Supplemental Appendix: Consumer Credit Reporting Data[*]

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Contents

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Introduction to Supplemental Appendix

This Supplemental Appendix provides a variety of more detailed resources to assist users of consumer credit reporting data in conducting research, and to enable potential users to evaluate the potential to do so.

Section A provides a 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 first subsection briefly describes examples in the literature that use credit reporting data to study various topics. The second subsection focuses on the use of these data to understand issues pertaining to credit reporting itself. The third subsection provides a more exhaustive list of relevant papers, without descriptions, with citations grouped by *Journal of Economic Literature* (JEL) codes.

Section B provides details on the credit reporting process.

Section C provides details on each of the credit reporting files, summarized in Table 1 of the main paper.

Section D provides details on the debt products contained in the tradeline consumer credit reporting data. It includes subsections on each of the main classes of debt products: Mortgages & Home Equity Lines of Credit (HELOCs), Credit Card Accounts, Auto Loans, Student Loans, and Other Loans.

Section E provides additional details on economic measures. Subsections E.2 and E.3 provide additional details on measuring delinquency and new account openings respectively. Subsection E.4 provides additional approaches for using credit card spending as a measure of consumption to complement those presented in the main paper. For each of these measures, we note their limitations.

Section F provides additional details on credit scoring.

Section G provides additional details on accessing credit reporting data. This includes Subsection G.1 that expands on Table 4 in the main paper by providing a summary of each of the consumer credit reporting panels that are potentially available to researchers. These are accurate at the time of writing; the institutions with panels and the contents of such panels change over time.

Section H provides a summary of code available to assist researchers work with these data. We highlight some published papers that have public code and provide some additional examples for common tasks using these data.

Finally, references to all papers cited across this Supplemental Appendix are can be found at the end of this document, in Section I.

A Literature Review

In this section, we provide a 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 first subsection briefly describes examples in the literature that use credit reporting data to study various topics. The second subsection focuses on the use of these data to understand issues pertaining to credit reporting itself. The third subsection provides a more exhaustive list of relevant papers, without descriptions, with citations grouped by JEL codes.

A.1 Review of Literature Using Consumer Credit Reporting Data

The earliest well-known research using credit reporting data are studies of the 2007–2008 US financial crisis, such as 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 et al., 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 et al., 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 et al., 2013; Benmelech et al., 2017; Chatterjee et al., 2023). Researchers have also used credit reporting data to study the drivers and dynamics of the business cycle (e.g., Gross et al., 2020).

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.[1] 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 et al., 2022), student loans (e.g., Di Maggio et al., 2023), payday loans (e.g., Gathergood et al., 2019a), and FinTech (e.g., Fuster et al., 2019). As examples of the effects of specific policy interventions, Butcher and Munoz (2017) and Conway et al. (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 geographic 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 et al., 2020; Batty et al., 2022). Others have used credit data linked to health-related data sources to document the financial consequences of health events such as hospital admissions (Dobkin et al., 2018), abortions (Miller et al., 2023) and Alzheimer's diagnosis (Nicholas et al., 2021; Gresenz et al., 2024). Meanwhile, the growing use of medical credit cards and financing plans remains largely unexplored using credit reporting data.

Credit reporting data have 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 et al., 2024, 2021), as have studies using a consumer reporting agency'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 (2025), and Braxton et al. (2024b) 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 et al., 2012; Cooper et al., 2020; Gopalan et al., 2021b). Similarly, several studies have analyzed the determinants and consequences of participation in the gig economy using credit data (e.g., Buchak, 2024; Fos et al., 2025). Relatively little work has explored intra-household and inter-generational behavior, but there is great potential in this avenue (e.g., Dokko et al., 2015; Bleemer et al., 2017; Benetton et al., 2022; Bach et al., 2023).

Additionally, the coverage of these data—including nearly all US adults and following their movements over long periods of time—makes them well-suited to studying issues in ***environmental economics*** and ***urban economics***. For example, several studies have

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

investigated the effects of natural disasters on credit (e.g., Gallagher and Hartley, 2017; Billings et al., 2022) and non-credit outcomes such as migration (e.g., Bleemer and van der Klaauw, 2019; DeWaard et al., 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 et al., 2019) and to help inform whether these reflect place-based or person-based factors (e.g., Keys et al., 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 et al., 2010), and public policies such as the moving-to-opportunity program (Miller and Soo, 2021), housing vouchers (Davis et al., 2021), eviction protections (Collinson et al., 2024; Humphries et al., 2024), the EITC (Caldwell et al., 2023), traffic fines (Mello, 2024), and unconditional cash transfers (Bartik et al., 2024). At the same time, there is little work studying the relationship between debt and different retirement saving systems; exceptions are Beshears et al. (2022, 2024)'s analyses 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 et al., 2010; Brown et al., 2019). However, the wide geographical coverage that can be shared down to a fine granularity (e.g., zip code, 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 et al., 2017; Gathergood et al., 2019b). ***Industrial organization*** and ***marketing*** research has used versions of these data merged with marketing offers to study consumer demand (e.g., Agarwal et al., 2010; Bertrand et al., 2010; Stango and Zinman, 2016; Han et al., 2018) or optimal regulation under imperfect competition (e.g., Galenianos and Gavazza, 2022; Nelson, 2023), 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, 2024; Blattner et al., 2021).

A.2 Review of Literature Studying Credit Reporting

In the previous subsection, we provided an overview of how consumer credit reporting data have been used to study topics across economic fields. In this subsection, we complement this by specifically reviewing additional literature that studies consumer credit reporting.

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) provide experimental evidence to understand the circumstances in which firms voluntarily share data and its implications for lending. Closely related, in addition to the studies referenced in the main paper, there is also an information economic theory literature on information sharing (e.g., Raith, 1996) and the economics of data (e.g., Bergemann and Bonatti, 2019; Acemoglu et al., 2022) including potential social gains from sharing given data are non-rival (e.g., Jones and Tonetti, 2020). Einav and Levin (2014) discuss the gains to researchers from new "big" datasets becoming available. In such theoretical literature, credit reporting agencies (CRAs) can be viewed as "information intermediaries" (Bergemann and Bonatti, 2019).

For readers interested in credit reporting around the world, we refer them to Jappelli and Pagano (2002); Djankov et al. (2007); Miller (2003); International Finance Corporation (2012) and World Bank (2012). There is international and historical variation in what information is recorded in CRAs, often distinguished by "negative-only," which only shows delinquencies, and "positive," which also includes other information such as balances and credit limits. Jappelli and Pagano (2002) provide cross-country evidence showing that countries with credit bureaus have more lending and lower defaults. They document that public credit registers are more common in countries where creditor rights are less protected and where private consumer reporting agencies 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). Bruhn et al. (2013) show a credit bureau is less likely to emerge in economies with a high bank concentration as sharing information would reduce the large incumbents' informational rents. 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; Xu, 2023), Chile (e.g., Foley et al., 2022; Madeira, 2024), India (e.g., Fiorin et al., 2023; Ghosh and Vats, 2023), Mexico (e.g., Seira et al., 2017; Castellanos et al., 2022), Peru (e.g., Lee et al., 2024b), 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; Adams et al., 2022; Guttman-Kenney et al., 2025; Beshears et al., 2024). A variety of empirical studies have examined the effects of adding information to credit reports. Hertzberg et al. (2011) show 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 (2025) show how mandating sharing information on credit card limits affects credit access and competition. Guttman-Kenney and Shahidinejad (2025) also show the value of actual payments information for predicting profitability and the fragility of voluntary information sharing to innovations enabling targeted marketing.

Credit reports contain many sources of exogenous variation for researchers to use to study credit and non-credit behaviors. For example, research has examined the removal of past delinquencies (e.g., Bos et al., 2018; Liberman et al., 2019; Blattner et al., 2022; Guttman-Kenney, 2025; Madeira, 2024), bankruptcies (e.g., Musto, 2004; Dobbie et al., 2020; Gross et al., 2020; Herkenhoff et al., 2024, 2021; Jansen et al., 2023), public records (e.g., Fulford and Nagypál, 2023), medical debts in collections (e.g., Batty et al., 2022), and the exclusion of inquiries from credit scores (e.g. Madeira, 2024). Other sources of variation include geographic moves (e.g., Keys et al., 2023) and exposure to geography-based treatments (e.g., Gallagher and Hartley, 2017; Bleemer and van der Klaauw, 2019; Billings et al., 2022), and variation in firms' policies.

A variety of work studies credit scores. Avery et al. (2009) analyze how credit scoring has affected the availability and affordability of credit. Meier and Sprenger (2012) show time discounting predicts credit scores. Israel et al. (2014) show credit scores also predict cardiovascular health. Homonoff et al. (2021) show that when consumers receive information about their credit score, they make fewer late payments. A handful of studies examine the effects of fraud (e.g., Mikhed and Vogan, 2018; Blascak et al., 2019; Mohr and

Kohli, 2024). Brevoort et al. (2013) and Blizard et al. (2025) consider the impacts on credit scores of including accounts held by authorized users (i.e., users of an account, such as a credit card, who can use but are not financially responsible for the account).

A variety of studies examine the value of alternative data sources in predicting consumer defaults. Khandani et al. (2010); Norden and Weber (2010); Puri et al. (2017); Tobback and Martens (2019), and Lee et al. (2024b) show the value of bank transactions data. Alexandrov et al. (2023) shows cashflow data measured in survey data predicts default. 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); Chioda et al. (2024) 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., 2024; Robinson et al., 2023).

An emerging literature studies the implications of open banking, where a consumer can grant permission for their banking data to be shared with other institutions (e.g., Babina et al., 2025; He et al., 2023; Rishabh, 2024). Lenders around the world appear to be increasingly using such open banking data in addition to or even instead of traditional credit reporting data.

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); research on how credit reporting data either express notions of public morality or rather "hold people accountable for actions that are not really their fault" (e.g., Kiviat, 2019, 2021); literature on the design of scoring systems (e.g., Bonatti and Cisternas, 2020; Frankel and Kartik, 2022; Liang et al., 2021); and 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).

A.3 Summary of Literature, By JEL Code

This subsection groups papers by their *Journal of Economic Literature* (JEL) codes, and topics within these. This list is not intended to be comprehensive. We assign papers to a single JEL code, but many papers could be regarded as being relevant to multiple JEL codes.

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

  Machine Learning - Albanesi and Vamossy (2019); Blattner and Nelson (2024); 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. (2023).

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

  Consumption - Musto and Souleles (2006); Fulford and Schuh (2024); Di Maggio et al. (2017); Demyanyk et al. (2017); Berger et al. (2018); Gross et al. (2020); Ganong and Noel (2020); Agarwal et al. (2023a, 2018); Athreya et al. (2019); Lee and Maxted (2024).

  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); Pinto and Steinbaum (2023).

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

- **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 (2023); Adams et al. (2022); Guttman-Kenney et al. (2025); De Giorgi et al. (2023); Chava et al. (2023a); Xu (2023).

  Mortgages - Elul et al. (2010); Bhutta and Canner (2013); Brevoort and Cooper (2013); Piskorski et al. (2015); Bayer et al. (2016); Chan et al. (2016); Bond et al. (2017); Fuster et al. (2018); Gupta (2019); Lambie-Hanson and Reid (2018); Abel and Fuster (2021); Laufer and Paciorek (2022); Hossain et al. (2023); Gao et al. (2024); Zhang (2023a); Pal (2024).

Student Loans - Di Maggio et al. (2023); Black et al. (2020); Yannelis and Zhang (2023); Herbst (2022); Chakrabarti et al. (2023); Hampole (2024); Sauers (2022); Dinerstein et al. (2024); Chava et al. (2023b); Hamdi et al. (2024); Gallagher et al. (2023a).

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); Xie et al. (2023); Correia et al. (2024); Di Maggio et al. (2025).

Debt Collection - Brevoort and Kambara (2015); 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); Kluender et al. (2024).

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); Zhang (2023b); Chioda et al. (2024).

Credit File Forbearance - Cherry et al. (2021); Allen et al. (2022); Kim et al. (2022); Guttman-Kenney (2025); Xie and Moulton (2023).

Credit Reporting - Avery et al. (2009); Brevoort et al. (2013); Brown et al. (2015); Garmaise and Natividad (2017); Arya et al. (2013); Mikhed and Vogan (2018); Blascak et al. (2019); Fulford and Nagypál (2023); Jansen et al. (2023); Blattner et al. (2022); Foley et al. (2022); Guttman-Kenney and Shahidinejad (2025); Burke et al. (2023); Madeira (2024); Mohr and Kohli (2024).

Credit Unions - Shahidinejad (2025).

- **H: Public Economics:** Mian et al. (2010); Demyanyk et al. (2019); Aneja and Avenancio-León (2021); Davis et al. (2021); Dupor et al. (2022); Mello (2024); Fulford and Shupe (2021a); Miller and Soo (2021); Beshears et al. (2022); Bornstein and Indarte (2022); Fulford and Nagypál (2023); Zhong et al. (2023); Andre et al. (2024); Beshears et al. (2024); Dobridge et al. (2024); Bartik et al. (2024).

- **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. (2025); Frisancho (2023); Dooley and Gallagher (2024); Bruhn et al. (2023); Butler et al. (2022); Andre et al. (2023); Gresenz et al. (2024); Lee et al. (2025).

- **J: Labor and Demographic Economics:** Aaronson et al. (2012); Dokko et al. (2015); Ghent and Kudlyak (2016); Herkenhoff et al. (2024); Bos et al. (2018); Bleemer et al. (2017); Dettling and Hsu (2018); Dobbie et al. (2020); Ballance et al. (2020); Braxton et al. (2024b); Cooper et al. (2020); Mezza et al. (2020); Bellon et al. (2021); Gopalan et al. (2021a); Herkenhoff et al. (2021); Fos et al. (2025); Fritsch and Heimer (2020); Gopalan et al. (2021b); Benetton et al. (2022); Buchak (2024); Cortés et al. (2022); Di Maggio et al. (2022); Bach et al. (2023); Flamang and Kancherla (2023); Moulton et al. (2023); Braxton et al. (2024a); Butler et al. (2023b).

- **K: Law and Economics:** Bankruptcy - Musto (2004); Dobbie et al. (2017); Albanesi and Nosal (2024); Gross et al. (2021); Nagel (2024).

- **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); Mayer (2024); Chan et al. (2022); Granja and Nagel (2024).

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

- **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. (2023b); 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 (2023); Hwang and Ding (2020); Keys et al. (2023); Mabille (2023); Fonseca and Liu (2024); Liebersohn and Rothstein (2025).

B Details on Credit Reporting Processes

Below, we further explain the practicalities of how credit reporting data are furnished, or transferred from consumer-facing firms to consumer reporting agencies (CRAs) 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 can easily result from misunderstanding the furnishing process). This section also briefly explains potential sources of measurement error, such as incomplete coverage of debts and people, fragmented records, reporting lags, and stale information.

Reporting Changes over Time

As discussed in the main text, the Fair Credit Reporting Act (FCRA) is the primary law regulating US consumer credit reporting information, and this law has been amended several times over the last 50 years by Congress to address persistent issues with accuracy and the ability of consumers to access remedies. For example, the 1996 amendment added a new 30-day limit for CRAs to respond to consumer-initiated disputes, imposed new requirements about the deletion and potential re-insertion of disputed information, and placed obligations on data furnishers for the first time, primarily regarding data accuracy. A 2003 amendment, meanwhile, added more protections to help those affected by identity theft, among other changes.

More recent changes have arisen due to rule-makings by federal agencies, and some have focused on the information reported on credit records. For example, a 2009 rule issued pursuant to the 2003 amendments generally mandated the reporting of credit limits, which some lenders had chosen to not report. Regulators stated the omission of this field could create a misleading assessment of a consumers' creditworthiness.

Other changes have arisen in response to changes in various credit markets. For example, following the Great Recession, the US government introduced the Home Affordable Modification Program (HAMP) in 2009 to help homeowners under stress. However, the existing credit reporting system at that time had no means to accommodate this new program and reported them as "making partial payment," which harmed 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. By contrast, at the start of the pandemic, Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act which, in part, amended the FCRA to define pandemic-related accommodations and outlined how the payment status should be reported for accounts with an accommodation (15 U.S.C. §1681s-2). Prior to the COVID-19 pandemic, payment deferrals and loan modifications were typically ad-hoc and varied by market and over time.

Credit Reporting Processes

Credit reports only exist for individuals with a credit record, which are a subset of adults in the population (discussed in Supplemental Appendix Section G.1). Researchers therefore need to consider the implications for their study of individuals unobserved in credit reports (also referred to as "credit invisibles" in Brevoort et al., 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 reports 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 a result of these fragments, there are more credit records than adults in the US,[2] 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. (Supplemental Appendix Section G.1 below provides guidance on this issue.)

Additionally, credit file data used by researchers are not real-time data. Researchers will typically analyze credit reports 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). A credit "archive" reflects the best available information furnished by lenders as of that date instead of reflecting consumers' real-time credit outcomes as of a given point in time. While furnishing broadly operates at a monthly frequency, with new data being furnished by different lenders throughout the month, some lenders do not 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 across different credit products and different consumers. Researchers should keep in mind that this may create issues with research designs that require precise timing. Researchers may be able to use date information (such as balance date) from the credit report to realign periods to suit their research design (see H.2.14 for an example).

Reporting lags are especially likely when accounts are opened, transferred, or severely

[2]A small number of these records may be credit records that correspond to children under the age of 18 but where the birth year is not reported. This is more likely in earlier years before changes in reporting standards that increased the reporting of birth year.

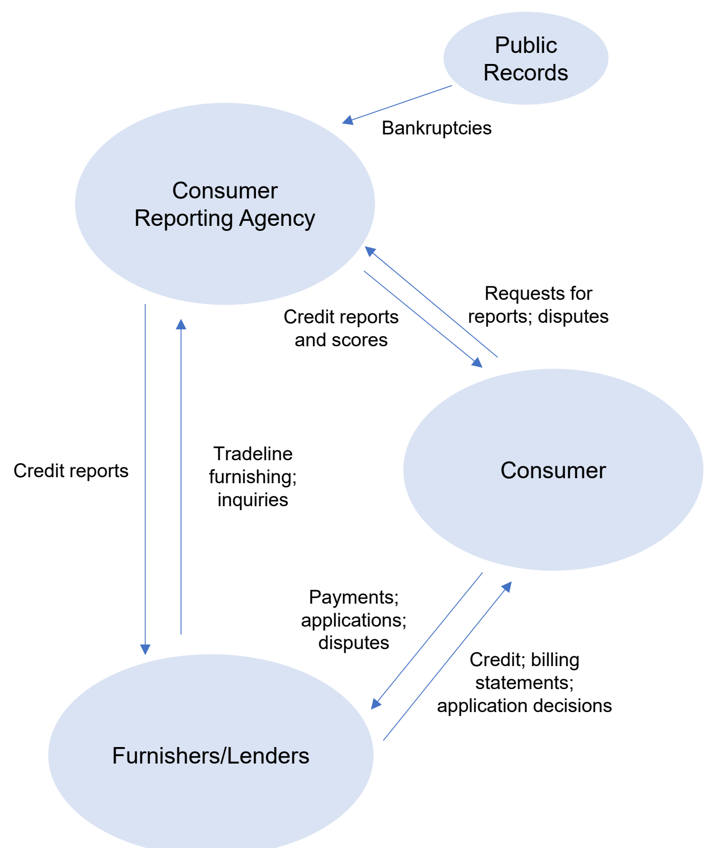
delinquent. Such gaps complicate the tracking of loans over time, as well as the computation of aggregate outstanding debt, often requiring imputation of debt balances that remain outstanding. There can be lags between an account opening and when it first appears in a credit file, and these lags vary 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 reporting data for a few months before reappearing with a new furnisher. Accounts in collections or charge-off are also 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 reports. 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 reports of deceased individuals. Data furnishers and CRAs do not always have timely and accurate death information. Failure by researchers to account for inactive individual credit records will naturally lead to incorrect population counts and per-capita debt calculations.[3] Importantly, the inclusion of deceased-person credit reports implies a divergence between credit reports-implied population counts and other population benchmarks that is strongly increasing with age, with a relatively large number of credit reports associated with individuals over age 70. While credit reporting data do typically include a deceased flag, these flags tend to be sparsely populated, especially in earlier years, 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. Lee et al. (2024a) 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, their primary sample has an age distribution that looks like the Census target. Similarly, Brennecke et al. (2025) use a threshold of four years of inactivity (that is, no inquiries and no open non-collection accounts) to remove records that may correspond to a deceased person whose death has not yet been reported to the CRA.

[3] In Q3 2016, for example, the Federal Reserve Bank of New York's Consumer Credit Panel (FRBNY-CCP), which only includes records with a SSN (and should, therefore, exclude many fragment records), 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 reporting data because they do not have formal credit records.

Figure B1 is adapted from Consumer Financial Protection Bureau (2012b) and displays the flow of information to create credit reporting data. This shows how lenders (and other furnishers of data) send tradeline data to the CRAs. The CRAs then collate this, along with public records information such as bankruptcies, and return credit reports for lenders and other customers to use. Consumers interact with the system by filing disputes with the lenders or CRA, and by applying for credit which trigger hard inquiries. For more details on the US credit reporting system, see Consumer Financial Protection Bureau (2012b).

Figure B1: The Consumer Credit Reporting System



Flow of information between entities in consumer credit market. *Source: Consumer Financial Protection Bureau (2012b).*

C Details on Credit Reporting Datasets

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 reports, and of the type of information typically extracted from them when pulling samples. We differentiate between traditional types of credit reporting data (tradelines, 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.

Some important household finance information is *not* found on credit reports. Notable missing information includes interest rates and prices, the identity of the lender (as opposed to furnisher), checking or savings account data, assets, 401(k) loans (loans from oneself), stock margin loans, individual and household income, most expenditures, and individual transactions on a credit card.

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. Later in this Supplemental Appendix, we highlight key features of these data, interpretation issues, and best practices as exemplified by leading papers from the literature separately for each product type. 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 the differentiation between lender types and the reporting of repossessions. We also include 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 these sections for important further details.

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

C.1 Header File

Each credit report includes a header file which contains identifying information, such as the person's social security number, date of birth, name (including alternate spellings), phone number(s), current address (including state, county, and zip code), and previous addresses. For those with joint accounts, the names of co-borrowers may also be listed. The header files available to researchers are redacted of personal information.

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 a 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 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 a new mailing address.

C.2 Tradeline File

Credit reports include tradeline (i.e., account) data 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 closed-end loans such as mortgages, auto loans, student loans, and personal loans. Each tradeline includes specific information about the account provided by the lender, including both (mostly) static information and information that may change monthly. Information that rarely changes includes the type of debt, type of account (e.g., revolving, installment), date or month the account was opened, origination loan amount or credit limit, (partial) account number, information about the lender (name and address),[4] and the so-called Equal Credit Opportunity Act (ECOA) designator (i.e., whether the individual's legal responsibility over the account is as an authorized user, joint account holder, individual account holder, or co-signed account holder).[5] In addition, the tradeline data include more dynamic information such as the current payment status, the current account balance, date of last activity, monthly scheduled payment, and some information about the recent payment and payment history.

Tradeline payment history is usually reported as a payment "pattern" or "grid" show-

[4]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 later in Supplemental Appendix Section G.1.

[5]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"). ECOA only requires the reporting of this information for spouses, but as noted in Brevoort et al. (2013), in practice furnishers provide this information for all associated borrowers regardless of marital status.

ing 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 long period of time.[6] Thus, the payment performance profiles obtained from credit reports will to some extent reflect different reporting practices of creditors. Typically, these payment histories are not retroactively changed, but there are occasionally exceptions.

The scheduled monthly payment amount for each account is the required minimum monthly 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 a periodic account statement. Credit limit is a 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 the highest balance ever reported; 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 any accounts that have already been charged off from their delinquency statistics. 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 furnisher 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 charged-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

[6] Researchers can align payment status with calendar time by using the reported balance or status date. See H.2.14 for an example.

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 statistics typically continue to include them as past due amounts.

Although 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 reveals 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. Closed tradelines with a negative history are generally dropped within seven years of the reported delinquency, while account closures following full payment (positive information) generally remain on credit reports up to ten years.

As most revolving and non-revolving 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 appear to have been paid off. However, sometimes, typically due to some servicer transfers, accounts without reported updates for more than three months, are later reported again, which necessitates the data user to fill in the intervening period to make up the disappearing accounts. These gaps are more frequent in earlier periods of data, such as in the early 2000s, but even now those gaps and lapses do occur.

C.3 Public Records File

Credit reports contain data on some public records. Public record information is sourced from county, state, and federal courts, and historically included 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 nonbusiness 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 who are 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 a 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 ten years.

Other public records historically included civil judgments and tax liens, collected from city, state, and federal courthouses by third-party vendors. Information on the amount of the judgment or amount due, filing date, and status is typically included. 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 (e.g., home, car, bank account) made by the government when a person fails to pay taxes, such as income or 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 been a reduction in the number of public records added to credit reports due to new policies adopted by CRAs since 2017 (for details see Clarkberg and Kambara, 2018; Brennecke et al., 2019). The new policies limit the inclusion of public records to those that contain, at a minimum, the consumer's name, address, and Social Security number or date of birth. The public record information must also 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).

C.4 Inquiries File

Credit reports also 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 the 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 loan application 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. The availability of raw versus de-duplicated inquiry data for researchers may vary across CRAs.

By contrast, soft pulls or soft credit checks typically occur when someone (such as an employer or utility company) checks a person's credit as part of a background check or when an individual 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 generally not displayed on credit reports provided to third parties. Recently, some lenders have also offered soft pulls to consumers for an initial credit application and only initiate a hard pull if the consumer chooses to proceed.

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.

Credit inquiries only show one part of a consumers' search process. It does not show consumers who searched but did not reach the credit application stage (e.g., they expected to be rejected or were deterred from applying). Similarly, if credit is not taken out, it is not clear whether this is because the consumer was rejected, changed their mind, or rejected the terms presented, although some (such as Brennecke et al. (2025)) treat all inquiries of certain types (such as credit cards and auto loans) as unsuccessful if the account does not open because an approval on terms the consumer does not want can also be thought of as a rejected application. To learn more generally about consumer search behaviors, users may want to examine other complementary datasets, such as the National Survey of Mortgage Originations (Avery et al., 2017; Durbin et al., 2021).

C.5 Collections File

Credit reports include a dataset of debts in collections (third-party collections or collection tradelines). These 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 Consumer Financial Protection Bureau (CFPB) report (Consumer Financial 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.

We recommend that researchers study both the flow and the stock of debt in collections. The flow is generally a more accurate measure because of the low persistence in collections accounts on credit records. For some research, such as studies of medical debt in collections, the stock itself may be important.

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, in July 2022, CRAs stopped adding new, unpaid medical collections debts until they are one year old—up from the six months imposed under the 2017 NCAP settlement—and also stopped reporting paid medical collections debts (Kluender et al., 2021); in April 2023, CRAs stopped reporting unpaid medical collections debt less than or equal to $500. The No Surprises Act of 2022 prohibits surprise medical bills for emergency services and therefore debts arising from such events no longer appear in credit reports. For more details on these changes see Sandler and Nathe (2022) and Brown and Wilson (2023). In September 2023, the CFPB proposed a policy to remove medical debt entirely from credit reports. In recent years, many states have debated or enacted laws to ban medical debts in collections from appearing on credit reports. For example, Colorado's House Bill 23-1126 and New York's Fair Medical Debt Reporting Act both passed in 2023. Finding new data sources to study unreported medical debt is an increasingly important challenge for researchers.

Another type of information included on credit reports for some individuals is unpaid child support, alimony, and separate maintenance payments under a divorce decree or separation agreement. In many states, the state or local child support enforcement agency is required to report unpaid child support debts once they reach $1,000, but they may also report smaller amounts. However, many states do not report to all three nationwide CRAs. 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 a custodial parent), or as a separate tradeline. Unpaid child support or alimony payments can remain on credit reports for up to seven years.

C.6 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 roughly the prior two years, though the time range varies by CRA.

The distinction here is subtle. Each cross-section of credit reporting data contains some backwards-looking variables—for example, bankruptcy filings from up to 10 years prior. However, in standard consumer-level aggregated 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.

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 may 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 since the underlying data does not contain a tradeline's pricing, and so these estimates may be measured with error. Trended data also include estimated credit card spending and repayment behaviors, such as which consumers pay their balance in full each month and which instead "revolve" a balance on the card.

C.7 Alternative Data

In recent years, CRAs have started to collect additional financial data beyond 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 Buy Now Pay Later (BNPL) lenders. Alternative credit data also includes user-permissioned bank statements, utility and telecommunications bill payments, and rent payment history (Cochran et al., 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) the employer name and location, date employed, date left, and position.

D Details on Debt Products

This section provides details on the debt products contained in tradeline consumer credit reporting data. Each subsection provides details on each of the main classes of debt products: Mortgages & Home Equity Lines of Credit (HELOCs), Credit Card Accounts, Auto Loans, Student Loans, and Other Loans.

D.1 Mortgages & Home Equity Lines of Credit (HELOCs)

At $12.4 trillion in Q1 2024, mortgage debt is the largest form of debt held by households, representing 70% of total household debt reported on credit reports. Together with Home Equity Lines of Credit (HELOCs), aggregate housing-related debt amounts to 72% 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 (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 provided by CRAs. 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, loans securitized by Government-Sponsored Enterprises (GSEs) can be reclassified as first mortgage loans since GSEs almost exclusively secure first liens. The same applies for Federal Housing Administration (FHA) loans and Veterans Affairs (VA) loans.[7]

It is easier to identify the lien status of a mortgage loan in the 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 primary mortgage without having to pay private mortgage insurance that lenders typically require when borrowers put less than 20% down. Such mortgages were very popular in the early to mid 2000s, when piggyback loans often permitted buying a home with a very small down payment. Since the global financial crisis, piggyback loans have been limited to 90% combined loan-to-value ratio.

Closed mortgage trades with a zero balance may, 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

[7] 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 stops being reporting altogether. Avery et al. (2003) examine non-reported mortgage accounts and found that, for many, a new mortgage account appeared around the time an 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 Home Mortgage Disclosure Act (HMDA), McDash, CoreLogic, and Black Knight (formerly Lender Processing Services, LPS), credit reporting data do not include the intended use and occupancy status reported on mortgage applications.

Credit reporting 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 holding a large number of first mortgages. They found misreporting to be especially prominent during the boom in the "sand states" (Arizona, California, Florida, Nevada, and Texas) and that such investors defaulted 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 reporting data.

An additional benefit of linking loan-level mortgage databases to credit reporting data is that they enable researchers using mortgage datasets to evaluate selection into their dataset compared to the more complete population of mortgages in credit reports, and, if desired, weight observations accordingly (Fuster et al., 2018). See H.2.8 for a code example of identifying first and second lien mortgages.

Remarks codes and joint account status

Descriptive codes (which may be referred to in different ways by each CRA) are usually provided for each mortgage account. 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). These codes 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, a loan modification or forbearance code may replace a previous narrative code. Panel data that allow a user to track and link loans over time can help prevent losing this information as codes change over time.

Each account also typically includes an identifier indicating whether the account is a joint or individual account. In individual-level analyses it is often appropriate to treat each joint account holder as responsible for repaying the entire balance. But researchers should avoid double counting joint accounts listed on two different individuals' 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 (see H.2.2 for examples).

Foreclosures

Foreclosures are a legal action initiated by mortgage lenders to take control of a property when a borrower fails to keep up their mortgage payments. They 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 remain on credit reports for seven years from the date of the 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 for less than is owed because a homeowner has proven an inability to make mortgage payments. Such borrowers may still remain responsible for making up the difference between the sale 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 and refinancing

New mortgage originations appear on credit reports without an indicator for whether the 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) mortgage without a change in mailing address. Users 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). As an example of such an approach, Haughwout et al. (2023) calculate the aggregate equity extraction from refinanced mortgages in the US since 2000.

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 points to a purchase origination. For this reason, it is advisable when acquiring credit reporting 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.[8] See Mian and Sufi (2022) for an example of such a strategy and H.2.7 for another example. For other examples of researchers measuring refinancing activity, see Bhutta and Keys (2016); Beraja et al. (2019), and Berger et al. (2021).

Forbearances and modifications

Credit reporting data do not always include a direct forbearance indicator, and furnishers notate forbearance in various ways. Some forbearances are notated in narrative codes such as "Natural Disaster" or "Forbearance." Other forbearances appear only as a change in payment amount to zero.

As discussed in Supplemental Appendix Section B, modifications related to the Home Affordable Modification Program (HAMP) after the global financial crisis now are identified by a new CDIA code designed to signify participation in the Making Home Affordable (MHA) program, including HAMP.

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 *servicer* of loans that reports the accounts, and they are not necessarily the same as the lenders or the owners of the debt. Therefore, one should avoid equating the furnisher identity with the lender identity.

D.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 (Brevoort and Kambara, 2017). As open-end credit,

[8] If the geographic information available to the researcher is coarse, classifying loans are refinances or new purchases will be measured with more noise because it is harder to determine if there was a change in the underlying address.

cards are also a channel frequently used both as a means of payment and as a source of short-term borrowing. As of Q1 2024 aggregate credit card balances stood at $1.1 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. Whereas we argued in Section 3.6.2 that retail credit cards are an important component of credit card spending, in this Appendix section we treat retail credit cards separately from general-purpose credit cards in order to discuss product-specific measurement issues and institutional details more precisely. Section D.2 focuses exclusively on general-purpose credit cards, and we then return to retail credit cards in Section D.5 on "Other Debt."

See Chernousov et al. (2024) for a comparison of the size of the credit card market using different data sources. Brown et al. (2015) shows credit card balances in credit reports are substantially higher than observed in surveys, such as the Survey of Consumer Finances, where there is a known issue of under-reporting (Zinman, 2009; Beshears et al., 2018).

Inactive credit cards that are open but not used by consumers are difficult to define but may greatly affect the estimated number of accounts in credit reports. Researchers interested in studying credit card behaviors may want to focus on accounts actually in use. Historically, once a credit card account has a zero statement balance for every month in the last year, it rarely gets used in the future. A credit card account may be inactive but may have a non-zero statement balance one month a year if it still charges an annual fee.

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 outstanding balances are revolving debt, and over 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; Chernousov et al., 2024).[9] 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 af-

[9]Consumers who repay their outstanding balances before the end of the reporting cycle will have a balance of zero dollars reported, but their card use may be inferred by observing payment dates and actual payments made (if reported). See E.4 for more details.

ter 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 and part will be carried-over debt. The former approximately equals the new balance minus the previous balance, plus the actual payment amount in the billing cycle. The carried-over balance approximately equals the new balance plus the actual payment amount, minus new transactions. Accordingly, for transacting accounts, the balance shown in credit reporting data indicates a monthly flow of expenditure, whereas for revolving accounts, the balance indicates a stock of debt.

It is difficult to distinguish between revolvers and transactors in credit reporting data. Account holders' actual payment amounts each month are sometimes, but not always, reported to CRAs. There has also been a downward trend in the prevalence of this reporting (see Herman et al., 2020, Guttman-Kenney and Shahidinejad, 2025, and McNamara, 2023). In cases where these data are reported, it becomes 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 Section 3.6.2 in the main 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, especially prior to a 2009 rule mandating the reporting of credit limits (see section B). 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 (2024) 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, especially prior to 2009. Such a measure is sometimes used to measure the extent to which a consumer is credit constrained, and it is used by many as a component of a measure of financial distress.

There also is evidence that credit card limits may not be updated as frequently in credit reporting data as they are changed 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 that 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

Anonymized credit reporting data sometimes include information on the company, subscriber, or furnisher, that reports a given account's data to the CRA. Furnishers are typically the entities that service a given account—that is, who receive payments from the consumer, keep track of the account status, and remit any net returns on the loan to an investor.

Credit card servicers may differ from the credit card issuers, 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 can make it difficult to make inferences 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.[10] 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 (see Hall, 2024 for a historical study of how and why the credit card market took over the retail cards market between 1970 and 2000).[11]

Initially, credit cards started as general-purpose 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, but 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 reporting data, a researcher may want to focus only on one of these categories or both categories together, depending on

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

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

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 were 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 in data from at least one CRA.

D.3 Auto Loans

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. These are installment loans, meaning they require equal monthly payments for a specific period of time. Credit reporting data also include the initial loan balance, current balance, and payment history. Car leases, though quite different from auto loans, are also usually reported to CRAs and are typically reported as leases.

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 consumer deposits. 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 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).

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."

D.4 Student Loans

Student loans, sometimes referred to as "education loans," are typically installment loans made to students or their families to finance higher education program enrollments. In contrast to other credit products, the federal government plays a large role as a lender 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 rates also drive trends in refinancing federal student loans into private student loans and the consolidation of federal student loans to lock in lower interest rates. Additionally, most borrowers typically have multiple student loans if they use multiple types of loans or borrow for multiple school years.

Credit reporting 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.[12]

Despite the inclusion of both federal and private student loans, total outstanding balances reported in credit reporting data were $1.6 trillion as of Q1 2024, slightly below the amount reported by the Department of Education. We believe one of the primary reasons for this discrepancy is the nonreporting of older defaulted federal loans that dropped off from credit reports but are still included Department of Education's portfolio and data (Gibbs, 2023). In compliance with FCRA and the Higher Education Act, these older defaulted loans are not reported by 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 led 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 from the intial delinquency.

Defaulted federal student loans are also subject to wage and tax-refund garnishments,

[12] 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.

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.[13] 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 reporting data, see below.

Delinquencies and defaults

The Department of Education has special requirements for the reporting of delinquent federal student loans that do not apply to private student loans. Specifically, federal student loans cannot be reported as delinquent to the CRAs 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 intermediate delinquency (e.g., 30 or 60 days past due) observed. Federal loans which fall further behind are categorized as in "default" after 270 or 360 days of delayed payments depending on the loan type and may be reported as a "government claim" or as a "collection" 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 loan. 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.[14] 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 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.[15]

[13]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.

[14]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 continued through September 2024 (Gibbs, 2023).

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

Federal versus private loans

Federal and private student loans are not typically directly distinguishable in the credit reporting 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.

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. By contrast, researchers can use 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 three 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 and some loans may have been in deferment during the entire payment suspension. Overall, users may be able to classify many loans as federal or private, but it is difficult to confidently categorize all loans (especially over long periods) and users should be aware that their estimates will likely be noisy as a result. For some a code example identifying different types of loans, see H.2.13.

Income-driven repayment

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 in these plans 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's enrollment drops below at least half time.[16] 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 often 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 options available such as deferred payment while in school or an "interest only payment" with principal loan payments deferred until the student leaves school, or their loan may be 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 temporary administrative forbearance while a servicing issue is resolved. See H.2.16 for a code example to identify forbearances in credit reporting data.

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 September 2023, all non-defaulted federal loans owned by the Department of Education were reported with a $0 scheduled monthly payment. Additionally, the

[16]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.

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 were not reported for another year after the end of the payment pause. Under the on-ramp policy, loans that were 90 days or more past due were put into a temporary administrative forbearance which cured the delinquency from November 2023 through October 2024. As a result, no past due federally-held loans were reported as delinquent until January 2024, and many loans were periodically reported as in forbearance during this period. For more information, see Conkling and Gibbs (2024) and Mangrum and Wang (2025).

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, which may service other student loans not owned by the Department of Education. Some federal loans (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.[17] 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 that 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 lower interest rate. Consolidations, meanwhile, combine existing federal student loans

[17]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.

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.[18] 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. See H.2.15 for an example with missing student loans in 2011–2012.

D.5 Other Loans

Other loans are, by definition, a residual catch-all category not captured by the main product categories explained in the preceding sections. As a result, the other loans category can contain a broad variety of product types. However, they can be generally considered as revolving accounts for consumer products not captured in the credit cards category or installment loans.

There may be differences in how these accounts are characterized across datasets and projects. For example, some researchers group retail cards (see Supplemental Appendix Section D.2 above) into one category, while others, like the Federal Reserve Bank of New York, group them into a larger category of "other" loans.

Some of these loans have remarks codes that provide specific types of relatively small product categories such as "recreational merchandise loans," "agricultural loans," and "business loans." Still some other loans are included in this residual category due to a lack

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

of identifying description of the nature of the loan. The nominal amount of outstanding debt in this category is fairly unchanged from 2003 to 2024 in the Federal Reserve Bank of New York's Consumer Credit Panel: measured at $0.49 trillion in 2003, troughing at $0.30 trillion in 2013 and reaching $0.54 trillion in Q1 2024.

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. The 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.

E Details on Constructing Economic Measures

In Section 3 of the main paper we show how consumer credit reporting data can be used by researchers to construct a variety of economic measures. The subsections of this section of the appendix provide additional details for users of these data who are interested in measuring delinquency, new account openings, or spending. Before this, we provide a high-level evaluation of these data.

E.1 Is Credit Reporting Data An Ideal Dataset?

We begin with an evaluation of the strengths and weaknesses of consumer credit reporting data, based on the framework of the ideal household finance dataset laid out by Campbell (2006). Although that analysis focused on assets rather than liabilities, many of the themes remain useful. Campbell (2006) writes: *"The ideal data set would have at least five characteristics. First, it would cover a representative sample of the entire population. It is particularly important to have good coverage by both age and wealth, since many aspects of financial behavior vary with these characteristics. Second, for each household the data set would measure both total wealth and an exhaustive breakdown of wealth into relevant categories. Third, these categories would be sufficiently disaggregated to distinguish among asset classes, and ideally would capture specific individual assets so that one could measure household diversification within asset classes. Fourth, the data would be reported with a high level of accuracy. Finally, the data set would follow households over time; that is, it would be a panel data set rather than a series of* *cross-sections."* How does consumer credit reporting data do?

First, **data representativeness**. By definition, consumer credit reports contain information for all consumers who have credit reports. This covers roughly nine-in-ten adults in the US (Brevoort et al., 2015), across the distributions of age and wealth. These data do not observe children. Adults without credit reports (the so-called "credit invisibles") are unobserved and can be inferred to have zero debt of the type reported to the CRAs). Credit invisibles disproportionately include some racial and ethnic minorities, younger consumers, and unbanked consumers. This form of selection is different from surveys where non-response can bias who responds (Dutz et al., 2025) and is becoming an increasingly important issue to address due to declining response rates (though, as we discuss in Section 5.2.3 of the main paper, surveys off of credit record data can help with non-response bias). It is also different from other sources of household financial data, such as that gathered from individual firms, where only consumers who use a product or consent to share data are observed (e.g., Baker, 2018; Baker and Kueng, 2022). In some non-US countries, checking accounts, mobile phones, and utilities appear on credit reports. We expect such developments to have further increased coverage of these data, though evidence is lacking on this.

Second and third, **data granularity and coverage**. As these data are built from individual accounts, they are highly granular. This enables researchers great flexibility in their approaches to classifying or aggregating different types of accounts. An obvious limitation of these data's coverage is that they only cover the liabilities side of a household's balance sheet, not their assets (although some inferences for autos and houses can be made). For these liabilities, they include some contract terms, and some others can be estimated; however, they do not contain the full contractual features that one may ideally desire. We also do not observe individuals' income, only estimates of it, and have partial coverage of their consumption. While these data include most of a consumers' liabilities, there are some important gaps. Some subprime loans are not typically furnished to CRAs (e.g., some subprime auto loans and payday loans), most unpaid medical, utility, or business bills, and most missed rent payments. Credit reports do not include information on a number of other financial products, including most BNPL loans, many business credit cards and loans, cash advance apps, car title loans, pawnshop loans, and tax refund anticipation checks. Informal lending (e.g., via family, friends, illegal lenders) is also never observed in credit reports. Argyle et al. (2021) label debt not observed in credit reports "shadow debt" and find that in their sample of bankruptcy filers 7.4% of total debts are not observed in credit reports from one CRA at the time of filing. Similar estimates for consumers more broadly are difficult to find as there are few comprehensive sources for this information.

Fourth, **data accuracy**. Lenders use these data in their decisions and have good incentives to accurately report data. Laws require consumer credit reporting data to be furnished accurately, and mis-reporting their customer's accounts may adversely affect their own business. The Federal Trade Commission (FTC) has conducted a series of reports reviewing credit file errors and estimated in 2012 that 5% of consumers' credit files contained errors that meaningfully adversely affected their credit access (Federal Trade Commission, 2012). Also see Avery et al. (2004); Staten and Cate (2005); Smith et al. (2013); Hynes (2017) for more information on such errors. Hunt (2005) argues that the ability and incentive to correct different types of errors differ for lenders, credit bureaus, and consumers which may result in the under-provision of data accuracy and suggest a role for regulation. While there are errors, credit reporting data line-up well with other sources (Brown et al., 2015) and do not suffer from the mis-measurement of credit card balances known to occur in survey data (Zinman, 2009; Beshears et al., 2018).

Fifth and finally, these are **panel data** and so researchers can follow individual consumers over time. We observe consumers' locations and have high coverage across geographic regions. Consumers who move remain in these data, unless they move outside the sampling frame (e.g., abroad). Depending on their dataset's sampling, researchers can not only observe individual consumers, but follow adults in "households." "Households" can both be by geography (e.g., living in the same residence) or by shared financial activities (e.g., sharing a joint account). This enables researchers to study both intra-household and inter-generational behaviors. As mentioned in the main paper, death can be difficult to measure and complicate the definition of a household in these data. This is a problem not encountered in survey data.

Overall, we consider consumer credit reporting data an extremely useful dataset for researchers. It complements other data sources, which have their own strengths and weaknesses. The ideal dataset does not exist; however, with developments such as increased merging credit reporting data to other sources we can get closer to the researcher's ideal dataset.

E.2 Details on Measuring Delinquency

Section 3.4.3 of the main paper describes ways to measure delinquency. This appendix provides some additional details on how to measure delinquency for users of these data.

A researcher needs to be aware of the difference between the measure of delinquency reported by a lender and the measure calculated from credit reporting data. When an account is charged off from a lender's portfolio and transfers to a collection, the account is excluded from the calculation of delinquency rate reported directly by the lender. However, the same account will continue to be reported to the CRAs for a varying duration of time and may be included in the delinquency rate calculated based on credit reporting data.

Researchers may want to use the flow of new accounts that become delinquent, as used by the Federal Reserve Bank of New York in its quarterly reports. These show the percent of balances or number of accounts that transition from being non-delinquent to being delinquent in a given time period (e.g., quarter). Delinquency measures based on the flow to delinquency typically do not have the problems faced by stock-based measures since they directly capture the transition from being current to becoming delinquent. They are robust to the varying charge-off rules by lenders and loan types and how long those accounts remain on credit reports. As a disadvantage, however, flow-based delinquency rates generally require a more granular level of data, such as panel data at the account level, and, if using more severe statuses, still ultimately depend on these being accurately reported. See Haughwout et al. (2019) for a discussion of two approaches of measuring delinquencies, and see H.2.11 for some code examples to construct these measures.

The threshold for measuring delinquency can vary depending on a researcher's needs. While in the main paper we suggest 30+ or 90+ days past due as a typical threshold, other thresholds may be relevant. For example, 60+ days may be useful as around half of accounts reported with a delinquency of 31–59 days are typically reported 60–89 days past due; whereas more than two-thirds of accounts reported with a 60–89-day delinquency are typically next reported with a 90–119-day delinquency (Brennecke et al., 2025).

As loans become increasingly severely delinquent, they may be reported in increasingly different ways by different lenders. One reason for this is because the debt may be transferred from the lender to a debt collector who has different reporting approaches.

The timing to charge off an account could vary across loan types and also by lender. For example, credit cards typically charge off after 180 days past due; by comparison, federal Direct student loans are never charged off. Some lenders report all of their severely delinquent accounts with zero outstanding balances, or do not update the delinquency status to the charge-off stage, and therefore a researcher may want to use the outstanding balance before a loan becomes severely delinquent to reflect how much debt is being charged-off. Account-level data may include a variable for the amount charged-off, however, reporting of this variable appears to be inconsistent across lenders. See Guttman-Kenney and Shahidinejad (2025) for an example estimating charge-offs.

When calculating delinquency, a researcher may need to account for how accommodations for the COVID-19 pandemic affected reporting. During the period March 2020 to August 2023 (120 days after the end of the National Emergency for COVID-19 on April 10 2023), amendments to the FCRA by the CARES Act required certain non-paying accounts to be recorded as having an accommodation added; in some analyses these accounts would most appropriately be interpreted as delinquent. When taking this approach, researchers can recode any remark codes on tradelines for deferred payments, forbearance, or being affected by natural disaster, and also recode open credit cards with positive statement balances where they have zero scheduled payments due. See Cherry et al. (2021); Dinerstein et al. (2024) for studies of COVID-19 accommodations and Guttman-Kenney (2025) for a study of natural disaster flags.

A neat feature of tradeline-level credit reporting data is that one cross-sectional archive of data contains a variable containing an 84-month array showing monthly historical delinquencies for the past seven years. However, these past delinquencies are most reliably observed for accounts that remain open, rather than having been closed or charged off. See Gross et al. (2021) and our Supplemental Appendix Section H.2.14 for examples. This feature is especially useful when studying data from the early 2000s when lenders often did not furnish data every month. If a lender only furnishes information quarterly, the payment status variable will not be updated with new information each month. However, when the array is updated each quarter, it will not only show information on the last month in a quarter, but the two prior months as well. These arrays are best used for measuring up to two years of history as some accounts' historic delinquency statuses will be removed from these arrays over time, and some will be updated (e.g., disputes) meaning that the array accurately records delinquency but not how delinquency was historically recorded on a consumers' report. As with other variables, if a lender stops updating the array, as may occur with severely delinquent or closed accounts, it becomes out-of-date.

E.3 Details on Measuring New Account Openings

If only consumer-level aggregated data are available, a researcher may, for example, use an increase in 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. In the case of mortgages, one may want to try to distinguish between new purchase originations and mortgage refinances, as discussed above in Section D.1.

Equation 1 calculates the value of new auto loans (a_t) using information on outstanding auto loan balances (b_t). When the difference in auto loan balances (b_t) is above a threshold κ, this increase is classified as a new auto loan. This measure is zero otherwise. Researchers should restrict to balances where the consumer is up-to-date on payments. If using such an approach, we recommend sensitivity analysis for how large an increase in loan balances is required to classify a new purchase. See Agarwal et al. (2023a) for an example of such an approach setting setting $\kappa = \$2,000$ (and testing sensitivities between $\$2,000$ and $\$5,000$). Consumer-level aggregated data may also contain CRA-created variables for the number of new accounts opened. For researchers without access to tradeline data, using the aggregated number of new accounts that are originated is sufficient for most purposes.

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

The above approaches can be improved using more granular tradeline data (e.g., Bhutta and Keys, 2016; Gross et al., 2020), to ensure that the timing and amount of loan originations are measured more precisely. 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 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 at least seven years.

Newly opened auto loans can be used as a proxy for auto purchases. Researchers use this as a measure of consumption, such as Benmelech et al. (2017) and Di Maggio et al. (2017). Over 80% of new auto purchases are purchased on finance (have "auto loans") (Benmelech et al., 2017). 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 (Low et al., 2021). Benmelech et al. (2017) and Di Maggio et al. (2017) verify the accuracy of this consumption measure. They show auto loan originations in credit reporting data match to external data and also track total sales (with and without loan financing). It is less common for used autos to be purchased on finance than it is for new autos. They estimate that, during 2022 and 2023, approximately 55% of used cars and 65% of total (new and used) cars were purchased on finance, and these shares appear stable over time.

Researchers with tradeline-level data can study the contract terms of these new accounts (e.g., origination amount, monthly scheduled payment, and scheduled loan duration). Section 3.5.4 of the main paper shows how researchers with tradeline-data can estimate interest rates; they can also purchase estimates from the CRAs. Researchers may be interested in calculating interest rates at loan origination (i.e., how much they would pay if they exactly follow the terms of the loan), using the first month of data observed (or first few months as required for mortgages), or over a loan's duration (i.e., how much they actually paid), using multiple months of data.

E.4 Details on Measuring 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, credit card does not include all of a consumer's consumption: it excludes consumption via debit cards, bank transfers, checks, cash, and payroll deductions. 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 different socio-economic groups.

The object of interest—'credit card spending' ($S_{c,t} = \sum_{C_i} s_{i,c,t}$)—is the total value of new purchases by a consumer (i), across their spending on each of their credit cards (c), at time t. We show four ways in which to attempt to measure this. These increase in complexity and data requirements. The first two measures can be calculated at the consumer-level or at the credit card account level and then aggregated up to the consumer-level. The last two measures require calculating at the individual credit card account level and then aggregating up to the consumer-level. Calculating from the account-level helps to ensure that the measure of spending produced is not being driven by changes in reporting practices over time on individual credit card accounts.

The simplest but least accurate measure of credit card spending is shown in $s_{c,t}^{simple}$ in Equation 2. This measures spending by the credit card statement balance ($b_{c,t}$). This is a likely inaccurate 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 considering it a consumption measure.

$$s_{c,t}^{simple} = b_{c,t} \tag{2}$$

A more accurate measure of credit card spending ($s_{c,t}^{GNW}$), as used in Gross et al. (2020), is the *change* in credit card statement balance. This is shown by Equation 3. 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, that 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 (2025) 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 aggregate data—including with non-consecutive periods, though doing so will further reduce this measure's accuracy.

$$s_{c,t}^{GNW} = \Delta b_{c,t} = b_{c,t} - b_{c,t-1} \tag{3}$$

Our third measure of credit card spending ($s_{c,t}^{GN}$) is shown in Equation 4, as used in Ganong and Noel (2020), and is the first of our measures that removes revolving debt. This measure takes the change in statement balances and adds payments ($p_{c,t}$). If this results a negative number, it is bounded at zero. This approach both subtracts revolving debt appropriately and includes spending that is repaid before the statement balance is issued; however this approach contains some error because it includes financing charges. This measure also relies on the researcher being able to observe the actual payment amount variable at the tradeline level. However, from 2015 to (at least) 2024 this actual payment amount 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, 2025). If using this measure, researchers need to restrict to studying only 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, the 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.

$$s_{c,t}^{GN} = \begin{cases} b_{c,t} - b_{c,t-1} + p_{c,t} & \text{if } \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Our final measure of credit card spending ($s_{c,t}^{GKS}$) is shown in Equation 5. This measure is introduced in Guttman-Kenney and Shahidinejad (2025). This adapts $s_{c,t}^{GN}$ to remove the estimated financing charges ($f_{c,t}$). All the caveats on the coverage of $p_{c,t}$ also apply to this measure. Financing charges are estimated following Guttman-Kenney and Shahidinejad (2025).

$$s^{GKS} = \begin{cases} b_{c,t} - b_{c,t-1} + p_{c,t} - f_{c,t} & \text{if } \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

It is also possible to produce estimates of spending using other methodologies. For example, 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 that researchers typically will not be told the algorithm used to create them. As CRA-created measures are commercially-sold products, CRAs can be sensitive to publishing quality assessment statistics, and without such assurance, it is difficult for readers to evaluate the accuracy 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 CRAs will struggle to accurately measure spending.

F Details on Credit Scoring

F.1 History of Credit Scoring

In this section we provide a brief history of credit scoring. The history of credit scoring is intertwined with the history of credit reporting, so interested readers wanting additional details should also consult Mester et al. (1997); Miller (2003); Barron and Staten (2003); Hunt (2005); Lauer (2017). Thomas (2009) and Thomas et al. (2017) provide a more detailed introduction to credit scoring, including its history.

The early history of credit scoring in the US is synonymous with FICO, the Fair Isaac Corporation. FICO was founded in 1956 by Bill Fair and Earl Isaac, and, by 1958, FICO produced their first credit scoring method to sell to lenders.[19] The passage of ECOA in 1974 helped stimulate the use of FICO's scoring method, as algorithmic approaches to underwriting aligned with ECOA's definition of a "credit scoring system" in which "all applicants [are treated] objectively...thus avoid problems of disparate treatment."[20] The use of FICO's scoring method grew in the 1970s and 1980s as CRAs and most national lenders started adopting FICO's products (Federal Reserve Board, 2007), facilitated by growth in information technology and credit card lending. It was not until 1981 that FICO created a credit score based on CRA data, and in 1989 the first version of what became the FICO score became available. By 1991, all three CRAs were using FICO scores.

Standardized credit scores became popular also in part because they enabled different loans to be compared and aggregated for securitization. In 1995, Freddie Mac recommended the use of FICO scores for all new mortgage applications, with Fannie Mae following shortly after (Lauer, 2017).[21] By 2024, the regulatory requirements for lenders to use FICO led to Community Home Lenders of America to state that the "combination of FICO's extremely high market share, and the fact that Washington agencies require lenders to use this company's product, means that FICO has unilateral, solid-gold market power, the type rarely seen in any US industry short of highly regulated utilities, whereby rates are set by public-utility boards or commissions".[22]

In response to the rise of FICO, the three major CRAs created a competing joint venture: VantageScore. VantageScore was designed to apply an identical model across all of the CRAs, so that the only reason an individual's score would differ across the CRAs would be due to differences in the underlying data on that person at each CRA. VantageScore was also designed to extend greater coverage across the population, reducing the fraction of Americans where credit scores such as FICO cannot be calculated due to insufficient data. However, the greater coverage of VantageScore to thin-file consumers also means that the score is based on less information for these consumers.

The introduction of VantageScore interfered with FICO's monopoly and provided an outside option for lenders to use in their negotiations with FICO. In 2021, for example, Synchrony Bank switched from FICO to VantageScore.[23] FHFA also announced a new requirement to use both FICO and VantagScore for GSE mortgage securitization.[24] Anec-

[19] https://time.com/3961676/history-credit-scores/

[20] See https://www.netinterest.co/p/monetising-an-algorithm and https://www.consumerfinance.gov/rules-policy/regulations/1002/interp-2/#2-p-Interp-2.

[21] See Bubb and Kaufman (2014) for more details on lenders' reactions to this change.

[22] https://www.communitylender.org/wp-content/uploads/2024/01/CHLA-Credit-Score-White-Paper-FINAL-VSN.pdf

[23] https://fintechtakes.com/articles/2024-01-12/fico-score/

[24] https://www.fhfa.gov/policy/credit-scores

dotally, VantageScore's entry into the market helped to keep prices down, although more research to establish whether this is the case, and if so how much by, would be valuable given the size of the economic markets served. Exactly which lenders use FICO and VantageScore and for what purposes is not well-established beyond marketing materials provided by individual lenders.

F.2 Proprietary Credit Scores

Sophisticated lenders typically create their own proprietary in-house credit scoring models. These proprietary are typically trained and tested on lenders' own datasets, which may include data not included in credit reports. Proprietary scores may use other credit scores, such as FICO or VantageScore, as one of their data inputs. While some of these in-house scores may share similarities with FICO and VantageScore, they are generally heterogeneous across lenders. Proprietary scores target outcomes specifically designed for their business needs, which may differ from FICO or VantageScore. Scores can be associated with deposit accounts, fraud detection, small businesses, alternative financial services, and internal scores used for account management by financial institutions based on private information on their own customers.

Einav et al. (2013) provide an example of how a large auto finance company's adoption of an automated in-house credit scoring increased their profitability through improved screening and targeting. They also find that the use of credit scoring crowded out "soft" information previously relied upon by dealership, a finding that relates to a broader organizational economics literature (Stein, 2002; Berger et al., 2005).

Some lenders have sharp cutoffs in their underwriting which can be used for regression discontinuity designs if the researcher observes the same score, calculated at the same time as used by the lender (e.g., Bhutta et al., 2015; Agarwal et al., 2018; Gathergood et al., 2019a; Argyle et al., 2023). If the researcher uses a different scoring model than the one used by the lender, those cutoffs will not align. However, Laufer and Paciorek (2022) have an innovative example for mapping a credit score used for lending decisions (FICO) to another credit score (Equifax Risk Score). Linking credit applications from data sources other than credit reports can be useful. For example, Bhutta et al. (2015) and Gathergood et al. (2019a) merge both successful and unsuccessful payday loan applications with credit scores used in lending decisions, enabling a regression discontinuity design to study the effects of payday loans on consumers' finances.

F.3 What Information Is Not In Credit Scores?

A credit scoring model is only as good as the data fed into it—-so factors such as errors, fraud and identity theft, incomplete coverage, and reporting lags that affect the credit reporting system also affect credit scores. Traditional credit scores only use as inputs information contained in credit reporting data, summarized in Table 1 of the main paper, with more detail in Supplemental Appendix D.

What information is not in traditional credit scores, such as FICO and VantageScore? Credit scores are not based on income, education, or occupation. Similarly, credit scores do not have information on liquid and illiquid assets, other than through the existence of secured loans to finance durable purchases such as mortgages and auto loans. Likewise, information not present on traditional credit reports is excluded from traditional credit scoring models. This includes information on the 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 or point of sale, and marketplace loans. Information on deposit accounts, bank overdrafts, and related financial activity are also not reported to CRAs and thus excluded from scoring models.

However, credit scores can be correlated with information that is not a direct input to credit scores. Chatterjee et al. (2023) provide a theory of credit scores, where credit scores are "in part, the market's assessment of a person's unobservable type, which here we take to be patience." Meier and Sprenger (2012) show time preferences predict FICO credit scores, with more patient consumers having significantly higher credit scores. Arya et al. (2013) find higher credit scores are correlated with lower impulsivity, greater patience, and greater trustworthiness but are not correlated with risk preferences.

The information used in credit scores changes over time. Historically, this can be due to regulatory pressure to exclude information. For example, medical debt in collections were found to be relatively uninformative (Brevoort and Kambara, 2015) and have been increasingly removed from credit scoring models over time. By contrast, information on tax liens and other civil judgement may still be used in credit scoring models, but this information has largely been removed from credit records (under the NCAP agreement) since 2017.

F.4 Uses of Credit Scores

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 rental, telecommunications, and insurance markets. Consumers also use them to learn about their own perceived creditworthiness and to build and monitor their credit. 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.

The cost to one lender of gathering a FICO score for an applicant can be up to $60 in 2024, quadrupling over the prior two years.[25] A white paper by the Community Home Lenders of America provides more numbers on the costs to mortgage lenders of purchasing credit scores and credit reports.[26]

The types of information used in credit scores generate important and sometimes counter-intuitive economic implications for consumers. For example, because consumers are penalized for new hard credit inquiries, consumers experience a short-term decline in credit scores when applying for credit. Although scoring models allow consumers to make several credit applications within a short span of time without additional penalty (e.g., 14 to 45 days, depending on the specific product and score version used), consumers may still be penalized for search behavior in practice. Thus, the details of how the most common credit scoring models are constructed may generate frictions and can have important implications for consumer search and price dispersion. See Woodward and Hall (2012); Stango and Zinman (2016); Alexandrov and Koulayev (2018), and Argyle et al. (2023) for evidence of price dispersion and lack of search in consumer credit markets.

Consumers are sometimes said to need credit to build credit (e.g., Kovrijnykh et al., 2023). 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 products 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.

F.5 Different Types Of Credit Scores

Credit scores visible to consumers can be different from those used by lenders (Consumer Financial Protection Bureau, 2012a). 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, 2012a). Since 2005, all US consumers have been able to request a free credit report from each CRA each year (Kumar, 2022) as

[25] https://www.thebignewsletter.com/p/inside-fico-and-the-credit-bureau

[26] https://www.communitylender.org/wp-content/uploads/2024/01/CHLA-Credit-Score-White-Paper-FINAL-VSN.pdf

a result of the Fair and Accurate Credit Transactions Act (FACTA) of 2003.[27] Since 2020, US consumers could access free reports weekly as a result of voluntary changes from the three CRAs during the pandemic.[28] FACTA also required CRAs to provide credit scores directly to consumers for a reasonable fee.

FICO and VantageScore have many versions.[29] Both scoring models are updated over time and span different uses such as account management versus account origination; predicting any default versus default on a given new tradeline; predicting default for a given population of borrowers; and predicting default on a given type of trade such as credit cards versus auto loans. See Bergemann et al. (2018) for a theoretical explanation for different demands from data buyers for scores.

The outcome variable being predicted may also differ across different versions of credit scores. The 24-month default rate predicted by a traditional model may be different or calculated differently in different versions. For example, it may cover new versus all accounts, all trades versus specific types (e.g., auto, credit card), or other outcomes.

Over time, CRAs and other providers of credit scores update their scoring models to reflect changes in available data and how the predictiveness of different data points changes over time. For example, among other things, FICO 9 decreased the weight given to unpaid medical collections and assigned no weight to paid collections, while FICO 10 increased the weight placed on credit utilization. Newer scoring model versions (such as FICO 10T and VantageScore 4.0) include updates such as using trended data (when available) to incorporate information on changes in balances over time. Typically, these models are unchanged within the same version number, but there are occasionally exceptions, such as when VantageScore updated their VantageScore 3.0 and 4.0 models to change the treatment of accounts reported in forbearance early in the pandemic.[30]

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 CRAs can have different approaches to cleaning or aggregating data.

[27] https://www.pbs.org/wgbh/pages/frontline/shows/credit/more/scores.html

[28] https://consumer.ftc.gov/consumer-alerts/2023/10/you-now-have-permanent-access-free-weekly-credit-reports

[29] https://www.capitalone.com/learn-grow/money-management/when-did-credit-scores-start/

[30] https://web.archive.org/web/20200602033654/https:/www.vantagescore.com/news-story/340/vantagescore-credit-scores-and-covid-19-pandemic

G Details on Accessing Credit Reporting Data

G.1 Established Consumer Credit Reporting Panels

Table 4 of the main paper lists the established US consumer credit reporting panels we are aware of. In this appendix subsection we provide additional details about these datasets. Researchers using such data should expect the CRAs to review outputs prior to them being released but should consult the access terms.

The most established dataset is the **Federal Reserve Bank of New York's Consumer Credit Panel**, using data from Equifax (FRBNY-CCP/Equifax). These data are accessible to researchers across the Federal Reserve system. Researchers outside the Federal Reserve system can co-author on research projects that use these data but generally are not able to access the underlying data (unless they have an employee status, such as with an internship). Lee and van der Klaauw (2010) provide a comprehensive introduction to these data, with additional data dictionary and frequently asked questions documents online. These data are an anonymized 5% sample of consumers with a credit report in the US, based on the last two digits of SSN, and, for these consumers, they also observe all consumers with the same address. These are quarterly data from Q1 1999 to the present. Tradeline-level information on all major loan types is available. Each quarter, the Federal Reserve Bank of New York releases a report on trends in these data. They also release public summary data at the national and state level.[31] A large body of research is released through the Federal Reserve blogs and working paper series, see (Haughwout et al., 2024) for an overview. Some key examples of research include: Albanesi et al. (2022); Athreya et al. (2019); Bhutta (2014); Bhutta and Keys (2016); Bleemer and van der Klaauw (2019); Brown et al. (2016); Chakrabarti and Pattison (2019); Davis et al. (2021); Foote et al. (2021); and Mazumder and Miller (2016).

The **University of Chicago Booth School of Business**'s Consumer Credit Panel, housed at the Kilts Center for Marketing, uses data from TransUnion. Researchers outside the University of Chicago system can co-author on research projects that use these data but are not able to access the underlying data. These data are an anonymized 10% sample of consumers with a credit report in the US. Data are monthly from July 2000 to the present. Data include the tradeline file. See footnote for the latest details on these data, terms of access, and links to papers using these data.[32] Examples of research using these data include: Gathergood et al. (2019b); Kluender et al. (2021); Blattner et al. (2022); Mian and Sufi (2022); Jansen et al. (2023); Keys et al. (2023); Yannelis and Zhang (2023); Cookson

[31] https://www.newyorkfed.org/microeconomics/hhdc/background.html

[32] https://www.chicagobooth.edu/research/kilts/research-data/transunion

et al. (2025); Dinerstein et al. (2024); Granja and Nagel (2024); Guttman-Kenney (2025); Guttman-Kenney et al. (2022); Guttman-Kenney and Shahidinejad (2025); and Shahidinejad (2025). See Keys et al. (2023) and Dinerstein et al. (2024) for examples with public code. For researchers with access to this panel, Booth has a non-public internal depository that contains data cleaning code.

The **Consumer Financial Protection Bureau**'s Consumer Credit Information Panel (CFPB-CCIP) uses data from one of the three nationwide consumer reporting agencies. This panel is only accessible to CFPB staff, although researchers outside the CFPB can co-author with CFPB staff but they are not able to directly access the data. The CFPB-CCIP is a 1:50 sample of deidentified credit records based on an internal identification number beginning in 2002. Since 2014, the data are monthly. The data are tradeline-level, include information on coborrowers, alternative data (including payday and high-cost installment loans, and rental payments), and have been used as a sampling frame for multiple surveys (see, for example, Consumer Financial Protection Bureau (2017), Fulford and Shupe (2021b), and Caldwell et al. (2024)). The CFPB provides regular releases of some data based on the CFPB-CCIP on its website.[33] The CFPB credit reporting data have been used for a variety of CFPB reports (Brevoort and Kambara, 2017; Conkling and Gibbs, 2019, and Brennecke et al., 2021)[34] and independent research (e.g., Brevoort et al., 2015, Romeo and Sandler, 2021, Nelson, 2023, and Fulford and Nagypál, 2023).

The **University of California**'s Consumer Credit Panel (UC-CCP), at the California Policy Lab, uses data from one of the three consumer credit reporting agencies. These data are accessible to researchers affiliated with the University of California or the California Policy Lab. Un-affiliated researchers can co-author with affiliated researchers, but un-affiliated researchers are not be able to access the underlying data. As of 2024, researcher data access costs $6,929 per project, and linking data costs $12,981, with grants available to researchers. These data are an anonymized 2% sample of consumers with a credit report in the US. It also contains a 100% sample of Californians (with a credit report) who lived in California at any point between 2004 and 2019 or who move to California after 2019. The data also include consumers who share an address or a tradeline with consumers in these samples. Data are quarterly from July 2004 to the present, with monthly data in 2020. Data include the tradeline file. A unique feature of these data is the ability to link them with administrative datasets, including those facilitated by the California Policy Lab. See the footnote for the latest details on these data, terms of access, and links to papers using

[33] https://www.consumerfinance.gov/data-research/consumer-credit-trends/

[34] See https://www.consumerfinance.gov/data-research/research-hub/ for more examples.

these data.[35] Examples of research using these data include: Flamang and Kancherla (2023); Liebersohn and Rothstein (2025); Papich (2023), and Pinto and Steinbaum (2023).

University of Illinois at Urbana-Champaign Gies College of Business's Consumer and Small Business Credit Panel (GCCP) uses data from one of the three consumer credit reporting agencies. Researchers outside the University of Illinois at Urbana-Champaign can co-author on research projects that use these data but are not be able to access the underlying data. The GCCP represents an anonymized 1% sample of consumers with a credit report in the US. Consumer data are annual from 2004 to the present, however, the data are the trended data product that enable a history of monthly tradeline data to be observed from each annual cross-section. These also contain alternative credit records ("Clarity"), containing details of alternative sources of credit, such as payday loans, from 2012 onwards. A unique feature of this panel is they include small business credit reports annually from 2009 to 2022, and these are linked to entrepreneurs' consumer credit reports. Examples of research using these data include: Fonseca (2023); Howard and Shao (2023); Fonseca and Wang (2024); Fonseca and Liu (2024), and Correia et al. (2024).

The Ohio State University's Consumer Credit Panel uses data from Experian. These data are an anonymized 1% sample of consumers with a credit report in the US. It also contains a 100% sample of Ohioans (with a credit report). Data are quarterly from 2017 to the present. See Moulton et al. (2023) for an example of research using these data.

The consumer credit panel at **Rice University Jones Graduate School of Business** uses data from Experian. These are an anonymized 1% sample of consumers with a credit report in the US, sampled based on the last two digits of SSN. Data are annual from 2004 to the present. Examples of research using these data include: Berger et al. (2018); Butler et al. (2023b,a); Mayer (2024), and Xu (2023).

The **Georgia Institute of Technology Scheller College of Business**'s Consumer Credit Panel uses data from Equifax. These are an anonymized 1% sample of consumers with a credit report in the US, sampled based on the last two digits of SSN. Data are semi-annual from 2005 to 2008, and monthly thereafter to the present. Data include the tradeline file. Examples of research using these data include Chava et al. (2023a,b), and Zhang (2023b).

The **Urban Institute**'s consumer credit panel consists of an anonymized 2% sample of consumers with a credit report in the US from one of the three consumer reporting agencies, sampled based on the last two digits of SSN. Data are annual from 2010 to the present. The Urban Institute releases derived data in its data catalog on an ad hoc basis.[36]

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

[36] For examples, see Financial Health and Wealth Dashboard 2022: https://datacatalog.urban.org/dataset/financial-health-and-wealth-dashboard-2022 and Debt in America: An Interactive Map: https://apps.urban.org/features/debt-interactive-map/?type=overall&variable=totcoll

For examples of research using these data see Wei et al. (2016) and Braga et al. (2019).

Researchers have linked credit reporting data to public Home Mortgage Disclosure Act (HMDA) data themselves using data on mortgage characteristics (e.g., loan amount, loan origination date, geography, birth date)—see Bayer et al. (2016), Bartlett et al. (2022), Bhutta and Hizmo (2021), and Shahidinejad (2025) for examples—and researchers with access to more granular confidential HMDA can potentially do more precise merges (e.g., Bhutta and Canner, 2013). Recent richer mortgage datasets, such as the expanded HMDA data and the National Mortgage Database, enhance the value of linking credit reports to these.[37] A final benefit of these linked data is that they enable researchers using mortgage datasets to evaluate selection into their dataset compared to the more complete population of mortgages in credit reports.

In addition to the above panels, we are aware researchers at some other institutions purchase an off-the-shelf product, the Equifax Analytic Dataset. This contains monthly data (including the tradeline file) from 2005 to the present, for a 10% sample of US consumers with credit reports. For examples using these data see Cherry et al. (2021) and Piskorski and Seru (2021). We understand that Experian and TransUnion can construct similar products.

G.2 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 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 reporting 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.[38] As discussed in the main text, two of the most common ways to draw and main-

[37] The FHFA/CFPB's National Mortgage Database is based on Experian credit reporting data on mortgages linked to various administrative databases from Fannie Mae, Freddie Mac, Federal Housing Administration, the U.S. Department of Veterans Affairs, and the Rural Housing Authority. https://www.fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx

[38] Alternatively, some researchers have relied on static panels, which follow a given set of birth cohorts

tain 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 identification number assigned by the CRA. These result in similar but not identical panels.[39] The social security number method will miss records that do not have an SSN or similar identification number (Lee and van der Klaauw, 2010). The internal identification number method will include more fragment files, which researchers need to account for when constructing consumer-level measures as discussed below. Because credit records are regularly merged and split, using an external identification number method such as the SSN will provide a representative sample of people (with that identification number) while the internal identification number method will provide a representative sample of records.[40] 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).

Cookson et al. (2025) find that approximately 80 percent of "consumers" without missing birth dates who appear in tradeline data at any point over 2000 to 2023 have SSNs. Examination of "consumers" who appear in credit reports but who lack SSNs suggests that they are likely fragmented records—they typically have younger ages and credit reports that do not persist over time, suggesting that these "consumer" records were later consolidated with another credit record.

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. Brown et al. (2015) find aggregate debt estimates from credit reporting data to line up well with estimates from the Survey of Consumer Finances (SCF). However, when distinguishing by loan type, they find considerable under-reporting 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.

The CRAs suppress a small subset of records for use by researchers to comply with laws and internal guidelines, such as excluding records for those under age 18. CRAs typically apply other filters to their data relevant for business purposes, such as only

of individuals or loan origination vintages. Representative static panels can be drawn using the same sampling approaches as applied for representative dynamic panels.

[39] The credit panels we know to be in existence at the time of writing were created using both sampling approaches.

[40] 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 credit record files are regularly merged or split as CRAs receive more information.

including tradelines with a recently reported update or excluding records with only accounts considered "inactive." Researchers often have different purposes than other users of credit reporting data, and they may wish to 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 for 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, 2024). Each CRA has requirements for the types of flags they will provide and the minimum number of furnishers covered by such flags.

Researchers who construct panels may also want to consider the geographic unit to cover. Some panels such as the University of California's Consumer Credit Panel, include consumers in California and track if they move to other states. The CRAs include some areas other than US States (and DC), like US territories (e.g., Puerto Rico) and US Armed Forces bases, which may be of interest to some researchers, but other researchers may also want to exclude these. If a consumer moves overseas, their location and non-US debts are unobserved.

G.2.1 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 FRBNY-CCP and the UC-CCP samples include credit records of individuals living at the same address, while the UC-CCP and CFPB-CCIP 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 the computation of household-level debt aggregates, comparable to household-level debt measures from the SCF. Calculating aggregate individual and household-level statistics based on such expanded population samples requires applying appropriate sampling weights to avoid double-counting debts held by multiple people (see Supplemental Appendix Section H.2.3 and 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, as previously discussed. 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.

G.2.2 Data Frequency and Aggregation

If researchers are interested in studying credit reports *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.

While credit reporting data are typically updated monthly, researchers might 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 reporting data at a lower frequency. For example, many ad hoc panels are constructed at an annual or biannual level (Butler et al., 2023a and Mezza and Sommer, 2016).

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).

H Code

H.1 General Practical Guidance

Credit reporting data are large datasets. Here we provide useful practical advice for researchers working with these large datasets.

- First, reduce the size of variables you are working with. A researcher's dataset may contain anonymized identifiers (e.g., for individual consumers, tradeline accounts, or furnishers) created by the CRA that are very long alphanumeric strings. Creating a lookup file mapping these to short numeric versions and using these more concise identifiers can substantially reduce the size of these datasets a researcher is loading and working with.
- Second, reduce the number of variables you are working with. Credit reporting data contain a large number of variables. For example, the CRA aggregated datasets often contain hundreds, or sometimes thousands, of variables. Often only a handful of these are used, so researchers only need to be load these (or save a subset of these data). For the tradeline data, some variables may be long strings, such as the 84-month array variable, which may be dropped if not being used.
- Third, save the raw data in an efficient format for load it. If you have access to a very large credit reporting dataset (e.g., tradeline-level, large sample of consumers), it may be efficient to save the raw data in parquet files. These can often be queried quicker than csv or other formats for initial processing.

H.2 Code for Common Tasks

We now describe several common tasks researchers perform with credit reporting data and offer some overarching guidance to approaching these tasks, code snippets, or references to existing code repositories from published papers. Unless otherwise specified, these code examples rely on tradeline-level data.

We do not include code for loading and cleaning data. We instead refer readers to the following examples of public code depositories that contain complete code from loading raw data to conducting analysis. Ganong and Noel (2020) and Keys et al. (2023) use tradeline-level TransUnion data. Bhutta and Keys (2016) and Laufer and Paciorek (2022) use FRBNY-CCP Equifax data. Gross et al. (2020) use tradeline-level CFPB-CCP data. Beshears et al. (2022) use consumer-level Experian data. Beraja et al. (2019) and Berger et al. (2021) use CRISM data.

H.2.1 Variable Names

In the code we provide, we have standardized the variable names and noted whether the unit of observation is at the tradeline- or consumer-level. The exact variable names will differ across credit reporting datasets and, therefore, will differ in public code depositories accompanying papers. A public data dictionary for Equifax Analytic Dataset is available at the time of writing.[41]

[41] https://aws.amazon.com/marketplace/pp/prodview-vgmxklm42lhmq#dataSets

Table H1: Variable Names

Variable Name	Variable Description	Variable Unit of Observation
date	Archive furnishing date	Consumer/Tradeline
personid	Anonymous consumer identifier	Consumer
hhid	Anonymous household identifier	Consumer
state	State of consumer's primary residence	Consumer
address	Anonymous address identifier	Consumer
loanid	Anonymous account identifier	Tradeline
servicerid	Anonymous identifier for a tradeline's servicer	Tradeline
ecoa_code	Sole, joint, or other user of tradeline	Tradeline
account_type	Tradeline account type	Tradeline
balance	Outstanding balance	Tradeline
status	Delinquency status or manner of payment (MOP)	Tradeline
schpayment	Scheduled payment amount	Tradeline
actpayment	Actual payment amount	Tradeline
payment_history	Array of status history	Tradeline
balance_date	Date corresponding to balance	Tradeline
open_date	Account opening date	Tradeline
origination_amt	Account origination amount	Tradeline
terms_frequency	Account frequency	Tradeline
terms_duration	Account term duration	Tradeline
special_comment_code	Narrative codes from Metro 2	Tradeline
inquiry_date	Date of inquiry	Inquiry

H.2.2 Joint Account Adjustment

As explained in Section 3.2.3 of the main paper, researchers often need to de-duplicate accounts that are jointly-held or have authorized users to calculate accurate aggregated population-level statistics. Joint account information is typically contained in an ECOA variable. This SQL code example applies to data which include authorized users.

```
-- Using Metro 2 codes:
CASE
    -- individual ('1'):
    WHEN ecoa_code IN ('1') THEN 1
    -- authorized user ('3'), deceased ('X'):
    WHEN ecoa_code IN ('3','X') THEN 0
    -- joint contractual liability ('2'), co-maker
    -- or guarantor ('5'), maker ('7'):
    WHEN ecoa_code IN ('2','5','7') THEN 0.5
    -- obsolete codes for joint ('4') and on-behalf-of ('6')
    WHEN ecoa_code IN ('2','6') THEN 0.5
END AS wgt
```

CRAs may use different ECOA codes formats. Analogous SQL code for TransUnion's letter codes are:[42]

```
CASE
    -- individual ('I'):
    WHEN ecoa_code IN ('I') THEN 1
    -- authorized user ('A'), deceased ('X'):
    WHEN ecoa_code IN ('A','X') THEN 0
    -- joint contractual liability ('C'),
    -- liable but co-signer has liability if the maker defaults ('M'),
    -- shared account participant ('P'), co-signer ('S'):
    WHEN ecoa_code IN ('C','M','P','S') THEN 0.5
END AS wgt
```

Analogous SQL code for Equifax's letter codes are:

```
CASE
```

[42] https://www.transunion.com/docs/rev/business/clientResources/HowToReadCreditReport.pdf

```
    -- individual ('I'):
    WHEN ecoa_code IN ('I') THEN 1
    -- authorized user ('A'), deceased ('X'):
    WHEN ecoa_code IN ('A','X') THEN 0
    -- joint contractual liability ('J'), co-maker ('C'),
    -- maker ('M'), shared ('S'):
    WHEN ecoa_code IN ('C','M','J','S') THEN 0.5
END AS wgt
```

H.2.3 Household Weights

Based on the FRBNY-CCP, primary samples are selected based on certain combinations of Social Security numbers representing 5% of population with Social Security numbers, and all those sharing the same addresses are selected as household samples. As a result, a 1-person household member is selected with 5% probability, and a 2-person household is selected with probability $1 - 0.95^2$, and households with N members are selected with probability $1 - 0.95^N$.

This example uses Stata code and a 5% sampling rate.

```
egen N_hh = sum(1), by(hhid)

* number of household members in hhid
gen hh_wgt = 1 - 0.95^N_hh

* example of aggregation
table state [iw=hh_wgt], stat(sum balance) stat(mean balance)
```

H.2.4 Population Counts with Credit Reports

It is estimated that roughly 1-in-10 US adults do not have a credit report (Brevoort et al., 2015). This share is calculated by estimating the number of adults *with* a credit report, dividing by Census/ACS population counts, and subtracting from 1. While seemingly straightforward, measuring this share requires taking a stance on which credit records are fragment files. By definition, a fragment file is a non-unique credit record for a given individual (see Supplemental Appendix Section B), so fragment files should be excluded when computing the count of individuals with a credit report. Common approaches to removing fragment files include removing records that do not persist for at least four years (or some other threshold), inquiry-only credit records, collection-only credit records, public-record-only credit records, and/or credit records with missing consumer age or birth year. The choice of which approach is used to drop fragment records can change by 10 million or more the implied count of consumers without a credit record (see Appendix A Table 1 in Brevoort et al. (2015)). An example of code to calculate these ratios can be found in 03_count_with_trade.py and 03_sumstats.do in the replication package to Keys et al. (2023).[43]

H.2.5 Mobility

Mobility can be measured by a change in a consumer's address in credit reporting data. Often researchers will not observe the exact address of a consumer in their credit reporting data. The replication package of Keys et al. (2023) identifies and analyzes movers across coarsened geographies such as commuting zones (02_mover.py, main function defined in lines 128 to 178).[44]

If a researcher observes a consumer's (anonymized) address, they can use the following Stata code that examines the address history of a person and flags it as a move only when the address is new in the entire history of the person.

```
sort personid address time
by personid address: gen move= (_n==1)
* first appearance of new address is flagged as a move.
```

Another example of similar Stata code for measuring mobility at different frequencies can be found in 2_clean_efx_moves.do in the replication package to Abel and Fuster (2021).[45]

Readers measuring geographic mobility in credit reporting data should also review the caveats discussed in Section 3.7 of the main paper.

It is sometimes important for researchers to exclude real-estate investors who hold multiple properties. These individuals' primary residence often cannot be well-established in credit reports. This makes it challenging to assess moves and whether new mortgages are for new properties or for refinancing. The replication package of Bhutta and Keys (2016) contains an example for identifying these individuals (see lines 100 to 109 of dofiles/datasets/create_extraction_dataset.do).[46] In their paper, "A borrower is classified as an investor if (i) he has three or more mortgage accounts; (ii) he has exactly two closed-end mortgages where the smaller loan is at least one-third the size of the larger; or (iii) he

[43] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/G85KDR
[44] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/G85KDR
[45] https://www.openicpsr.org/openicpsr/project/116461/version/V1/view
[46] https://www.openicpsr.org/openicpsr/project/116153/version/V1/view

has two or more HELOCs, or a HELOC with a line size that is more than 50 percent the size of his only closed-end loan: 3+ accounts; 2 closed end accounts of 'similar' size; large HELOC relative to closed; or two HELOCs."

Mian and Sufi (2022) construct three measures of housing speculators, which they show to be highly correlated. They write:

- "First, a mortgage origination is classified as being taken out by a speculator if the individual taking out the mortgage in question also takes out another distinct first-lien purchase mortgage in a 2-year period around the origination in question. We refer to this as the 'multiple houses' categorization of a speculator.
- "Second, a given first-lien purchase origination is classified as being taken out by a speculator if the first-lien purchase mortgage is subsequently closed within a year, and there is no associated refinancing for the individual in the six months after the purchase mortgage is closed. We refer to such an individual as a 'short-term' trader, where we are making the assumption that the closed mortgage reflects a sale.
- "Third, a given first-lien purchase origination is classified as being taken out as a speculator if the individual taking out the mortgage already has at least two existing first-lien mortgages on his balance sheet at the time of the new origination. We refer to such an individual as a '2+ mortgage' speculator."

H.2.6 Merging CCP Mortgages with Other Mortgage Datasets

With a wide array of non-CCP mortgage datasets available, researchers sometimes merge CCP and non-CCP mortgage data at the loan level. A challenge is that details such as loan balance or loan date may vary slightly between datasets depending on when the loan was recorded or which aspects of the loan transaction were recorded in each dataset. To address this, a common approach is to use a "fuzzy" merge that allows close, but not exact, matches, and then to select the closest match based on various criteria available in both datasets. While particulars will vary depending on the two datasets in question, an example of this strategy is in lines 47–74 of empirics/CRISMcleaning/re4_match_efx_lps.do from the replication package to Beraja et al. (2019).[47] The replication package of Berger et al. (2021) use a similar, slightly updated approach, see empirical_code/CRISM_Data_Processing/4_match_efx_lps.do, lines 52–164.[48]. Similarly, see 4_match_efx_lps.do in the replication package of Abel and Fuster (2021).[49]

[47] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GETNJK
[48] https://www.openicpsr.org/openicpsr/project/134161/version/V1/view
[49] https://www.openicpsr.org/openicpsr/project/116461/version/V1/view

H.2.7 Mortgage Purchases and Refinances

We first identify a new origination by observing the first observation of a loan. A new origination is either a purchase origination or a refinance origination. We flag refinance originations first and code the rest as purchase originations. To be classified as a refinance origination, we check 1) if there is a preceding prepaid/closed mortgage loan not too long before, such as within 12 months, and 2) if the address of the person at the time of the origination is a new one for the person in the entire history.

```
* stata code for FRBNY CCP

drop if balance == 0
* to drop the trailing zero balances after pay off

* create new address indicator
sort personid address date
by personid address: gen new_address==1 if _n==1

* create indicators for first and last observations of a loan

sort personid loanid date
by personid loanid: g startofloan=1 if _n==1
by personid loanid: g endofloan=1 if _n==_N


* now flag refinance
sort personid date
by personid: gen purpose="refinance" if startofloan==1
& endofloan[_n-1]==1 & date<date[_n-1]+12 & new_address==0

* impose condition of refinance such that there should be
a preceding loan within 12 month before the startofloan,
and the address should be a new one in the history of the person

replace purpose="purchase" if purpose=="" & startofloan==1
```

If using the above approach, it is important to note that loans are typically censored at the beginning of sample periods, so a researcher should modify the purchase/refinance indicators that existed from the beginning of sample periods.

The code below is adapted from Mian and Sufi (2022) for their tightest definition of mortgage refinancing. We thank the authors for allowing us to publish this code. If using the code below, please cite the source as Mian and Sufi (2022). In this code, numbmor is a consumer-level variable recording the number of mortgages outstanding, and censgeocode is the census tract of the consumer. These two variables are measured at different time periods denoted by the suffix (l12, l6, l3, l1, f1, f3, f6, f12), where l12 is twelve months prior to the date of mortgage origination and f12 is 12 months after the date of mortgage origination.

```
gen refi=1 if numbmor\_l1==numbmor\_f6
& censgeocode\_l1==censgeocode\_f6
replace refi=1 if numbmor\_l1==numbmor\_f3
& censgeocode\_l1==censgeocode\_f3
replace refi=1 if numbmor\_l1>numbmor\_f6
& censgeocode\_l1==censgeocode\_f6
replace refi=1 if numbmor\_l1==0 & numbmor\_f6==1
& censgeocode\_l1==censgeocode\_f6
replace refi=. if censgeocode\_l1==.
```

The replication package of Beraja et al. (2019) contains code (empirics/CRISMcleaning/5_link_new_lps_loans.do) for identifying refinanced loans in CRISM data.[50] They write in their Online Appendix:

- "We thus use the following rules to identify refinances. We start by looking for any loan in the Equifax data set that has an open date within 4 months of the McDash loan's termination date. We find at least one such loan for about 81% of the voluntary terminations in 2008 and 2009. We classify these new loans as a refinance if either:
  - The loan also appears in McDash and is tagged as a refinance in the purpose-type variable (61% of the McDash-matched loans).

[50] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GETNJK

- The loan also appears in McDash and is tagged as an 'Unknown' or 'Other' purpose type, and has the same property zip code as the original loan.
- The loan appears only in Equifax but the borrower's Equifax address does not change in the 6 months following the termination of the original loan."

A similar, slightly updated approach is taken in Berger et al. (2021)'s replication package code (empirical_CRISM_Data_Processing/5_link_new_lps_loans.do).[51] They write in their Online Appendix:

- "As in our primary analysis, we begin with all remaining outstanding fixed rate first liens in the McDash which are voluntarily paid off. We then look for any loan in the Equifax data set that has an open date within 4 months of the McDash loan's termination date. We classify these new loans as a refinance if either:
  - "The loan also appears in McDash and is tagged as a refinance in the purpose-type variable.
  - "The loan also appears in McDash and is tagged as an 'Unknown' or 'Other' purpose type, and has the same property 5 digit zip code (where available, or 3-digit zip code and MSA-div where not) as the original loan.
  - "The loan appears only in Equifax but the borrower's Equifax address does not change in the 6 months following the termination of the original loan."

H.2.8 Identifying First and Second Liens Mortgages

For mortgage accounts, identifying first and second liens usually come from account type and narrative codes. HELOCs have account type of "R," revolving. Within mortgages, first and second lien installment mortgages can be derived from narrative codes. Mortgage security types such as Fannie, Freddie, FHA, VA can be classified as first mortgages, and accounts with narrative codes of "second mortgage," "home equity loan," and "home improvement loan" can be classified as second liens. Among those that are not classified before, one can use the origination amount as a proxy for first lien vs. second lien. The New York Fed uses a threshold of $40,000 to draw a distinction.

```
variables: narrative = narrative code
account_type: "R" if revolving, "I" if installment
```

[51] https://www.openicpsr.org/openicpsr/project/134161/version/V1/view

```
gen mortgage_type ="heloc" if account_type =="R"
* "R" = revolving accounts

replace mortgage_type="second lien" if account_type=="I"
& inlist(narrative, "home equity loan", "home improvement loan",
"second mortgage")

replace mortgage_type="first lien" if account_type=="I"
& (narrative=="Fannie Mae" | narrative=="Freddie Mac"
| narrative=="FHA" | narrative =="VA" )
```

Alternatively, Mian and Sufi (2022) use a threshold of less than 30% of CLTV to designate which loans are a second lien, as in the following block of Stata code which takes as input a dataset of (only) mortgage tradelines.[52]

```
egen currtotal=sum(balance), by(personid date)
gen frac=balance/currtotal
gen second_lien=(frac<=0.3)
```

For an example of code identifying second lien balances based on CRISM matched data see 2_second_lien_balances.do in the replication package to Abel and Fuster (2021).[53]

The replication package of Beraja et al. (2019) contains code (empirics/CRISMcleaning/5_piggybackseconds.do) for identifying piggyback second liens.[54] They define a piggyback second lien as one that: "(1) Has the same open month in Equifax within three months of the matched loan's Equifax open month. (2) Has an origination balance of less than 125% of the LPS loan's origination balance if it's a CES [closed-end second] or HELOC, OR (3) Has an origination balance of less than 25% of the LPS loan's origination balance if it's a first mortgage." A similar approach is taken in Berger et al. (2021)'s replication package code (empirical_CRISM_Data_Processing/5_piggybackseconds.do).[55] They define a piggyback

[52]We are grateful to Amir Sufi for sharing this code, which we have adapted to follow the naming convention in Table H1.

[53]https://www.openicpsr.org/openicpsr/project/116461/version/V1/view

[54]https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GETNJK

[55]https://www.openicpsr.org/openicpsr/project/134161/version/V1/view

second lien as one that: "(1) Has the same open month in Equifax within three months of the matched loan's Equifax open month, (2) Has an origination balance of less than 125% of the LPS loan's origination balance (if it's a CES or HELOC), OR (3) Has an origination balance of less than 25% of the LPS loan's origination balance (if it's a first mortgage)."

H.2.9 Mortgage Cash Out Refinance

The cash-out amount from mortgage refinance can be measured by first identifying refinance mortgages (as using code in the prior sections), and then taking the difference between the mortgage loan origination amount and the outstanding mortgage balance in the prior month. The Stata code below provides a simple example for calculating this, however, we refer readers to replication packages for more refined approaches.

```
sort personid date
by personid: gen cashout = origination_amount - balance[_n-1]
if purpose=="refinance"
* purpose as defined in code in earlier section
```

An example of similar Stata code for measuring equity extraction can be found in create_extraction_dataset.do (especially lines 111 to 113) in the replication package to Bhutta and Keys (2016).[56]

The replication package of Beraja et al. (2019) contains code (empirics/CRISMcleaning/6_cashout_panel.do) for identifying cash-out refinancing in CRISM data.[57] A similar, slightly updated approach is taken in Berger et al. (2021)'s replication package code (empirical_CRISM_Data_Processing/6_cashout_panel.do).[58] Both of these papers contain Online Appendix documentation describing their methods in detail.

H.2.10 Cost of Borrowing

While interest rates are not directly reported in credit reporting data, the costs of borrowing can be estimated by researchers from tradeline-level data or purchased from the credit reporting agencies. For fixed-rate installment loans, such as auto loans and unsecured personal loans, once a researcher observes the principal origination amount ($origination\_amt$), origination term duration ($terms\_duration$), and scheduled monthly payment amount ($schpayment$), they can calculate the interest rate (i) at origination using a root-solver

[56] https://www.openicpsr.org/openicpsr/project/116153/version/V1/view
[57] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GETNJK
[58] https://www.openicpsr.org/openicpsr/project/134161/version/V1/view

shown in Equation 6. For cases where $origination\_amt \geq schpayment \times terms\_duration$, loans are assumed to have zero-percent interest rates. Researchers may also wish to top-code unreasonably high interest rates. See Yannelis and Zhang (2023) for an example of this methodology.

If estimating interest rates, the interest rate's n-th digit is unlikely to be of use and may provide false precision. We therefore recommend rounding the interest rate to two-to-four decimal places.

$$schpayment = \frac{origination\_amt \times i}{1 - (1+i)^{-terms\_duration}} \quad \text{if} \quad origination\_amt < schpayment \times terms\_duration \tag{6}$$

The cost of borrowing on mortgages at origination can be calculated using a similar methodology, as developed by Shahidinejad (2025). Equation 7 shows the root-solver equation to calculate the interest rate at origination (i), using data from the first few months (e.g., months two to seven) of the loan. This uses the outstanding balance ($balance$) at two points in time j and k, and origination term duration ($terms\_duration$). Importantly, this methodology accounts for the fact that the scheduled payment variable observed in credit reporting data typically include taxes, insurance, or homeowner association (HOA) fees, as well as the interest and principal payment, which would mean estimates of borrowing costs produced using Equation 6 would often be biased. As Shahidinejad (2025) is a working paper, the exact methodology to estimate borrowing costs may develop over time, and we encourage readers to examine updated version of this paper to locate code.

$$\frac{balance_j}{balance_k} = \frac{(1+i)^{terms\_duration-j} - 1}{(1+i)^{terms\_duration-j} - (1+i)^{k-j}} \tag{7}$$

Across auto loans, mortgages, and other installment loans, if a researcher is interested in the realized effective interest rate, to capture costs changing post-origination, researchers can use these same methodologies using multiple observations after origination. For one example, see Conkling and Gibbs (2019).

For computational reasons, it may be more efficient to calculate rates by searching over a grid restricted to reasonable range (e.g., 0% to 50%) and decimal place increments, instead of using a root-solver. This is especially likely to apply if researchers are calculating realized interest rates where substantially more data is required compared to calculating interest rates at origination.

Without using a root-solver, we also provide Stata code below to estimate realized effective interest rates. This will not be accurate for many mortgages, for the reasons discussed above, as the scheduled payment variable includes non-interest and non-principal components. In addition, it also requires an assumption that the scheduled payment is equal to the actual payments made; this will not be the case in months when a consumer prepays a loan.

```
sort loanid date
by loanid: gen cost =  schpayment[_n-1] - (balance[_n-1] - balance)
by loanid: gen rate = cost / balance[_n-1]
```

Separately from installment loans, Guttman-Kenney and Shahidinejad (2025) develop a methodology for estimating financing charges on credit cards, which uses the institutional details of credit card minimum payment formulae to infer borrowing costs. In particular, credit cards' minimum payments follow a deterministic formula where the minimum payment is the maximum of (i) $\$\mu$ amount (e.g., $10, $25), and (ii) $\theta\%$ statement balance, plus interest and fees. This formula structure means that if a researcher can work out a credit card's μ and θ, a researcher can then work out, the minimum payment before financing charges (sum of interest and fees) each month for each card, and compare this to the observed minimum payment in credit reporting data (the scheduled payment amount) to estimate the costs of borrowing. The terms μ and θ can be deduced by researchers using tradeline data to examine the relationships between statement balances and scheduled payment amounts. Researchers can more accurately deduce these terms with more granular credit reporting data available (e.g., actual payment amounts, anonymized furnisher identifiers). As Guttman-Kenney and Shahidinejad (2025) is a working paper, the exact methodology may develop over time, and we encourage readers to examine updated versions of this paper to locate code.

H.2.11 Flow Delinquency

The flow of new accounts into delinquency can be measured by comparing the number of accounts in stages of delinquency over time. Delinquency information is contained in the "status" variable.

```
sort loanid date
by loanid: gen flow_delinquent = delinquent[_n-1]==0
& status !="1" if _n>1
```

H.2.12 Linking Tradelines Across Transfers

Users may have CRA-supplied tradeline identifers, but these IDs typically change when the tradeline is transferred between servicers or when a credit card replaces a lost/stolen card. Usually, the account opening dates carry over enabling account linking. The Stata code below creates a new variable loanid2 that links loanid over transfers. Account transfers are distinguished from mortgage refinances since the latter is a new origination and with new account opening date.

```
gen loanid2=loanid
sort personid origination_date date
by personid origination_date: replace loanid2 = loanid2[1]
```

Note: The data can be more complicated than this simple example. There may be multiple loans with the same origination date in each date t, in which case a researcher may use additional information such as ”credit limit” or ”origination amount” to make the loans more unique to separate among multiple such loans. For example,

```
gen loanid2 = loanid
sort personid origination_date origination_amount date
by personid origination_date origination_amount:
replace loanid2 = loanid2[1]
```

Below we provide some more general guidance to link the same tradeline over time for a variety of credit products (assuming the origination date for the trade does not change), but users may wish to do something slightly different for specific products or contexts:

- For installment loans: group based on loan product, person identifier, open date, loan amount.
  - For student loans still in deferment, users may need to allow the loan amount to change within the first 6-9 months after origination (many of these loans have a second disbursement the semester after origination).

  - Installment loans with the same new identification number in the same time period and the same repeated balance dates (and/or different, non-zero dollar balance amounts) are likely separate loans that should have different IDs. This is especially common with student loans where a borrower may have multiple loans open on the same day.

- For revolving accounts: group based on loan product, person identifier, open date.
  - This ignores credit limit because limits can change over time.
  - Revolving accounts with the same new identification number in the same time period but with different credit limits are likely different accounts.
  - Revolving accounts with the same new identification number in the same time period and the same credit limits but different balances, scheduled payment, or actual payment amounts are likely difference accounts.

- In all cases: if the CRA-supplied tradeline identifier match for conflicting identification numbers based on the above groupings, reassign the new identification number so it matches. For example, if tradelines A and C share a new identification number based on the above and tradelines A and B share a CRA-supplied tradeline identifier, tradelines A, B, and C should all have the same new identification number.

H.2.13 Identifying Direct Student Loans versus FFELP Student Loans

If the student servicer identification numbers are available in the data, a researcher can assign student loans servicers between the Direct Loan Program and the Federal Family Education Loan Program (FFELP) among federal student loans using the COVID-19-related administrative student loan forbearance that only affected Direct and federally-held FFELP loans. FFELP loans are student loans made by private lenders and guaranteed by federal government. FFELP loans those that were still held by commercial lenders in 2020 were not subject to the same policy. This Stata code assumes that each servicer is exclusively servicing Direct loans or FFELP loans; if a servicer identification number services both of them under one identification number, it will create a problem.

```
egen test1 = sum((payment ==0)*(t=="June 2020")*(balance>0)),
by(servicerid)
* number of accounts with payment 0 in June 2020
```

```
egen test2 = sum((t=="June 2020")*(balance>0)) , by(servicerid)
* number of accounts with positive balance in June 2020

g test3 = test1 / test2
* share of payment=0 accounts among those with positive balance
in June 2020 by servicers

g direct = (test3>0.99)
* If zero payment share is 99%, it's a direct loan servicer.
One needs to to check the distribution of test3 to determine
the right threshold.
```

Note: this will separate Direct loan servicers from FFELP and private loans servicers, but it will not distinguish between FFELP servicers and private student loan servicers. To distinguish between the FFELP and private student servicers, users needs to check other information such as timing of originations (FFELP loans stopped originating new loans in 2010), origination amounts, joint account behavior, credit scores, etc. Some servicers might service both types of loans under the same servicer ID, in which case the distinction at the servicer level is not possible.

Additionally, the code for Dinerstein et al. (2024) presents a slightly different approach in 02_IdentifyLoanType.py and 05_AlternativeClassification.py.[59]

H.2.14 Delinquencies from payment history

When researchers want to construct the monthly payment status history for a tradeline without monthly data, they can pull this information from the payment history if it is included in their data. This variable is typically a grid showing of monthly payment history with the most recent month in the leftmost position based on Metro2 guidance. The payment history takes values corresponding to 30-day increments in delinquency and has additional values for other statuses, such as collections and charge-offs.

To align the payment history information correctly, users must also use the balance date for the same data archive. See below for an example in Stata transforming the data into a long dataset with the last 12 months of payment history.

```
forvalues i = 0/11 {
```

[59] See https://www.openicpsr.org/openicpsr/project/193167/version/V1/view

```
    gen payment_status`i' = substr(payment_history,`i'+1,1)
}
reshape long payment_status, i(tradeline_id) j(payment_month)
replace payment_month = mofd(balance_date) - payment_month
format payment_month %tmMonCCYY
```

For another example calculating delinquencies in the any month in the prior quarter, see starting at line 561 in process_bk_sample.do in the code repository for Gross et al. (2020).[60]

H.2.15 Missing Loans

Occasionally loans disappear from credit reporting data for several months due to reporting issues or transfers between furnishers. Sometimes these gaps are long and sizeable, such as with student loans from December 2011 to June 2012 and in 2023. To impute missing loan balances for the former period with consumer-level data, Beshears et al. (2022) use linear interpolation starting at line 1148 in ae_sample_compile_all.do.[61]

Note that, especially when accounting for balances of new originations, users may want to use seasonal patterns from other years rather than a linear trend. To impute missing delinquency statuses during these periods, users can refer to the payment grid after the tradeline reappears as described in H.2.14.

H.2.16 Forbearances

Accounts are placed into forbearance (or deferment) when borrowers are not required to make payments. This is most common for student loans, but it can also happen with mortgages and other types of credit, especially during natural disasters or other major events such as the COVID-19 pandemic. There is a special comment code ("CP") and loan term frequency ("D") that identify many of these forbearances. Sometimes furnishers do not report these deferment codes and users must infer the forbearance when a tradeline with a positive balance also has a $0 scheduled payment; however, researchers need to check whether a furnisher is reporting the scheduled payment variable across its portfolio, otherwise it may erroneously interpret a $0 as a deferment when it is not.

```
gen forbearance = (balance_amount > 0 & payment_amount == 0)
```

[60] See https://www.openicpsr.org/openicpsr/project/115211/version/V1/view

[61] https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fjofi.13069&file=jofi13069-sup-0002-ReplicationCode.zip

```
replace forbearance = 1 if special_comment_code == "CP"
    | terms_frequency == "D"
```

We also refer interested readers to Cherry et al. (2021) and Dinerstein et al. (2024) as these studies of COVID-19 accommodations include deferments and forbearance.

While deferments and forbearances are different things for federal student loans, they are not reliably reported over time and across furnishers. As a result, it is difficult to separately categorize deferments and forbearances in the credit reporting data.

H.2.17 Aggregating Balances Across Loan Types

Consumer-level aggregated CRA data include numerous—sometimes hundreds—of variables reporting the sum of a consumer's outstanding debt across all loans in various categories. When using these aggregates to create other aggregate measures, care should be taken that the variables used have applied comparable filters to which underlying tradelines are included: only loans or also non-loan tradelines such as medical collections; all loans or only currently open ones, as loans are sometimes closed but have a nonzero balance; all loans or only "verified" ones, which have been recently reported by a furnisher (e.g., in the last 90 days). Care should also be taken not to add to variables where one is a superset of the other. For example, a measure of a consumer's total "installment" debt likely already includes student loans, mortgage loans, and auto loans (each of which is sometimes referred to as an installment loan because the consumer pays in periodic installments).

For an example of such aggregation exercises, see lines 1230–1349 of ae_sample_compile_all.do from the replication package for Beshears et al. (2022).[62] Also see the replication package code 03_ConstructPanel.py in Dinerstein et al. (2024).[63]

H.2.18 Consumption: Automobile Purchases and Credit Card Spending

Two types of consumption that can be usefully studied in credit reporting data are automobile purchases and credit card spending. These are further described in Section 3.6.1 and 3.6.2 of the main paper. Helpful examples of code to compute these two consumption measures can be found in 11_make_tu_creditcard_file.R and 12_make_tu_auto_file.R in the replication package to Ganong and Noel (2020).[64]

[62] https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fjofi.13069&file=jofi13069-sup-0002-ReplicationCode.zip
[63] https://www.openicpsr.org/openicpsr/project/193167/version/V1/view
[64] https://www.openicpsr.org/openicpsr/project/118401/version/V1/view

H.2.19 Determining Inquiry Success

When users have data with non-aggregated inquiries that include the date of the inquiry, they can match those inquiries to new tradeline openings to calculate inquiry success (or credit tightness). Users must first define the time period after an inquiry happens that a new account must open by. Common search windows are 7 days for credit cards, 14 days for auto loans, 120 days for mortgages, and 30 days for all other types of credit.

Users should keep in mind that they are unlikely to observe all inquiries that might be part of a consumer's search window (except for mortgages prior to 2024) because the inquiries corresponding to an application may have gone to a CRA other than the researcher's data source. To partially account for this, it is helpful to collapse down to the consumer-search window level. Below we provide an example in SQL.

```
-- Define relevant search window by credit product type
CASE WHEN loan_product = 'credit_card' THEN 7
     WHEN loan_product = 'auto_loan' THEN 14
     WHEN loan_product = 'mortgage' THEN 120
     ELSE 30
END AS search_window
-- Join inqs w/trades based on inquiry dates and opening dates
matched AS (
SELECT * FROM inquiries AS a
    LEFT JOIN trades AS b
    WHERE a.person_id = b.person_id
    AND datediff(day,a.inquiry_date,b.open_date) <= a.search_window)
-- Collapse to person-time period level (time_period)
SELECT *,
    CASE WHEN MAX(open_date) IS NOT NULL THEN 1
        ELSE 0
    END AS inquiry_success
    FROM matched
    GROUP BY person_id, loan_product, time_period
```

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