Consumer Credit Reporting Data

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Following the financial crisis, economists are increasingly drawing on credit reporting data in their research. We explain the information economics of these data and review the institutional details on their content currently available to consumers, firms, and researchers, including variables such as credit scores. We offer practical guidance to researchers to show how these data can be and are used to study a broad range of topics across economics fields. We discuss how to create new panels, construct surveys that sample from credit reporting data, and merge credit reporting data with external datasets. Finally, we use examples from the literature to explain how to use these data to construct economic measures such as credit access, financial distress, consumption, and mobility and discuss key measurement issues.
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1. Introduction

Consumer credit reporting data—also known as credit files, credit records, or credit bureau data—are arguably among the most economically consequential and informative data collected. These data are a market response to fundamental economic challenges of information asymmetry between borrowers and lenders (e.g., Jaffee and Russell, 1976; Stiglitz and Weiss, 1981). The market has designed a system where tens of thousands of firms voluntarily share information each month to produce data containing a history of consumers' borrowing and repayment behaviors for roughly nine-in-ten adults in the US (Brevoort, Grimm and Kambara, 2015), primarily recorded by three consumer credit reporting agencies (CRAs)—Equifax, Experian, and TransUnion. These data on borrowing, repay-

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ment, and other interactions with credit markets are the main information source for millions of lending decisions. And increasingly, these data inform research across a breadth of economic topics, extending well beyond their initial use in macroeconomics and household finance research.

In this paper we aim to explain the credit reporting processes and content of credit reporting data, provide practical guidance that helps standardize best practices, reduce barriers to entry for new researchers, support the work of journal editors and reviewers, outline frontiers for future research, and generally promote greater understanding among researchers about the challenges and opportunities of using these data. With these goals in mind, we begin in Section 2 with a summary literature review of how researchers have used these data to study topics across fields of economics.

To better understand how to use credit reporting data, it is helpful to understand why these data exist and how they are generated. Section 3 reviews theoretical work on information economics and credit market design to help to understand the existence and structure of credit reporting data.

We then discuss US credit reporting data in practice. Laws and regulations, industry standards, interruptions in data reporting, and legal settlements with credit reporting agencies have shaped how reporting occurs and what gets reported, but there is no comprehensive source documenting these complexities and describing the implications for academic research.[1] Accordingly, Section 4 summarizes the mechanics of the process creating these data to help researchers studying topics that do not readily align with how firms collected and use these data.

Section 5 then provides guidance on how researchers can construct credit reporting datasets including creating loan-level, individual-level and household-level panels, and how credit reports can be used as a sampling frame for surveys. Table 1 shows the credit reporting panels we know to be available for research at the time of writing. We also discuss the linking of credit reporting data to other data sources.

Section 6 provides an overview of the content of consumer credit reporting data for a general reader. Credit reporting data contain monthly data on consumers' outstanding credit accounts, debts in collection, applications for credit, public records such as bankruptcy, summary information created from these data, and demographic information such as consumers' age and primary residence. Further details specific to each different type of credit account (including home-based loans, credit cards, auto, and student loans) in credit reporting data are included in the Online Appendix that we would encourage users of these data to consult.

Credit scores are often used by researchers as summary statistics about consumers. In Section 7 we provide a general introduction to what credit scores—such as FICO and VantageScore—are, what does and does not go into their construction, and differences across scores.

Section 8 uses examples from the literature to provide practical guidance for researchers considering using these data

[1] Prior work describing the academic use of consumer credit reporting data only covers the early emergence of these data (Furletti, 2002; Avery et al., 2003; Miller, 2003), with much having changed since. Other early work focused exclusively on a specific example of these data (the New York Fed credit panel, Lee and Van der Klaauw (2010)).

to create economic measures of financial distress, credit access, consumption, and mobility. Finally, Section 9 briefly concludes.

2. Literature Review

Here we provide a brief summary of the literature using credit reporting data, highlighting both key contributions as well as the wide range of economic fields in which they have been used. The Online Appendix provides a more exhaustive list of relevant papers by JEL code.

The earliest well-known research using credit reporting data are studies of the 2007–2008 US financial crisis, for example work by Mian and Sufi (2009). Research on the financial crisis then expanded from this early work using aggregated credit reporting data to explore the lessons from individual-level data (e.g., Mian and Sufi, 2011; Adelino, McCartney and Schoar, 2020) and has shed light on the role of labor markets in the crisis (Mian and Sufi, 2014). Since the crisis, additional work in ***macroeconomics*** has also shown the value of credit reporting data in areas including monetary economics, fiscal policy, consumption behavior, and the study of business cycles.

In the study of monetary policy, this is particularly true with respect to the role of home mortgage borrowing, which leads to path dependence in the effectiveness of monetary policy (e.g., Berger et al., 2021) and regional heterogeneity in monetary policy's implications for inequality (e.g., Beraja et al., 2019). This work also highlights the importance of equity extraction and mortgage refinancing (e.g., Bhutta and Keys, 2016; Di Maggio, Kermani and Palmer, 2020).

Complementing this work on monetary policy, macroeconomic studies of the effectiveness of fiscal policy have also benefited from credit reporting data and have focused on loan products beyond mortgages (e.g., Mian and Sufi, 2012). Similarly, macroeconomists have used these data to study consumption and overall borrowing behavior (e.g., Mian, Rao and Sufi, 2013; Benmelech, Meisenzahl and Ramcharan, 2017; Chatterjee et al., 2020). Researchers have also used credit reporting data to study the drivers and dynamics of the business cycle (e.g., Gross, Notowidigdo and Wang, 2020; Patterson, 2023).

A large body of ***finance*** research also uses these data. The ability to observe the portfolio of debt held by consumers over time enables an understanding of household finances and measurement of how policy changes can affect credit access and financial distress.[2] Research using these data has studied lending and borrowing via auto loans (e.g., Chakrabarti and Pattison, 2019), credit cards (e.g., Keys and Wang, 2019), mortgages (e.g., Bhutta, Hizmo and Ringo, 2022), student loans (e.g., Di Maggio, Kalda and Yao, 2023), payday loans (e.g., Gathergood, Guttman-Kenney and Hunt, 2019), and FinTech (e.g., Fuster et al., 2019). As examples of the effects of specific policy interventions, Butcher and Munoz (2017) and Conway, Glazer and Plosser (2023) evaluate the impact of the Community Reinvestment Act on consumer credit access and outcomes.

The use of credit reporting data in research goes well beyond the macroeconomics and finance fields. Using credit reporting data in ***health economics*** to better understand the effects of health policies and events is a relatively new use of these data that saw significant growth starting in the 2010s. Several studies have used ge-

[2]For reviews of the field of household finance research see (Guiso and Sodini, 2013; Beshears et al., 2018; Gomes, Haliassos and Ramadorai, 2021) in which these data have proven valuable.

ographic or birth year information to show reductions in financial distress following expansions of health insurance coverage (Mazumder and Miller, 2016; Hu et al., 2018; Brevoort, Grodzicki and Hackmann, 2020; Batty, Gibbs and Ippolito, 2022). Others have used credit data linked to other data sources to document the financial consequences of health events such as hospital admissions (Dobkin et al., 2018), abortions (Miller, Wherry and Foster, 2023) and Alzheimer's diagnosis (Nicholas et al., 2021). Meanwhile, the growing use of medical credit cards and financing plans remains largely unexplored using credit record data.

Credit reporting data has also been used to inform studies in ***labor economics***. For example, studies linking credit and census data have advanced understanding of labor search and entrepreneurship (e.g., Herkenhoff, Phillips and Cohen-Cole, 2023, 2021), as have studies using a CRA's wage data from payroll records (e.g., Di Maggio et al., 2022). For example, Dobbie et al. (2020), Corbae and Glover (2018), Bartik and Nelson (2022), and Braxton, Herkenhoff and Phillips (2020) study the interaction between credit histories and labor market outcomes. Several analyses have relied on credit data to study the impact of minimum wage increases on spending, debt and access to credit (e.g., Aaronson, Agarwal and French, 2012; Cooper, Luengo-Prado and Parker, 2020; Gopalan et al., 2021). Similarly, several studies have analyzed the determinants and consequences of participation in the gig economy using credit data (e.g., Buchak, 2022; Fos et al., 2021). Relatively little work has explored intra-household and intergenerational behavior, but there is great potential in this avenue (e.g., Dokko, Li and Hayes, 2015; Benetton, Kudlyak and Mondragon, 2022; Bach et al., 2023).

Additionally, the coverage of these data—including nearly all US adults and following their movements over a long periods of time—makes them well-suited to studying issues in ***environmental economics*** and ***urban economics***. For example, several studies have investigated the effects of natural disasters on credit (e.g., Gallagher and Hartley, 2017; Billings, Gallagher and Ricketts, 2022) and non-credit outcomes such as migration (e.g., Bleemer and van der Klaauw, 2019; DeWaard, Johnson and Whitaker, 2020). Gallego and Meisenzahl (2022) study internal migration patterns following the Financial Crisis. Differences in credit profiles between renters and home owners were analyzed by Li and Goodman (2016), while the impact of tuition and student debt on home ownership was studied using credit data by Mezza et al. (2020) and Bleemer et al. (2021). These data can also be used to document regional disparities (e.g., George, Newberger and O'Dell, 2019) and help inform whether these reflect place-based or person-based factors (e.g., Keys, Mahoney and Yang, 2023).

There are many other fields where credit reporting data have only made small inroads so far, but where there is still a wealth of potential for their application by researchers. For example, there is work in ***public economics*** studying the impacts of fiscal stimulus, as with the cash for clunkers program (Mian, Sufi and Trebbi, 2010), and public policies, such as the moving-to-opportunity program (Miller and Soo, 2021), housing vouchers (Davis et al., 2021), EITC (Caldwell, Nelson and Waldinger, 2023), and traffic fines (Mello, 2023). At the same time, there is little work studying the relationship between debt and different retirement saving systems; an exception is Beshears et al. (2022)'s analysis of the effects of pension auto-enrollment on debt, tax changes, and borrowing decisions. Likewise, there is only a small existing ***political economy*** literature using these data (e.g., Mian, Sufi and Trebbi, 2010; Brown, Cookson and Heimer, 2019). However, the wide geographical coverage that can be shared down to a fine granularity (e.g., zipcode, census tract, or census block group) makes these data well suited to studying this topic by exploiting spatial variation; in principle, voter registration data and election participation data in some states may be linkable with credit reporting data.

These data have also been used in ***behavioral economics*** frameworks to, for example, better understand credit card borrowing (e.g., Meier and Sprenger, 2010; Ponce, Seira and Zamarripa, 2017; Gathergood et al., 2019). ***Industrial organization*** and ***marketing*** research has used versions of these data merged with marketing offers to study consumer demand (e.g., Agarwal, Chomsisengphet and Liu, 2010; Bertrand et al., 2010; Stango and Zinman, 2016; Han, Keys and Li, 2018) or optimal regulation under imperfect competition (e.g., Galenianos and Gavazza, 2022; Nelson, 2022), but there is considerable untapped potential to extend industrial organization and marketing research using these data. Finally, these data can be useful in informing topics of ***economic measurement***, especially for researchers looking for "big data" to take their machine learning and AI methods to (e.g., Albanesi and Vamossy, 2019; Blattner and Nelson, 2022; Blattner, Nelson and Spiess, 2021).

3. *Economics of Credit Reporting Data*

While CRAs and credit bureaus exist in many countries, there is considerable variety in credit reporting systems and in the type of consumer credit activity recorded. For a broader international perspective we refer the reader to Jappelli and Pagano (2002); Miller (2003); International Finance Corporatation (2012); World Bank (2012). To help understand these differences, and also how different credit reporting systems have many commonalities, we next review a literature that considers credit reporting data from a theoretical perspective. What role do these data play in addressing asymmetric information or other market failures? How does market structure affect the form of, and equilibrium effects of, credit reporting data? What potential roles are there for public policy in shaping the role of credit reporting data? We start with the topic of asymmetric information.

Many readers will have a sense that credit reporting data can help address information asymmetries. A rich body of research has sought to formalize this idea. In one early contribution, Pagano and Jappelli (1993) show how lenders may choose endogenously to share information with each other about their borrowers when facing adverse selection. In their model, information sharing is particularly helpful for screening with a set of borrowers who "migrate" from other banks, and when the propensity for "migration" is sufficiently high, it becomes privately optimal for banks to join a credit bureau, even if the credit bureau only has partial coverage across all banks. A key mechanism in this model is that banks can only access the information in the credit bureau if they agree to furnish such information themselves—a "give to get" participation rule that matches some real-world credit bureaus' de jure or de facto requirements.

Extending the literature on adverse selection and credit reporting data, Shaffer (1998) has some similar forces as in

Pagano and Jappelli (1993) but focuses on potential borrowers whose applications get rejected by one or more lender, generating a winner's curse for lenders who ultimately approve a previously rejected borrower; credit bureaus can expand credit supply by partially obviating these winner's curse concerns. Chatterjee et al. (2020) use a quantitative model that also delivers rich theoretical insights about the role of credit bureaus in equilibrium: the borrowing history observable through a credit bureau allows lenders to form a posterior about borrowers' (potentially dynamic) type, and this posterior is effectively a "type score" or a credit score that can reduce adverse selection. Blattner, Hartwig and Nelson (2022) likewise consider theoretically and quantitatively how credit histories are revealing of borrowers' dynamic types, focusing on two-dimensional hidden types that generate adverse selection à la Chiappori and Salanie (2000) and Mahoney and Weyl (2017).

A companion literature has focused on credit reporting data's role in reducing moral hazard. Papers in this area tend to share the Diamond (1989) insight that reputational incentives discipline moral hazard in debt markets with repeated interaction. There are several variations on this idea, however, that are specific to credit bureaus: Vercammen (1995) analyzes the optimality of finite credit histories (i.e., histories designed to have finite memory) in disciplining moral hazard when types are sufficiently persistent; Padilla and Pagano (1997) notes that the formation of a credit bureau helps discipline moral hazard in part because it commits *banks* not to extract future rents from borrowers who exert effort to repay their loans; Padilla and Pagano (2000) note that credit bureaus are most effective at disciplining moral hazard when only negative information (e.g., non-repayment), rather than positive information (e.g., a history of successful repayment) is recorded in the bureau. This distinction between "negative-only" and "positive" bureaus is reflected in actual credit bureaus, which have taken both forms in different places and times (Miller, 2003).

A particular form of moral hazard that credit bureaus may help address is sequential banking (Bizer and DeMarzo, 1992): a lender may be concerned that its borrower will take on additional debt from other lenders at a later date, increasing default risk above what the original loan was underwritten for. While it can be ambiguous whether subsequent credit access raises or lowers default risk (Hunt, 2005), this channel appears important in both practice and theory as a motivation for the use of credit bureau data: Bennardo, Pagano and Piccolo (2015) illustrate how credit reporting data address a sequential banking problem, and Bar-Isaac and Cuñat (2014) develop this idea focusing particularly on the role of "hidden lenders" who may create a sequential-banking externality that limits credit supply in the formal banking sector.

The emergence of and the role of credit bureaus also depends importantly on market structure. Here the essential economic idea draws on Petersen and Rajan (1995): lenders can extract information rents when they know more about their own borrowers than their competitors know (i.e., when there is asymmetric information between "inside" and "outside" lenders), and it may not be privately or socially optimal for lenders to share this information with each other. Similar analyses are developed in Sharpe (1990) (see also a correction by Von Thadden (2004)), Dell'Ariccia and Marquez (2004), and Dell'Ariccia (2001), and discussed in Hunt (2005). Pagano and Jappelli (1993) develop this formally in the context of credit bureau formation, showing that credit bureaus may be less likely to emerge when incumbent banks face more threat of competitor entry. Similarly, Marquez (2002) shows how large banks may have less incentive to join a credit bureau than small banks, given their inherent information advantage in lending to a larger share of the potential borrower pool. The economic forces here are often subtle, however: Hauswald and Marquez (2003) study how privately and publicly available information together affect credit supply, while Bouckaert and Degryse (2006) analyze how the interaction between market structure and information sharing depends crucially on the severity of adverse selection in the market.

Finally, a natural question is whether there is a role for public policy in spurring or regulating banks' participation in credit bureaus. Indeed, some countries mandate participation and have state-operated credit bureaus ("credit registers"). Even when credit bureaus are private entities, public policy tends to regulate what information gets reported, how long it is retained, and which parties are able to access that information. One line of theoretical research has focused on how long credit bureaus are optimally permitted to retain information (Elul and Gottardi, 2015; Bhaskar and Thomas, 2019; Kovbasyuk and Spagnolo, 2023). Other work asks which data points should be reported to a credit bureau when there is a trade-off between the inherent informativeness of, and the manipulability of, a particular signal (Ball, 2023).[3] An applied example of this manipulabitlity concern is the regulatory distinction in the United States between a "hard inquiry" and a "soft inquiry" when pulling a consumer's credit report, where the former is observable and has an adverse effect on a consumer's score and perceived default risk while the latter is not and does not; responding to consumer demand for avoiding a hard inquiry, some lenders recently have advertised that they will avoid using hard inquiries when pulling an applicant's credit, even though this depletes the value of credit reporting information for other lenders subsequently.

For brevity we do not review some other large literatures that are implicated in the regulation of credit reporting data, including work on discrimination and policy remedies for it (Charles and Guryan, 2011; Small and Pager, 2020), the literature on design of a scoring system (Bonatti and Cisternas, 2020; Frankel and Kartik, 2022), and the literature on consumer demand for privacy (Goldfarb and Tucker, 2012; Acquisti, Taylor and Wagman, 2016; Nissenbaum, 2020).

4. Credit Reporting Processes

Having explained *why* credit reporting data are collected, we next turn to the practicalities of *how* these data are constructed. Credit reporting data in the US are subject to a myriad of laws, regulations, and industry standards, which affect what data can be collected, in what form, and how they can be used.

The Fair Credit Reporting Act (FCRA) is the primary federal law regulating credit record data, credit reporting agencies (CRAs)—such as Equifax, Experian and TransUnion—and those who report credit information

[3] Ball (2023) aptly cites the following from Mark Zandi of Moody's to motivate the concern about manipulability in the context of consumer credit reporting: "The scoring models may not be telling us the same thing that they have historically, because people are so focused on their scores and working hard to get them up." See also Frankel and Kartik (2019) on manipulation in a single-signal environment.

to CRAs ("furnishers") in the United States. The FCRA was originally enacted to "require that consumer reporting agencies adopt reasonable procedures [...] with regard to the confidentiality, accuracy, relevancy, and proper utilization" of credit record information.[4] Notably, the FCRA does not require companies to "furnish" (i.e., provide) data on their lending agreements to any CRAs,[5] but it does require accuracy in what is furnished, and it specifies some information that must be reported if a furnisher provides any credit information. For example, conditional on reporting on an account, furnishers must report the credit limit, whether the account was voluntarily closed by the consumer, and the date of delinquency for any accounts in collection or charge-off if applicable.

The FCRA also has several requirements related to adverse information on credit records. For example, most negative information such as delinquencies and collection accounts can only remain on a credit report for up to seven years, except accounts discharged in some types of bankruptcy (Table 2). Furnishers must also notify consumers within 30 days of first furnishing this type of information to a CRA.[6]

Several other federal laws affect what and how credit data are reported. The Equal Credit Opportunity Act (ECOA), for example, requires that, conditional on furnishing credit information, lenders must furnish information for both spouses on any accounts where both spouses are liable for or able to use the account. As noted in Brevoort, Avery and Canner (2013), in practice furnishers provide this information for all associated borrowers (joint borrowers, cosigners, and authorized users) regardless of marital status. Additional laws, such as the Fair Credit Billing Act and Fair Debt Collection Practices Act, have implications for how disputed debts are investigated and reported. In addition, settlements and agreements with CRAs can change reporting standards, as is the case with collections and public records under the National Consumer Assistance Plan (NCAP).[7]

These laws are periodically updated in response to changes in various credit markets. Prior to the COVID-19 pandemic, payment deferrals and loan modifications were typically ad-hoc and varied by market and over time. For example, following the Great Recession, the US government introduced the Home Affordable Modification Program (HAMP) in 2009 to help homeowners under stress, but the existing credit reporting system at that time had no means to accommodate this new program and reported them as "making partial payment," harming credit scores. After the US Treasury recommended that the industry address the issue, the Consumer Data Industry Association (CDIA) created a new code designed to signify participation in the Making Home Affordable program including HAMP. Following the addition of the new code, credit score algorithms were adjusted to pick

[4]§602b 15 U.S.C. §1681a

[5]Other laws or federal rules, however, may require that some types of credit are reported. For example, in 2008 the Higher Education Act was amended to require companies to furnish information on all federal student loans they service so limit credit record differences for borrowers due to their servicer or lender (20 U.S.C. §1080a).

[6]The FCRA has additional requirements and restrictions relating to identify theft, permissible uses for credit report access, and medical information, among other things. For additional information, see 15 U.S.C. §1681 *et seq.*

[7]Even while NCAP has removed some collections and public records from recent credit reporting data, CRAs may still include these when data archived from prior 2018 are used for research (e.g., Fulford and Nagypál, 2023).

up the new code, as well. By contrast, at the start of the pandemic, the Coronavirus Aid, Relief, and Economic Security (CARES) Act amended the FCRA to define pandemic-related accommodations (e.g., mortgage loan forbearance) and outlined how the payment status should be reported for accounts with an accommodation (15 U.S.C. §1681s-2).

A consistent format for furnishing data is managed by CDIA, the primary trade association for the credit reporting industry. These formatting rules, known as the "Metro2" format, are also updated over time to reflect credit market developments (e.g., codes were added in 2022 for buy now, pay later (BNPL) products). Some fields are always required to be reported for all credit agreements (e.g., outstanding balances and delinquency status) and are prescriptive (e.g., how to define stages of delinquency). Other fields are not always required to be reported (e.g., payment amount) or provide a variety of options allowing furnishers discretion when deciding which reporting approach to use (e.g., forbearance).

Below, we further explain the practicalities of how credit reporting data are furnished, or transferred from consumer-facing firms to credit reporting agencies that aggregate and standardize the data before they are shared with researchers. Understanding this data generation process enables researchers to better anticipate and mitigate challenges for their research designs (e.g., confusion between stocks and flows, and a lack of stock-flow coherence, can both easily result from misunderstanding the furnishing process). This section also explains potential sources of measurement error, such as incomplete coverage of debts and people, fragmented records, reporting lags, and stale information.

4.1 Mechanics and Rules of Data Furnishing

If a firm (e.g., a lender) decides to furnish information, it may do so to one or more credit reporting agencies (CRAs). In practice, the firm enters a commercial data sharing agreement with a CRA to access software used to furnish information, typically with a fixed cost and a cost per batch of information furnished. Although the largest furnishers typically furnish information to all three nationwide CRAs, this is not the case for some smaller firms. Even some large firms have occasionally furnished to only one CRA (Harney, 2003). This means that credit file data do not contain all debts for all people. It can also mean data coverage can vary across CRAs,[8] credit products, and over time.

While each CRA has a duty under the FCRA to ensure data are accurate and to investigate disputed information, errors still exist in credit files. Tradelines (the industry's term for individual accounts) may be duplicated, for example due to being reported by both a loan originator and servicer; may include incorrect or outdated information, such as implying an account is open or delinquent when it is not; or may appear on the wrong person's credit file, due either to linkage errors or identify theft.

Under the FCRA, consumers can dispute incorrect information on their credit file through the CRA or the firm that furnished the information.[9] When this

[8] The CRAs themselves note that there may be differences in credit scores across sources due to "differing data sources and [the fact that] not all financial institutions report activity to all three bureaus" (see, TransUnion, "'Tri-Merge to Bi-Merge: A Look at the Repercussions to the Credit Ecosystem' available at https://www.transunion.com/content/dam/-transunion/global/business/documents/fs2023/-bimerge-analysis.pdf.

[9] Consumers may also dispute debts with a debt

occurs, the affected tradeline under investigation for a potential error receives a flag "Account In Dispute" that temporarily removes it from the consumers' credit file until the furnisher or CRA has conducted a review of its accuracy.

Across regulated credit, issues with credit reporting top those in the Consumer Financial Protection Bureau's (CFPB) consumer complaints database.[10] This is especially so during the COVID-19 crisis, possibly reflecting the broad range of idiosyncratic accommodations lenders took that left much potential for errors. In 2022, the CFPB reported deficiencies in how agencies responded to such complaints during the pandemic (Consumer Financial Protection Bureau, 2022).

Researchers need to be aware that accounts in dispute may drop in and out of the time series of data and may experience updates that reflect correcting a previous error rather than a change in consumer behavior. The Federal Trade Commission (FTC) has conducted a series of reports reviewing credit files errors and estimated in 2012 that 5% of consumers' credit files contained errors that meaningfully adversely affected their credit access (Federal Trade Commission, 2012).

4.2 Reporting Practices

As noted above, the furnishing of data to credit reporting agencies is voluntary, and, therefore, credit files do not contain all consumer debts for all people. Argyle et al. (2021) label debt not observed in credit files "shadow debt" and find that in their sample of bankruptcy filers, 7.4% of total debts are not observed in credit files from one CRA at time of filing; likewise, Guttman-Kenney and Hunt (2017) find differences across CRAs in the credit files of UK payday lending customers. Shadow debt may include some subprime loans not typically furnished to CRAs (e.g., some subprime auto loans and payday loans), unpaid medical, utility, or business bills, and missed rent. Informal lending (e.g., via family or friends) is also never observed in credit files.

Credit files only exist for individuals with a credit record, which are a subset of adults in the population (discussed in Section 5). Researchers therefore need to consider the implications for their study of individuals unobserved in credit files (also referred to as "credit invisibles" in Brevoort, Grimm and Kambara (2015)).

Even when an individual has a credit file, sometimes this file is a "fragment" record whereby the CRA is unable to consolidate an individual's credit data into the same credit file. Instead, one individual may have multiple, unlinked credit files for some periods. Fragmented records are especially likely to occur for credit records with lower quality identifying information (e.g., without social security numbers or SSNs), for individuals who move frequently, or who have common names. As result of these fragments, there are more credit records than adults in the US, and not accounting for this results in average debts per credit file to be lower than average debts per person.

Fragment records may merge into older records as the CRA receives new or corrected information, or if the CRA changes its matching algorithm. Existing records may also split into different records via the same processes when the CRA determines parts of a record belong to another record. These changes can make it difficult to properly define a panel of consumers over time. (Section 5

collector under the Federal Debt Collection Practices Act and Fair Credit Billing Act, which should also result in the removal of the debt from their credit record during the investigation.

[10] https://www.consumerfinance.gov/data-research/consumer-complaints/

below provides guidance on this issue.)

Additionally, credit file data are not real-time data. Researchers will typically analyze credit files in the form of "archives" or "retros" which recreate how a credit file appeared at a point-in-time (typically at the end of a calendar month). Instead of reflecting consumers' real-time credit outcomes as of a given point in time, a credit "archive" reflects the best available information furnished by lenders as of that date. While furnishing broadly operates at a monthly frequency, with new data being furnished by different lenders throughout the month, some lenders fail to report all new credit activity within a calendar month, leading to reporting lags. That is, a given archive may contain information for different calendar months for different credit products and different consumers.

Reporting lags are especially likely when accounts are opened, transferred, or severely delinquent. Such gaps complicate the tracking of loans over time as well as the computation of aggregate outstanding debt, often requiring imputation of debt balances that remain outstanding. There can be lags between an account opening and when it first appears in a credit file, and these lags vary across lenders, asset classes, and over time. For example, new credit card originations tend to appear much faster than new mortgage originations. It is also not uncommon for large transfers of accounts to disappear from the credit record data for a few months before reappearing with a new furnisher. Accounts in collections or charge-off are also sometimes more likely to not be updated regularly by the furnisher. These reporting lags can result in "stale" trades whereby tradelines not furnished with updated information (e.g., account closed, updated balance, or delinquency status) persistently remain on credit files. These delays raise issues and require special attention when relating individual and aggregate-level activities on credit reports to high frequency events.

In addition to reporting gaps and delays, another common feature of credit reports is the continued reporting and updating of credit files of individuals following their death. Data furnishers and CRAs do not always have timely and accurate death information. Failure by researchers to account for inactive individual credit records will lead to incorrect population counts and per-capita debt calculations.[11] Importantly, the inclusion of deceased-person credit files implies a divergence between credit files-implied population counts and other population benchmarks that is strongly increasing with age, with a relatively large number of credit files associated with individuals over age 70. While credit record data do typically include a deceased flag, these flags tend to be sparsely populated, especially in earlier years when CRAs had more limited linkages with the Social Security Administration's Master Death file, and this can vary across CRAs. Patterns in the data suggest these flags can feature both type-1 and type-2 errors in measuring deceased status; in particular, deceased flags can be observed to turn "on" and "off" for some consumers over time.[12]

[11] In Q3 2016, for example, the Equifax-data-based New York Fed Consumer Credit Panel (NYFed CCP) implied a total adult population of 264.9 million, which is well above the Census Bureau's adult population estimate of 249.5 million in 2016, despite the fact that many adults do not appear in credit record data because they do not have formal credit records.

[12] Lee et al. (2023) have proposed an algorithm for removing inactive records likely associated with deceased individuals, based on the absence of outstanding debt balances, account flags, public filings, and credit inquiries. After implementing this adjustment, the primary sample has an age distribution that looks like the Census target.

For more details on the US credit reporting system, see Consumer Finance Protection Bureau (2012).

5. Constructing Credit Panels

Researchers can encounter and construct credit reporting data in a variety of forms, including samples based on individuals or loans drawn directly from a CRA's database, as well as samples constructed via a match to a preexisting data source. In this section we briefly provide guidance on how to construct different types of data panels, how to merge credit data with other data sources, and and how to run surveys off of credit data panels, with special attention to maintaining confidentiality and to where issues may arise if researchers do not account for the nature and structure of the credit record data. The specific requirements of a data agreement may vary, but the CRAs typically prohibit reidentification of consumers and require a right to review research before public circulation to ensure that researchers are properly using the data.

Often researchers want a panel that remains representative over time, which requires dynamically updating the data to include records newly created since the start of the panel.[13] Two of the most common ways to draw and maintain a nationally representative sample are to select the sample based on the last few digits of the social security numbers on the credit records or the internal ID assigned by the CRA. These result in similar but not identical panels.[14] The social security number method will miss records that do not have an SSN or similar ID number, but most records with active debt have a social security number or tax identification number (Lee and Van der Klaauw, 2010). The internal ID method will include more fragment files, which researchers need to account for when constructing consumer-level measures as discussed below. National estimates of various measures of consumer credit align well when comparing datasets using these two different approaches, but there can be larger differences in some areas, such as with third-party collections.[15]

Because credit records are regularly merged and split, using an external ID method like SSN will provide a representative sample of people (with that ID) while the internal ID method will provide a representative sample of records.[16]

All these approaches can be readily applied to the nearly full population of adults with a credit record or to a subset of consumer records (e.g., by age, geography, or presence of specific tradeline types, as is the case with the National Mortgage Database). The CRAs suppress a small subset of records for use by researchers to comply with laws and internal guidelines, like excluding records for those under age 18. CRAs typi-

[13] Alternatively, some researchers have relied on static panels, which follow a given set of birth cohorts of individuals or loan origination vintages. Representative static panels can be drawn using the same sampling approaches as applied for representative dynamic panels.

[14] The credit panels we know to be in existence at the time of writing, listed in Table 1, were created using both sampling approaches.

[15] Brown et al. (2015) find aggregate debt estimates from credit reporting data to line up well with estimates from the SCF. However, when distinguishing by loan type, they find considerable underreporting of credit card debt in the SCF, a finding consistent with evidence presented by Zinman (2009) based on a comparison of credit card debt in the SCF with aggregate credit card debt estimates from the G.19 and call reports.

[16] Other methods of drawing a panel are less common because they offer fewer advantages. For example, CRAs can also draw a sample by assigning random numbers to all records. Maintaining a dynamic representative sample can be difficult with this approach because, as previously discussed, credit record files are regularly merged or split as CRAs receive more information.

cally apply other filters to their data relevant for business purposes, such as only including tradelines with a recently reported update or excluding records considered "inactive" accounts. Researchers often have different purposes than other users of credit record data, and they should confirm with the CRA if any filters have been applied and how they are defined. They may want to adjust these filters to their needs; for example, some researchers may want to exclude or include inquiry-only files.

Credit record panels almost always only include anonymized IDs for consumers (and possibly furnishers) in order to protect consumers' privacy and comply with CRA requirements. If researchers need the ability to identify specific subsets of furnishers, they may be able to work with the CRA to construct flags for these furnishers (as in Di Maggio and Yao (2021); Granja and Nagel (2023)), but each CRA has different requirements for the types of flags they will provide and the minimum number of furnishers covered by such flags.

5.1 Household-Level Analysis

In constructing a panel, the population of records may include just a primary sample of records or may also include records for borrowers who have some sort of association with the primary sample. For example, both the NYFed CCP and the University of California Consumer Credit Panel (UC-CCP) samples include credit records of individuals living at the same address, while the UC-CCP and Consumer Financial Protection Bureau's (CFPB) Consumer Credit Panel (CFPB-CCP) include credit records of associated borrowers, defined as borrowers who share a credit account with a primary sample borrower (joint, cosigned, or authorized user) even if they are not at the same address. These types of linkages permit computation of household-level debt aggregates, comparable to household-level debt measures from the Survey of Consumer Finance (SCF) (a comparison further discussed in Section 8). To calculate aggregate individual and household-level statistics based on such expanded population samples requires applying appropriate sampling weights (Lee and Van der Klaauw, 2010).

Constructing households or "decision making units" based on shared addresses or credit accounts can present problems. For example, some records have "generalized" addresses where only the main street address is captured for multi-unit dwellings without unit number, such as those living in a mobile home park, a college dorm, or military barrack. In those cases, the "household" constructed around the primary sample member contains both the valid household members and their neighbors and leads to the creation of unrealistically large (because they are actually multi-unit) households. Researchers can attempt to validate these cases by considering other information such as shared accounts, ages, and geographic history. In the other direction, relying on shared tradelines to construct "households" may miss household members who do not share credit accounts. Borrowers may also share accounts with people who are not part of the household and live elsewhere, but, again, researchers can rely on other information in the data (such as geography and age) to help address these cases.

An additional concern with drawing representative samples of households relates to the continued inclusion of records of deceased persons, discussed earlier in Section 4. If a deceased person is sampled as a primary sample member and then a "household" is inferred based on all other individuals currently living at the deceased's former address, then the computed sampling weights can be invalid and this can produce biases in derived household-level aggregate statistics.

5.2. Data Frequency and Aggregation

If researchers are interested in studying credit files *as the information appears to lenders* (e.g., to study how lenders respond to credit information), then reporting lags may not cause an issue. However, if researchers are interested in other aspects that require consistent timing (e.g., following an individual's credit accounts and debt over time), then they will need to create a time series incorporating information on the timing of furnishing updates to help remove noise in the data and reflect the timing of debt balances and performance. Section 8 discusses how to implement such approaches.

While credit record data are typically updated monthly, researchers should also consider whether their project could potentially use less frequent data extracts. As previously noted, CRAs typically store their data as archives, or snapshots in time, so the various data elements can be measured at different times. But many of these data elements do not change over time or change infrequently. Some measures, such as the payment history of an account, include up to seven years of monthly history. As a result, researchers may be able to save money (or acquire more data) by obtaining credit record data at a lower frequency. For example, many ad hoc panels are constructed at an annual or biannual level (Butler, Mayer and Weston (2023) and Mezza and Sommer (2016)).

5.3 Consumer-Level Aggregates

CRAs typically have archives available for both tradeline-level data and for consumer-level measures. These consumer-level aggregates, or "roll-ups," are often the inputs to scoring models, so they may be a useful alternative to the raw account-level data for some users. However, these variables are sometimes opaquely defined by the CRAs, the definitions may vary across CRAs, and the variables are created to serve as inputs to scoring models and may not be well-suited for other types of research.

5.4. Linking Credit Reporting Data to Other Data Sources

Increasingly researchers have been merging other types of data to enhance existing credit panels, or creating ad hoc panels using merges other data sources. Linking to other data sources allows researchers to enhance credit record information and analyze populations that cannot be readily identified in credit data alone, but the process to merge these data sources is often complicated by important steps to protect consumers' privacy and comply with various regulations.

Most matches are done using consumer name, birth date, address, and/or social security number. Match rates tend to be particularly high when using social security number (see, for example, Collinson et al. (2023), Dobkin et al. (2018), and Miller et al. (2021)). Researchers beginning with a dataset that includes this sort of information may be able to send it to a CRA to link the data (as in Finkelstein et al. (2012) to match medical records, and Miller and Soo (2021) to match to HUD Moving to Opportunity (MTO) records). When the non-credit record data contains sensitive data, such as medical information as in Miller, Wherry and Foster (2023), researchers may need to send additional records from another source to help mask from the CRA which records are in the source data. Another approach to such a merge involves a three-party data agreement where the matching variables are salted and hashed by the CRA and the third-party. For example, the CRA and the third-party data source agree on a hashing algorithm and then separately send their data with the hashed matching information to the researcher (e.g., Chakrabarti et al., 2023).[17] In this arrangement the CRA and third party will not need to share their data. The researcher has no access to the hashing algorithm and typically destroys the hashed variables after the match. Nicholas et al. (2021) develop a methodology to match Medicare data to credit reports without exchanging personal information by working out unique consumers in both datasets.

In recent years the number and range of different linkages with credit reporting data has grown rapidly. In addition to previously mentioned studies that linked to health records, payroll data, marketing offers, and HUD MTO data, credit reporting data have been linked to payday loan data (Bhutta, 2014), tax return data from a sample of tax filers (Meier and Sprenger, 2010), bankruptcy filing records (Argys et al., 2020; Dobbie, Goldsmith-Pinkham and Yang, 2017), and education records from specific universities and the National Student Clearinghouse (Scott-Clayton and Zafar, 2019; Chakrabarti et al., 2023). The costs of accessing and linking data can vary with data requirements as well as over time—the UC-CCP provides some public estimates.[18]

[17]An alternative is for the CRA to provide a cross-walk between anonymous identifiers in both datasets.

[18]https://www.capolicylab.org/data-resources/university-of-california-consumer-credit-panel/

5.5 Surveys Using Credit Data

Using credit records to draw survey samples is a relatively new approach to augment credit record data, and it can be done with a sample flagged by the CRA or flagged by researchers using an existing credit panel. Researchers can ask for a sample among consumers in a particular region or among consumers with a specific loan type. For example, the CFPB and Federal Housing Finance Agency (FHFA) began the National Survey of Mortgage Originations in 2014 based on a 1-in-20 sample of new mortgage originations from a CRA and added another sample of existing mortgages (ASMB) in 2016 (Avery et al. (2017) and Durbin et al. (2021)). Separately, the CFPB has surveyed borrowers on their experiences with debt collection (Consumer Financial Protection Bureau, 2017), making ends meet (Fulford and Shupe, 2021), and student loan experiences by drawing survey samples from existing credit panels.

As detailed in Consumer Financial Protection Bureau (2017), this approach offers several advantages to credit data alone and to some other survey sampling strategies. First, researchers can more readily target and oversample specific populations of interest to increase sample sizes. Additionally, researchers have the full credit record for the initial sample to adjust survey weights and nonresponse bias. The credit data can also help clarify some incomplete, conflicting, or uncertain responses.

When conducting a survey directly from a sample of credit records, researchers will typically need to work jointly with the CRA, and potentially with a third party, to field the survey in order to protect consumers' confidentiality and to comply with internal policies and external regulations. As with creating a general panel of consumer credit records, the specific constraints involved in or willingness to conduct a survey from credit records may vary by CRA. Researchers may instead match existing survey data to credit records. For example, Miller, Wherry and Foster (2023) link prior survey data from another study to credit records and help reduce privacy concerns by including additional people in the matched sample to prevent the CRA from knowing which records were part of the prior survey. In other cases researchers may decide to explicitly ask survey participants' consent for pulling their credit files (Caldwell, Nelson and Waldinger, 2023).

6. *Credit Reporting Data*

In this section we explain the structure of consumer credit reporting data itself. We begin with a high-level discussion of the general content of credit files, and of the type of information typically extracted from them when pulling samples. We differentiate between traditional types of credit reporting data (tradeline, collections, public records, inquiries, and attributes) as well as newer types that have emerged in the last ten years (e.g., alternative credit data, trended data, and non-credit data). We also discuss the types of consumer debts historically missing from credit reports.

In discussing the information available at the tradeline level we focus in this section on generic issues that researchers encounter in its use. Credit reporting data cover a broad set of credit products with heterogeneous structures and idiosyncrasies in reporting. In the Online Appendix we highlight separately for each product type key features of these data, interpretation issues, and best practices as exemplified by seminal papers from the literature. Among others, for home based loans this includes a discussion of home equity lines of credit (HELOCs), mortgages, loan modifications, refinances and forbearances. For credit cards we cover different card types and the challenges in differentiating revolvers and transactors. For auto loans we comment on differentiation between lender types and the reporting of repossessions. The Online Appendix also includes an extensive discussion of idiosyncratic aspects of student loan reporting, including servicer transfers, reporting of delinquencies, federal versus private loan differentiation, deferments, forbearances, refinances, and consolidations. We strongly encourage researchers working with tradeline data on specific types of accounts to review the appendix for important further details.

The primary components of credit reports are the header file, containing personal information of the consumer, tradelines (account details), public records, inquiries, and collections. We discuss each of these in more detail next.

6.1 Header File

An individual's credit file contains identifying information, including the person's social security number, date of birth, name, phone number(s), current address (including state, county, and zipcode) and previous addresses. For those with a joint account, the co-borrower's name may also be listed. Addresses listed on the credit report are typically the mailing addresses reported by creditors. The type of residence associated with an address may further include a flag for Single Family or Apartment complex, and for some individuals the address can be a post office box. When an individual moves and provides his/her new residential address to creditors, the new account address gets reported to the CRAs when the lender updates the account information. Using their own proprietary algorithms, CRAs then update the main mailing address associated with an individual, usually made after the end of the billing cycle (some 30 to 45 days after the new address is reported). The algorithm will consider all recently reported addresses associated with all of the individual's reported account as well as the reliability of each source to determine whether there is sufficient evidence that the borrower has moved to a new location.

6.2 Tradeline File

Typical credit reports include a tradeline (i.e., account-level information) for each revolving and installment credit account that belongs to an individual. Revolving tradelines include credit cards and lines of credit such as HELOCs, while installment tradelines include mortgages, auto loans, student loans and personal loans. Each tradeline includes specific information about the account provided by the lender, including the current account balance, type of debt, type of account (e.g., revolving, installment) and account ECOA designator (e.g., whether the individual's legal responsibility over the account is as an authorized user, joint account, individual account, or co-signed account). In addition, it includes information about the lender (name and address), (partial) account number, current payment status, date or month the account was opened, origination loan amount or credit limit, date of last activity, monthly payment, and some information about the recent payment and payment history.

For confidentiality reasons, samples containing tradelines pulled from credit reports usually exclude lender names but do often include product or industry codes indicating whether the lender is a bank, credit union, finance company, or some type of specialized lender. A few important exceptions are studies that have analyzed credit report records of individuals who took out loans with a specific lender or group of lenders, discussed earlier in Section 5.

Tradeline payment history is usually reported as a payment "pattern" or "grid" showing between 24 and 84 months of payment history as a sequence or string of payment status codes. Payment or delinquency status varies between current (paid as agreed), 30-days late (between 30 and 59 days late; not more than 2 payments past due), 60-days late (between 60 and 89 days late; not more than 3 payments past due), 90-days late (between 90 and 119 days late; not more than 4 payments past due), 120-days late (at least 120 days past due; 5 or more payments past due), and a number of categories that indicate the loan is charged-off or otherwise in some "severely derogatory" terminal state of default (e.g., foreclosure, repossession, collections, etc.). The payment status may also indicate that the account was included in a bankruptcy filing by the credit recipient. Not all creditors provide updated information on payment status, especially after accounts have been "derogatory" for a longer period of time. Thus the payment performance profiles obtained from credit reports will to some extent reflect reporting practices of creditors.

The scheduled payment amount listed for each account is the required payment amount. In case of a mortgage account (and installment loans more generally) it represents the required payment between payment cycles. For revolving accounts, the scheduled payment amount typically represents the minimum payment amount required as displayed on the statements. Highest credit is a data field with varying meanings depending on the type of loan: for revolving loan products such as HELOCs or credit cards it is the credit limit (if reported) or else is the highest balance ever observed; for installment loans it is typically the original loan principal; for other accounts it is typically the highest balance reported during the history of the loan.

The reporting of delinquencies on credit reports differs in an important way from delinquencies as conventionally reported by industry. The latter typically remove from their delinquency statistics any accounts that have already been charged off. However, after lenders charge-off non-performing balances from their books, the borrower's credit report will have a past-due balance until the debt is repaid or sold to a third-party debt collector, or the lender gives up attempting to collect. As long as the servicer continues to report and update these outstanding debts, they typically will be included in credit-data-based household debt delinquency measures. Haughwout et al. (2019) show that dropping charge-off debts that continue to report to CRAs yield revised delinquency stock measures that are very comparable to industry measures. While discharged private loans of different types will eventually stop being reported and may show up instead as collection accounts, this is not the case for delinquent federal student debt, which cannot be charged off and will typically continue to be reported to CRAs until the debt can no longer be reported under the requirements of the FCRA and Higher Education Act. In the case of a moratorium or forbearance of debt payments, such as during the early phases of the pandemic, while CRAs stopped recording such loans as being delinquent, industry numbers typically continue to include them as past due amounts.

While credit reports pulled at a specific date yield useful measures of debt stock delinquencies by indicating the amount of debt at various stages of delinquency, observing loan-level longitudinal panel data will reveal richer detail on delinquency transition rates by showing the amount of debt transitioning into and out of various stages of delinquency.

If a consumer closes an account, that account will typically remain on the credit report as a tradeline for seven years, though in some cases the account can fall off the report sooner. Tradelines with a negative history are generally dropped after seven years, while account closures following full payment (positive information) generally remain on credit reports up to 10 years (summarized in Table 2).

As most revolving and open nonrevolving accounts with a positive balance require monthly payments if they remain open, a sudden halt in reporting of an account often indicates that it has been closed. Derogatory accounts can remain unchanged for a long time when the borrower has stopped paying and the creditor may have stopped trying to collect on the account, Avery et al. (2003) report that some of these accounts in fact appeared to have been paid off. However, sometimes, typically due to some servicer transfers, accounts that stopped being reported for more than three months, start being reported again which necessitate the data user to fill in the intervening months/quarters to make up the disappearing accounts. These gaps have been more frequent in the early periods of data, such as in the early 2000s, but even now those gaps and lapses do occur.

6.3 Public Records File

Another important component of credit files is public record information. Such information is maintained on a consumer's file in compliance with the

FCRA. Public record information is obtained from county, state, and federal courts, and includes bankruptcies, foreclosures, civil judgments, and state and federal tax liens. How long such information is reported on credit reports varies by the type of record.

Bankruptcy information includes the filing date and the form of bankruptcy, called "chapters", according to chapters in bankruptcy law. The most common types of non-business bankruptcy for consumers are chapter 7 and chapter 13 bankruptcies. Chapter 7 is the most common among consumers and allows borrowers who cannot afford to make payments to discharge all eligible debts. Chapter 13 bankruptcies instead are structured as a repayment plan that lasts between three and five years. They are used by individuals with regular income and not eligible for Chapter 7, as well as individuals who want to retain certain assets or to get caught up on their mortgage payments. As regulated by the FCRA, chapter 7 bankruptcy filings generally remain on credit reports for up to ten years, while Chapter 13 bankruptcies generally drop off credit reports after seven years. In addition to a bankruptcy flag, credit reports usually include information on which debts were discharged or included in the bankruptcy filing. Once discharged, such accounts generally show with zero balance. Accounts included in a bankruptcy will usually drop off from credit reports after seven years, while the bankruptcy itself may remain up to 10 years.

Foreclosure actions, loan modifications, short sales, deeds in lieu of foreclosures, civil judgments, and tax liens are discussed in greater detail in the Online Appendix.

6.4 Inquiries File

In addition to tradelines and public records information, credit reports include information on credit inquiries, which log the views or "pulls" of the consumer's credit file over the past two years. Such reviews may be initiated by current and prospective lenders and also by employers, landlords, and the person him/herself. The only information included on credit reports for inquiries is the date of the inquiry and identity of the company or person who requested a copy of the credit report. In anonymized data available to researchers, the information may be coded as a type of business for the company and a type of account the inquiry is for.

There are two types of credit inquiries, corresponding to two different permissible purposes under FCRA: so-called hard and soft pulls. Hard pulls are usually triggered by an application for a new loan or, in some cases, for an apartment rental. Hard pulls generally have a modestly negative effect on a consumer's credit score, and a large number of hard inquiries within a short time has a more substantial negative effect, as this type of "credit-seeking" behavior can be predictive of later default. An exception to this is when a large number of hard inquiries are for the same type of loan in a short window. Because this might indicate shopping for a single loan, for example a mortgage or auto loan, CRAs typically have a de-duplicated version where the multiple inquiries are collapsed into a single inquiry for use in credit scoring models.

Soft pulls or soft credit checks instead typically occur when someone (such as an employer or utility company) checks a person's credit as part of a background check or when someone requests a copy of his/her own report. Since July 2020 new phone and internet service inquiries, which used to count as hard inquiries, are classified as soft inquiries. Soft inquiries do not affect credit scores, and they also are not displayed on credit files provided to third parties.

Each CRA only has information on the inquiries that are submitted to that specific CRA. As a result, when a lender only pulls a credit report from one or two of the major consumer reporting agencies (as is common for most non-mortgage credit inquiries), researchers will not observe all credit inquiries in their data and which ones they observe may vary over time.

6.5 Collections File

Credit reports of some consumers include another type of information: third-party collections or collection tradelines. They represent unpaid bills or other unpaid accounts, typically unsecured such as credit cards and personal loans, sold to or managed (for a fee) by a collection agency. These debt collection companies sometimes furnish such collection accounts to CRAs. Debt collectors' reporting practices are not uniform and not all delinquent accounts appear on credit reports. A recent CFPB report (Consumer Finance Protection Bureau, 2023) found that collection agencies collecting debt for a fee primarily furnish medical collections as well as telecommunications and utilities accounts, while the owners of delinquent debt primarily furnish financial and retail collection tradelines. The report found large declines in the aggregate number of collections over the past five years which primarily reflected a decline in the reporting of collection tradelines, not in actual collection activities themselves. It also found collection tradelines to largely be low-balance, non-financial accounts, with medical collections representing the majority of collection tradelines.

Interestingly, medical accounts (and on-time payments on them) are otherwise not regularly reported to CRAs, so these accounts often appear for the first time as collections tradelines. Most collections firms do not report paid medical debts, or unpaid medical debts under $500. There are changes over time in the reporting of medical collections debt to be aware of, for example, from July 2022 credit agencies stopped adding new, unpaid medical collections debts until they are one year old (up from six months from 2015) and also stopped reporting paid medical collections debts (Kluender et al., 2021), and from April 2023 they stopped reporting unpaid medical collections debt less than or equal to $500. For more details on these changes see Sandler and Nathe (2022) and Brown and Wilson (2023).

Another type of information included on credit files for some individuals is unpaid child support, alimony, and separate maintenance payments under a divorce decree or separation agreement. In most states the state or local child support enforcement agency is required to report unpaid child support debts once they reach $1,000 but may also report lesser amounts. Unpaid child support may show up on a credit report as a collection account, court judgment (initiated by either the child support enforcement agency or custodial parent), or as a separate tradeline. Unpaid child support or alimony payments can remain on credit reports for up to seven years.

6.6 Linking Mortgage Data

A productive area of research has been linking credit reports with product-level data on mortgages. This is a valuable merge as some mortgage originations data do not show mortgage repayment after origination or the other debts held by a consumer over time, though this information is observed in credit reports. Moreover, the linked data enable researchers to observe detailed mortgage product features (e.g., government-backed, securitized, property type and estimated value) as well as a richer array of demographic information.

A variety of existing linked datasets are available to researchers. The most prominent example in the literature is the Black Knight Financial Services Credit Risk Insight Servicing McDash (CRISM) database, an anonymous loan-level match between mortgage servicing data and Equifax CRA data used in Berger et al. (2021); Beraja et al. (2019); Agarwal et al. (2022). Also available is Moody's Analytics data (previously known as Blackbox Logic) that links mortgage originations data with Equifax credit reports (see Piskorski, Seru and Witkin, 2015; Di Maggio et al., 2017; Gupta, 2019; Varley, 2023). Another example is a match between the credit reports and loan-level data from CoreLogic (e.g., Haughwout et al., 2011; Bhutta, Dokko and Shan, 2017). Researchers have also linked public Home Mortgage Disclosure Act (HMDA) data themselves using data on mortgage characteristics (e.g., loan amount, loan origination date, geography, birth date)—see Bartlett et al. (2022), Bhutta and Hizmo (2021), and Shahidinejad (2023) for examples —and researchers with access to more granular confidential HMDA can potentially do more precise merges. Recent richer mortgage datasets, such as the expanded HMDA data and National Mortgage Database, enhance the value of linking credit reports to these. A final benefit of these linked data is it enables researchers using mortgage datasets to evaluate selection into their compared to the population of mortgages in credit reports and, if desired, weight observations (Fuster, Guttman-Kenney and Haughwout, 2018).

6.7 Trended Data

Beginning in 2013, the credit reporting agencies developed a new product referred to as "trended data." Prior to this development, credit reporting data used by lenders was based only on the latest cross-section available. Trended data combines this cross-section with a panel dimension of characteristics from a consumer's credit report from the prior two years.[19]

By combining information across archives, credit reporting agencies create new variables that show trends such as whether balances, utilization, and credit risk are trending over time. Interestingly, because the panel dimension of the data can be necessary for inferring how a loan is amortizing, trended data also include estimated borrowing costs: estimated interest rates for mortgages, and estimated effective APRs for auto loans, credit cards, and unsecured loans. These estimated borrowing costs are calculated based on undisclosed proprietary algorithms, as the underlying data does not contain a tradeline's pricing, and so may be measured with error. Trended data also include variables revealing credit card revolving behavior: which consumers pay their balance in full each month, and which instead "revolve" a balance on the card.

6.8 Alternative Credit Data

In recent years CRAs have started to collect additional financial data beyond

[19]The distinction here is subtle. Each cross-section of credit reporting data contains backwards-looking variables—for example, bankruptcy filings from up to 10 years prior. However, in standard attribute data, some data fields such as credit card utilization are only observed contemporaneously. Trended data can be thought of as "lags" of what were previously only contemporaneously observed data fields.

the traditional sources listed above and have begun to use such new data in some of their credit scoring models. Such alternative credit data, also known as expanded FCRA-regulated data, can be used to evaluate an individual's creditworthiness but is not included in traditional credit reports.

To comply with the FCRA, alternative credit data must be displayable, disputable, and correctable. These may include alternative financial services data on small-dollar installment loans, auto title loans, rent-to-own agreements, and point-of-sale financing, including information provided by at least one of the four largest BNPL lenders. Alternative credit data also includes user-permissioned bank statements, utility and telecommunications bill payments, and rent payment history (Cochran, Stegman and Foos, 2021), as well as payroll income, gig economy income, and insurance and childcare payments.

At least one CRA has started to include employment information on credit reports. This information may be based on an employment verification database built from payroll records, or information provided by lenders. Some lenders may include, as part of the account information, the name of up to three employers (current and two previous), including (to extent available) employer name and location, date employed, date left and position.

Alternative credit data allow CRAs to compute alternative credit scores to be used by prospective lenders for individuals not scored through traditional credit data, the so-called "credit invisibles" as well as those with unscorable credit files (Consumer Financial Protection Bureau, 2015; Di Maggio, Ratnadiwakara and Carmichael, 2022).

6.9 Information Not in Credit Reports

It is important to discuss what can currently *not* be found on credit reports. With respect to credit and financial information generally missing are: interest rates and prices, the identity of the lender (as opposed to furnisher), and information on a number of alternative credit or financial products, including Buy-Now-Pay-later (BNPL) loans, payday loans, many business credit cards and loans, cash advance apps, car title loans, pawnshop loans and tax refund anticipation checks. Furnishers will start reporting BNPL loans in the near future, but the loans will not initially be included in credit score computations. Also missing from credit reports are checking or savings account data, assets, 401(k) loans (loans from oneself), stock margin loans, the individual's salary and total household income, most expenditures, actual items purchased by credit card, bankruptcies more than ten years old, charged-off debts or collection items more than seven years old. Another important limitation is, for individuals who have one or more first-lien mortgages, it is unknown which mortgage is associated with the current mailing address, and the addresses of other properties owned typically are not known.

Because not all debts appear on credit records because of furnishing practices and federal regulations, the relative size of a credit market according to credit record data may differ than in other sources. For example, the Federal Reserve Board's G.19 data show student loan debt as the second largest form of household debt and auto debt as the third largest as of 2023, but most credit record data suggest the relationship is flipped.

7. Credit Scores

7.1 What Are Credit Scores?

Fundamentally, credit scores are a measure of default risk on financial products that appear on credit reports. The two most widely-used families of commercial credit scores in the United States are FICO and VantageScore ("Vantage" going forward). This section describes the basic features common to these two major credit scoring models.[20]

Credit scores are primarily designed to provide a standardized index of default risk across individuals to assist lenders in evaluating new credit applications. As credit scores have become more widely adopted, they are also used for a broader array of purposes including account management of existing portfolios and as a screening tool in non-credit markets such as the labor, rental, telecom, and insurance markets. Consumers also use them to learn about their own creditworthiness and to build and monitor their credit, and creditors and third-party providers give access to consumer credit scores as a way to build consumer loyalty and serve as a platform for advertisements.

FICO and Vantage scores arise from logit models of 24-month forward-looking default risk. The definition of "default" is typically three consecutive months of payments below the minimum contractual payment, also termed the "90-day" default rate or "90 days past due" (Federal Reserve Board, 2007). Scoring models use the information available at time t on an individual's credit report with one of the three major CRAs to predict default between dates $t+1$ and $t+24$ months. These scores are affine transformations of the log odds of default based on the logit models, mapped to an integer scale typically ranging from 300 to 850 (Thomas, 2009), although some versions have slightly different ranges. Because scores are linear in log odds, a given absolute change in credit scores has different implications for default risk at different ranges. For example, a 100-point score decrease from 800 to 700 corresponds to a much smaller change in predicted default rate than a decrease from 600 to 500.[21] Because the ranking of consumers stays relatively stable over the business cycle, credit scores can be thought of as an ordinal ranking of credit risk across consumers.

While the exact formulas used in commercial credit scores are proprietary, and researchers are generally prohibited contractually from attempting to reverse-engineer these exact formulas, the basic ingredients of these logit models are well-known and publicly disclosed by score providers. By following the guidelines described below, researchers with access to CRA data can build their own credit models that are highly correlated with commercially-available models without knowing their exact formulas.

7.2 What Goes Into Credit Scores?

FICO and Vantage scores have many versions, which are both updated over time and span different uses such as account management versus account origination; predicting any default versus de-

[20] While the generic term "credit score" primarily refers to FICO or Vantage scores in the United States, the CRAs also have their own credit risk scores such as the Equifax Risk Score observed in the Federal Reserve Bank of New York's credit panel. There are many other types of scores including those associated with deposit accounts, fraud detection, small businesses, and alternative financial services, and internal scores used for account management by financial institutions based on private information on their own customers. While some of these scores may share similarities with FICO and Vantage, they are generally much more heterogeneous across providers and not covered in this section.

[21] See the VantageScore RiskRatio tool for an illustration https://www.vantagescore.com/lenders/risk-ratio/

fault on a given new tradeline; predicting default for a given population of borrowers; predicting default on a given type of trade such as credit cards versus auto loans.

The logit models underlying credit scores typically take attributes derived from credit reports as inputs, and various measures of default as the outcome being predicted. The major types of attributes that are included as inputs into credit scoring models include payment history (e.g., 90+ day delinquency on various types of tradelines, collections trades, public records such as bankruptcies and tax liens), amount owed and utilization (e.g., total debt, balances as a fraction of available credit lines), length of credit history (e.g., age of oldest account), credit mix (the variety of different trade types on a consumer's record), and new credit (e.g., the number of credit inquiries within the last year, number of new accounts).[22]

The types of information used in commercial credit scores generate important and sometimes counter-intuitive economic implications for consumers. Because consumers are penalized for new credit inquiries, consumers experience a short-term decline in credit scores when shopping for credit. Although current rules allow consumers to make several credit applications within a short span of time without additional penalty (e.g., 14-45 days, depending on the specific version used), in practice consumers may be penalized for search behavior. Thus, the details of how the most common credit scoring models are constructed may generate frictions and have important implications for consumer search and price dispersion.[23]

Consumers may also need credit in order to build credit. The legal and historical evolution of the credit reporting system has led to scores that depend primarily on a consumer's credit history, and not on other factors such as income, occupation, assets, non-credit financial accounts, and many other factors that could theoretically predict default risk. Because credit cards are the most common and often the first major form of credit used by consumers in the United States, the importance of credit cards in building credit may drive consumers to use credit cards even without a liquidity need. More broadly, there is potential for "credit history hysteresis" that makes disadvantage persistent, via credit scores, for historically disadvantaged groups.

Another economic feature of credit scores is that the reliance on payment history does not distinguish between idiosyncratic and systematic drivers of default. Thus, consumers who enter delinquency during recessions or due to mass layoffs, health shocks, or other arguably exogenous factors are treated the same way as those to become delinquent due to moral hazard or idiosyncratic factors. Thus, credit scores reduce the insurance value of credit with respect to many types of shocks consumers face (Avery et al., 1996). Potentially important avenues of research include studying the economic causes of defaults and also developing credit scoring systems that can better distinguish bad luck from bad types.

7.3 What Is Not In Credit Scores?

Just as important as understanding the inputs that go into credit scores,

[22] See, for example https://www.myfico.com/credit-education/whats-in-your-credit-score.

[23] See, e.g., Woodward and Hall (2012); Stango and Zinman (2016); Alexandrov and Koulayev (2018), and Argyle, Nadauld and Palmer (2023) for evidence of price dispersion and lack of search in consumer credit markets.

many factors researchers may think would (and empirically do) affect default risk are not included in standard credit scoring models by law, by practice, or due to technical limitations. The ECOA governs that information related to sex, race, and other protected classes are not allowed to be included in credit scoring models.

Income is also typically excluded from standard credit scoring models, as well as related information such as education and occupation. No information on liquid and illiquid assets is included in credit scores, other than through the existence of secured loans to finance durable purchases such as mortgages and auto loans. And finally, information not present on traditional credit reports, such as usage of payday loans, subprime auto loans, and other alternative financial services and new or marginal forms of credit such as buy-now-pay-later / point of sale, marketplace loans are also excluded from credit scoring models. Information on deposit accounts, bank overdrafts, and related financial activity are also not reported to CRAs, and thus excluded from scoring models. As new data sources become available and used by lenders instead of, or in combination with, traditional credit reports, it is important for researchers to study their effects. For example, Berg et al. (2020) study the information content of digital footprints.

7.4 Different Types Of Credit Scores

A given consumer does not possess a single unique credit score. Moreover, the scores consumers can purchase from CRAs or obtain from free score tracking services provided by many financial institutions and third-party platforms may not be the score used by an individual lender to underwrite a specific credit application (Consumer Financial Protection Bureau, 2012). When obtaining observational data from industry sources, researchers may need to consult with the data provider to understand the exact model version used and whether model versions have changed over the sample period, but they can request specific model versions when procuring data directly from CRAs.

The FICO score, developed by Fair Isaac Corporation, was first developed in the 1950s and grew in adoption over the 1980s and 1990s (Federal Reserve Board, 2007). Vantage is a joint venture created by the three major CRAs in 2006 to compete with FICO. Vantage was designed to apply an identical model across all the CRAs, so that the only reason an individual's score would differ across the agencies is due to differences in the underlying data on that person. Vantage was also designed to extend greater coverage across the population, reducing the fraction of Americans who are "credit invisible" under that score. However, the greater coverage of Vantage to thin-file consumers also means that the score is based on less information for these consumers.

Any given model, such as FICO 9, may also produce different results when calculated based on the data from each of the three consumer reporting agencies. These differences can arise because each CRA includes slightly different data for each individual in the population based on its unique data-collection process and the network of furnishers that report to that CRA. It can also arise because the specific attributes created by each CRA to summarize consumer characteristics may differ in their exact definitions, and the credit scoring models thus take these slightly different variable definitions as inputs.

Another difference across models is that model developers market different scores for lenders and for consumers. Since the 2010s, consumers have increasing options to access "educational" scores to monitor and improve their own credit scores, offered by firms such as banks, credit card companies, and third-party platforms such as CreditKarma (Consumer Financial Protection Bureau, 2012). The outcome variable being predicted may also differ across different model versions. The 24-month default rate predicted by the model could cover new versus all accounts, all trades versus specific types (e.g., auto, credit card), or other variations. The coefficients of the scoring models may also be recalibrated toward different underlying samples as the macro-economic environment changes and to tailor models toward different subpopulations.

Regardless of the model, it is important to keep in mind that a credit scoring model is only as good as the data fed into it-—so factors such as mistakes, fraud and identity theft, incomplete coverage, and reporting lags that affect the credit reporting system also affect credit scores. Credit scores are a useful yet noisy predictor of default risk.

8. *Constructing Economic Measures*

In this section we explain how researchers can construct a variety of economic measures from these data. Section 8.1 provides overarching guidance to researchers for using consumer credit reporting data. Section 8.2 explains how to define populations of consumers and accounts in credit reports. Sections 8.3 to 8.6 then explain how to construct various measures of economic interest, highlighting approaches used in prior literature and making some recommendations to encourage greater standardization of what we consider best practices. Across this section, we also acknowledge that researchers have a broad variety of use cases, and data availability constraints will mean some researchers will take different approaches to our recommendations. Section 8.3 shows a variety of measures of financial distress: bankruptcy, collections, delinquency, and other approaches. Section 8.4 explains how to construct measures of credit access: credit scores, new accounts, credit limits, inquiries, and borrowing costs. Section 8.5 covers measures of consumption: new autos, credit card spending, and cash-out equity from mortgage refinancing. And finally, Section 8.6 discusses how to use these data to measure mobility.

8.1 Overarching Guidance

Our overarching recommendation for researchers is to be clear and precise on how their measures are constructed. At a minimum we suggest researchers should clearly state: (1) which components of credit reports the measures are calculated from (e.g., tradeline, collections, public records, or aggregated consumer-level roll-ups data); (2) the frequency the measures are calculated from (e.g., monthly, quarterly, annually) (3) which data restrictions are applied (e.g., criteria for excluding inactive accounts, fragmentary credit records, or deceased consumers); and, if the researcher calculates a measure themselves (4) the formula used for calculation (e.g., deterministic, regression, ML) including whether any inference is made for missing data.

If tradeline-level data are available, this will enable researchers to produce measures closest to the target economic parameters of interest. Constructing measures from tradeline-level data also ensures the measures used are transparent. In cases where it is necessary to instead rely on consumer-level "roll-up" data (aggregates), it is important to be clear on these data's limitations.

8.2 Populations

First, we explain how to define various populations or sample frames of interest. Answering a seemingly-straightforward question like "how many consumers have a credit file?" would vary depending on how a "consumer" is defined in these data; different approaches generate answers that differ by tens of millions of consumers (Brevoort, Grimm and Kambara, 2015). Similarly straightforward statistical exercises, like answering how many credit products and how much debt a consumer holds, can vary by several multiples depending on which types of variables in the data are used.

8.2.1 Populations of Consumers

We recommend researchers typically use the following sample restrictions:

1) Remove observations after a consumer is deceased.
2) Remove consumers with a missing date of birth or a birth date that is unrealistic (e.g., if using data from 2020 exclude those with birth dates before 1920). Some researchers may be interested in stricter age restrictions (e.g., prime-age consumers).
3) Restrict observations to geography of interest (e.g., exclude non-US locations in US CRA data unless interested in this population).

After these steps, there are more judgment calls to be made. Researchers may wish to restrict their analysis to consumers with SSNs / ITINs; these are less likely to be fragment files, but this choice may also remove some groups of consumers of particular interest. Researchers may also wish to restrict to consumers based on the number of observed tradelines, as credit files with more tradelines may be less likely to be fragment files. For example, a researcher could restrict to consumers who have held at least one credit product over the last ten years, or even may limit to consumers that appear in tradeline data over a sustained period of time. Using this typically produces an aggregate number of consumers which is plausible given the size of the US adult population. Researchers may also want to add in consumers with collections or public records if their research is focused on this aspect, though doing so leads to the inclusion of additional fragment files, as evidenced by sample sizes that imply an implausibly large US adult population. We generally recommend researchers do not include consumers who only have inquiries. Inquiry-only consumers are often fragmented records.

8.2.2 Populations of Active Accounts

Credit accounts remain on credit reports long after they are no longer in use or have been closed. If using consumer-level roll-up variables, then the criteria a CRA used for including inactive accounts may be unclear. If a researcher is using tradeline-level data, then they can specify their own criteria, which ensures greater accuracy and transparency in measures.

Researchers may want to remove accounts that have not been recently furnished. Accounts that are not recently furnished may have been closed, have different balances, or have become inactive. Different reporting agencies have different approaches for this, ranging from removing accounts not updated in the last 1, 3, 6, or 12 months. Researchers should check the time series to ensure it is not generating artificial jumps in aggregates, and loosening the threshold as needed. These issues are particularly important for credit reporting data from the 1990s and early 2000s. Regardless of the time period, we recommend researchers be clear what criteria they use.

Inactive credit cards that are open but not used by consumers are difficult to define but greatly affect the number of accounts in credit reports. Researchers interested in studying credit card behaviors may want to focus on accounts actually in use. In expectation, once a credit card account has a zero statement balance for every month in the last year, it rarely gets used in the future.

Researchers should also be aware that accounts in dispute are suppressed by CRAs during the investigation process, so researchers may need to contend with missing observations (e.g., fill in using preceding month if the account reappears with a reference to a prior dispute).

8.2.3 De-duplicating for Aggregate Statistics

Once the sample population has been defined, researchers may need to de-duplicate accounts that are jointly-held or have authorized users, depending on the sampling strategy. As noted in Section 4, whether accounts are individual or jointly held is reported to comply with ECOA requirements (and so this information is sometimes referred to as the "ecoa code"). To avoid double-counting jointly held or cosigned accounts, weights are commonly assigned to accounts not reported as held by an individual. For example, individual accounts may receive a weight of one; jointly held or cosigned accounts may receive a weight of one-half, and authorized user accounts may receive a weight of zero (because it may be difficult to determine how many authorized users there are for an account without additional data). This approach is detailed in Lee and Van der Klaauw (2010). These weights are commonly used to calculate aggregate balances, number of accounts, or delinquency rates, but are not commonly used when calculating averages or aggregates for types of consumers (e.g., total debt for those ages 65 or older).

8.3 Financial Distress

A broad set of measures of financial distress can be constructed from credit reporting data. In this section we summarize some of these measures. Often researchers will want to study a handful of measures to capture different stages of financial distress. For example, both Finkelstein et al. (2012) and Keys, Mahoney and Yang (2023) study financial distress by examining bankruptcy, debts in collection, and delinquency.

8.3.1 Bankruptcy

One form of financial distress is bankruptcy. Consumer bankruptcy is typically filed under either Chapter 7 or Chapter 13 of the bankruptcy code. Credit reporting data show when and whether a bankruptcy is filed, dismissed, or discharged. If the exact timing of a bankruptcy is required, this can measured from the filing date in the public records dataset as used in Keys, Mahoney and Yang (2023). When measuring bankruptcy, researchers may need to be aware of changes to the bankruptcy code over time, for example the 2005 Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA), which led to a sharp increase in filing just prior to the reform followed by a large decline.

8.3.2 Collections Debts

Another form of financial distress is debts in collections. Approximately half of debts in collections reported by third-parties are medical debts (Keys, Mahoney and Yang, 2023), and the medical debt component is often a measure of special focus (e.g. Batty, Gibbs and Ippolito, 2022; Kluender et al., 2021;

Guttman-Kenney et al., 2022). One useful measure of debt in collections is the flow of the number of, or value of, new accounts in collections. This is because debt in collections is infrequently updated and therefore the stock may be out-of-date. We normally recommend researchers also report the stock of debt in collections as a robustness check and, for some research, such as studies of medical debt in collections, the stock itself may be important. Additionally, there are meaningful differences in the persistence of different types of collections that users should be aware of (Consumer Financial Protection Bureau, 2014). As with bankruptcy, this can be measured using consumer-level roll-up data, although richer analysis more precisely isolating the timing, value, and type of collections is possible using tradeline data as done in Keys, Mahoney and Yang (2023). Researchers should be mindful of the idiosyncrasies in the reporting of medical debt discussed in Section 6.5.

8.3.3 Delinquency

A broadly-used measure of financial distress is accounts in delinquency. Measures of delinquency can be calculated in a variety of ways. Researchers may study whether any accounts are delinquent, the number of delinquent accounts, the value of delinquent balances, or percentages of any of these as a share of the consumer's outstanding balances. Researchers can use different definitions for stages of delinquency depending on how many days past due the debt is (e.g., 30+, 60+, 90+, 120+, 150+, 180+). Each of these measures can also be calculated for different asset types and over different time horizons. This is useful for studying different aspects of financial distress, however, it can also make it bewildering to know what delinquency measure to choose. We provide some practical guidance on this aspect.

We recommend researchers generally use one of two delinquency measures: (1) number of trades measured as 30+ days past due, (2) number of trades measured as 90+ days past due. The first measure is useful as it captures any form of financial distress including early-stage financial distress that may not lead to charge-offs. The second measure is useful as it closely relates to the binary outcome that main credit scoring models are trained on—whether a consumer has any trades 90+ days past due over 24 months—and will capture more severe financial distress. Depending on a researcher's focus these may be calculated by aggregating all credit accounts held by a consumer, or instead only doing so a particular type of credit (e.g., credit cards) held by a consumer. If interested in measuring consumer distress (e.g., fraction of consumers with who are delinquent), it is important to not drop non-delinquent consumers and instead manually code consumers with zero open accounts as zeros (similarly as zero balances if calculating balances or percentages of open accounts or open balances), unless the population of interest is consumers holding a product (e.g., a market-level default rate).

When calculating delinquency a researcher may need to account for how accommodations for the COVID-19 pandemic affected reporting. This measure is problematic during the period March 2020 to August 2023 (120 days after the end of the National Emergency for COVID-19 on April 10 2023) due to amendments to the FCRA by the CARES Act. During this period, accounts with an accommodation that were not previously delinquent are current by credit reporting (and from the consumer perspective) but delinquent for the finance/portfolio management perspective. For the latter, researchers may wish to produce a measure of delinquency that also includes accounts listed with the accommodations: any remark codes on tradelines for deferred payments, forbearance, affected by natural disaster, as well as for open credit cards with positive statement balances where they have zero scheduled payments due.

Consumer-level roll-up variables can also capture delinquency measures. However, we recommend, where possible, using tradeline data to produce cleaner measures. Not all tradelines are furnished each month. If a tradeline is not furnished that month, the delinquency status from the previous month is carried forward to that month's archive. However, when a tradeline is updated it reports the last 84 months of delinquency statuses in one array. Gross, Notowidigdo and Wang (2020) and Gross et al. (2021) provide a methodology for extracting information from this array to update historical delinquency statuses. This adjustment is important when using data before 2010 data when reporting was commonly infrequent. Over time, greater regulatory scrutiny has meant most tradelines are furnished monthly.

8.3.4 Other Measures

Researchers may be interested in constructing debt-to-income or payment-to-income. We recommend using public income data (e.g., IRS zipcode) or linking in individual-level income measures. CRAs also construct estimates of income from credit data and other sources—see Blattner and Nelson (2022) for a comparison to mortgage applications and Mello (2023) for comparisons to IRS and payroll data.

Researchers may also construct their own composite measures of financial distress. See Miller, Wherry and Foster (2023) for an example of this. Such composite measures may also include variables not covered in this section, such as high credit card utilization as a proxy for pre-delinquency financial distress.

Alternative datasets will increasingly enable more complete measures of financial distress to be developed in the US. For example, all our measures are based on the liabilities side of a consumers' balance sheet. Linking checking and savings account data with credit reports can enable richer measures such as observing overdraft and non-sufficient funds (NSF) use (e.g. Gathergood, Guttman-Kenney and Hunt, 2019) and liquid cash balances (e.g. Alexandrov, Brown and Jain, 2023; Guttman-Kenney et al., 2023).[24]

8.4 Credit Access

8.4.1 Credit Scores

A credit score is often used as a summary statistic for credit access. This is useful but paints an incomplete picture, as changes in credit scores do not always translate into changes in credit access. See Agarwal et al. (2018), Dobbie et al. (2020) and, Laufer and Paciorek (2022) for examples studying the relationships between credit scores and other measures of credit access.

As most credit scores are highly correlated with each other, researchers may be able to use the cheapest score available from a CRA. Researchers may want to use older versions of credit scores in particular, as these are not only cheaper, but also were potentially available to lenders in the historical time period studied. A reason why researchers may want to use a particular proprietary credit score is if their identification strategy requires it. For example, some lenders have sharp cutoffs in their underwriting which

[24] See Baker and Kueng (2022) for a review of household financial transaction data.

can be used for regression discontinuity designs if the researcher observes the same score the lender uses (e.g., Agarwal et al., 2018; Argyle, Nadauld and Palmer, 2023).

Credit scores have been used as proxies for financial sophistication (e.g., Agarwal, Rosen and Yao, 2016; Amromin et al., 2018; Bhutta, Fuster and Hizmo, 2021; Agarwal et al., 2023) based on the rationale credit scores are correlated with these. It is important for researchers to be aware of the limitations of doing so. For example, credit scores may conflate sophistication with the opportunities consumers have historically faced given how maps of credit scores (e.g., Keys, Mahoney and Yang, 2023) correlate with maps of historical racial inequities. High credit-score consumers assumed to be financially sophisticated may not be sophisticated in other ways such as in their choice of credit product, refinancing, or retirement saving decisions. Despite such limitations, if researchers take such an approach, we recommend checking the robustness of their results to other proxies for financial sophistication (e.g., Agarwal et al., 2009; Varley, 2023).

8.4.2 New Accounts

Useful measures of credit access are those examining the extensive and intensive margins: the number of new accounts a consumer has opened and, if so, how much new credit is granted. For installment loans, this is the origination amount. For lines of credit (credit cards and HELOCs), this is the credit limit. Both are best measured at the tradeline level, but it also possible to construct these at the consumer level.

If only consumer-level roll-up data are available, a researcher may, for example, use an increase in non-delinquent, auto loan balances as a proxy for a new auto loan being taken out. This approach is only applicable for installment loans, such as auto loans, mortgages, and unsecured personal loans. As discussed earlier in Section 4, in the case of mortgages one may want to try to distinguish between new purchase originations and mortgage refinances. Equation 1 calculates the value of new auto loans (a_t) using information on outstanding auto loan balances (b_t). This calculates the difference in auto loan balances (b_t) and, when this difference is above a threshold κ, this increase is classified as a new auto loan. This measure is zero otherwise. If using such an approach we recommend sensitivity analysis for how large an increase in non-delinquent loan balances is required to classify a new purchase. See Agarwal et al. (2022) for an example of such an approach setting setting $\kappa = \$2,000$ (and testing sensitivities between $\$2,000$ and $\$5,000$). Consumer-level roll-up data may also contain CRA-created variables for the number of new accounts originated. For researchers without access to tradeline data, using the aggregated number of new accounts originated is sufficient for most purposes.

$$(1) \quad a_t = \begin{cases} b_t - b_{t-1} & \text{if } b_t - b_{t-1} > \kappa \\ 0 & \text{otherwise} \end{cases}$$

The above approaches can be improved using more granular tradeline data (e.g., Bhutta and Keys, 2016; Gross, Notowidigdo and Wang, 2020), to ensure the timing and amount of loan originations are more precisely measured. Because there may be a lag between when a loan is originated and when a loan first appears on a credit report, we recommend using the origination amount, rather than the outstanding balance in the month when the loan is first observed, and the origination date, rather than the date on which the loan is first observed. This measure is can be computed by researchers who have lower-than-monthly frequency data of tradeline data (e.g., annual or quarterly), because one cross-section of tradeline data includes origination details for all of a consumer's accounts (opened and closed) over the last ten years.

An analogous approach can be used for calculating the number of new originations: replacing origination amount with a count of new trades opened. This can be done for both installment loans and lines of credit. For lines of credit, we recommend researchers use the first non-zero credit limit value on the account as the best estimate of the credit limit at origination (e.g., Gross, Notowidigdo and Wang, 2020; Laufer and Paciorek, 2022; Guttman-Kenney, 2023).

8.4.3 Credit Limits

Consumers can also access credit through their existing accounts. Credit cards and HELOCs are the most common credit lines a consumer can flexibly draw from. These credit limits can increase and decrease over time. See Gross, Notowidigdo and Wang (2020) for an example studying the changes in a consumer's credit card limits.

The amount of credit limits constructed from consumer-level roll-up variables can differ depending on how cards are classified as active. To address this we recommend, where possible, researchers calculate the total available credit card limits from tradeline-level data, using all open credit card tradelines. In the 1990s and early 2000s, not all lenders reported credit limits, but from 2010 onward, credit limits are required to be reported under the FCRA. If cards do not have credit limits, then we suggest either using the variable showing the highest balance recorded on the account or, if limits are observed later on those accounts, backfilling the missing limits.

Researchers may also wish to examine the amount of available credit: credit limits on open accounts less outstanding balances on those accounts. Such measures are often used to capture consumer liquidity, in the form of available credit (e.g. Gross and Souleses, 2002; Brennecke et al., 2023). Those with accounts with a utilization rate, defined as the balance divided by the credit limit, above 90 percent, are often regarded to be facing binding liquidity constraints.

8.4.4 Inquiries

Credit inquiries data can provide a measure of credit demand (e.g. Han, Keys and Li, 2018), the difficulty of accessing credit (e.g. Romeo and Sandler, 2021), and rejected applications (e.g. Blattner and Nelson, 2022).[25]

Romeo and Sandler (2021) provide an example of how to use inquiries data. They create a binary measure where an inquiry is successful if a new account is originated within 14 days, and unsuccessful if no new account is opened. Blattner and Nelson (2022) use a window of three quarters for interpreting when a mortgage application does not translate into a new origination. Researchers may also use a ratio of new account openings to inquiries as a measure of credit supply (Brennecke et al., 2023).

A main caveat for researchers to be aware of when using inquiries data is that data from a single CRA have in-

[25]Linking credit applications data from other sources to credit files can be useful. For example, Bhutta, Skiba and Tobacman (2015); Gathergood, Guttman-Kenney and Hunt (2019) merge in payday loan applications (that are successful and unsuccessful) with credit scores used in lending decisions, enabling a regression discontinuity design to study the effects of payday loans on consumers.

complete coverage of credit inquiries (whereas originated loans are furnished more commonly to all CRAs). As discussed in Section 6, for many credit applications lenders will only conduct inquiries from one or two CRAs. An exception to this is mortgage applications where lenders typically conduct inquiries across all three CRAs.

8.4.5 Costs of Borrowing

Credit reports do not contain variables showing the costs of borrowing. However, researchers are increasingly able to estimate these from tradeline data. Researchers may also purchase consumer-level roll-up variables estimating borrowing costs, but it may be unclear to the user how the CRA estimates these.

For fixed-rate installment loans, such as auto loans and unsecured personal loans, once a researcher observes the principal origination amount (P), origination term (n), and scheduled monthly payment amount (A), they can calculate the interest rate (i) at origination using a root-solver shown in Equation 2 (Yannelis and Zhang, 2023). Some loans will not solve if they have zero-percent interest rates. If a researcher is interested in realized effective interest rates or realized financing charges, it may be valuable to calculate this at several different ages of the loan after origination, in case the loan terms change over time (Conkling and Gibbs, 2019).

$$A = \frac{P \times i}{1 - (1+i)^{-n}} \tag{2}$$

For mortgages, the above calculation does not work because the scheduled payment amount may include taxes, insurance escrow, and other fees such as home owner association fees. Shahidinejad (2023) develops an algorithm using changes in outstanding balances over time to estimate interest rates and verifies its accuracy against market data.

Separately from installment loans, Guttman-Kenney and Shahidinejad (2023) develop a methodology for estimating financing charges on credit cards. The intuition is that credit card minimum payments are a deterministic function of statement balances, following a generic formula structure. With sufficient data, a researcher can estimate each credit card furnisher's minimum payment formula, and can then recover financing charges. Observing financing charges on credit cards in this way opens up new frontiers to study consumer and firm behavior.

8.5 Consumption Measures

8.5.1 New Autos

Auto purchases are an important component of consumption and used as indicators of changes in macroeconomic conditions. In credit reporting data we observe autos purchased on finance ("auto loans") – over 80% of auto purchases are have auto loans (Benmelech, Meisenzahl and Ramcharan, 2017). New auto loans can be calculated as previously explained in Section 8.4.2 Some subprime auto loan providers do not appear in credit reports. and therefore credit report measures will not include some auto purchases by this segment. Benmelech, Meisenzahl and Ramcharan (2017) and Di Maggio et al. (2017) verify the accuracy of this consumption measure. They show auto loans originations in credit reports match up to external data and also track total sales (with and without loan financing).

8.5.2 Credit Card Spending

Credit cards are broadly used by US consumers with high coverage across geography and credit scores. The amount of spending on credit cards therefore makes them well-suited as a measure of consumption. When calculating credit card spending, we generally recommend combining (general-purpose) credit cards with (private-label) retail credit cards (which can only be used at one or a small group of merchants). However, when using credit card spending as a measure of consumption, it is an important caveat to note that this will not include all of a consumer's consumption: it excludes consumption via debit cards, bank transfers, checks, or cash. Approximately, 30% of payments are made via credit cards, and this share is growing over time, whereas the share of cash and checks are declining over time (e.g. Cubides and O'Brien, 2023).

The target economic parameter of interest—"credit card spending" (s_t)—is the total value of new purchases on a credit card at time t. Our preferred measure of credit card spending (s_t^{GN}) is shown in Equation 3, as used in Ganong and Noel (2020). This measure takes the changes in statement balances and adds payment amounts (p_t). If the measure produces a negative number, it is bounded at zero. Making this adjustment not only removes revolving debt but also includes spending repaid before the statement balance is issued.[26] Measuring credit card spending relies on the researcher being able to observe the actual payment amount variable at the tradeline-level over time. If using this measure, researchers need to restrict to only study the cards of furnishers who consistently report the actual payment amounts. For example, Ganong and Noel (2020) exclude furnishers where over 90% of card months are zero or missing. From 2014 to (at least) 2023, credit card actual payments amounts are only observed for a small, selected subset of credit card lenders (Consumer Financial Protection Bureau, 2020; Guttman-Kenney and Shahidinejad, 2023), but reporting of this variable may increase in the future. We recommend that researchers who want to use this measure confirm the reporting coverage of the actual payment amounts variable for the time period they are planning to study before using or purchasing data. It is also possible to produce estimates of credit card spending without observing actual payment amounts using other methodologies which we discuss in the Online Appendix.

$$(3) \quad s_t^{GN} = \begin{cases} b_t - b_{t-1} + p_t & \text{if } \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

We note that the concepts of credit card debts and balances are related to, but distinct from, credit card spending. While the literature has not defined these terms consistently, we suggest for clarity that researchers refer to outstanding credit card (statement) balances as "credit card balances," reserving "credit card debt" for the share of these balances that is *not* new expenditure, and "credit card spending" for the share of these balances that *is* new expenditure. Such "credit card debt" (d_t) can be measured in credit reports by taking the preceding month's statement balance (b_{t-1}) less actual payments made since (p_t), and if $d_t < 0$, setting it to zero. This approach recognizes that the credit card actual payment amount observed in credit report cross-section t corresponds to the payment made against the credit card statement balance and credit card scheduled payment observed in credit re-

[26] This contains some error as it includes financing charges (the sum of interest and fees) but the Online Appendix shows how Guttman-Kenney and Shahidinejad (2023) address this by estimating and deducting financing charges.

port cross-section $t-1$. As discussed above, this approach typically requires studying the subset of credit card lenders that consistently report actual payment amount p_t. Bornstein and Indarte (2022) provide an alternative example using a CRA's estimates of revolving debt. Fulford and Schuh (2023) provide an example of a machine learning approach to estimating which balances mostly represent debt or new expenditure.

8.5.3 Cashed-Out Equity

Researchers can use credit reporting data to estimate the amount of equity a consumer extracts from a home when refinancing, or "cash-out" refinances.

Researchers without access to linked mortgage data can use the approach in Bhutta and Keys (2016) to identify equity extractions in credit reports. This approach identifies increases to consumers' outstanding mortgage debt by more than 5% over a one year period (with a minimum increase of $1,000), while inferring lien status from tradeline data. Beraja et al. (2019) provide an example doing this, while (Berger et al. (2021) use a similar method) using a mortgage origination dataset linked to credit reports (such as CRISM) and verifies this method against external data. We refer interested readers to their paper's Online Appendix for the detailed criteria for how to do so. The intuition behind their methodology is to first find loans recorded as refinances in origination data, and for these consumers, compare the difference in value between the value of a new mortgage originated to the mortgage(s) previously outstanding, in order to isolate the amount of equity cashed-out.

8.6 Mobility

Credit reports contain information on a consumer's primary address. Tracking changes in these addresses over time enables researchers to have a useful measure of mobility for a large panel of consumers over a long period. DeWaard, Johnson and Whitaker (2019) and Whitaker (2018) help validate this data source for measuring mobility against other sources of data, and Bleemer and van der Klaauw (2019) provide an example of using mobility data, studying the long-run effects of Hurricane Katrina on consumer changes of address, county, and state. Other examples of use include Keys, Mahoney and Yang (2023), who use mobility for identification of person vs. place-based factors in credit markets, and Howard and Shao (2022), for constructing a gravity model of migration. Molloy and Shan (2013) analyzes the post-foreclosure residential destinations of households.

A caveat to using these mobility measures is that they rely on a CRA's view of a consumer's primary address. The CRA may only update a consumer's primary address with a lag, due to delays in information arrival and in determining whether a new address is primary. The timing of address changes in credit reports can also depend on when and whether a consumer chooses to update their address with their financial institutions. Given this caveat, researchers may wish to examine address changes quarterly (e.g. Keys, Mahoney and Yang, 2023) or at annual (or longer) horizons (e.g. Bleemer and van der Klaauw, 2019).

Moreover, an apparent residential move in credit reporting data may be the CRA reassigning the consumer's primary address; especially for some demographic groups, this may not indicate an actual move. Students often have multiple concurrent addresses (e.g., their parents' address and a college address), and consumers with multiple homes can make it difficult to establish which is their primary residence.

CRAs' algorithms for identifying primary addresses have considerably improved since the early 2000s, with fewer cases of moves between locations A and B appearing as multiple moves back and forth; see Varley (2023) for an example of how to account for spurious moves.

Measuring mobility is difficult in general, so—despite the caveats above—credit reporting data likely offer one of the most promising opportunities for researchers to study the causes and consequences of mobility. This is especially true given the long panel dimension, details on household structure, and rich covariates observed in these data.

9. *Conclusions*

This paper provides a general overview of the economics and use of consumer credit reporting data to increase awareness of these data's research potential. We show examples of how these data can be used to answer questions across the breadth of economic fields and provide advice for how to do so. We encourage *users* of these data to read the Online Appendix which contains more detailed information on these data.

We end this paper by emphasizing some especially exciting open avenues for researchers to explore. One area of great promise is linking credit reports with other datasets. Research linking data on consumers' assets, liquidity, income, expenditures, or utilities can be especially valuable for filling in important aspects of consumer cashflows and balance sheets that are missing from credit reporting data. Linking sources such as voting records or social networks can enable researchers to study links between financial and other behaviors. Few studies currently link surveys with credit reports, but doing so has great potential, for example to study the role of expectations in households' economic behavior.

There has also been exciting recent innovation in credit reporting for small and medium enterprises (SMEs). While distinct from consumer credit reporting, SME credit reporting is related in that entrepreneurs may finance SMEs through a combination of personal and business credit, and accordingly, consumer CRAs are developing datasets to track SME credit in a format similar to, and linkable with, consumer credit report data (see e.g., Bellon et al., 2021; Benetton, Buchak and Garcia, 2022; Fonseca and Wang, 2022; Haughwout et al., 2021). These data offer promising avenues for studying consumer as well as firm behavior.

While our paper focuses on US credit reports, there is exciting untapped potential to research credit reports from other countries. Data from other countries contain variables not observed in US reports, as well as sources of variation arising from different legal structures. Studying credit reporting across international domains can help to understand fundamental issues such as the role of the financial system in enabling access to efficiently priced credit. The issues surrounding the use big tech or social media data for consumer credit decisions are especially interesting to study, and these are issues where non-US domains can be especially fruitful.

Finally, there is a wealth of fascinating topics to explore using credit reporting data without needing to link these data to other sources. Recent methodological developments have unlocked new opportunities for studying prices and related consumer and firm behavior within credit reporting data alone. Meanwhile, the longer time series of credit reporting panels that now exist enable researchers to study life cycle topics of consumer behavior, including within the household and across generations.

Table 1—US Consumer Credit Reporting Panels

Credit File Panel	Starting Year	Frequency
Federal Reserve Bank of New York Consumer Credit Panel / Equifax	1999	Quarterly
University of Chicago Booth School of Business / TransUnion	2000	Monthly
Consumer Financial Protection Bureau Consumer Credit Information Panel	2002	Monthly
University of California Consumer Credit Panel	2004	Quarterly
University of Illinois at Urbana-Champaign Gies Consumer and Small Business Credit Panel / Experian	2004	Annual
Ohio State University / Experian	2017	Quarterly

Notes: In nearly all cases, researchers with access to credit panels can have external coauthors, but external coauthors do not get data access. The Federal Reserve Bank of New York Panel is available to researchers across the Federal Reserve System. Data confidentiality agreements mean not all panels can disclose which credit reporting agency data are sourced from. The credit reporting agencies offer off-the-shelf products for purchase—the names and contents of these frequently change. This table is accurate at the time of writing but contents will change over time with panels being created or no longer being updated, additional data added to existing panels to extend its coverage or provide more information.

Table 2—How Long Does Information Remain On Consumer Credit Reports?

Credit File Information	Maximum Reporting Duration
Hard Credit Inquiry	2 years from inquiry date
Open Credit Agreement	Indefinitely
Closed, Non-Delinquent Credit Agreement	10 years from agreement's last activity
Delinquent Credit Agreement	7 years from payment first 30 days past due
Debt in Collections (Medical and Non-Medical)	7 years
Bankruptcy - Chapter 13 - Chapters 7, 11, 12	7 years 10 years

Notes: This table is accurate at the time of writing. Laws change over time so researchers should check the latest versions for current practices.

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Online Appendix: Consumer Credit Reporting Data

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A Additional Details on Accounts Tradeline Files

This Online Appendix section provides additional information on the tradeline consumer credit reporting data. These data are created by consumer credit reporting agencies (CRAs), also known as credit bureaus.

A.1 Mortgages & HELOCs

At $11.9 trillion at the end of 2022, mortgage debt is the largest form of debt held by households, representing 71% of total household debt. Together with HELOCs aggregate housing related debt amounts to 73% of total household debt. Credit reports include account level information on all mortgage installment and revolving accounts. The former includes mortgage installment loans such as first mortgages and home equity installment loans/home improvement loans/second mortgages (HELOANs), sometimes referred to as closed-end second liens, secured by housing collateral. Home equity revolving loans (also known as Home Equity Lines of Credit or HELOCs) are home equity loans with a revolving line of credit where the borrower can choose when and how often to borrow up to a given credit limit.

Some care should be taken in using the mortgage installment account classification. In addition to lender and account information, some CRAs may use the loan origination balance to classify a mortgage as a first or second HELOAN. As a result, relatively small first mortgage loans (such as those for mobile homes) may be misclassified as home equity installment loans, while some larger home equity installment loans are sometimes incorrectly classified as a first mortgage. Remarks codes associated with each mortgage loan can often be used to reclassify such loans. For example, as GSEs secure first liens almost exclusively, loans securitized by GSEs can be reclassified as first mortgage loans. The same applies for FHA loans and VA loans. Users should also be aware that the classification of mortgage loans that was applied by the CRA does not immediately provide the position of the lien. For example, for a consumer with a HELOAN but no first mortgage, the home equity installment loan would sit in the first position.

It is relatively easier to identify the lien status of a mortgage loan in case of "piggyback" second mortgages, made at the same time as the main mortgage. The purpose of such loans is to allow borrowers who are not able to make a 20% down payment to borrow additional funds in order to qualify for a main mortgage without having to pay private mortgage insurance that lenders would require when putting less than 20% down. Such mortgages were very popular in the early to mid 2000s, when piggyback loans often permitted buying a home with very small down payment. Since the housing crisis, piggyback loans have been limited to 90% combined loan-to-value.

For each mortgage and HELOC, credit reports typically include the loan origination date (year and month), origination amount, current balance, requested payment amount or term of the loan, credit limit (on HELOCs), individual/joint account type, and payment status. This includes closed mortgage trades with a zero balance that, temporarily, continue to be reported by creditors. When linking individual loans over time, such reported trades help confirm that a loan was indeed paid off and closed and did not disappear for other reasons.

It is not always the case that an account continues to be reported with a zero balance before it stops being reporting altogether. Avery et al. (2003) examined non-reported mortgage accounts and found that for many, a new mortgage account appeared around the time the account stopped being reported, suggesting a refinance or that the servicing was sold.

Primary versus Second/Investor Home Mortgage

Unlike loan-level mortgage databases such as HMDA, McDash, CoreLogic and Black Knight (formerly LPS), credit report data do not include the intended use and occupancy status reported on mortgage applications. Whether the home will serve as primary residence, vacation home, or investment property generally will affect the mortgage rates available and the requirements needed to be approved for a home loan. Generally, homeowners have an incentive to appear as owner occupants to be eligible for lower rates and certain tax credits.

Credit report data can reveal whether a given borrower has multiple first mortgages, although it does not include the locations or purchase prices of the homes. Haughwout et al. (2011) use this information to characterize borrowers with two, and three or more first mortgage loans over a continuous 2-quarter period as second homeowners, and investors, respectively. By linking to LPS administrative data, they were able to assess the accuracy of self-reported intended occupancy status and found extensive misreporting (see also Garcia (2022) and Elul et al. (2023)). Many mortgage borrowers who listed an intention to move into the property never did so, while often reporting holding a large number of first mortgages. They found misreporting to be especially prominent during the boom in the sand states, and found such investors to default at much higher rate during the housing bust. This research raises concerns about the quality of such occupancy variables of traditional mortgage databases, while illustrating the value of credit report data.

Remarks codes, lender industry type and joint account status

Associated with each mortgage products are usually descriptive codes (called remark codes by TransUnion, narrative codes by Equifax, and enhanced special comment codes by Experian). For example, Equifax credit reports traditionally include up to two narrative codes for each mortgage account (newer credit reports have up to four narrative codes) which provide additional information regarding the product type of the accounts, the security type of mortgage account, including whether it was guaranteed by one of the GSEs or FHA or VA, whether the mortgage was for a mobile home, or a second mortgage/home equity loan/home improvement loan and whether the account was included in a bankruptcy or foreclosure.

Importantly, over the life of a loan, new narrative codes may be added, for example in case of a loan modification or forbearance, which replaces a previous narrative code. For this information not to get lost, panel data that allows a user to track and link loans over time is useful.

Another important data field is an identifier that typically accompanies each account indicating whether the account is a joint or individual account. While it may be warranted to treat the person as responsible for repaying the entire balance for individual-level analysis, it is important to avoid double counting of joint accounts listed on two different individual's credit reports when computing household level or aggregate level debt balances. A standard way to do so is to divide joint balance amounts by two, assuming joint accounts are held jointly by roughly two persons on average.

Foreclosures

Foreclosures, a legal action initiated by mortgage lenders to take control of a property when a borrower fails to keep up their mortgage payments, show up on credit reports soon after filing and often provide information on when the foreclosure proceeding has been completed (which in some states could take a year or longer). They stay on credit reports for seven years from the date of first missed payment that led to the foreclosure action (also known as the "date of delinquency").

Alternatives to foreclosure include a loan modification, short sale and a deed in lieu of foreclosure. The latter, also called a mortgage release, is an arrangement where a mortgage servicer agrees to let the homeowner turn over the deed to the home and move out, instead of waiting for the servicer to foreclose. In exchange, the servicer will release the borrower from their mortgage obligations. A preforeclosure sale or short sale is the pre-approved sale of a property by a homeowner who has proven an inability to make mortgage payments for less than is owed. Such borrowers may still remain responsible for making up the difference between the sales price and the outstanding mortgage balance. This could show up on a credit report as a deficiency judgment. Both short sales and deeds in lieu are borrower-initiated and typically will remain on credit report for up to seven years. Like foreclosures, they typically are reported on the credit report through Remarks Codes such as "short sale" or "forfeit deed-in-lieu of foreclosure."

Modifications & Refinancing

New mortgage originations appearing on credit reports do so without an indicator for whether the new loan represents a new purchase or refinance mortgage. Individual and mortgage account level panel data can be used to help distinguish refinances. New refinance mortgages typically follow a recently closed (prepaid) mortgages without a change in mailing address. In doing so one may want to allow for a reporting gap of up to three quarters following the closed loan (although usually the new loan appears in one or two quarters).

A new address appearing on the credit report around the time of the mortgage origination, or a mortgage origination without a preceding mortgage that was paid off, instead point to a purchase origination. For this reason it is advisable when acquiring credit report data from CRAs to request inclusion of an anonymous or scrambled address identifier, or at a minimum the census block or tract corresponding to the address. See Mian and Sufi (2022) for one example of such a strategy.

Forbearances

Credit report typically do not include a direct forbearance indicator, and lenders/servicers notate forbearance in various ways. Some of the forbearances are notated in narrative codes such as "Natural Disaster" or "Forbearance". Other forbearances appear only as a change in payment amount to zero. During the recent pandemic, analysis based on the FRBNY CCP showed that about 30% of mortgage forbearances were not updated in April 2020, due to such reporting issues. With panel data, forbearance may be possible to identify by following a loan and its narrative codes over time. See Cherry et al. (2021); Dinerstein et al. (2023) for studies of COVID-19 accommodations and Guttman-Kenney (2023) for studies of natural disaster flags.

Civil judgments and tax liens

Other public records include civil judgments and tax liens, collected from city, state and federal courthouses by third-party vendors. Information included is the amount of the judgment or amount due, filing date and status. Civil judgments are court filings in favor of a creditor, often a debt collector trying to recover unpaid debts. Tax liens instead are legal claims against a person's property (home, car, bank account) made by the government when a person fails to pay taxes, such as income and property taxes.

Most civil judgments and tax liens remain on a person's credit report for up to seven years after they are filed with the court. However, due to the National Consumer Assistance Plan (NCAP) settlement reached in 2015 between CRAs and 31 state attorneys general, there has since 2017 been a reduction in the number of public records added to credit reports due to new policies adopted by CRAs (for details see Clarkberg and Kambara (2018)). The new policies limit the inclusion of public records to those containing, at a minimum, the consumer's name, address and Social Security number or date of birth. The public record information must be updated/verified (with a courthouse visit) at least once every 90 days. As a result of the change, civil judgments and tax liens are generally no longer included in credit reports since 2018, though CRAs may still include these when data archived from prior 2018 are used for research (e.g., Fulford and Nagypál, 2023).

Servicer versus lender

Researchers may also use credit reporting data to understand lender, rather than consumer, behavior, and may use lender variation as a source of identification. This requires an understanding of how lenders are observed in these data. Crucially, it is the *furnisher* of loans who report the accounts, and they are not necessarily the same as the lenders or the owners of the debt. Therefore, one should avoid equating furnisher identity to the lender identity.

A.2 Credit Card Accounts

Credit cards are the most widely held formal credit product in the US and the most likely to be a consumer's first-ever tradeline. As open-end credit, cards are also a channel frequently used both as a means of payment and as a source of short-term borrowing. As of Q2 2023 aggregate credit card balances stood at just over $1.0 trillion. Credit cards come in a variety of forms and are used in a variety of ways, which researchers should be mindful of when using credit card CRA data. As discussed in more detail below, our definition of credit cards, as well as the total credit card debt reported, includes balances on credit cards and charge cards, but excludes store or retail cards; this choices follows how CRAs sometimes view these data, though we recognize it differs from how some regulators and lenders view the market (Consumer Financial Protection Bureau, 2021). We will discuss the latter types of cards in the section on "Other Debt."

Revolver versus transactor

There is an important distinction between "revolving" and "transacting" use of a credit card. *Transacting* refers to credit card accounts where the user (a "*transactor*") fully pays off the past month's (or billing cycle's) balance at each due date. *Revolving* refers to accounts where the user (a "*revolver*") does not. Typically about two-thirds of account-months in which accounts have nonzero balance involve revolving debt, and roughly half of credit card holders have at least one account on which they revolve at any given time with persistence in revolving behavior over time (Keys and Wang, 2019; Consumer Financial Protection Bureau, 2021; Grodzicki and Koulayev, 2021; Board of Governors of the Federal Reserve System, 2023). Except in cases where an account has a 0% interest rate, for example as a promotion offered by the card issuer, revolving typically implies a user incurs an interest charge or finance charge on their balance. Transactors who have recently transitioned from revolving also may incur interest or finance charges, typically in the first month after such a transition from revolving while their so-called grace period has not yet been restored.

For a typical revolver, part of the balance will be associated with new transactions (the transaction balance) and part will be carried-over debt (the revolving balance). The former approximately equals the new balance minus the previous balance, plus the actual payment amount in the billing cycle. The revolving balance approximately equals the new balance minus the actual payment amount.

Differentiating the two

It is difficult to distinguish between revolvers and transactors in credit report data. Accordingly, for transacting accounts, the balance shown in credit report data indicates a monthly flow of expenditure, whereas for revolving accounts, the balance indicates a stock of debt.

Account holders' actual payment amount each month is sometimes, but not always, reported to CRAs. There has also been a downward trend recently in the prevalence of this reporting (see Herman et al. (2020), Guttman-Kenney and Shahidinejad (2023), and McNamara (2023)). In cases where these data are reported, it does become possible to infer which accounts are revolving or transacting, and these data can be used to train predictive models of which accounts are revolving or transacting to be used in cases where actual payment is not reported. For more details see sections 8.1 and 8.5.2 in the paper.

Utilization and missing credit card limits

Researchers may be interested in data features other than just the balance on the credit card. The credit limit, for example, is the total credit line that is nominally available to a consumer. In practice, some credit card issuers may approve transactions that bring a user's balance above the credit limit, which generates a nontrivial share of accounts that can be observed with utilization rates greater than 100%. Credit limits are not always reported to CRAs. In such cases, the credit limit may appear as missing, or may reflect the "high credit," on the account, which is the highest balance ever reported to the CRA for that account. Fulford (2015) and Fulford and Schuh (2017) discuss how to address such data features when trying to measure variability in consumers' credit limits over time. Care should therefore be taken in using reported credit limits to identify whether a credit card holder is "maxed out" on a card. Such a measure is sometimes used to measure the extent to which someone is credit constrained, and it is used by many as component of a measure of financial distress (see Brennecke et al. (2023)).

There also is evidence that credit card limits may not be updated as frequently in credit report data as they change for the credit card account holder. For example, accounts that transition into delinquent status are sometimes observed to have a coincident increase in their credit limit, which, given how credit limit increases are unlikely for delinquent accounts, could reflect prior credit limit increases that had not been reported to the CRA.

Issuer versus servicer versus card network

Another data feature sometimes available in anonymized credit report credit card data is the subscriber, or furnisher, that reports a given account's data to the CRA. Furnishers are typically the entity that services a given loan – that is, who receives payments from the consumer, keeps track of the account status, and remits any net returns on the loan to an investor.

Credit card servicers may differ from the credit card issuer, especially in cases of small-scale credit card issuers such as small banks or credit unions. Moreover, banks that service their own credit card portfolios may use different subscriber codes for different parts of their portfolio. This makes it difficult to make inference about market structure or about bank-consumer relationships using anonymized subscriber identifiers alone. We also note that both the issuer and the servicer are often distinct from the card network (e.g., Visa, Mastercard), though the issuer and the card network do coincide in some cases (e.g., Discover, American Express). For more background on the structure and history of card networks, see Evans and Schmalensee (2004).

Intrinsic differences across different types of cards versus semantic-only differences

Another important distinction among credit cards is between general-purpose credit cards and private-label credit cards.[1] General-purpose cards can be used at all merchants who accept cards from a given payment network. Private-label cards, also referred to as store cards or retail cards, can only be used at a limited set of stores, for example a single retailer or a family of retail brands.[2] While credit cards started as general-purpose

[1]Prepaid credit cards are not loans, so they are not reported to CRAs.

[2]Confusion may arise when general-purpose credit cards are co-branded, whereby a retailer's or other

credit cards issued by credit card companies, banks and credit unions, and "retail cards" and "consumer finance cards" were issued by finance companies for specific stores, over time those distinctions have become less binding. Approximately 90% of outstanding credit card balances and 69% of cards are general-purpose credit cards Consumer Financial Protection Bureau (2021). While these two types of cards are classified differently in credit report data, a researcher may want to focus only on one of these categories, or both categories together, depending on the setting.

As retail cards, including department, furniture and jewelry store cards, are classified differently from credit cards issued by banks and credit card companies, a transfer of card accounts between different types of lenders can lead to sudden shifts in outstanding aggregate credit card and retail card balances. For example, such a shift occurred when Walmart store cards issued by Synchrony where sold to Capital One Bank. While the loan product did not really change, its re-classification on credit reports led to a larger increase in aggregate credit card balances and a reduction in retail card balances.

A.3 Auto Loans

Auto loan debt is currently the second largest form of household debt on consumer credit reports, with an aggregate outstanding balance of $1.6 trillion as of the end of Q2 2023. Auto loans are closed-end loans used by consumers to finance the purchase of a new or used auto, where the auto is used as collateral for the loan. Auto loans are generally approved with terms of three to eight years with longer terms becoming more common in recent years. These are installment loans, meaning they require equal monthly payments for a specific period of time. They also record the initial loan balance, current balance, and payment history. Even though quite different from auto loans, auto loan accounts reported to CRAs typically include car leases and are typically narrated as such.

Type of Car Loan Lender

There are five categories of auto lenders with different business models. The first two are banks and credit unions which use funding from deposits from consumers to make loans including auto loans. The third type, auto finance companies, provide auto loans to consumers using alternative sources of funding, often through securitizing the loans they originate. The fourth type of lender, "captives" are similar to finance companies in the way they fund their lending, but they typically are owned by or affiliated with auto

firm's branding is used on the card. A co-branded general-purpose card might include a card that offers rewards at a particular merchant such as an airline, while the card can still be used at all merchants in a given payment network, not just to make purchases from that airline.

manufacturers to help finance purchases of their cars. Captives have a high market share among both prime and subprime consumers. Finally, there are also "buy-here-pay-here" lenders which provide loans directly for the vehicles they sell, primarily in the subprime market. Not all auto lenders furnish information to the CRAs, and that is particularly true for this last category (Low et al., 2021).

Repossessions in payment status and/or remarks code

Auto loan delinquencies, even short-duration delinquencies, can lead to car repossessions, which typically show up either as a payment status or a remark code of "repossession."

A.4 Student Loans

Student loans, sometimes referred to as "education loans," are typically installment loans made to students and/or their families to finance higher education programs. In contrast to other credit products, the federal government plays a large role in the student loan market with federal loans making up the overwhelming majority of student loans. The role of the government as a large lender in this market, along with the large share of loans made to borrowers with limited or no income at the time of origination leads to some unique patterns and reporting for student loans. For example, originations of student loans tend to track school activities and academic years and thus exhibit a seasonal pattern, although interest rate trends also drive trends in refinancing federal student loans into private student loans and the consolidation of some federal student loans to lock in lower interest rates. Additionally, most borrowers typically have multiple student loans if they borrow multiple types of loans or for multiple school years.

Credit record data include both federal and private student loans. Federal student loans include loans originated by the government through the Federal Direct Student Lending (Direct) Program, federally guaranteed loans made by private lenders through the Federal Family Education Loan (FFEL) Program, and federally subsidized Perkins loans made by schools.[3]

Despite the inclusion of both federal and private student loans, total outstanding balances reported in credit record data are \$1.6 trillion as of 2Q 2023, slightly below the amount reported by the Department of Education. We believe the primary reason for this

[3] All non-Perkins federal loans originated since June 30, 2010 have been made by the government under the Direct Program. Prior to this, private lenders could also make federally guaranteed loans under the (FFEL) Program. The Perkins loan program ended in 2017 and there have been no disbursements since 2018.

discrepancy is the nonreporting of older defaulted loans held by the Treasury Department. In compliance with FCRA and the Higher Education Act, these older defaulted loans are not reported to CRAs, although borrowers still owe these debts.

As with other debts, defaulted student loans drop off credit records after seven years, although the date that period is measured from may be later. Federal student loans can be reported with a negative payment history for seven years from the time of default (rather than the initial delinquency that lead to default) under the Higher Education Act. This is true for both Direct and FFEL loans. For private loans, the loans will only appear for up to seven years when charged off. Defaulted federal student loans are also subject to wage and tax refunds garnishments under Treasury / IRS, but it is unclear how reliably this information appears on credit records. Some federal student loans are discharged or forgiven, but there are no special codes to identify when this occurs.[4] When the Department of Education forgives or discharges a student loan, the balance drops to zero, and the loan is reported as paid and closed, the same way a loan repaid by the borrower directly would be reported. For more on the differences between federal and private student loans in credit record data, see below.

No delinquencies reported until 90+ days

The Department of Education has special requirements for the reporting of delinquencies federal student loans that do not apply to private student loans. Specifically, federal student loans cannot be reported as delinquent to the CRA until they are at least 90 days past due. As a result, delinquent federal loans will often be reported as "current" and then "90 days past due" or more with no transition. Federal loans which fall further behind are categorized as in "default" after 270 days of delayed payments and may be reported as a "government claim" on credit records. Defaulted federal loans are then transferred to another servicer, either a guaranty agency or a collections agency depending on the type of loans. As a result, defaulted loans often move between furnishers and may have changes in reported tradeline or account numbers depending on how the CRA assigns these numbers. Defaulted loans which are rehabilitated and brought current are then transferred again to a new servicer.[5] By contrast, private student loans may be reported as delinquent at 30 or more days past due and may be reported as "charged off" when

[4]See https://studentaid.gov/manage-loans/forgiveness-cancellation and https://studentaid.gov/manage-loans/forgiveness-cancellation/closed-school for more information on the requirements for forgiveness and discharge.

[5]In late 2022, the Department of Education implemented a program called "Fresh Start" to give borrowers with defaulted federal student loans an opportunity to access benefits to help get and stay out of default. As a result of this program, all federal student loans reported as in default in credit data were newly reported as current; this happened in late 2022 for defaulted Direct loans and in early 2023 for defaulted FFELP loans and will continue for one year (Gibbs, 2023).

severely delinquent.

Defaulted federal student loans can be cured if the borrower repays the loan in full, consolidates the loan (see below), or rehabilitates the loan. In the event the borrower successfully rehabilitates the loan, the default status is deleted from consumer's credit record, and the payment history is replaced with a '-' in months where the default was reported. When the borrower consolidates a defaulted loan, the prior default will still appear on the credit record (as a closed loan), and the consolidated loan will appear as a new loan.[6]

Federal versus private and IDR

Federal and private student loans are not typically directly distinguishable in the credit record data without access to the names of the furnishers, and those may still leave some ambiguity. Private education loans are reported much the same way as federal student loans and some furnishers have both types of loans in their portfolios which can make it difficult to distinguish between them in credit record data.

Users can try to infer loan types based on some remarks codes or loan characteristics. For example, users can try to leverage differences in term lengths or interest rates for federal and private loans, but users need to remember that federal loans may have atypical term lengths or interest rates due to income-driven repayment (IDR) plans, extended repayment plans, consolidations, and differences across federal loan types which may complicate these distinctions.

Additionally, certain remarks or narrative codes or other indicators only apply to certain types of loans. For example, a cosigner on the account indicates a private student loan and is typically reported for the life of the loan unless a borrower obtains a release from the lender for the cosigner. In contrast, users can have a designation of "permanently assigned to the government" or "government claim" to identify defaulted federal loans, but these codes are only used when the loan is in default. The CARES Act and subsequent administrative actions provide a unique opportunity to help classify loans into federal and private. Through the CARES Act, all direct federal student loans went into an automatic payment suspension and interest rates were lowered to 0 percent for more than two years starting in March 2020.

Both private loans and privately-owned federal loans were not covered by the CARES Act. As a result, users can infer that a loan is federal based on scheduled monthly payments during the pandemic, but some loans that continued to have scheduled monthly payments of zero may still be federal loans under the FFEL Program. Overall, users may

[6]For more on federal student loan default, see https://studentaid.gov/manage-loans/default.

be able to classify many loans as federal or private, but it is difficult to confidently categorize all loans and users should be aware that their estimates will likely be noisy as a result.

IDR plans for federal student loans offer alternative repayment plans for borrowers and have become increasingly common. There are no remarks codes that specify whether a loan is enrolled in an IDR plan, so users must infer enrollment based on other reported information such as loan term, balance amount, scheduled payment amount, and changes in these measures. For example, some loans are reported with $0 scheduled monthly payments but not in deferment or they have scheduled monthly payments that would imply a negative or improbably low interest rate. These changes should be reported for a year since IDR plans have a one-year enrollment period and typically require re-certification to maintain lower payments, but borrowers can resubmit documentation early. In general, reported loan terms should be the maximum number of months for repayment (including accounting for potential forgiveness outside of Public Service Loan Forgiveness), but users should expect that this may not be consistent, especially with older data. For further discussion on identifying loans enrolled in IDR, see Conkling and Gibbs (2019).

Deferments and forbearances

Payment deferments and forbearances are not necessarily indicators of financial distress for student loans. Most student loans are put into a deferred payment status when originated if the student is still in school. This is automatic for federal loans borrowed by the student and is followed by an automatic six-month grace period once the student drops below at least half time.[7] These loans may re-enter deferment if the borrower returns to school. These deferments and grace periods may be reported with a remarks code of "payment deferred" or "account in forbearance," depending on the furnisher and these codes have sometimes been used interchangeably. More recently, servicers of federal student loans have been told to furnish loans in deferment, grace, or forbearance as in deferment to avoid sending potentially negative signals to lenders.

Meanwhile, private student loan borrowers may have the option of a deferred payment while in school, or they may instead have loans put into an "interest only payment" with principal loan payments deferred until the student leaves school or have their loans classified as "in repayment" as soon as the loan is originated.

Forbearances, meanwhile, may occur due to borrower distress or for administrative reasons. Borrowers, for example, may request a temporary suspension of payments due to a hardship such as job loss. Borrowers of federal student loans may also be placed in a

[7] For Perkins loans, the grace period is nine months. For Parent PLUS loans, the deferment is not automatic but is currently available to all Parent PLUS borrowers.

temporary administrative forbearance while

To provide relief to borrowers during the pandemic, payments on all federally-held student loans were paused through the CARES Act and subsequent administrative actions but without any narrative code indicating a payment accommodation. From March 2020 through August 2023, all non-defaulted federal loans owned by the Department of Education were reported with a $0 scheduled monthly payment. Additionally, the payment status for all delinquent non-defaulted loans were changed to current and no new delinquencies were reported for federally-held loans. The Department of Education also instituted a 12-month "on-ramp" for borrowers so that delinquencies on federally-held student loans are reported for another year after the end of the payment pause.

Servicer versus lender

While the Department of Education owns most student loans, they do not service any of their portfolio. Instead. servicing is split across several companies, all of which service other student loans not owned by the Department of Education. Some federal loans (Federal Family Education, or FFEL, Program loans) are serviced by the owner of the loans (either the original private lender or another private lender who has purchased the loans since origination) or a third-party servicer if a lender does not service their own loans or in the case of federally-held FFEL Program loans.[8] Prior to 2013, all Direct loans were serviced and furnished by one company, but the Department of Education has since revised its servicing contracts, and all Direct loans were transferred to other servicers. Over the last several years, some of these servicers have left the system triggering additional large transfers of student loans which can sometimes make it difficult to link individual loans over time. Some of these servicers also furnish information on FFEL loans (made by themselves or other lenders they provide servicing for) and private student loans. Large transfers of student loans may be the result of a change in federal contracting, contracting by private lenders who do not service their loans in-house, or by private lenders selling off their portfolios. As a result, users cannot typically separate loans types by relying on furnisher codes, though it is possible some servicers report different types of loans under different sub-furnishers.

Refinancing and consolidations

In addition to new loans to immediately finance education, student loan originations may also be refinances or consolidations of existing loans. Both federal and private student loans can be refinanced into new private student loans typically in the pursuit of a

[8]Several private lenders, for example, sold off their FFEL portfolio to the government during the Great Recession or to other lenders (Wells Fargo, for example, sold their portfolio to Navient). SoFi is an example of a private lender that outsources its servicing to another company, MOHELA.

lower interest rate. Consolidations, meanwhile, combine existing federal student loans into a single new federal loan. A consolidated loan has a new interest rate that is the weighted average of the rates on the prior loans and the new loan may have a longer term, depending on the total loan amount.[9] Consolidations are also an option to help borrowers rehabilitate federal student loans in default which can make it difficult to track some loans over time. Federal consolidation loans also have specific maximum repayment terms ranging from 10 to 30 years based on the total loan amount. The relationship between loan term and loan amount and the weighted interest rate structure of consolidated loans can help researchers distinguish between consolidations and refinances when researchers have loan-level data.

Servicer transfers and reporting gaps

As previously noted, furnishers occasionally stop reporting accounts temporarily. This is often, though not always, associated with a servicer transfer. Most gaps due to transfers are three months or shorter, but there are exceptions. Data users in these cases may need to fill in the intervening periods to account for the missing tradelines. These gaps have been particularly frequent in recent years in reporting by student loan servicers because of the large number of federal servicing transfers. A common practice by some researchers has been to repeat the most recently reported status of the loan (or interpolate the missing periods based on the statuses in the surrounding periods) in cases where there is a simultaneous large drop in reported loans by a specific anonymized furnisher.

A.5 Other Loans

Other loans are, by definition, a residual catch-all category not captured by the main product categories explained in preceding sections. As a result it can contain a broad variety of product types. However, they can be generally considered as installment or revolving loans for consumer products that are not captured in the credit cards category. A natural split that CRAs use to differentiate within this category is into revolving loans (i.e., with a credit limit) and non-revolving loans (i.e., installment loans).

There may be differences in how these accounts are characterized across datasets and projects. For example, some researchers group retail cards (see section A.2 above) into one category while others, like the NY Fed, group them into a larger category of "other" loans.

Some other loans have remarks codes "recreational merchandise loans" and "agricultural loans." Still some other loans are included in this residual category due to a lack of

[9] Older variable rate loans are changed to fixed rate loans during consolidation.

identifying description of the nature of the loan. The amount of outstanding debt in this category is fairly unchanged from 2003 to 2021 in the FRBNY-CCP: peaking at \$0.49 tr in 2003, troughing at \$0.30 tr in 2013 and reaching \$0.44 tr in 2021.

Given the heterogeneity within this product category and the smaller market sizes, these loans are less frequently the focus of research. Sometimes, however, researchers are able to use institutional knowledge, such as information on the servicer or loan characteristics, to isolate the subset of accounts they are interested in studying. For example, Di Maggio and Yao (2021) identify loans provided by FinTech lenders. In general, it is more common for researchers to only examine this as one disaggregation of a household's debt or as an input to a predictive model. Classifications of loans within this category may change over time as new products develop and reporting categories are generated. For example, CRAs are developing new ways to classify buy now pay later (BNPL) loans.

B Additional Measures of Credit Card Spending

Credit cards are broadly used by US consumers with high coverage across geography and credit scores. The amount of spending on credit cards therefore makes them well-suited as a measure of consumption. However, when using credit card spending as a measure of consumption, it is an important caveat to note that this will not include all of a consumer's consumption: it excludes consumption via debit cards, bank transfers, checks, or cash. Approximately, 30% of payments are made via credit cards and this share is growing over time whereas the share of cash and checks are declining over time (e.g. Cubides and O'Brien, 2023). Researchers will often use these measures by comparing them to a control group.

When calculating credit card spending, we generally recommend combining (general-purpose) credit cards with (private-label) retail credit cards (which can only be used at one or a small group of merchants). Retail cards are a much smaller market (Consumer Financial Protection Bureau, 2021) but are useful to include as they cover a different socio-economic groups.

The target economic parameter of interest – 'credit card spending' ($s_{i,t}$) – is the total value of new purchases on a credit card i at time t.

We show four ways to attempt to measure this. These increase in complexity and data requirements.

A bad measure of credit card spending is shown in $s_{i,t}^{BAD}$ in Equation 1. This measures spending by the credit card statement balance ($b_{i,t}$). This is a bad measure of spending as it includes spending from previous periods that was revolved as debt. It also includes financing charges (the sum of interest and fees) and excludes spending repaid before the statement balance is issued. If using this we would recommend defining it as credit card statement balances, a useful but different object, and not consider it a consumption measure.

$$s_{i,t}^{BAD} = b_{i,t} \tag{1}$$

A better measure of credit card spending ($s_{i,t}^{GNW}$), as used in Gross et al. (2020), is the *change* in credit card statement balance. This is shown by Equation 2. This measure removes some double counting of revolved debt. However, changes in statement balances are the net of the change in new spending less the change in payments and change in financing charges. This means, for example, a credit cardholder whose new spending is unchanged but reduces their payments may, by this measure, appear to spend more even though their spending is unchanged. Guttman-Kenney and Shahidinejad (2023) shows this is a biased measure of spending. It is preferable to calculate this at the tradeline-level as doing so enables the researcher to account for changes in tradeline reporting which may erroneously affect aggregates. This measure can also be calculated from consumer-level roll-ups data – including with non-consecutive periods though doing so will further reduce this measure's accuracy.

$$s_{i,t}^{GNW} = \Delta b_{i,t} = b_{i,t} - b_{i,t-1} \tag{2}$$

Our third measure of credit card spending ($s_{i,t}^{GN}$) is shown in Equation 3, as used in Ganong and Noel (2020) is the first of our measures that removes revolving debt. This measure takes the changes in statement balances and adds payments ($p_{i,t}$). If the measure produces a negative number, it is bounded at zero. Making this adjustment not only removes revolving debt but also includes spending repaid before the statement balance is issued. This contains some error as it includes financing charges. This measure relies on the researcher being able to observe the actual payment amounts variable at the tradeline-level. However, from 2015 to, at least, 2023 this actual payment amounts variable is only reported for a highly selected subset of credit card lenders and this subset excludes the six largest lenders (Guttman-Kenney and Shahidinejad, 2023). If using this measure, researchers need to restrict to only study the cards of furnishers who consistently report the actual payment amounts (e.g., Ganong and Noel, 2020, exclude furnishers where over 90% of card months are zero or missing). In the future reporting of this variable may increase. We therefore recommend that researchers who want to use this measure should confirm the reporting coverage of the actual payment amounts variable for the time period they are planning to study before using or purchasing data.

$$s_{i,t}^{GN} = \begin{cases} b_{i,t} - b_{i,t-1} + p_{i,t} & \text{if } \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Our final measure of credit card spending ($s_{i,t}^{GKS}$) is shown in Equation 4. This measure is introduced in Guttman-Kenney and Shahidinejad (2023). This adapts $s_{i,t}^{GKS}$ to remove estimated financing charges ($f_{i,t}$). All the caveats on the coverage of $p_{i,t}$ also apply to this measure. Financing charges are estimated following Guttman-Kenney and Shahidinejad (2023).

$$s^{GKS} = \begin{cases} b_{i,t} - b_{i,t-1} + p_{i,t} - f_{i,t} & \text{if } \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

It is also possible to produce estimates of spending using other methodologies. Researchers may create their own predictive models. Researchers may also purchase measures of spending calculated by the CRAs. A challenge of these CRA-created measures is researchers typically will not be told the algorithm used to create them. As CRA-created measures are commercially-sold products, agencies can be sensitive to publishing quality assurance. Without such assurance it is difficult for readers to evaluate the bias of such CRA-created measures. Ultimately, unless both statement balances and actual payment amounts are consistently observed in the underlying tradeline data, models created by researchers or agencies will struggle to accurately measure spending.

C Additional Literature On Credit Reporting

In the main paper, we provide an overview of how consumer credit reporting data has been used to study topics across economic fields. In this Online Appendix, we complement this by specifically reviewing additional literature studying consumer credit reporting.

Diamond (1984) and Ramakrishnan and Thakor (1984) provide theoretical rationales for firms to form coalitions to share information, and to delegate monitoring to an intermediary such as a consumer credit reporting agency (CRA). Following Pagano and Jappelli (1993), a series of studies understand the formation of information sharing regimes across domains (e.g., Brown et al., 2009; De Janvry et al., 2010; Doblas-Madrid and Minetti, 2013; Brennecke, 2016; Liberti et al., 2022). Brown and Zehnder (2007) provides experimental evidence to understand the circumstances when firms voluntarily share data and its implications for lending. Closely related, in addition to the studies referenced in the main paper, there are also a information economic theory literature on information sharing (e.g., Raith, 1996)

Jappelli and Pagano (2002) provides cross-country evidence showing countries with credit bureaus have more lending and lower defaults. They document public credit registers are more common in countries where creditor rights are less protected and where private credit reporting agencies (CRAs) have not naturally developed. Corroborating evidence on the importance of creditor rights is also provided in La Porta et al. (1997); Djankov et al. (2007). Mian (2012) makes the case for public credit registers. Early studies of US credit bureaus show the value of observing such data on consumers and businesses (e.g., Avery et al., 1996; Barron et al., 2000; Barron and Staten, 2003; Kallberg and Udell, 2003)

A series of papers study relationship lending and related competitive issues in business credit and consumer credit markets (e.g., Petersen and Rajan, 1994, 1995, 2002; Bouckaert and Degryse, 2004; Hauswald and Marquez, 2006; Gehrig and Stenbacka, 2007; Schenone, 2010; Sutherland, 2018; Bank et al., 2023; De Giorgi et al., 2023). Dell'Ariccia and Marquez (2006) show how information sharing may not arise endogenously and mandating information sharing may increase lending volume but increase the probability of a banking crisis.

Researchers have examined credit reports (from private credit bureaus and public credit registers) across the world including Argentina (e.g., Hertzberg et al., 2011), Canada (e.g., Agarwal et al., 2020; Allen et al., 2022), Chile (e.g., Foley et al., 2022), India (e.g., Fiorin et al., 2022; Ghosh and Vats, 2023), Mexico (e.g., Seira et al., 2017; Castellanos et al., 2022), South Africa (e.g., Bertrand et al., 2010), South Korea (e.g., Hahm and Lee, 2011), Sweden (e.g., Bos et al., 2018), and the UK (e.g., Gathergood et al., 2019a; Guttman-Kenney et al., 2023). A variety of empirical studies have examined the effects of adding information to credit reports. Hertzberg et al. (2011) shows lending decisions become more coordinated when information is made public. Foley et al. (2022) show the competitive effects of sharing ("positive") information that covers information on non-defaulted credit cards. Guttman-Kenney and Shahidinejad (2023) shows how mandating sharing information on credit card limits affects credit access and competition. Guttman-Kenney and Shahidinejad (2023) also shows the value of actual payments information for predicting profitability and the fragility of voluntary information sharing to innovations enabling targeting marketing.

There have also been a series of studies examining the effects of removing different types of information from credit reports. For example, the removal of past delinquencies (e.g., Bos et al., 2018; Liberman et al., 2019; Blattner et al., 2022; Guttman-Kenney, 2023), bankruptcies (e.g., Musto, 2004; Dobbie et al., 2020; Gross et al., 2020; Herkenhoff et al., 2023, 2021; Jansen et al., 2023), public records (e.g., Fulford and Nagypál, 2023), and medical debts in collections (e.g., Batty et al., 2022).

A variety of work studies credit scores. For example, Meier and Sprenger (2012) shows time discounting predicts credit scores. Israel et al. (2014) shows credit scores also predict cardiovascular health. Homonoff et al. (2021) shows that when consumers receive information about their credit score, this reduces late payments. A handful of studies examine the effects of fraud (e.g., Mikhed and Vogan, 2018; Blascak et al., 2019).

A variety of studies examine the value of alternative data sources to predicting consumer defaults. Khandani et al. (2010); Norden and Weber (2010); Puri et al. (2017); Tobback and Martens (2019) show the value of bank transactions data. Djeundje et al. (2021) show the value of email usage, psychometrics, and demographic variables. Consumer Financial Protection Bureau (2014) examine remittance histories. Björkegren and Grissen (2018, 2020) study mobile phone data. Wei et al. (2016) study social media data and Lin et al. (2013) study social networks. Berg et al. (2020); Fu et al. (2020) examine digital footprints. These alternative data sources can be especially important for evaluating credit risk in countries where banking systems are less developed (e.g., Burlando et al., 2023; Robinson et al., 2023).

There are many other related literatures implicated in the regulation of credit reporting data. For example, work on discrimination and policy remedies for it (e.g., Charles and Guryan, 2011; Small and Pager, 2020), the literature on design of a scoring system (e.g., Bonatti and Cisternas, 2020; Frankel and Kartik, 2022; Liang et al., 2021), and the literature on consumer demand for privacy (e.g., Goldfarb and Tucker, 2012; Acquisti et al., 2016; Nissenbaum, 2020). There is a substantial computer science and operations research on the methods for constructing credit risk models (e.g., Hand and Henley, 1997; Thomas, 2009).

D Papers Using Consumer Credit Reporting Data, By JEL Code

This list is not intended to be comprehensive. We assign papers to a single JEL code but many could be regarded as being relevant to multiple JEL codes. Readers who know of papers not included in this list should please email the corresponding author.

- **C. Mathematical and Quantitative Methods:**

  Machine Learning - Albanesi and Vamossy (2019); Blattner and Nelson (2022); Blattner et al. (2021); Bono et al. (2021); Bartlett et al. (2022); FinRegLab et al. (2022).

- **D: Microeconomics:**

  Behavioral Economics - Meier and Sprenger (2010, 2012); Ponce et al. (2017); Gathergood et al. (2019b); Agarwal et al. (2020); Gopalan et al. (2023).

  Information, Knowledge, and Uncertainty - Chava et al. (2021); Kovrijnykh et al. (2022)

- **E: Macroeconomics and Monetary Economics:**

  Consumption - Musto and Souleles (2006); Fulford and Schuh (2017); Di Maggio et al. (2017); Demyanyk et al. (2017); Berger et al. (2018); Gross et al. (2020); Ganong and Noel (2020); Agarwal et al. (2022, 2018).

  Great Recession - Mian and Sufi (2009, 2011, 2012); Mian et al. (2013); Mian and Sufi (2014); Avery and Brevoort (2015); Bhutta (2015); Bhutta and Keys (2016); Benmelech et al. (2017); Bhutta et al. (2017); Mian and Sufi (2017); Foote et al. (2021); Piskorski and Seru (2021); Albanesi et al. (2022); Mian and Sufi (2022)

  Monetary Policy Beraja et al. (2019); Di Maggio et al. (2020); Berger et al. (2021)

  Household Butler et al. (2023b)

- **G: Financial Economics:**

Auto Loans - Chakrabarti and Pattison (2019); Yannelis and Zhang (2023); Butler et al. (2023a); Argyle et al. (2023).

Buy Now Pay Later - Zeballos Doubinko and Akana (2023); Shupe et al. (2023); Papich (2023)

Credit Cards - Fulford (2015); Debbaut et al. (2016); Keys and Wang (2019); Fulford and Schuh (2023); Nelson (2022); Adams et al. (2022); Guttman-Kenney et al. (2023); De Giorgi et al. (2023); Chava et al. (2023a).

Mortgages - Brevoort and Cooper (2013); Piskorski et al. (2015); Bond et al. (2017); Fuster et al. (2018); Gupta (2019); Abel and Fuster (2021); Laufer and Paciorek (2022); Hossain et al. (2023)

Student Loans - Di Maggio et al. (2023); Black et al. (2020); Yannelis and Zhang (2023); Herbst (2022); Chakrabarti et al. (2023); Hampole (2022); Sauers (2022); Dinerstein et al. (2023); Chava et al. (2023b).

Payday Loans - Bhutta (2014); Bhutta et al. (2015, 2016); Carter and Skimmyhorn (2017); Desai and Elliehausen (2017); Gathergood et al. (2019a); Miller and Soo (2020); Fulford and Shupe (2021b).

Debt Collection - Brevoort et al. (2020); Fedaseyeu (2020); Kluender et al. (2021); Guttman-Kenney et al. (2022); Romeo and Sandler (2021); Cheng et al. (2021); Fonseca (2023).

FinTech - Fuster et al. (2019); Berg et al. (2020); Di Maggio and Yao (2021); Jagtiani and Dolson (2021); Ben-David et al. (2022); Mishra et al. (2022); Balyuk (2023).

Credit File Forbearance - Cherry et al. (2021); Allen et al. (2022); Kim et al. (2022); Guttman-Kenney (2023); Xie and Moulton (2023).

Credit Reporting - Brown et al. (2015); Haughwout and van der Klaauw (2015); Garmaise and Natividad (2017); Fulford and Nagypál (2023); Jansen et al. (2023); Blattner et al. (2022); Foley et al. (2022); Guttman-Kenney and Shahidinejad (2023); Burke et al. (2023).

Credit Unions - Shahidinejad (2023)

- **H: Public Economics:** Mian et al. (2010); Demyanyk et al. (2019); Davis et al. (2021); Dupor et al. (2021); Mello (2023); Fulford and Shupe (2021a); Miller and Soo (2021); Beshears et al. (2022); Bornstein and Indarte (2022); Fulford and Nagypál (2023); Zhong et al. (2023).

- **I: Health, Education, and Welfare:** Finkelstein et al. (2012); Mazumder and Miller (2016); Brown et al. (2016); Bhole (2017); Hu et al. (2018); Dobkin et al. (2018); Nicholas et al. (2021); Argys et al. (2020); Goldsmith-Pinkham et al. (2021); Batty et al. (2022); Blascak and Mikhed (2023); Miller et al. (2023); Smith et al. (2020); Frisancho (2023); Dooley and Gallagher (2023); Bruhn et al. (2023); Butler et al. (2022).

- **J: Labor and Demographic Economics:** Aaronson et al. (2012); Ghent and Kudlyak (2016); Herkenhoff et al. (2023); Bos et al. (2018); Dobbie et al. (2020); Ballance et al. (2020); Braxton et al. (2020); Cooper et al. (2020); Mezza et al. (2020); Bellon et al. (2021); Herkenhoff et al. (2021); Fos et al. (2021); Gopalan et al. (2021); Benetton et al. (2022); Buchak (2022); Cortés et al. (2022); Di Maggio et al. (2022); Bach et al. (2023); Moulton et al. (2023).

- **K: Law and Economics:** Bankruptcy - Musto (2004); Dobbie et al. (2017); Albanesi and Nosal (2018); Gross et al. (2021).

- **L: Industrial Organization. & M: Business Administration and Business Economics; Marketing; Accounting; Personnel Economics:** Agarwal et al. (2010); Bertrand et al. (2010); Stango and Zinman (2016); Han et al. (2018); Galenianos and Gavazza (2022); Jiang et al. (2021, 2023); Jiang (2022); Chan et al. (2022); Granja and Nagel (2023).

- **O. Economic Development, Innovation, Technological Change, and Growth:** Seira et al. (2017); Castellanos et al. (2022); Fiorin et al. (2022); Ghosh and Vats (2023); Agarwal et al. (2023)

- **P. Political Economy and Comparative Economic Systems** - Brown et al. (2019); Mian et al. (2010).

- **Q. Agricultural and Natural Resource Economics; Environmental and Ecological Economics** - Gallagher and Hartley (2017); Roth Tran and Sheldon (2017); Bleemer and van der Klaauw (2019); DeWaard et al. (2020); Billings et al. (2022); Benjamin et al. (2022); Cookson et al. (2022); Gallagher et al. (2023); Cookson et al. (2023).

- **R: Urban, Rural, Regional, Real Estate, and Transportation Economics:** Brevoort (2011); Haughwout et al. (2011); Whitaker (2018); DeWaard et al. (2019); Bleemer et al. (2021); Howard and Shao (2022); Keys et al. (2023); Mabille (2023); Fonseca and Liu (2023); Liebersohn and Rothstein (2023).

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