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Wage Garnishment in the United States: New Facts from Administrative Payroll Records†

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Wage garnishment allows creditors to deduct money from workers' paychecks to repay defaulted debts. We document new facts about wage garnishment between 2014 and 2019 using data from a large payroll processor that distributes paychecks to approximately 20 percent of US private-sector workers. By 2019, over 1 in every 100 workers was being garnished for delinquent debt. The average garnished worker experiences garnishment for five months, during which approximately 11 percent of gross earnings is remitted to their creditor(s). The beginning of a garnishment is associated with an increase in job turnover but no intensive margin change in hours worked. (*JEL* G51, J22, J63)

When consumers default on their financial obligations, creditors engage in a variety of practices to recoup what they are owed. These debt collection practices can range in severity from placing a simple phone call to pursuing court-ordered wage garnishment. While an effective and transparent system of debt collection is crucial to ensure well-functioning credit markets, some debt collection practices may impose heavy burdens on consumers. Despite both the importance of debt collection for well-functioning credit markets and its potentially damaging effects, surprisingly little is known about the prevalence and impact of different collection practices.

In this paper, we provide new descriptive evidence on an important yet little-studied form of debt collection: wage garnishment. Wage garnishment occurs when the government or a private creditor obtains a court order to recover money a worker owes directly out of her wages. Consumers can face wage garnishment for a range of defaulted debts, including credit cards, student loans, and unpaid medical bills.[1] Unlike other forms of debt collection, garnishment operates directly

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[1] The term "wage garnishment" is also sometimes used to refer to payments preemptively and often voluntarily deducted from workers' paychecks to satisfy financial obligations to parties other than creditors. For example, voluntary child support payments may come directly out of wages. In this paper, we focus attention on garnishments

through a worker's wages and may thus have important consequences not only for individual workers but also for the broader labor market. However, a dearth of data has frustrated attempts to document even basic facts about the reach and impact of this institution.

Drawing on data from the largest payroll processor in the United States, Automatic Data Processing Inc. (ADP), we provide the most comprehensive descriptive analysis of wage garnishment to date. ADP is responsible for distributing paychecks on behalf of employers to approximately 20 percent of all private-sector US workers. In fulfilling these duties, ADP also provides employers with a set of tools to implement garnishment orders. As a result, our data includes not only monthly hours and earnings but also garnishment amounts by type for a large and roughly representative sample of employees between 2014 and 2019. Using these data, we establish five first-order descriptive facts about garnishment that were previously unknown and that will hopefully inform and motivate future study of the topic.

First, we document that garnishment is fairly widespread. In any given month, nearly 1 percent of all workers in our sample are being garnished for some type of delinquent debt, and roughly 0.16 percent of workers transition into becoming newly garnished. These figures have been increasing in recent years, driven primarily by a rise in new student debt garnishments. The garnishment rates we document are on par with similar statistics for consumer bankruptcy, which has been the focus of considerably more academic research.[2]

Second, although many workers in the United States experience garnishment, we document that the average garnishment spell is relatively short lived. Conditional on being garnished, the average worker in our sample is garnished for approximately five months. Garnishment orders at a given job remain active until the worker either pays off the debt or, for nonstudent loans, files for bankruptcy. These relatively short-lived spells may therefore reflect either low debt levels or high bankruptcy filing rates. This latter possibility provides support for recent empirical work studying possible interactions between bankruptcy filing and state-level differences in regulations that govern garnishment (Lefgren and McIntyre 2009; Keys, Mahoney, and Yang 2020; Argyle et al. 2021).

Third, garnishment is stringent. The average garnished worker in our sample has 11 percent of gross earnings remitted to creditors each month—a larger income share than the average US household devotes to food in a typical month (US Bureau of Labor Statistics 2020). The magnitude of these collections raises the possibility that unexpected wage garnishment could severely strain workers' budgets and cause them to fall behind on other bills, thus potentially perpetuating a cycle of debt.

that occur outside of bankruptcy and that arise as a result of a demonstrated failure to pay creditors or other goods and service providers.

[2]For example, statistics from the US Courts indicate that the average number of new personal bankruptcy filings per month in 2019, the last year of our data, was 62,676 (US Federal Courts 2020). This implies that roughly 0.03 percent of the US adult population transitioned into filing for bankruptcy during each month of that year. Similar statistics from the Federal Reserve Bank of New York's Consumer Credit Panel indicate that 0.08 percent of all consumers transitioned into a new bankruptcy during the average quarter in our sample period (Federal Reserve Bank of New York 2021). These latter statistics exclude the roughly 10 percent of the US population that does not have a credit report. These consumers are likely to be only marginally attached to the labor force and therefore also unlikely to appear in the ADP data.

Fourth, the garnishment burden is unequally distributed. We find substantial heterogeneity in the prevalence of garnishment across industry, age, earnings, race, and education. At the individual level, garnishment rates are particularly high among middle-aged and middle-income workers employed in the manufacturing, healthcare, education, and transportation industries. At the zip code level, garnishment rates are increasing in both the share of residents who are Black and the share of residents without a college degree. These latter two results, which echo the findings from Waldman and Kiel (2015) based on court records from three municipalities, hold even after conditioning on worker-level income. This suggests that the disparities we document may not be fully driven by cross-sectional differences in the ability to service debt.

Fifth, the onset of garnishment is associated with an increase in job turnover rates but no intensive margin change in hours worked. In a matched sample of garnished and nongarnished workers, we find that garnished workers separate from their jobs at slightly higher rates than nongarnished workers in the months immediately following garnishment. However, conditional on remaining in their jobs, garnished workers do not exhibit any change in hours worked relative to observationally similar nongarnished workers. While not conclusive, these results are consistent with a potentially small causal effect of garnishment on worker separations and no effect on hours worked.

Our paper contributes to a large empirical literature studying various aspects of consumer financial distress. A natural focus in this literature has been on bankruptcy, which, for many people, is the main source of relief from financial hardship. The widespread availability of data on consumer bankruptcy has facilitated work on many aspects of the institution. For example, recent empirical work on the topic has significantly advanced our understanding of why consumers file for bankruptcy (Indarte 2023; Keys, Mahoney, and Yang 2020; Argyle et al. 2021), how bankruptcy affects equilibrium credit market outcomes (Gross et al. 2021), what the causal effects of receiving bankruptcy protection are for individual consumers (Dobbie and Song 2015; Dobbie, Goldsmith-Pinkham, and Yang 2017), and how the broad-based debt relief offered through the bankruptcy system affects aggregate outcomes during economic downturns (Auclert, Dobbie, and Goldsmith-Pinkham 2019). The facts we document in this paper provide new information about what happens to many consumers prior to filing for bankruptcy protection.

Our paper is also closely related to the much smaller literature on debt collection. Most existing work on debt collection focuses on consumers' informal experiences with debt collectors that occur prior to the onset of formal wage garnishment. For example, several papers explore how state statutes targeting debtor harassment affect outcomes such as bankruptcy filing (Dawsey, Hynes, and Ausubel 2013) and credit provision (Fedaseyeu 2020; Fonseca, Strair, and Zafar 2017; Romero and Sandler 2021). In related theoretical work, Fedaseyeu and Hunt (2018) and Drozd and Serrano-Padial (2017) explore how creditors' use of third-party collectors and the use of information technology by those collectors affect equilibrium credit supply and consumer welfare. Our paper contributes to this literature by focusing on wage garnishment, which is the most direct and formal means outside of the bankruptcy court by which creditors and third-party debt collectors are able to recoup defaulted payments.

Outside of our paper, there are relatively few academic studies focusing on wage garnishment itself. Dobbie and Song (2015) show that receiving Chapter 13 bankruptcy protection increases labor earnings and argue that this occurs in part because bankruptcy shields some earnings from garnishment. Similarly, Cheng, Severino, and Townsend (2021) show that borrowers fare better when settling debts through the court rather than through informal negotiations and argue that this is because limits on court-ordered garnishment rates result in more borrower-friendly repayment plans. The only other large-scale empirical explorations of wage garnishment that we are aware of are two ADP white papers that describe the prevalence of wage garnishment in 2011–2013 and 2016 using similar data as we use here (Yildirmaz and Goldar 2014; ADP 2017). As in our work, these studies find relatively high overall garnishment rates that are unevenly distributed across industries, age, and worker earnings. Our paper contributes by providing a new set of facts that go beyond documenting the mere cross-sectional prevalence of garnishment to also describe what the typical garnishment experience involves (e.g., how long garnishment lasts and what fraction of earnings are lost) and how garnishment rates have evolved over time. In addition, our paper is also the first to provide direct evidence on the relationship between garnishment and labor supply.

I. Institutional Background and Data

A. *Institutional Background on Wage Garnishment*

When a borrower defaults on a loan, creditors can turn to property seizure, bank garnishment, or wage garnishment to collect the money owed. To obtain a wage garnishment, private creditors must file in state court. While procedures vary by state, borrowers must receive notice of the creditor's filing. A borrower's timely response can lead to time-consuming judicial proceedings, including, in rare cases, a trial. Most often, however, the borrower fails to respond within the required period (generally 20–50 days) and the creditor wins a default judgment. The creditor can then request that the court issue a garnishment order, which requires the defaulted borrower's employer to withhold a portion of the borrower's paycheck. This withholding—wage garnishment—begins around a week to two months after notice is sent to the borrower. Garnishment stops when the debt is paid off, the worker files for bankruptcy, or the worker and creditor renegotiate the debt. If the worker leaves her job during garnishment, the creditor must receive a new judicial order to commence collections through a new employer.

At the federal level, the Consumer Credit Protection Act (CCPA) of 1968 lays out a suite of borrower protections that limit the extent to which private creditors can garnish wages. The legislation shields a portion of each paycheck from garnishment and prohibits employers from firing workers for a single garnishment. States, meanwhile, remain free to adopt more stringent protections.

Under the CCPA, the weekly amount that a private creditor can garnish may not exceed the lesser of 25 percent of disposable earnings or the amount by which disposable earnings exceed 30 times the federal minimum wage. Currently, 23 states follow these federal limits, and 27 have enacted laws that lower the garnishment ceiling below the federal level. In four of these states

(North Carolina, Pennsylvania, South Carolina, and Texas), private creditor garnishments are banned entirely. In the remaining 23, garnishments are permitted but at lower levels. The typical state law achieves these higher borrower protections either by exempting a larger portion of earnings from garnishment (e.g., 35, 40, or 50 times the federal minimum wage) or by lowering the maximum garnishment rate on earnings above the exempt amount (e.g., 10 or 20 percent of disposable earnings).[3] In nine states, the exempt amount is further increased by setting it as a multiple of the state or local minimum wage rather than the federal minimum wage. Due to differences in state regulations and the definition of disposable earnings across states, we calculate garnishment rates using the fraction of *gross* earnings deducted.[4]

Garnishment laws for federal student loans differ from those for private debts in two ways. First, unlike private creditors, the federal government can bypass the judicial system and begin garnishment after sending direct notice to the borrower. Second, borrower protections for federal student loans are stronger and limit garnishments to at most 15 percent of disposable income in all states. However, student loan garnishment is not automatic and informal enforcement policies may vary from one administration to another. While standard state-level limits apply to private student loans, the vast majority of student debt is federal and therefore governed by these alternate protections.

B. *Data*

We use anonymized administrative payroll data from ADP, which processes payroll for approximately 20 percent of US private-sector workers each month. This dataset captures worker-level information needed to generate paychecks and W2s, including hours, earnings, retirement contributions, taxes, basic demographics, and a variety of garnishment variables. If a worker receives multiple paychecks per month in a given job, ADP aggregates all the variables to produce one observation per worker-job-month.

ADP classifies garnishments into one of five categories: tax, student loan, child support, bankruptcy, and other (creditor) garnishments. The child support category contains both voluntary payments, in which a parent agrees with the court to pay through his wages, and involuntary payments, in which the court extracts delinquent support. The "other" garnishment category primarily includes payments for delinquent private creditor debt or medical debt, though additional court-ordered payments (i.e., for fees or unpaid parking tickets) may also show up in this category. For every paycheck, ADP records the amount of money deducted to satisfy each type of garnishment and the number of active garnishment orders within each category.

[3] State-level restrictions on garnishment remained constant throughout our sample period in all but four states (California, Massachusetts, South Dakota, and West Virginia) and the District of Columbia, which either increased their exempt amounts or decreased their maximum garnishment rates at some point during the sample.

[4] For the purpose of determining garnishment amounts, "disposable earnings" is defined as all earnings left over after legally required deductions have been made. These required deductions may vary by state but will typically include deductions for federal, state, and local taxes, as well as the employee's share of Social Security, Medicare, and state unemployment insurance taxes.

We focus our analysis on the student loan and other creditor garnishment categories, which contain garnishments triggered by delinquency and default.[5]

For our primary analysis sample, we work with a 1 percent random sample of all workers aged 16–64 living outside the four states that explicitly prohibit creditor garnishment. Because garnishment information is only measured consistently beginning in April 2014, we further restrict our sample to months between April 2014 and December 2019 in all analyses. We can follow each worker within and across any ADP jobs held during this period. If a worker appears in multiple ADP jobs in a given month, we add hours, earnings, and garnishment amounts across jobs and keep the industry of the higher-earning job. In analyses that require us to measure a worker's hourly wage or number of hours worked, we will also sometimes restrict the sample to include only workers who are paid on an hourly basis (i.e., nonsalaried). We will refer to these two samples as the "full sample" and "hourly worker" sample, respectively.

Table 1 provides descriptive statistics for both ADP analysis samples as well as a representative sample of all US workers from the Current Population Survey (CPS). The CPS sample includes data from all monthly Outgoing Rotation Group files between 2014 and 2019 and is similarly restricted to include only workers aged 16–64 living outside the four states that prohibit creditor garnishment. The statistics in column 1 reveal that the ADP data have broad coverage across worker demographics, industry, and geographic region. However, as noted by Grigsby, Hurst, and Yildirmaz (2021), selection into the ADP data occurs at the firm level and is biased toward larger firms. This fact is reflected in the differences between columns 1 and 3, which show that workers in the ADP data are generally higher income, more concentrated in the Northeast, and overrepresented in the manufacturing, professional services, and finance industries relative to education and health services. As expected, those in the hourly worker sample are generally lower-income and younger than both the average US worker and the average worker in the full ADP sample.

II. Results

This section establishes five new facts about wage garnishment in the United States. While these facts are inherently descriptive and are not intended to bear a causal interpretation, we view them as important in their own right and as providing a useful view into an otherwise opaque means of debt collection.

A. *Fact 1: Garnishment Is Widespread*

Pooling across our entire sample, we find that approximately 0.88 percent of US workers were being garnished for some type of delinquent debt in any given month between April 2014 and December 2019. This prevalence statistic, reported in the bottom panel of column 1 in Table 1, depends both on the proportion of workers

[5] Because our data for child support and tax garnishments combine voluntary and involuntary payments, we do not focus on these categories. Bankruptcy garnishments are excluded since our field in the data includes payment plans agreed upon during Chapter 13 bankruptcy and thus are not involuntary payments to creditors.

TABLE 1—SUMMARY STATISTICS

	ADP full sample	ADP hourly workers	CPS
Monthly gross income ($)			
Raw average	5,727.62	3,179.85	—
With CPS top-coding	4,499.06	3,063.34	4,086.92
Worker demographics (%)			
Female	46.08	48.99	48.28
Age			
16–24	12.90	17.81	14.12
25–34	25.94	26.31	24.66
35–44	22.49	19.94	22.06
45–54	21.92	19.82	22.06
55–64	16.75	16.12	17.10
Industry (%)			
Natural resources and mining	0.81	0.86	1.48
Construction	1.60	1.70	5.74
Manufacturing	16.24	16.23	10.93
Trade, transportation, and utilities	18.45	19.82	18.94
Information	3.26	2.21	2.04
Finance, insurance, and real estate	8.14	6.77	6.66
Professional and business services	16.40	13.46	11.06
Education and health services	13.57	14.98	23.87
Leisure and hospitality	7.56	9.77	9.82
Other services	3.47	3.47	4.23
Public administration	1.11	1.09	5.24
Census region (%)			
Midwest	25.18	25.92	26.54
Northeast	22.60	20.94	16.64
South	24.63	25.37	28.68
West	27.90	28.07	28.13
Monthly garnishment prevalence (%)			
All debts	0.88	1.11	—
Private creditor	0.64	0.83	—
Student loan	0.25	0.30	—
Number of workers	470,812	376,447	
Number of worker-months	10,082,839	6,673,019	

Notes: This table reports summary statistics for our two analysis samples of workers from the ADP data and a benchmark comparison sample from the CPS. Column 1 reports statistics for the full analysis sample containing a 1 percent random sample of all workers present in the ADP data between April 2014 and December 2019 who are aged 16–64 and live outside the four states that prohibit creditor garnishment. Column 2 restricts to the subset of workers in column 1 who are paid hourly (versus salaried). The CPS sample includes data from all monthly Outgoing Rotation Group files between 2014 and 2019 and is similarly restricted to include only workers aged 16–64 who live outside the four states that prohibit creditor garnishment. Earnings in the CPS are measured weekly and top-coded at $2,884.61 per week. We convert weekly CPS earnings to monthly by multiplying by $(365/12)/7$. For comparison, the second row of the table also reports mean monthly earnings in the ADP data imposing the implied CPS top-code of $2,884.61 $\times$ $(365/12)/7$.

who start a new garnishment in a particular month (incidence) and on the proportion of workers who remain in a state of garnishment from the prior month (duration).

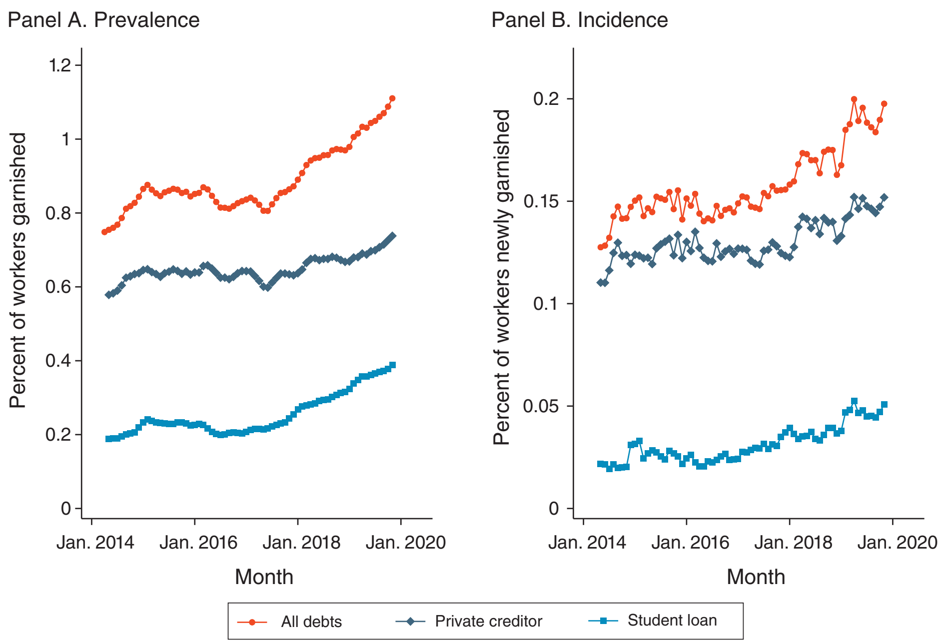

Figure 1. Trends in the Prevalence and Incidence of Wage Garnishment

Notes: This figure plots monthly trends in the prevalence (panel A) and incidence (panel B) of wage garnishment. Prevalence is measured as the percent of all workers in a given month who are being garnished that month. Incidence is measured as the percent of workers in a given month who begin a new garnishment that month. Each series is smoothed using a simple three-month moving average centered at the month of observation. The sample includes all worker-months from the main analysis sample described in column 1 of Table 1.

Because an individual garnishment order can span multiple months, we should expect lower incidence than prevalence. Indeed, only 0.16 percent of workers in an average month transition into a new garnishment spell.

Figure 1 plots the evolution of these prevalence (panel A) and incidence (panel B) statistics over time using a three-month moving average separately by garnishment type. The overall prevalence of garnishment has risen substantially during the last several years. In 2014, roughly 0.8 percent of workers were being garnished; by the end of 2019, this figure had increased to just over 1.1 percent.

This increase in the overall garnishment rate is driven primarily by a rise in student loan garnishments during the second half of the sample. As panel A of Figure 1 shows, the prevalence of both student loan (light-blue series) and private creditor garnishments (dark-blue series) remained roughly constant between 2014 and 2017. Between 2017 and 2019, however, the fraction of workers being garnished for delinquent student loans roughly doubled, while the prevalence of creditor garnishment increased by about 15 percent. By the end of 2019, approximately 0.7 percent of all workers were being garnished for at least one nonstudent debt, and 0.4 percent of workers were being garnished for at least one student loan. Because the formal laws governing student debt garnishment didn't change over our sample period, the differential rise in student loan garnishment likely reflects a combination of rising overall student debt levels and potential informal changes to Department of Education enforcement practices.

Panel B of Figure 1 plots the noisier time series for incidence. Paralleling the results from panel A, the figure reveals an increase in overall incidence from an average of 0.14 percent in the years 2014–2015 to 0.18 percent in the years 2018–2019, with a substantially larger percentage rise in the incidence of student loan garnishments.

Contrasting the results in panel B with those in panel A also reveals that there is a larger relative gap in incidence between private creditor and student loan garnishments than there is in prevalence. On average, over the full sample, a worker is roughly 4.2 times more likely to begin a new private creditor garnishment spell in a given month as she is to begin a new student loan garnishment spell. However, that same average worker is only about 2.5 times as likely to be currently experiencing private creditor garnishment than she is to be experiencing a student loan garnishment. The larger relative gap in incidence could be driven, in part, by longer student loan garnishment spells—a statistic explored in the next section.

These trends reveal the broad impact of garnishment in the United States: by 2019, more than 1 in 100 US workers experienced a creditor wage garnishment in any given month. To better understand the gap between prevalence and incidence, the next section examines garnishment duration.

B. *Fact 2: Garnishment Is Short Lived*

Garnishment orders remain active until the worker pays off the debt, separates from her job, renegotiates the terms of the debt, or, for nonstudent loans, discharges the debt in bankruptcy. Because we cannot observe separate garnishment orders, we measure garnishment duration using "spells." A spell begins when a worker who didn't experience a garnishment during their previous month of employment experiences a garnishment this month. The spell ends the first subsequent month of employment without a garnishment.

Panel A of Table 2 presents the distribution of spell length by garnishment type. Pooling across student loan and private creditor garnishments, the average garnishment spell lasts for approximately 5.4 months. Student loan garnishments tend to last longer than other creditor garnishments: the mean student loan spell length is 7.6 months, compared to a mean of 4.8 for other creditor garnishments. This difference in means reflects, in part, the long right tail of student loan garnishment duration. The median length for student loan garnishment is 4 months, with a twenty-fifth percentile of 2 months and a seventy-fifth percentile of 10 months; the median length of other creditor garnishments is 3 months, with a twenty-fifth percentile of 1 month and a seventy-fifth percentile of 5 months.

Several forces could explain the relative brevity of spells. First, because garnishment ends when a worker separates from her employer, high job turnover rates or strategic attempts to avoid garnishment through separation could lead to shorter spells. Indeed, as Table 2 reports, roughly 23 percent of observed garnishment spells are right censored.[6] However, as we will show in Section IIE, job separation

[6] A spell is "censored" if it starts in the worker's first month of the sample ("left censored") or ends in the worker's last month in the sample ("right censored").

Table 2—Duration and Stringency of Garnishment by Garnishment Type

	Panel A. Garnishment spell duration (months)									
	All spells						Uncensored spells	Percent censored		
	p5	p25	p50	p75	p95	Mean	Mean	Any	Left	Right
All debts	1	2	3	6	19	5.4	4.4	30.0	8.6	23.0
Private creditor	1	1	3	5	16	4.8	4.1	26.3	8.1	19.4
Student loan	1	2	4	10	26	7.6	5.9	43.9	10.1	36.7
	Panel B. Garnishment stringency (%)									
	All states						Federal limit states		Nonfederal limit states	
	p5	p25	p50	p75	p95	Mean	Mean	p75	Mean	p75
All debts	1.6	6.3	10.5	13.9	21.4	10.8	11.8	17.9	9.7	12.2
Private creditor	1.3	5.3	10.0	16.5	21.8	10.8	12.2	19.4	9.4	12.5
Student loan	2.9	9.1	11.2	12.1	13.5	10.2	10.3	12.2	10.1	12.0

Notes: This table reports statistics on the distribution of garnishment spell lengths (panel A) and garnishment stringency (panel B) by garnishment type. In panel A, the level of observation is a garnishment spell, which is defined to include all consecutive months of garnishment, beginning when a worker who did not experience a garnishment during their previous month has a garnishment this month. The first six columns report the distribution of spell lengths for all garnishment spells observed in the data, including those that are censored because they either begin in the first month a worker appears in the data (left censoring) or end in the last month they appear (right censoring). Column 7 reports the mean spell length among the subset of spells that are neither left nor right censored. Columns 8–10 report the share of all spells that are censored by type of censoring (left, right, or either). In panel B, the level of observation is the worker-month and stringency is measured as the share of a worker's total gross pay deducted due to garnishment in that month. The first six columns report the distribution of stringency rates for all months belonging to any of the garnishment spells, censored or uncensored, observed in the data (i.e., the set of months comprising the spells analyzed in the same columns in panel A). Columns 7 and 8 restrict the sample to workers in states whose garnishment limits align with the federal limits. Columns 9 and 10 restrict the sample to workers in states whose garnishment ceiling is below the federal level.

is unlikely to be the sole source of shorter spells: nearly 50 percent of garnished workers remain in their jobs 20 months after garnishment begins, by which time all but 5 percent of garnishment spells have ended. Moreover, the average spell length would only rise from 5.4 to 7 months even if all censored spells lasted three times as long as the mean uncensored spell.[7] Second, workers may be ending garnishment by informally renegotiating with their creditors or by formally declaring bankruptcy. Finally, it's possible that many workers face garnishment for relatively small debts that are repayable in less than a year. These latter two possibilities are consistent with the relatively longer duration of student debt garnishment spells. Unlike private creditor debt, student debt cannot be discharged in bankruptcy. It is also subject to a lower statutory limit on garnishment amount, which mechanically increases the number of garnishment months needed to repay a constant amount of delinquent debt.

[7] This figure is calculated using the numbers from the top row of Table 2 as follows: $0.7 \times 4.4 + 0.3 \times (4.4 \times 3) = 7$.

C. *Fact 3: Garnishment Is Stringent*

While garnishments may be relatively short lasting, they absorb a substantial portion of workers' paychecks. Panel B of Table 2 reports the distribution of garnishment stringency by garnishment type, where stringency is measured as the fraction of a garnished worker's monthly gross pay remitted to creditors in a given month. Mean stringency is roughly 10 percent for student loan garnishments and 11 percent for private creditor garnishments. While the means are similar, differences emerge in dispersion: the interquartile range for private creditor garnishments is 11.2 percentage points, compared to just 3 percentage points for student loan garnishments.

The larger dispersion in private creditor stringency likely arises from regulatory heterogeneity across states. Unlike federal student loan garnishments, subject to a constant 15 percent national limit, private creditor garnishments face restrictions beyond the federal protections in 23 states. Indeed, the last four columns of the table show that the seventy-fifth percentile of private creditor garnishment stringency in states following federal garnishment limits is 19.4 percent, compared to only 12.5 percent in states with additional statutory protections. In contrast, the seventy-fifth percentile of student loan garnishment stringency is nearly identical across these two groups of states.

Pooling across all garnishment types, the average garnished worker loses approximately 11 percent of her gross earnings to garnishment in a given month. As a point of comparison, this is roughly equal to the average share of household income spent on food in a given month (US Bureau of Labor Statistics 2020). Garnishment may therefore pose a large economic burden on those who experience it. While the ability for creditors to garnish wages at these rates likely facilitates expanded access to credit, this benefit comes at a cost of a potentially heavy garnishment burden conditional on delinquency.

D. *Fact 4: The Garnishment Burden Is Unequally Distributed*

The aggregate statistics presented so far mask considerable heterogeneity across workers. In this section, we first examine heterogeneity using worker-level covariates available in the raw ADP data: wage level, worker age, and industry. We then turn to zip code–level data to document how garnishment rates are distributed across race and education levels. Figure 2 presents these results.

The top two panels of Figure 2 plot the monthly prevalence of garnishment across the joint distribution of worker age and hourly wage levels. In both panels, the sample includes only worker-months from the hourly worker sample. Panel A plots raw prevalence rates, while panel B plots prevalence rates that net out geographic heterogeneity in garnishment levels using zip code fixed effects.

Both sets of estimates reveal a nonmonotone relationship between garnishment prevalence and worker age and wage levels. Within each wage level, workers aged 35–44 tend to experience the highest garnishment rates. Similarly, at any given age, garnishment rates are generally highest among workers earning between $11 and $20 per hour. These two facts combine to imply that more than 2 percent of 35–44-year-old workers earning between $11 and $20 per hour are garnished in any given month. This is more than 1.7 times the rate of garnishment experienced by

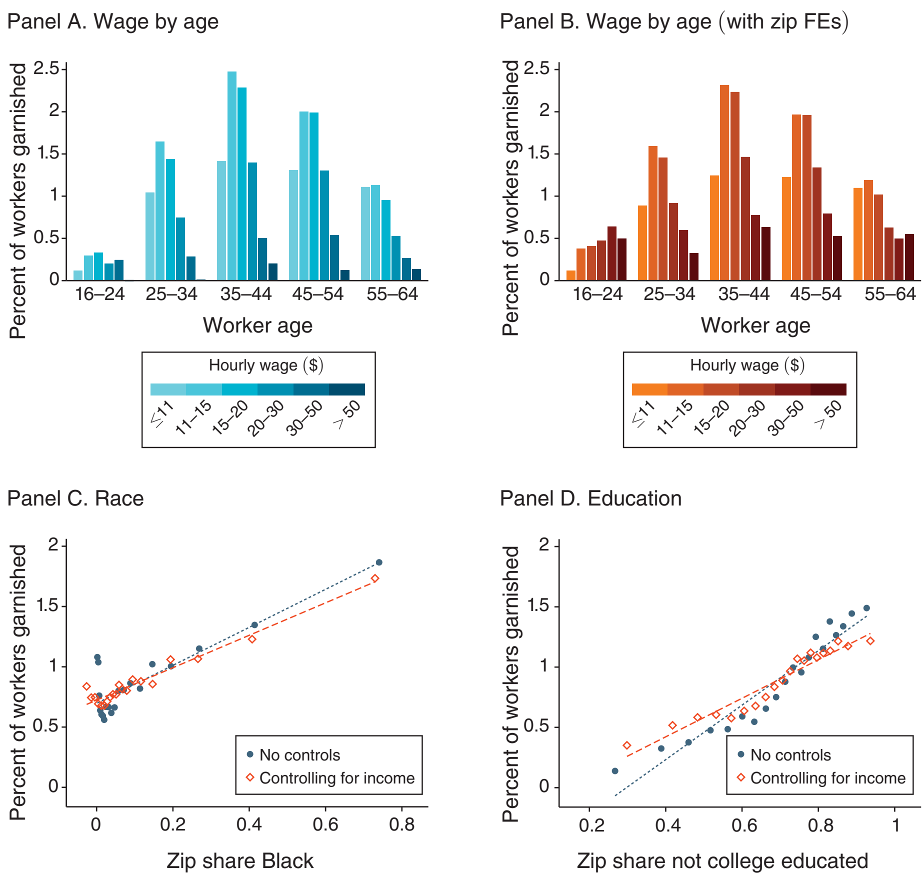

Figure 2. Garnishment Prevalence by Worker and Zip Code Characteristics

Notes: This figure documents heterogeneity in the prevalence of garnishment across various worker and zip code–level characteristics. Garnishment prevalence is measured as the percent of all workers in a given month who are being garnished that month. Panels A and B plot prevalence rates across the joint distribution of worker age and hourly wage levels. In both panels, the sample includes only worker-months from the hourly worker sample described in column 2 of Table 1. Panel A plots raw prevalence rates within each indicated bin of worker age and hourly wage level. Panel B plots prevalence rates that adjust for worker zip code. To adjust for zip code, we regress an indicator for whether a worker is being garnished in a given month on a series of zip code and age-by-wage bin fixed effects. The adjusted prevalence rates are the coefficient estimates on the age-by-wage bin dummies (multiplied by 100 to convert to percentage points). To aid comparison across panels, we add back the raw prevalence rate in the omitted bin (age 16–14, wage $\leq$ \$11) to each estimate. Panels C and D present binscatter plots measuring prevalence rates across the distribution of zip code minority and college-educated share. In both panels, the sample includes all worker-months from the main analysis sample described in column 1 of Table 1. Each dot in these figures plots the prevalence rate within an equal-sized bin of the sorting variable measured on the *x*-axis. Dashed lines report the OLS fit between the two variables in the underlying microdata. Blue dots report raw averages, whereas orange diamonds first residualize both the *x* and *y* variables against a set of fixed effects for worker-level monthly gross income deciles and then report means of these residuals within each bin (after adding back the sample mean of each variable to its residuals). Zip code characteristics are taken from the 2010 census (US Census Bureau 2010).

workers at any wage level who are between 16 and 24 years old or 55 and 64 years old, and over 1.4 times the rate experienced by workers of any age earning less than \$11 or more than \$50 per hour.

Consistent with these results, we also find that the industries with higher fractions of middle-income work—manufacturing, trade/transportation/utilities, and education/health services—have the highest levels of garnishment prevalence (1.07, 1.03, and 0.98 percent, respectively). In contrast, business services, a high-income industry, has a low garnishment rate of 0.71 percent, and other services (excluding leisure/hospitality, education/health, and business), a relatively low-income industry, has a rate of only 0.64 percent.

Our zip code–level demographic data allow us to further examine garnishment burdens by race and education. The bottom two panels of Figure 2 present these relationships using binscatter plots, which first divide the observations into equal-sized bins along the x-axis and then compute the garnishment rate within each bin. In panel C, we sort worker-months into bins based on the share of Black residents living in the worker's zip code. In panel D, we sort according to the share of residents in the zip code who do not have a college degree. Each dot in the figure represents the mean garnishment rate within a bin. The dashed lines report the OLS fit between the two variables in the underlying microdata. We plot both the raw relationship (blue circles) and a version of that relationship that controls for worker-level income (orange diamonds).

Panel C shows that garnishment rates are significantly higher among workers who live in neighborhoods with a high share of Black residents. The monthly prevalence of garnishment is approximately 0.7 percent in zip codes with the lowest shares of Black residents and more than doubles to 1.8 percent in zip codes that are more than 75 percent Black. This gap narrows only slightly when we control for workers' individual-level income.

Panel D repeats this analysis using the fraction of zip code residents without a college degree as the sorting variable. Garnishment rises sharply as the education level in a worker's zip code falls. In zip codes where more than 70 percent of residents have a college degree, the garnishment rate is roughly 0.14 percent. This rate rises to 1.5 percent for the least-educated zip codes, where less than 10 percent of residents are college educated. As with race, this relationship is attenuated slightly but remains strong and positive when we control for individual worker–level income.

While these descriptive facts indicate that the burden of garnishment is highly unequally distributed across workers, they cannot speak directly to the underlying causes of that dispersion. However, the results for race and education, which condition on worker-level income, indicate that the dispersion we find may not be fully explained simply by differences across workers in the ability to service debt. These results also parallel findings from the literature on personal bankruptcy, which has found that the bankruptcy filing rate is nearly twice as high in fully White or college-educated zip codes relative to those that are fully Black or noncollege educated (Lefgren and McIntyre 2009).

E. *Fact 5: Garnishment Is Associated with an Increase in Job Turnover but No Change in Hours Worked*

The beginning of a new wage garnishment generates a reduction in the worker's effective wage rate. This reduction in wage rate could affect labor supply through either standard income and substitution effects or behavioral factors such as discouragement. However, two features of garnishment distinguish it from a standard income tax. First, garnished wages directly reduce a worker's future debt burden.

Second, garnishment ends when a worker separates from her employer and only resumes again if the creditor pursues her at her next job. Relative to a standard income tax, the first effect should reduce garnishment's effective distortion of labor supply choices, while the second effect should increase it by incentivizing job turnover.

This section presents a descriptive examination of the dynamics of labor supply around the onset of a worker's first garnishment. We construct a matched sample that pairs each garnished worker from our main analysis sample to a randomly selected never-garnished worker who had the same job tenure as the garnished worker in the month that their first garnishment began (the "reference month"). In addition to job tenure, we also require the matched worker to belong to the same decile of the overall distributions of monthly gross income and age and to be of the same gender and pay type (hourly versus salaried) in the reference month. We then plot the evolution of job turnover rates and hours worked for both groups of workers around the reference month.

Panel A of Figure 3 presents the results for job turnover. Each solid line reports the share of workers of a given type remaining in their job as of a given month relative to when the garnished worker's first garnishment spell begins. The left axis measures these survival probabilities, which we construct using the Kaplan-Meier estimator. The dashed line, measured on the right axis, reports the cumulative difference in survival probabilities between nongarnished and garnished workers. The results indicate that garnished workers separate from their jobs at slightly higher rates than nongarnished workers following garnishment and that the majority of this difference materializes during the first year after garnishment begins. Twelve months after garnishment onset, roughly 61 percent of garnished workers remain in their jobs, compared to 65 percent of matched nongarnished workers. This gap grows to a maximal difference of about 5 percentage points four years after garnishment and then converges back to 4 percentage points by year five.

Panel B of Figure 3 turns to the intensive margin by showing how workers' hours trajectories evolve around the onset of garnishment. Each line plots median hours worked per month conditional on remaining in the job. In this panel, the sample is limited to the subset of garnished workers who are paid hourly and their matched never-garnished workers. The figure reveals that the onset of garnishment is not associated with any meaningful changes in hours worked. The median number of hours is roughly constant at about 166 per month and does not exhibit any sharp changes around the time that garnishment begins.[8] In unreported results, this same pattern obtains if we restrict the sample to workers who were continuously in their jobs for the entire 12-month period leading up to and following garnishment.

The descriptive evidence in this section is consistent with a small causal effect of garnishment on worker separations and no effect on hours worked. However, the separation result should be interpreted with caution. Our matched sample necessarily conditions on garnished and matched workers surviving in the job up until the

[8] Notably, we do not observe any drop in either gross income or hours worked leading up to garnishment. This suggests that garnishments are not triggered by loss of income. However, workers may be driven into financial duress by expense shocks, which cannot be observed in our data. This story would be consistent with the findings of Low (2023) and Ganong and Noel (2023), who show that most mortgage defaults are triggered by expense rather than income shocks.

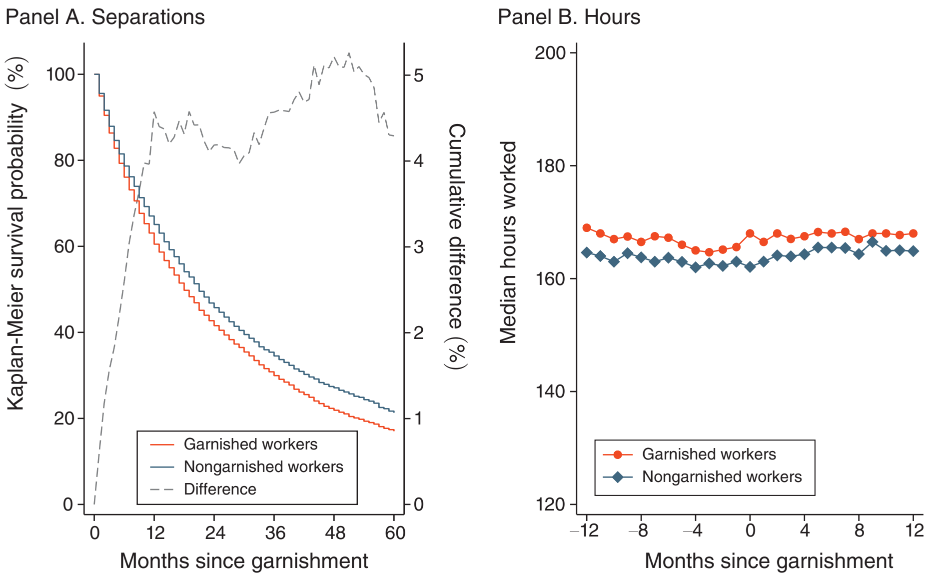

Figure 3. Labor Supply Responses to Garnishment Onset

Notes: This figure shows how job turnover and hours worked change around the onset of a worker's first garnishment. These outcomes are shown both for garnished workers and for a matched sample of never-garnished workers. To construct the matched sample, each garnished worker is randomly matched (with replacement) to a never-garnished worker who had the same job tenure as the garnished worker in the month that their garnishment began and who was of the same gender, had the same pay type (hourly versus salaried), and fell into the same decile of the overall distributions of monthly gross income and worker age in that month. Panel A plots Kaplan-Meier job survival curves. The sample in this panel includes all garnished workers from the main analysis sample described in column 1 of Table 1 and their randomly matched never-garnished workers. Each solid line reports the share of workers of a given type remaining in their job as of a given month relative to when the garnished worker's first garnishment spell began (left axis). The dashed line reports the cumulative difference in survival probabilities between nongarnished and garnished workers (right axis). Panel B plots median hours worked per month (conditional on working) relative to the month in which garnishment begins. The sample in this panel includes all garnished workers from the hourly worker sample described in column 2 of Table 1 and their randomly matched never-garnished workers.

same month of tenure. If garnished workers differ from nongarnished workers in ways that are correlated with baseline turnover rates but not captured by the other matching variables, then differences in separations after garnishment could still emerge even in the absence of any direct causal effect of garnishment itself.

III. Concluding Remarks

Consumer financial distress is a common phenomenon in the United States; in credit report data, roughly one-third of individuals have at least one delinquent debt in collections (Keys, Mahoney, and Yang 2020). While filing for consumer bankruptcy can provide relief from financial distress, many consumers who would benefit from bankruptcy are either slow to file or never seek protection (White 1998; Gross, Notowidigdo, and Wang 2014). Absent this protection, such consumers may be subject to potentially substantial creditor wage garnishments. However, little is known about the prevalence or nature of these garnishments.

This paper uses large-scale administrative payroll data to provide new facts about wage garnishment. We document that in any given month, nearly 1 percent of workers in the United States are having their wages garnished to satisfy delinquent debts. This share has been rising in recent years, particularly for student loan garnishments, and is almost twice as high among middle-income workers living in predominantly Black or less-educated neighborhoods. Garnishment is also stringent: the average garnished worker in our sample remits over 10 percent of monthly gross income to her creditor(s) each month. Finally, we find that the onset of garnishment is associated with an increase in job separations but no intensive margin change in hours worked.

Our findings are consistent with prior work demonstrating substantial benefits from bankruptcy filing and shed new light on one of the key mechanisms through which these benefits may arise. Filing for bankruptcy places an immediate hold on wage garnishments, leading to an increase in both disposable income and effective marginal wage rates. This may explain part of why bankruptcy protection has been shown to causally increase both labor earnings and broad-based measures of consumer financial health (Dobbie and Song 2015; Dobbie, Goldsmith-Pinkham, and Yang 2017). However, in contrast to the literature on bankruptcy, research on the direct causal effects of garnishment on worker outcomes is essentially nonexistent. Our hope is that the facts we provide in this paper provide a useful starting point and motivation for future analyses exploring these effects.

REFERENCES

ADP. 2017. "The US Wage Garnishment Landscape: Through the Lens of the Employer." Roseland, NJ: ADP Research Institute.

Argyle, Bronson, Benjamin Iverson, Taylor D. Nadauld, and Christopher Palmer. 2021. "Personal Bankruptcy and the Accumulation of Shadow Debt." NBER Working Paper 28901.

Auclert, Adrien, Will S. Dobbie, and Paul Goldsmith-Pinkham. 2019. "Macroeconomic Effects of Debt Relief: Consumer Bankruptcy Protections in the Great Recession." NBER Working Paper 25685.

Cheng, Ing-Haw, Felipe Severino, and Richard R. Townsend. 2021. "How Do Consumers Fare When Dealing with Debt Collectors? Evidence from Out-of-Court Settlements." *Review of Financial Studies* 34 (4): 1617–60.

Dawsey, Amanda E., Richard M. Hynes, and Lawrence M. Ausubel. 2013. "Non-Judicial Debt Collection and the Consumer's Choice among Repayment, Bankruptcy and Informal Bankruptcy." *American Bankruptcy Law Journal* 87 (1): 1–26.

DeFusco, Anthony A., Brandon Enriquez, and Maggie Yellen. 2024. "Replication data for: Wage Garnishment in the United States: New Facts from Administrative Payroll Records." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/E186941V1.

Dobbie, Will, Paul Goldsmith-Pinkham, and Crystal S. Yang. 2017. "Consumer Bankruptcy and Financial Health." *Review of Economics and Statistics* 99 (5): 853–69.

Dobbie, Will, and Jae Song. 2015. "Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection." *American Economic Review* 105 (3): 1272–311.

Drozd, Lukasz A., and Ricardo Serrano-Padial. 2017. "Modeling the Revolving Revolution: The Debt Collection Channel." *American Economic Review* 107 (3): 897–930.

Fedaseyeu, Viktar. 2020. "Debt Collection Agencies and the Supply of Consumer Credit." *Journal of Financial Economics* 138 (1): 193–221.

Fedaseyeu, Viktar, and Robert Hunt. 2018. "The Economics of Debt Collection: Enforcement of Consumer Credit Contracts." Federal Reserve Bank of Philadelphia Working Paper 18-04.

Federal Reserve Bank of New York. 2021. *Quarterly Report on Household Debt and Credit 2021: Q1*. New York: Federal Reserve Bank of New York.

Fonseca, Julia, Katherine Strair, and Basit Zafar. 2017. "Access to Credit and Financial Health: Evaluating the Impact of Debt Collection." Unpublished.

Ganong, Peter, and Pascal Noel. 2023. "Why Do Borrowers Default on Mortgages?" *Quarterly Journal of Economics* 138 (2): 1001–65.

Grigsby, John, Erik Hurst, and Ahu Yildirmaz. 2021. "Aggregate Nominal Wage Adjustments: New Evidence from Administrative Payroll Data." *American Economic Review* 111 (2): 428–71.

Gross, Tal, Raymond Kluender, Feng Liu, Matthew J. Notowidigdo, and Jialan Wang. 2021. "The Economic Consequences of Bankruptcy Reform." *American Economic Review* 111 (7): 2309–41.

Gross, Tal, Matthew J. Notowidigdo, and Jialan Wang. 2014. "Liquidity Constraints and Consumer Bankruptcy: Evidence from Tax Rebates." *Review of Economics and Statistics* 96 (3): 431–43.

Indarte, Sasha. 2023. "Moral Hazard versus Liquidity in Household Bankruptcy." *Journal of Finance* 78 (5): 2421–64.

Keys, Benjamin J., Neale Mahoney, and Hanbin Yang. 2020. "What Determines Consumer Financial Distress? Place- and Person-Based Factors." NBER Working Paper 26808.

Lefgren, Lars, and Frank McIntyre. 2009. "Explaining the Puzzle of Cross-State Differences in Bankruptcy Rates." *Journal of Law and Economics* 52 (2): 367–93.

Low, David. 2023. "What Triggers Mortgage Default? New Evidence from Linked Administrative and Survey Data." *Review of Economics and Statistics*. https://doi.org/10.1162/rest_a_01371.

Romero, Charles, and Ryan Sandler. 2021. "The Effect of Debt Collection Laws on Access to Credit." *Journal of Public Economics* 195: 104320.

US Bureau of Labor Statistics. 2020. *Consumer Expenditures Report 2019*. Washington, DC: US Bureau of Labor Statistics.

US Census Bureau. 2010. "Census Tabulation Files, 2010." Social Explorer. https://www.socialexplorer.com/tables/C2010/R10565015 (accessed November 5, 2020).

US Federal Courts. 2020. "Caseload Statistics Data Tables F-2 (One Month)." https://www.uscourts.gov/statistics-reports/caseload-statistics-data-tables?tn=F-2+%28One+Month%29&pn=All&t=All&m%5Bvalue%5D%5Bmonth%5D=&y%5Bvalue%5D%5Byear%5D= (accessed December 6, 2022).

Waldman, Annie, and Paul Kiel. 2015. "Racial Disparity in Debt Collection Lawsuits: A Study of Three Metro Areas." Unpublished.

White, Michelle J. 1998. "Why Don't More Households File for Bankruptcy?" *Journal of Law, Economics, and Organization* 14 (2): 205–31.

Yildirmaz, Ahu, and Mita Goldar. 2014. "Garnishment: The Untold Story." Roseland, NJ: ADP Research Institute.