and cluster standard errors by 2-digit ZIP codes.³⁶ Columns 1 and 2 reproduce the univariate results from panel A of Table 9, suggesting a drop in default rates of 1.3–1.4 PP after October 19, 2015. This simple difference design relies on the assumption that default rates would have remained stable in absence of the changes to the screening technology (introduction of digital footprint and expanded use of credit bureau score). The digital footprint was introduced on the same day for all purchases (October 19, 2015) precisely because it is so easy to access for the E-commerce firm. Therefore, unfortunately, the data at hand does not lend itself to a difference-in-difference design.

In the following columns, we provide further robustness tests to narrow down the required set of assumptions for a causal interpretation of digital footprint usage on default rates. First, default rates in the post period can be lower due to a change in the composition of purchases (such as purchases coming from different regions, different item categories, or a different gender

³⁶ Results are robust to using a logistic regression model (results are available on request).

Table 10
Development of default rates around the introduction of the digital footprint (multivariate results)

Dependent variable	(1) Difference post vs. pre	(2) Default (0/1) Difference post vs. pre, add categories	(3) Default (0/1) Add time trend, controls and FEs	(4) Default (0/1) Add subcategories	(5) Default (0/1) Narrower window around Oct. 19, 2015	(6) Default (0/1) Placebo test, 1-year later
Method	±6 weeks	±6 weeks	±6 weeks	±6 weeks	±4 weeks	±4 weeks
Sample						
Post	-0.014*** (-9.12)					
Post x ScoreAndDFAdded		-0.014*** (-5.88)	-0.014*** (-5.88)	-0.015*** (-6.13)	-0.015*** (-4.30)	0.001 (0.29)
Post x DFAdded		-0.013*** (-3.85)	-0.012*** (-3.04)			
Post x "DFAdded / High score"				-0.001 (-0.19)	0.000 (0.00)	0.002 (0.78)
Post x "DFAdded / Medium score"				0.003	0.003	0.004
Post x "DFAdded / Low score"				(0.65)	(0.46)	(1.07)
Post x "DFAdded / Unscorable"				-0.026** (-2.51)	-0.021* (-1.70)	-0.015 (-1.50)
				-0.052*** (-2.72)	-0.059*** (-2.66)	0.007 (0.43)
Time trend	No	No	0.000 (0.29)	0.001 (0.53)	0.001 (0.15)	-0.002 (-0.80)
Category FE (=variables from interaction terms as noninteracted variables)	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	No	Yes	Yes	Yes	Yes
Observations	44,703	44,703	44,703	44,703	30,322	28,905
Adj. R ²	.002	.003	.012	.021	.020	.012

We estimate changes in default rates around the weeks of October 19, 2015. The dependent variable is a default dummy which is equal to one if the claim has been transferred to a debt collection agency. Column 1 provides a regression using a sample window of ±6 weeks around the week of October 19, 2015. Column 2 splits up the post-effect into two categories: the category *ScoreAndDFAdded* consists of all observations where the October 19th rule change introduced both a credit bureau score and the digital footprint; the category *DFAdded* consists of all observations where the October 19th rule change introduced the digital footprint but a credit bureau score was requested both prior and after October 19, 2015. Column 3 adds a time trend (measured in months relative to October 19, 2015, for example, for an order on October 4, 2015, the variable takes on value of -0.50) and controls for order amount and for region fixed effects and fixed effects for the category of the purchased item. Column 4 further splits up the *DFAdded* category into four subcategories, and Column 5 uses a ±4-week window around the week of October 19, 2015. Column 6 provides a placebo test 1 year later. The sample includes both scorable and unscorable customers. All models are estimated using a linear regression model with standard errors clustered by 2-digit ZIP codes. For variable definitions, see Table A1.

composition). We therefore control for the observable characteristics of the purchases (category of the purchased item, the logarithm of the order amount, as well as gender and region fixed effects) in Column 3 of Table 10. Second, there might be an overall downward trend in default rates, for example, because of an overall improvement in the economy that we wrongly attribute to the change in screening technology. We therefore introduce a time trend as well in Column 3 of Table 10. Neither the controls nor the time trend has any measurable impact on our estimates, see Column 3 of Table 10. Column 4 splits the “DFAdded” category into four subcategories (same subcategories as in panel B of Table 9). Again, we see that the reduction in default rates is driven by unscorable customers and customers with a low credit bureau score. In all specifications, we have used a time window of ± 6 weeks around October 19, 2015, and we further narrow down this time to a ± 4 -week window in Column 5 of Table 10. A narrower window rules out all alternative explanations that are based on slowly moving economic variables. Finally, one might be concerned that payment behavior in September and beginning of October is generally different than payment behavior in November and December (e.g., customers might behave differently during Christmas time). To shed light on this, Column 6 provides a placebo test that uses October 19, 2016 (i.e., exactly 1 year later), as the event date. The placebo test gives a null result, suggesting that default rates were lower 6 weeks post-October 19 relative to 6 weeks pre-October 19 only in 2015 (when the screening technology was changed) and not in 2016 (when the screening technology remained unchanged).³⁷

Table 11 provides the same set of multivariate tests for the access to credit. Again, results from the univariate results (column “Invoice offered”) from Table 9 are confirmed. Taken together, the digital footprint allows some unscorable customers to gain access to credit while customers with a low-to-medium credit score can either gain or lose access to credit depending on their digital footprint. Default rates significantly drop upon inception of the digital footprint, demonstrating the large gains to adopting this information for the E-commerce firm.

To shed light onto how much the introduction of the digital footprint affected the profitability of the firm, we provide a simplified back-of-the-envelope calculation: on average, the firm conducted 18,000 transactions per month with an average purchase volume of EUR 320 yielding monthly net sales of EUR 5.76 mn. The average default rate of the sample with credit bureau score prior to the adoption of the digital footprint is around 2.5%. At the same time, the results in Tables 9 and 10 suggest that the introduction of the digital footprint decreases defaults by roughly one-third, yielding a decrease in default rates

³⁷ Two further tests are available on request: First, we compare default rates (as reported for consumer loans by the main credit bureau) and personal bankruptcy filings for the whole German population in 2016 relative to 2015 and do not find a comparable drop as in our sample after the introduction of the digital footprint. Second, we run a placebo test in every week in 2015/2016 within our sample. The drop in default rates reported in Table 10 is larger than in all fifty-two placebo tests constructed this way in our sample.

Table 11
Development of access to credit around the introduction of the digital footprint (multivariate results)

Method	(1) Invoice offered (0/1) Difference post vs. pre	(2) Invoice offered (0/1) Difference post vs. pre, add categories	(3) Invoice offered (0/1) Add time trend, controls and FEs	(4) Invoice offered (0/1) Add subcategories	(5) Invoice offered (0/1) Narrower window around Oct. 19, 2015	(6) Invoice offered (0/1) Placebo test, 1-year later
Sample	±6 weeks	±6 weeks	±6 weeks	±6 weeks	±4 weeks	±4 weeks
Post	0.002 (0.50)					
Post x ScoreAndDFAdded		-0.066*** (-25.18)	-0.054*** (-10.31)	-0.046*** (-10.48)	-0.054*** (-9.59)	0.002 (0.25)
Post x DFAdded		0.011* (1.85)	0.017** (2.63)			
Post x "DFAdded / High score"				0.030*** (3.78)	0.008 (0.82)	0.020 (1.62)
Post x "DFAdded / Medium score"				0.044*** (4.37)	0.022* (1.81)	-0.003 (-0.29)
Post x "DFAdded / Low score"				-0.022** (-2.58)	-0.030*** (-2.81)	0.001 (0.09)
Post x "DFAdded / Unscorable"				0.009 (1.57)	0.008 (1.32)	-0.044*** (-3.78)
Time trend	No	No	-0.007** (-2.26)	-0.013*** (-5.40)	-0.002 (-5.33)	-0.014* (-1.91)
Category FE (=variables from interaction terms as noninteracted variables)	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Fixed effects	No	No	Yes	Yes	Yes	Yes
Observations	110,438	110,438	110,438	110,438	74,417	65,602
Adj. R ²	.000	.323	.338	.582	.581	.414

We estimate changes in the quantity of lending around the weeks of October 19, 2015. The dependent variable is a dummy of whether or not payment by invoice was offered to a client. Column 1 provides a regression using a sample window of ±6 weeks around the week of October 19, 2015. Column 2 splits up the post-effect into two categories: the category *ScoreAndDFAdded* consists of all observations where the October 19th rule change introduced both a credit bureau score and the digital footprint; the category *DFAdded* consists of all observations where the October 19th rule change introduced the digital footprint but a credit bureau score was requested both prior and after October 19, 2015. Column 3 adds a time trend (measured in month relative to October 19, 2015, for example, for an order on October 4, 2015, the variable takes on value of -0.50) and controls for order amount and gender and for region fixed effects and fixed effects for the category of the purchased item. Column 4 further splits up the *DFAdded* category into four subcategories, and Column 5 uses a ±4-week window around the week of October 19, 2015. Column 6 provides a placebo test 1 year later. The sample includes both scorable and unscorable customers. All models are estimated using a linear regression model with standard errors clustered by 2-digit ZIP codes. For variable definitions, see Table A1.

of approximately 0.8 PP or around EUR 50,000 defaulted loans per month, equivalent to losses of EUR 35,000 per month/0.6 PP with a loss given default of 70%. Assuming a 5% operating margin, this would be an improvement in the operating margin of more than 10% that is attributable to the introduction of the digital footprint.³⁸

The appendix seeks to answer the question of whether the E-commerce firm is a special case or is representative in its use of digital footprints. To shed light on this, we provide anecdotal examples of firms that are known to use the digital footprint both for lending decisions and in insurance markets. These examples show that using the digital footprint is not restricted to this specific firm, but indeed applied more broadly for lending and even in insurance markets.

3.3 Access to credit for the unbanked

The lack of access to financial services affects around 2 billion working-age adults worldwide and is seen as one of the main drivers of inequality.³⁹ Particularly in developing countries, the inability of the unbanked population to participate in financial services is often caused by a lack of information infrastructure, such as credit bureau scores. Recent policy debates have centered on the use of alternative digital data sources to judge the creditworthiness of previously unscorable customers, including reports by the World Bank, the *Harvard Business Review*, and the G20.⁴⁰ While expectations are high, a dearth of rigorous research actually analyzes whether digital footprints are indeed informative in predicting consumer payment behavior. As digital footprint variables are available for any customers with a mobile device, analyzing borrowers' digital behavior may present an opportunity to boost financial inclusion.

We test whether the digital footprint can present an opportunity to facilitate access to finance for customers who do not have a credit bureau score, which we label unscorable customers in our analysis. Note, however, that information from the basic credit bureau still exists for these customers, potentially limiting the external validity of our findings in settings where even the existence of a customer cannot be verified.⁴¹ The average default rate of unscorable customers in our sample is 2.49% (see Table 12), thereby clearly exceeding the default rate

³⁸ As a comparison, the average net margin for the Retail (Online) industry in the United States is 3.72% as of January 2018 (see http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/margin.html).

³⁹ The World Bank Group identifies financial inclusion as a key enabler of reducing poverty and boosting prosperity and promotes new use of data and digital technology as an opportunity for expanding access to financial services. See, for example, <http://www.worldbank.org/en/news/video/2016/03/10/2-billion-number-of-adults-worldwide-without-access-to-formal-financial-services> and <http://www.worldbank.org/en/topic/financialinclusion>. See Demirgüç-Kunt et al. (2018) for statistics about the distribution of unbanked across countries and the role of technology on financial inclusion. See also Allen et al. (2012) and Demirgüç-Kunt and Klapper (2013) for a discussion of the drivers of access to financial services across countries.

⁴⁰ See, in particular, Kumar and Muhota (2012), G20 (2016), and Kendall (2017).

⁴¹ See Section 2.1 for details.

for scorable customers of 0.94% (see Table 2). This is not surprising, given that unscorable customers are customers without credit record where uncertainty about repayment is likely to be higher. Interestingly, the AUC of the model using the digital footprint only is similar for unscorable customers compared to the AUC for scorable customers (72.2% vs. 69.6%), see Table 13 and Figure 6. Adding gender, the loan amount, the category of the purchased item, and time and region fixed effects also does not affect our results (Column 3 of Table 13).

Digital footprints are unique among nontraditional data sources in their broad coverage of almost every individual worldwide. Prior research has looked at nontraditional data sources, such as transaction and checking account activity, rental and bill payment history, insurance payments, debit-card use, property/asset data, and public records.⁴² However, few of these data points are likely to be available for unscorable customers, in particular in emerging markets. However, with the dramatic increase in the number of people with mobile phones in emerging markets, digital footprints are available even in countries with few official and reliable records (see Demirgüç-Kunt et al. 2018). We therefore argue that digital footprints are unique in their ability to significantly extend access to credit for the unbanked.

Taken together, these results suggest that digital footprints may help to overcome information asymmetries between lenders and borrowers when standard credit bureau information is not available. We clearly have to be cautious in interpolating these results from a developed country to unscorable customers in emerging markets. Still, recent activity in the FinTech industry suggests this is an avenue that FinTechs aim to take. Motivated by a dramatic increase in the availability of digital footprints in developing economies, new FinTech players have emerged that use digital footprints to challenge traditional banking options and develop innovative financing solutions.⁴³ These FinTechs have the vision to give billions of unbanked people access to credit when credit bureaus scores do not exist, thereby fostering financial inclusion and lowering inequality (for the link between availability of credit scores, access to credit, and inequality, see Pagano and Japelli 1993; Djankov, McLiesh, and Shleifer 2007; Beck, Demirgüç-Kunt, and Honohan 2009; Brown, Jappelli, and Pagano 2009). Our analysis aims to provide a first piece of evidence about the informativeness of the digital footprint for consumer payment behavior.

4. Conclusion

In this paper, we have analyzed the information content of the digital footprint—a trail of information that people leave online simply by accessing or registering on a Web site—for predicting consumer default. Using more than 250,000

⁴² For nontraditional data sources before the use of digital footprints, see, in particular Maas (2008).

⁴³ See, for example Kendall (2017).

Table 12
Digital footprint variables and default rates (unscorable customers)

Variable	Value	Observations	Proportion (%)	Default rate (%)	t-test against baseline
Device	All	15,580	100	2.49	
	Desktop	9,183	59	2.16	Baseline
	Tablet	2,618	17	1.64	(-1.64)
	Mobile	1,546	10	6.21***	(9.07)
	Do-not-track setting	2,233	14	2.28	(0.37)
Operating system	All	15,580	100	2.49	
	Windows	7,763	50	2.19	Baseline
	iOS	2,424	16	2.35	(0.47)
	Android	1,646	11	4.80***	(6.00)
	Macintosh	1,420	9	1.69	(-1.20)
	Other	94	1	7.45***	(3.42)
	Do-not-track setting	2,233	14	2.28	(0.27)
E-mail host	All	15,580	100	2.49	
	Gmx (partly paid)	3,681	24	2.42	Baseline
	Web (partly paid)	3,349	21	2.63	(0.56)
	T-Online (affluent customers)	1,709	11	1.52**	(-2.12)
	Gmail (free)	1,691	11	3.61**	(2.46)
	Yahoo (free, older service)	731	5	3.15	(1.14)
	Hotmail (free, older service)	546	4	2.75	(0.46)
	Other	3,873	25	2.22	(-0.57)
Channel	All	15,580	100	2.49	
	Paid	6,446	41	2.89	Baseline
	Direct	3,257	21	1.87***	(-2.99)
	Affiliate	1,394	9	2.65	(-0.47)
	Organic	1,178	8	2.55	(-0.64)
	Other	1,072	7	2.15	(-1.36)
	Do-not-track setting	2,233	14	2.28	(-1.50)
Checkout time	All	15,580	100	2.49	
	Evening (6 p.m.-midnight)	6,343	41	2.05	Baseline
	Night (midnight-6 a.m.)	369	2	3.52*	(1.91)
	Morning (6 a.m.-noon)	2,959	19	2.74**	(2.08)
	Afternoon (noon-6 p.m.)	5,909	38	2.78***	(2.62)
Do-not-track setting	All	15,580	100	2.49	
	No	13,347	86	2.52	Baseline
	Yes	2,232	14	2.28	(-0.68)
Name in e-mail	All	15,580	100	2.49	
	No	4,432	28	3.93	Baseline
	Yes	11,148	72	1.92***	(-7.26)
Number in e-mail	All	15,580	100	2.49	
	No	12,958	83	1.99	Baseline
	Yes	2,622	17	4.96***	(8.91)
Is lowercase	All	15,580	100	2.49	
	No	14,557	93	2.21	Baseline
	Yes	1,023	7	6.45***	(8.43)
E-mail error	All	15,580	100	2.49	
	No	15,294	98	2.31	Baseline
	Yes	286	2	12.24***	(10.72)

This table provides default rates by category of each of the digital footprint variables. The sample is based on *unscorable* customers, that is, the set of customers for which a credit bureau score is *not* available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

Table 13
Default regressions (unscorable customers)

Variables	(1)		(2)		(3)	
	Digital footprint for unscorable customers		For comparison: Digital footprint for scorable customers (Column 2 of Table 4)		Digital footprint for unscorable customers, fixed effects	
	Coef.	z-stat	Coef.	z-stat	Coef.	z-stat
Computer & operating system						
Desktop/Windows	Baseline		Baseline		Baseline	
Desktop/Macintosh	-0.26	(-1.10)	-0.07	(-0.53)	-0.26	(-1.06)
Tablet/Android	-0.22	(-0.86)	0.29***	(3.19)	-0.11	(-0.44)
Tablet/iOS	-0.45*	(-1.72)	0.08	(1.05)	-0.45*	(-1.67)
Mobile/Android	1.07***	(5.97)	1.05***	(17.25)	1.08***	(5.38)
Mobile/iOS	0.63***	(2.69)	0.72***	(9.07)	0.69***	(2.76)
E-mail host ^a						
Gmx	Baseline		Baseline		Baseline	
Web	0.02	(0.11)	0.00	(0.00)	0.01	(0.04)
T-Online	-0.39	(-1.14)	-0.40***	(-3.90)	-0.42	(-1.21)
Gmail	0.33	(1.36)	0.34***	(3.81)	0.31	(1.34)
Yahoo	0.17	(0.61)	0.75***	(9.19)	0.11	(0.36)
Hotmail	-0.02	(-0.06)	0.35***	(3.70)	-0.13	(-0.41)
Channel						
Paid	Baseline		Baseline		Baseline	
Affiliate	-0.08	(-0.39)	-0.49***	(-5.35)	-0.07	(-0.34)
Direct	-0.42**	(-2.34)	-0.27***	(-4.25)	-0.52***	(-2.66)
Organic	-0.05	(-0.24)	-0.15*	(-1.79)	0.03	(0.13)
Other	-0.27	(-1.21)	-0.47***	(-4.50)	-0.18	(-0.82)
Checkout time						
Evening (6 p.m.-midnight)	Baseline		Baseline		Baseline	
Morning (6 a.m.-noon)	0.30*	(1.81)	0.28***	(4.50)	0.32*	(1.88)
Afternoon (noon-6 p.m.)	0.39***	(2.70)	0.08	(1.42)	0.40***	(2.76)
Night (midnight-6 a.m.)	0.44	(1.38)	0.79***	(7.73)	0.45	(1.38)
Do-not-track setting	-0.16	(-0.83)	-0.02	(-0.25)	-0.23	(-1.18)
Name in e-mail	-0.59***	(-4.67)	-0.28***	(-5.67)	-0.54***	(-4.24)
Number in e-mail	0.63***	(4.31)	0.26***	(4.50)	0.61***	(4.07)
Is lowercase	0.95***	(5.45)	0.76***	(13.10)	0.91***	(4.71)
E-mail error	1.66***	(7.81)	1.66***	(20.00)	1.67***	(6.85)
Constant	-3.80***	(-19.20)	-4.92***	(-62.87)	-6.00***	(-11.32)
Control for Gender, Item category, Loan amount, and month and region fixed effects		No		No		Yes
Observations		15,580		254,819		15,580
Pseudo R ²		.0906		.0524		.1645
AUC		0.722		0.696		0.803
(SE)		(0.014)		(0.006)		(0.011)
Difference to AUC=50%		0.222***		0.196***		0.302***
AUC (OOS)		0.684		0.688		0.659

This table provides regression results for a sample of *unscorable* customers utilizing the same model specifications from Table 4. We estimate default rate regressions where the dependent variable (*Default(0/1)*) is equal to one if the claim has been transferred to a debt collection agency. Column 1 provides results using the digital footprint variables as independent variables. Column 2 provides a comparison to the results for the sample of scorable customers. Column 3 adds additional controls (*Gender, Loan amount, Item type*) and month and region fixed effects. Age is provided by the credit bureau and thus not available for unscorable customers. All models are estimated using a logistic regression model. Standard errors are adjusted for 97 clusters by 2-digit ZIP codes. Out-of-sample AUCs are denoted by AUC (OOS) and are determined using the same methodology from Table 5. The sample in Columns 1 and 3 is based on *unscorable* customers, that is, the set of customers for which a credit bureau score is *not* available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

We only report coefficients for the 6 largest e-mail providers even though we use the largest 18 categories in the regression (all e-mail providers with at least 1,000 observations). Using only the 6 reported e-mail hosts does not significantly affect the results.

^a We omit the coefficients for the rare combinations that contain other operating systems, see Table A5 for descriptive statistics.

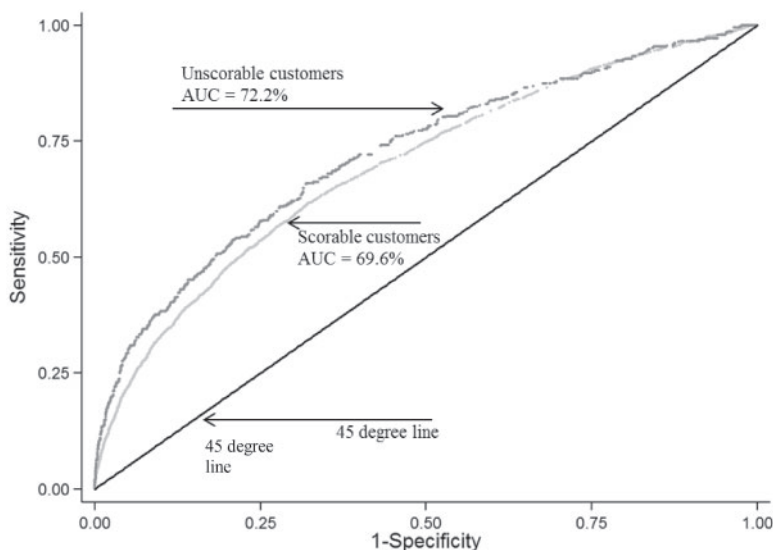


Figure 6

AUC for scorable versus unscorable customers

This figure illustrates the discriminatory power for different samples by providing the receiver operating characteristics curve (ROC curve) and the area under curve (AUC) for scorable customers (light gray) and unscorable customers (dark gray). The ROC curves are estimated using a logistic regression of the default dummy on the digital footprint. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

observations, we show that even simple, easily accessible variables from the digital footprint match the information content of credit bureau scores. Furthermore, digital footprints complement rather than substitute for credit bureau information, implying that a lender that uses information from both sources (credit bureau + digital footprint) can make superior lending decisions compared to lenders that only access one of the two sources of information. We document that default rates drop significantly after adoption of the digital footprint, and customers with good digital footprints gain access to credit while customers with poor digital footprints lose access to credit.

We also show that the discriminatory power for unscorable customers matches the discriminatory power for scorable customers. Given the widespread adaption of smartphones and corresponding digital footprints, the use of digital footprints thus has the potential to boost access to credit for some of the currently 2 billion working-age adults worldwide who lack access to services in the formal financial sector, thereby fostering financial inclusion and lowering inequality.

Our results are subject to the Lucas (1976) critique, with customers potentially changing their online behavior if digital footprints are widely used

in lending decisions. We argue that digital footprints also warrant an in-depth discussion if the Lucas critique applies. This is because if people change their online behavior due to the use of digital footprints, this may imprint people's everyday life by causing them to behave differently than they would otherwise. The digital footprint might evolve as the digital equivalent of the expensive suit that people wore before visiting a bank. The key difference is that managing one's digital footprints, as opposed to wearing an expensive suit, broadly affects one's everyday life. It is also crucially different from managing one's credit bureau score, which is related to prudent *financial* behavior as opposed to choices and habits in everyday life.

Regulators are likely to watch the use of digital footprints closely. Regulators worldwide have long recognized the key role of credit scores for consumers' access to key financial products. Accordingly, lending acts worldwide, such as the Equal Credit Opportunities Act in the United States, legally prohibit the use of variables that can lead to an unfair discrimination of specific borrower groups. Overall, lenders using digital footprints are therefore likely to face scrutiny whether the digital footprint proxies for information violating fair lending acts (see also Fuster et al. 2018 on this issue). Finally, it is also conceivable that incumbent financial institutions, threatened by competitors using digital footprints, use their well-established access to politicians and regulators to lobby for stricter regulation of the use of digital footprints on these grounds.

Appendix

This appendix seeks to answer the question of whether the E-commerce firm is a special case or is representative in its use of digital footprints. To shed light on the answer, we provide case studies of firms known to use the digital footprint, both for lending decisions and in insurance markets. This analysis aims to show that using the digital footprint is not restricted to this specific firm, but indeed applied more broadly for lending and even in insurance markets. Similar to banks, firms are usually silent about the specific parameters they are using for their internal scoring models.

Table A6 provides examples of companies that are known to be using the digital footprint for credit scoring, lending or insurance pricing. The aim of the table is not to provide a complete list, but rather to provide a sample of larger firm operating in various continents for which specific evidence on the use of digital footprint is available. Examples include, among others, Klarna, one of the largest payment service providers in Europe covering 90,000 merchants and 60 million end customers; Admiral, the largest U.K. car insurer, who admitted to charging Hotmail users higher car insurance premia in 2018; LenddoEFL, a firm providing credit scoring that was founded in Harvard's Entrepreneurial Finance Lab; Sesame Credit, the largest credit scoring provider in China; and Kreditech, one of the largest German FinTech startups that provides loans in various emerging markets. Overall, we observe that the use of digital footprints at our E-commerce firm is not special, but used by both FinTech start-up, large (European) payment service providers and even in the insurance sector. For two of the most prominent cases, Klarna and Admiral insurance, detailed use cases are available on request.

Appendix Figure and Tables

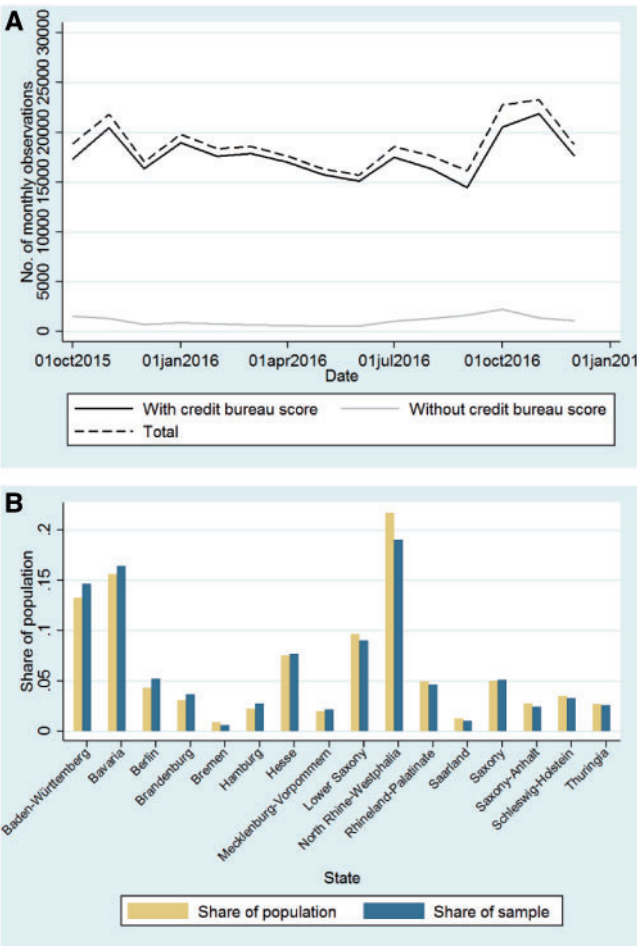


Figure A.1
Number of observations per month and geographic distribution of our sample compared to the German population
Panel A shows the monthly number of observations for scorable customers, unscorable customers, and the total sample. The sample period ranges from October 19, 2015 to December 2016. The number of observations for October 2015 is scaled up by a factor of 31/13 to make it comparable to a monthly figure. Panel B illustrates the share of customers by state in our sample compared to the German population by state. The German population by state is as of 2015 (*source*: German Federal Statistical Office). The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

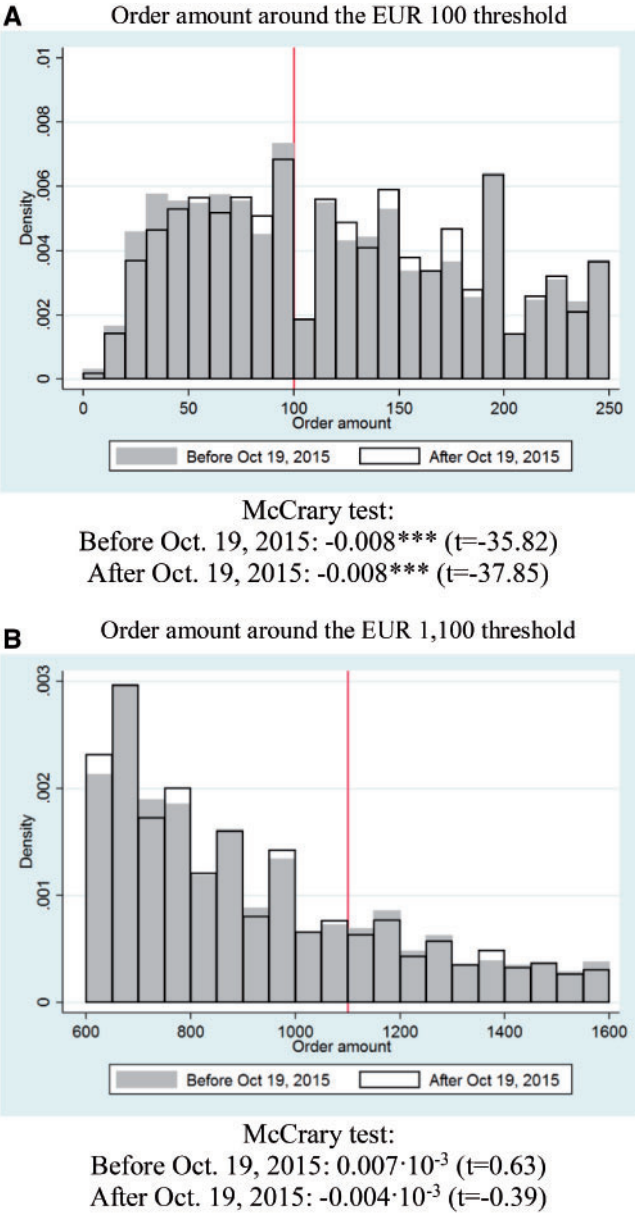


Figure A.2
Histogram of order amounts
This figure depicts a histogram of order amounts around the EUR 100 threshold (panel A) and the EUR 1,100 threshold (panel B). Results of a formal McCrary test for a discontinuity in the density are presented below each figure. In panel A, the EUR 100 threshold existed *after* October 19, 2015, but not before October 19, 2015. In panel B, The EUR 1,100 threshold existed *before* October 19, 2015, but not after October 19, 2015.

Table A1
Description of variables

Variable	Description	Unit
Order, customer, credit bureau score, and payment behavior		
<i>Order amount</i>	Purchase amount in EUR	Numerical variable
<i>Gender</i>	Gender of customer (female or male)	Dummy variable
<i>Age</i>	Age of customer in years. Information about age is obtained from the credit bureau.	Numerical variable
	Missing information on age indicate that the credit bureau does not have information about a customer's age	
<i>Region</i>	2-digit ZIP codes of the buyer's address	Numerical variable
<i>Credit bureau score</i>	Credit bureau score. The score is based on credit history data from various banks, sociodemographic data, as well as payment behavior data sourced from retail sales firms, telecommunication companies, and utilities	Numerical variable, 0 = worst, 100 = best
<i>Default</i>	Dummy variable equal to one if the claim is transferred to a debt collection agency (i.e., the customer did not pay the invoice after the third reminder of the firm)	Dummy variable
<i>LGD</i>	Loss given default, measured as a percentage of the purchase value	Numerical variable (between 0 and 1)
Digital footprint variables		
<i>Device type</i>	Device type. Main examples: Desktop, Tablet, Mobile.	Categorical variable
<i>Operating system</i>	Operating system. Main examples: Windows, iOS, Android, Macintosh	Categorical variable
<i>E-mail host</i>	E-mail host. Main examples: Gmx, Web, T-Online, Gmail, Yahoo, Hotmail	Categorical variable
<i>Channel</i>	Channel through which customer comes to Web site. Main examples: Paid (including paid and retargeted clicks), Direct, Affiliate, Organic	Categorical variable
<i>Checkout time</i>	Time of day of purchase	Numerical variable (0–24 hr)
<i>Do-not-track setting</i>	Dummy equal to one if customer does not allow tracking of device and operating system information, and channel	Dummy variable
<i>Name in E-mail</i>	Dummy equal to one if first or last name of customer is part of e-mail address	Dummy variable
<i>Number in E-mail</i>	Dummy equal to one if a number is part of e-mail address	Dummy variable
<i>Is lowercase</i>	Dummy equal to one if first name, last name, street, or city are written in lowercase	Dummy variable
<i>E-mail error</i>	Dummy equal to one if e-mail address contains an error in the first trial (Note: Clients can only order if they register with a correct e-mail address)	Dummy variable

Table A2
Comparability of default rates to other retail data sets

Study	Sample	Default rate (%)	Time horizon	Default rate (annualized, %)
This study This study	270,399 purchases at a German E-commerce company between October 2015 and December 2016	1.0	~4 mo.	3.0
Germany Berg, Puri, and Rocholl (2017)	100,000 consumer loans at a large German private bank, 2008–2010	2.5	12 mo.	2.5
Puri, Rocholl, and Steffen (2017)	1 million consumer loans at 296 German savings banks, 2004–2008	1.1	12 mo.	1.1
Schufa 2017 ^a (study by the major credit bureau in Germany)	17.4 million consumer loans covered by the main credit bureau in Germany in 2016	2.2	12 mo.	2.2
Schufa (2016) ^a (study by the major credit bureau in Germany)	17.3 million consumer loans covered by the main credit bureau in Germany in 2015	2.4	12 mo.	2.4
Deutsche Bank (2016) ^b	All retail loans of Deutsche Bank (i.e., the largest German bank)	1.5 (Basel II PD estimate)	12 mo.	1.5
Commerzbank (2016) ^c	All retail loans of Commerzbank (i.e., the second-largest German bank)	2.0 (Basel II PD estimate)	12 mo.	2.0
United States Federal Reserve ^d	Charge-off rate on consumer loans, Q4/2016	2.09	12 mo. (annualized quarterly data)	2.09
Federal Reserve ^d	Charge-off rate on consumer loans, Q4/2015	1.76	12 mo. (annualized quarterly data)	1.76
Hertzberg, Liberman, and Paravisini (2016)	12,091 36-mo. Loans from Lending Club issued between December 2012 and February 2013	9.2	~26 mo.	4.2
Lending Club (own analysis)	375,803 36-mo. Loans from Lending Club issued between October 2015 and December 2016	5.11	12 mo.	5.11
Iyer et al. (2016)	17,212 36-mo. Loans from Prosper.com issued between February 2007 and October 2008	30.6	36 mo.	10.2
Hildebrandt, Puri, and Rocholl 2017	12,183 loans from Prosper.com between February 2007 and April 2008	10.8%–18.6	per 1,000 d.	3.9–6.8

^a Schufa is the main credit bureau in Germany, comparable to Fair Isaac Newton in the United States, for example. For data on 2016 default rates, see Schufa (2017, p. 17, figure 2.11). For the data on 2016 default rates, see Schufa (2016, p. 18, figure 2.11).

^b See Deutsche Bank's (2016, p. 90, table) Pillar 3 Report, available via https://www.db.com/fr/en/download/Deutsche_Bank_Pillar_3_Report_2016.pdf.

^c See Commerzbank's (2016, p. 34, Table 12) Disclosure Report, available via https://www.commerzbank.de/media/aktionaere/service/archive/konzern/2017/Disclosure_Report_2016.pdf.

^d Series "CORCABAS" in FRED (see <https://fred.stlouisfed.org/series/CORCABAS>).

Table A3
Comparability of AUC to other retail data sets

Study	Sample	AUC using credit bureau score (%)	AUC change (PP)	Combined AUC (%)
AUC using the credit bureau score only This study	270,399 purchases at a German E-commerce company in 2015/2016	68.3	+ 5.3	73.6
Berg, Puri, and Rocholl (2017) ^a	100,000 consumer loans at a large German private bank, 2008–2010	66.6	+8.8	75.4
Puri, Rocholl, and Steffen (2017) ^a	1 million consumer loans at 296 German savings banks, 2004–2008	66.5	+11.9	78.4
Iyer et al. (2016)	17,212 36-mo. Loans from Prosper.com issued between February 2007 and October 2008	62.5	+5.7	68.2
Lending Club (own analysis)	375,803 36-mo. Loans from Lending Club issued between October 2015 and December 2016 ^b	59.8	+8.9	71.4
AUC and changes in the area under the curve using other variables in addition to the credit bureau score				
This study	Digital footprint versus credit bureau score only			
Berg, Puri, and Rocholl (2017) ^a	Bank internal rating (which includes credit bureau score) versus credit bureau score only			
Puri, Rocholl, and Steffen (2017) ^a	Bank internal rating (which includes credit bureau score) versus credit bureau score only			
Iyer et al. (2016)	Interest rates versus credit bureau score only			
Iyer et al. (2016)	All available financial and coded information (including credit bureau score) versus credit bureau score only			
Lending Club (own analysis)	Lending Club loan grade (which includes credit bureau score) versus credit bureau score only		+11.9	71.7

AUC, area under the curve.

^a These results are not in the original papers but were provided to us by the authors using exactly the same data set from the paper.

^b Results are very similar for 60-month loans.

Table A4
Descriptive statistics for computer and operating system category (scorable customers)

Variable	Value	Observations	Proportion (%)	Default rate (%)	t-test against baseline
Computer and Operating system	All	254,819	100	0.94	
	Desktop/Windows	123,092	48	0.74	Baseline
	Desktop/Macintosh	21,159	8	0.69	(−0.75)
	Desktop/other	1,628	1	0.74	(−0.03)
	Tablet/Android	15,111	6	1.11***	(4.86)
	Tablet/iOS	29,940	12	0.79	(0.88)
	Tablet/other	524	0	1.53**	(2.08)
	Mobile/Android	13,967	5	2.53***	(20.92)
	Mobile/iOS	11,531	5	1.80***	(11.90)
	Mobile/other	1,310	1	1.15*	(1.68)
	Do-not-track setting	36,557	14	0.88***	(2.70)

This table provides descriptive statistics for the computer and operating system category. The sample is based on scorable customers, that is, the set of customers for which a credit bureau score is available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

Table A5
Descriptive statistics for computer and operating system category (unscorable customers)

Variable	Value	Observations	Proportion (%)	Default rate (%)	t-test against baseline
Computer and operating system	All	15,580	100	2.49	
	Desktop/Windows	7,681	49	2.20	Baseline
	Desktop/Macintosh	1,420	9	1.69	(−1.23)
	Desktop/other	82	1	6.10**	(2.37)
	Tablet/Android	857	6	2.10	(−0.19)
	Tablet/iOS	1,737	11	1.44**	(−2.02)
	Tablet/other	24	0	0.00	(−0.73)
	Mobile/Android	789	5	7.73***	(9.15)
	Mobile/iOS	687	4	4.66***	(4.03)
	Mobile/other	70	0	4.29	(1.18)
	Do-not-track setting	2,233	14	2.28	(0.24)

This table provides descriptive statistics for the computer and operating system category. The sample is based on unscorable customers, that is, the set of customers for which a credit bureau score is not available. The sample period ranges from October 19, 2015 to December 2016. For variable definitions, see Table A1.

Table A6
Other use cases of digital footprint usage

Company	Main region	Company description/relevance	Digital footprint usage
Klarna	Europe	Swedish payment service provider covering 90,000 merchants and 60 million end customers in Europe. Klarna provides point-of-sale lending to its customers	Uses time-of-the-day in its scoring model, states that it collects e-mail host, device type, browser settings, operating system, and screen resolution to evaluate which payment methods to make available
Admiral Insurance Group	UK	The U.K.'s leading car insurance company with 3 million insurance plan owners	Drivers applying with a "Hotmail" e-mail address are charged higher insurance fees, as the company finds that some e-mail domain names are associated with more accidents than others
Sesame Credit	China	Run by Alibaba affiliate Ant Financial, Sesame Credit is the leading Chinese "social credit" rating firm with 520 million users ^d	Sesame Credit gives users a score based on five dimensions of information: personal information, payment ability, credit history, social networks and online behaviors
LenddoEFL	Emerging markets	LenddoEFL is a company that came into existence via the merger of the Harvard-based Entrepreneurial Finance Lab and Lenddo, a Singapore-based alternative credit scoring firm. LenddoEFL is a credit scoring provider, serving 6 million people and lending \$2 billion USD in emerging markets ^b	Uses variables, such as smartphone data, form-filling analytics, text length, browser data, mouse data, Wi-Fi networks used, or, even, phone battery life ^c
ZestFinance	United States	Founded by former Google CIO Douglas Merrill, ZestFinance provides "credit scores for hundreds of millions of prospective borrowers worldwide" and is one of the fastest growing technology start-ups in the United States ^d ZestFinance partners with JD.com, China's largest e-commerce business, and Baidu, China's dominant Web search provider ^e	Applies machine learning and "Google-like math to credit decisions," on thousands of potential credit variables including proper spelling and capitalization in online application forms, time of day making online purchases ^f

(Continued)

Table A6
(Continued)

Company	Main region	Company description/relevance	Digital footprint usage
Branch International	Africa	A U.S.-based start-up running the top finance app in Africa with 1 million borrowers ^g	Uses mobile phone data, including grammar and punctuation in text messaging, time of day of calls to evaluate potential borrowers ^h
Cignifi	Emerging markets	A U.S.-based start-up providing credit scores mainly in emerging markets. In 2016, Cignifi announced a "multi-year partnership" with Equifax, one of the largest consumer credit reporting agencies in the United States. ⁱ Cignifi's Board includes former CEO of FICO, the leading provider of consumer risk scores in the United States ^j	Partnering with leading global Telco brands, including Telefonica, AT&T, Globe Telecom, and Cignifi, uses mobile phone data, call duration, time calls are made, numbers frequently called, who initiates calls, or the frequency of adding airtime credit on prepaid phones ^k
Kredi'Tech	Emerging markets	A German real-time scoring technology provider, with over 2 million users ^l	Uses artificial intelligence and machine learning, processing up to 20,000 data points per application. Simple variables, such as device data and operating systems, are used. Also, different behavioral analytics (movement and duration on the Web page), or even the font installed on the computer, the time spent filling out the online application or whether the customer copy and pastes input data play a role in the scoring model ^m

This table provides examples of companies that are using the digital footprint for credit scoring, lending or insurance pricing based on anecdotal evidence. The aim of the table is not to provide a complete list, but rather to provide a sample of larger firms from various countries for which anecdotal evidence on the use of digital footprint is available.

^a Nieuwenhaus (2018).
^b <https://includefbillion.com/>.
^c King (2016).
^d <https://www.zestfinance.com/zaml>.
^e ZestFinance (2016).
^f Reisinger (2015) and O'Neill (2016).
^g <https://globenewswire.com/news-release/2018/03/28/1454819/0/en/Branch-International-Raises-70M-Series-B-to-Bring-World-Class-Financial-Services-to-Emerging-Markets.html>.
^h Cheney (2016).
ⁱ Business Wire (2016).
^j Cignifi (2017).
^k <https://cignifi.com/>.
^l <https://www.monedo.com/>.
^m See <https://www.kreditech.com/what-we-do> and DGAP (2012).

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