The Canary in the Coal Decline: Appalachian Household Finance and the Transition from Fossil Fuels*

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Abstract

Decarbonization presents transition risks for communities historically built around the fossil fuel industry. In this paper, we study how individuals in active coal-mining communities in Appalachia were affected by the decline in the coal industry between 2011 and 2018. We use individual-level credit data and exogenous variation in coal demand caused by the shift towards natural gas generation to identify how the credit outcomes of Appalachian residents were affected by the coal industry's decline. We find that the decline in coal demand negatively impacted household finances, decreasing Equifax Risk Scores and increasing credit utilization, amounts in third party collections, and bankruptcy rates. Although the worsening of credit was broad-based, we find differences in how the deterioration manifested across credit, age, and income groups. Capturing some of the costs of the current decarbonization in Appalachia, our results provide insights on what future decarbonization might look like in regions whose economic activity is concentrated around fossil fuel extraction and processing.

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Essential to mitigating climate change, decarbonization poses risks to fossil fuel firms, financial stability, and communities dependent on the fossil fuel industry (Carney (2015) and Morris, Kaufman, and Doshi (2019)). Macroeconomic studies have found that low-income households may disproportionately bear the costs of carbon pricing (Goulder, Hafstead, Kim, & Long, 2019; Williams III, Gordon, Burtraw, Carbone, & Morgenstern, 2015; Salee, 2019). Although fossil fuel extraction and processing industries are known to have negative impacts on health and environment, these industries have also traditionally provided well-paying jobs, important local tax revenue, and demand for local services. Communities dependent on the fossil fuel industry are particularly exposed to the costs of decarbonization and may understandably be resistant to policies aimed at mitigating carbon emissions. These communities include those mining coal in Appalachia and Wyoming, extracting oil in North Dakota and West Texas, refining oil along the Gulf Coast, and extracting natural gas in western Pennsylvania. Within these regions, individuals may have few comparable alternative sources for employment. Similarly, local governments and businesses may have few alternative sources of revenue to make up for the decline of the local fossil fuel industry. Decarbonization presents a unique set of transition risks for these communities that were historically built around the fossil fuel industry.

In this paper, we study how individuals were affected by the decline in the coal industry between 2011 and 2018, when low natural gas prices caused electricity generation to shift from coal to natural gas. We focus on Appalachia, an area that experienced significant declines in coal production during this period and is particularly vulnerable to a transition away from coal due to its persistently high rates of poverty and a long history of economic reliance on coal mining. Analyzing an existing decarbonization event provides insight on what future decarbonization might look like in regions whose economic activities are concentrated around fossil fuel extraction and processing.

We analyze data from the New York Fed/Equifax Consumer Credit Panel (CCP) to shed light on how a transition away from fossil fuels affects household finances in communities dependent on the fossil fuel extraction industry. We estimate how an exogenous measure of coal demand, coal consumed at power

plants within 200 miles (by rail) of active coal-mining counties within Appalachia, affects credit outcomes of individuals living in those counties. We find that declines in demand for coal negatively impacted household finances in Appalachian coal-mining counties, decreasing Equifax Risk Scores (a proprietary credit health summary measure designed to predict the likelihood of a consumer becoming 90 or more days delinquent within 24 months) and increasing credit utilization, amounts in third party collections, and bankruptcy rates. The effects are economically meaningful. A back-of-the-envelope estimate suggests that 2018 average Equifax Risk Scores (ERS) in our sample would have been about 2 points higher if not for the decline in coal demand, a relatively large effect given that the actual average ERS increased only about 3 points on net in our sample between 2011 and 2018.

Examining heterogeneous responses to declining demand for local coal based on individuals' baseline (pre-sample) Equifax Risk Scores, age cohorts, and the income profiles of the Census block groups where people live reveals variation in the nature of financial health declines. We find that individuals with relatively strong baseline credit tend to increase how much of their available credit they use. In contrast, individuals with relatively poor credit are more likely to enter bankruptcy. These results likely reflect differences in the options available to individuals responding to negative financial shocks, as individuals with low Equifax Risk Scores tend to have less access to credit and may have little recourse other than bankruptcy. We also find differences by age cohorts, where Millennials are less likely than Baby Boomers or members of Generation X to enter bankruptcy as a result of declining coal. However, Millennials appear to be driving the increases in amount in third party collections rather than older generations. Finally, we find that people living in Census block groups with relatively high poverty rates do not on average experience Equifax Risk Score decreases in response to declining coal demand.

Our paper makes three contributions. First, we provide important insights on the individual-level financial costs of decarbonization on areas dependent on the fossil-fuel industry. We use the recent coal decline in Appalachia to show that individuals living in regions with concentrated fossil fuel extraction may face similar negative financial consequences. This question is of key policy relevance because many

fossil-fuel extraction communities likely face similar market or policy-driven declines in the coming decades. The existing related literature has focused on macro level analyses of the distributional consequences of carbon pricing, providing useful country-wide or global perspective, rather than using individual-level data in a fossil fuel extraction region. (Nordhaus & Yang (1996); Goulder, Hafstead, Kim, & Long (2019); Williams III, Gordon, Burtraw, Carbone, & Morgenstern (2015); Salee (2019); Kanzig (2022).) Another strand of literature that has examined outcomes for individuals in fossil fuel extraction regions using micro data has found that households adjusted their borrowing and debt in response to these economic shocks. But this literature has focused on fossil fuel booms (sometimes along with the subsequent busts) rather than the decline we address here (Brown (2018), Cookson, Gilje, and Heimer (2020), and Jacobsen, Parker, and Winikoff (2021)). Welch and Murray (2020) use county-level data to show that impacts of booms and busts may not be symmetrical. Furthermore, we expand on this work by examining heterogeneous impacts in a low-income region to shed light on how decarbonization could exacerbate inequality with regard to household finances.

Second, our paper brings individual-level data and exogenous variation in coal demand to a literature that has examined impacts of booms and busts on county-level labor and local government outcomes in Appalachian coal mining communities. This literature finds that economic indicators like wages track with coal activity, while educational attainment and public assistance spending on disability insurance are countercyclical with coal. These papers suggest that coal demand reductions may have serious impacts on Appalachian coal communities (see Black, Daniel, & Sanders (2002); Betz, Partridge, Farren, & Lobao (2015); Deaton & Niman (2012); and Partridge, Betz, & Lobao (2013)). We bring to these findings an analysis with exogenous variation in coal demand and individual-level outcomes, which allow us to explore heterogeneous causal effects of the decline in coal.

Finally, our analysis of disproportionate outcomes for the most vulnerable populations within coal mining communities relates to recent literature in trade, labor, public, and environmental economics on inequality and the distributional consequences of economic and policy shocks. A recent series of

empirical papers shows that trade can generate economic winners and losers if the welfare gains from trade are not redistributed as workers are displaced (Costinot & Rodriguez-Clare, 2014; Samuelson, 1939; Wolla & Esenther, 2017). Workers displaced by trade can suffer persistent unemployment and lower earnings many years after losing their jobs (Hyman, 2018; Autor, Dorn, & Hanson, 2016). Recent public finance literature has explored the revenue-generating capacity of manufacturing and extraction industries (Fraenkel & Krumholtz, 2022; Welch & Murray, 2020; Morris, Kaufman, & Doshi, 2019). A decline in coal employment and production could generate differential declines in local government revenues for coal-producing areas both directly through coal-specific revenues and indirectly through reduced property tax revenues as home prices fall. Our paper examines one key channel through which Appalachian coal communities may lose economically when the electricity sector moves away from coal generation.

The rest of the paper is organized as follows: Section I provides background on Appalachia and the coal industry. Section II describes our data. Section III discusses our empirical design and identifications strategy. Section IV presents the results and Section V Concludes.

I. Background

Appalachia is particularly vulnerable to a transition away from coal. The region has persistently high rates of poverty and a long-running economic reliance on coal (Betz, Partridge, Farren, & Lobao, 2015; Bollinger, Ziliak, & Troske, 2011; Black, McKinnish, & Sanders, 2005). The share of the Appalachian population with a college degree has historically been lower than the rest of the United States, with the gap between the two widening in recent years (Appalachian Regional Commission, 2022). Even when compared with other rural areas in the US, incomes are lower and poverty rates are higher in rural Appalachia (Appalachian Regional Commission, 2022). Coal mining, which has paid more than similar jobs in other industries, has historically served as an economic base driving local employment and local government tax revenues (Itkin, 2006). A reduction in coal mining could negatively impact people living in coal-mining areas directly through lost coal jobs and coal tax revenues and indirectly through lost

service jobs and property tax revenues resulting from spillovers (Morris, Kaufman, & Doshi, 2019; Welch & Murray, 2020).

Although U.S. coal production did not start to decline until the early 2000s, coal employment has been waning for about a century. This long-term decline in employment has been driven largely by supply-side factors, as technological developments allowed coal mining firms to maintain high production with fewer coal workers (Eller, 2008). Air quality regulation in the 1990s induced a shift to low-sulfur coal from the Powder River Basin in Montana and Wyoming, which is more capital intensive than the generally higher-sulfur coal found in Appalachia, thereby further reducing total and Appalachian coal mining employment (Carlson, Burtraw, Cropper, & Palmer, 2000).

Since 2011, the declines in coal production and employment have been driven by a reduction in demand from the electricity generation sector. Technological developments in fracking have lowered costs of natural gas to such an extent as to make it cost-competitive with coal, thereby reducing demand for coal (Bowen, Christiadi, Deskins, & Lego, 2020; Linn & McCormack, 2019; Coglianese, Gerarden, & Stock, 2020)(Bowen, Christiadi, Deskins, & Lego, 2020)).[2] Between 2011 and 2018, Appalachian coal production and employment decreased 40 and 49 percent, respectively.

Despite the recent declines, coal remains an important economic and cultural force in Appalachia (Lewin, 2019). Efforts to address climate change which involve further reducing coal consumption may therefore have important implications for the region. Reducing coal production in Appalachia will bring costs and benefits to the area, including lost coal mining wages, lower severance tax revenues, reduced environmental degradations from strip mining, and improved health conditions.[3] In this paper, we examine a cost of coal mining reduction: the negative impact on household finances.

[2] A carbon price would similarly increase the price of coal generation relative to natural gas generation. It is possible that expectations of future carbon prices or regulations increased the speed of the coal-to-gas transition.
[3] Strip mining removes vegetation that can lead to flooding for years after the coal has been extracted. The climate transition can provide localized benefits to strip mining reduction. First, a direct effect of reducing strip mining

II. **Data**

We combine data on coal production, coal consumption at electric power plants, credit outcomes, and local demographics to study how changing coal demand has impacted individuals living in coal mining communities, along with some heterogeneities. We describe each of these data sets below.

Coal data

We focus our analysis on counties that had coal mining activity at some point between 2011 and 2018. We define counties as "active coal-mining counties" if, during this time, they report at least one year with non-zero coal production and at least one year with 10,000 hours or more of total annual employee hours in mining (roughly equivalent to five full-time workers) according to the U.S. Department of Energy's Energy Information Administration (EIA) and U.S. Mine Safety and Health Administration (MSHA).[4] Geographically, we include counties inside the EIA-designated Appalachian mining basins. Finally, we drop Allegheny County, PA, which contains Pittsburgh, because it is much more urban than and not representative of the Appalachian region overall. Figure 1 shows that there was significant variation in county coal production levels in 2011, the beginning of our sample. Figure 2 shows how by 2018, large declines in coal production were scattered across the region, affecting at least one county in nearly every Appalachian state. The heaviest concentrations of coal mining have historically been in Central Appalachia, which includes parts of Kentucky, West Virginia, Virginia, and Tennessee. Recent employment declines have affected Central Appalachia more than other areas in the region (Bowen, Christiadi, Deskins, & Lego, 2020). Our identifying variation, described in Section III below, affects Northern Appalachia the most (which includes parts of West Virginia, Ohio, Pennsylvania, and New York).

reduces new vegetation removal. Second, a legacy effect. Climate change increases the likelihood of extreme weather such as flooding, which is exacerbated by pre-existing strip mining areas. Reducing the likelihood of extreme weather reduces the impact of the negative effects of already strip mined areas.

[4] We include some county-year observations with zero coal production and/or zero coal mine employment.

We combine data from the publicly available EIA Form 923, which tracks the coal consumed at power plants in the US with data on the US rail network to generate an exogenous measure of coal demand. We describe this measure in detail in Section III.

Household finance data

We use the NY Fed / Equifax Consumer Credit Panel (CCP) to analyze the impact of coal declines on individual-level household finance. This dataset is a nationally representative 5 percent anonymized random sample of adults with Social Security numbers and a credit history.[5] It is an individual-level panel, which includes a large set of variables generally included in credit history reports that are used by lenders to determine whether and at what interest rate to lend to potential borrowers. The reports are also sometimes used in background checks by employers and landlords. With quarterly observations, the CCP includes data on where an individual lives (at the Census block level), their age, credit score (measured by the Equifax Risk Score), and outcomes like bankruptcies and outstanding debts.

To focus our sample on individuals likely to have experienced significant exposure to local economic conditions in active coal-mining counties, we include individuals of prime working age (25 to 64 years old), who are living in active Appalachian coal mining counties.[6] Our sample includes over one million individual-year observations. We examine the Equifax Risk Score, a summary of overall credit health,

[5] People typically start a credit history when they get their first credit card or student loan, which is generally at the age of 18 or older. The CCP sample includes people who have no active credit accounts for two main reasons: (i) people who have no credit accounts but have third party collections or public record item such as a bankruptcy and (ii) people who have closed accounts or accounts whether they are an authorized user but not the primary account holder. The sample excludes people who have "inquiry-only" files, meaning those who applied for a credit account but were either denied or they withdrew the application (Lee & van der Klaauw, 2010).

[6] Specifically, we drop individuals who are in the NY Fed/Equifax CCP data or in active coal-mining counties for fewer than 4 years. We drop observations when individuals are younger than 25 (as credit outcomes tend to be noisy when young adults are initially starting their credit histories) or older than 64 (an age at which people are more likely to retire and be less affected by the coal mining sector). Though the credit bureaus remove people who are known to have passed away, they do not have a systematic way of removing credit reports of people who have passed away (i.e. reporting from a government agency like the Social Security Administration). This issue affects the sample more for older age groups. We remove individuals who are known to have passed away.

and four variables that capture different phases of financial distress and different types of debt: delinquency, credit utilization, third party collections, and bankruptcy.

The Equifax Risk Score (ERS) is a proprietary summary measure designed to predict the likelihood of a consumer becoming 90 or more days delinquent within 24 months.[7] We use the average of the four quarterly ERS observations for each calendar year. Though this score shows considerable variation across people, it is not very sensitive to macroeconomic fluctuations. During the Great Recession, millions of people became behind on their mortgage payments, resulting in a sharp increase in mortgage delinquencies. However, average ERS and ERS by quartile moved little in response to the Great Recession (Federal Reserve Bank of New York, 2014). However, we observe substantial geographic variation in Equifax Risk Scores (see Appendix Figure A1), with higher scores in Northern Appalachia (PA, OH, and MD) and lower scores in Central and Southern Appalachia (KY, WV, TN, VA, and AL). Table 1 shows the ERS ranges from 313 to 840 with a mean of 677.

Credit utilization measures how much a person owes on all their credit cards as a percentage of their total credit limit across all their credit cards (including those issued by both banks and retailers). For example, a person with a $1,000 credit limit who owes their credit card companies $800 would have a credit utilization ratio of 80 percent. Individuals experiencing financial distress from negative shocks like income losses may charge more to their credit cards, pushing up their credit utilization ratios. While some may pay off their balances every month, others can owe more than their limit if they fall behind, accumulate interest, and find their balances growing larger than their original limit.[8] We use the maximum quarterly credit utilization ratio for an individual in each calendar year. The mean observed credit utilization ratio is 48 percent.

[7] The ERS is similar to the FICO scores generated by the 3 main credit agencies.

[8] Thus, credit utilization ratios can exceed 100%. However, we top code credit utilization at 300% as we assume larger numbers are mostly due to errors (either with unreasonably small credit limits or unreasonably large balances). We also drop observations with credit limits less than $100.

Delinquency, or missing a payment on a credit account, is an early indicator of financial distress. Credit accounts include mortgages, auto loans, credit cards, student loans, retail loans, and consumer finance loans.[9] Accounts such as medical bills, utility bills, and phone bills would not show up in this measure of delinquency, as these types of creditors do not regularly report to credit bureaus. We measure delinquencies as a flow variable: the percentage of people who have gone from having no accounts 60 days past due (DPD) to having at least one account 60 DPD or worse in a calendar year.

While credit utilization and 60 DPD outcomes are limited to individuals with traditional credit accounts, third party collections include (i) accounts not regularly reported to credit bureaus and (ii) individuals who do not have traditional credit accounts. People owe money to third party debt collectors when their original creditors sell the debt to a collection agency. Around two thirds of third party collections accounts are attributable to medical bills, utility bills, or telecommunications bills (Consumer Financial Protection Bureau, 2014).[10] Payments for these types of bills are not regularly reported to credit bureaus and would not show up in standard measures of delinquency (unlike credit card payments, for example). Instead, these debts typically reach the credit bureaus only once they are in the collections phase.[11] Therefore, individuals who do not have traditional credit accounts can appear in our sample if they have third party collections. This allows us to capture a population that has less access to traditional credit, which may be important for lower-income areas. We use the maximum amount of third-party collections reported for an individual within each calendar year. The average person in our sample has around $450 per year in third party collections (about 1 percent of average household income), though some people owe hundreds of thousands of dollars.

[9] Retail loans include direct loans from department stores, home furnishing stores, clothing stores, and other retail outlets. Consumer finance loans include loans through sales finance companies and personal loans (for example, people may use personal loans to consolidate high interest rate debt, pay for a large purchase, or cover a major expense).

[10] Reporting rules have changed over time. For example, many medical debts were removed from credit reports in 2017.

[11] No standards exist as to when a debt must be reported as in collections. Therefore, only a limited relationship exists between whether a bill is sent to third party collections and how long the bill is past due or how much a person owes (Consumer Financial Protection Bureau, 2014).

Finally, we analyze bankruptcy, an extreme measure of financial distress. Bankruptcy (either Chapter 7 or Chapter 13) is the final stage for a borrower who is in default and unable to pay their debts. Like entry into delinquency, we use an indicator for entry into bankruptcy in a given calendar year. Table 1 shows that entry into bankruptcy is much less common than delinquency. In a typical year, about 4 percent of the sample goes from current on all accounts to at least 60DPD or worse on at least one account (Trade 60DPD), while just 0.5 percent of the sample enters bankruptcy, the most severe measure of financial distress in our analysis.

Demographic data

To understand how individuals living in low- and high-income communities are affected differently by changes in coal demand, we supplement the coal and credit data with US Census Bureau demographic data at the Census block group level from the 2000 Decennial Census.[12] In particular, we use poverty rates (and per capita income) to understand how the socioeconomic status of a neighborhood affects credit outcomes for people living there.[13] The maps in Appendix Figure A2 show that the active coal mining counties in Kentucky, Virginia, and southwestern West Virginia appear to have relatively high poverty rates and low incomes.

III. Empirical design

In this section we describe the identification strategy we use to estimate the causal impacts of reductions in coal demand on Appalachian household finance outcomes. We identify the causal impact of coal mining demand shocks in Appalachia using the electricity generation sector's shift towards natural gas generation. This shift was driven by the natural gas cost declines that started around 2009 during the fracking boom (Linn & McCormack, 2019; Coglianese, Gerarden, & Stock, 2020). These external market

[12] We rely on the 2000 Decennial Census due to missing information about observation's 2010 Decennial Census Block group before 2014. We run robustness checks with a smaller sample using the 2010 Decennial Census and Figure A2 compares the variables of interest between the two decennial censuses.

[13] Recent research has shown that neighborhoods can have substantial, direct impacts on the economic circumstances of people living there (though more solid evidence exists for children than for adults). See Rothwell (2015) for a summary of the neighborhood effects debate from the late 1980s to the early 2010s.

forces shifted electricity generation away from coal generators and towards natural gas generators. We capture the coal-to-gas shift by computing the amount of coal burned at electricity generators within 200 miles of a coal mine measured via the rail network.

We use the coal burned at electricity generators within 200 miles of a coal county, which can be seen in Figure 3, to capture coal demand for three reasons. First, it is exogenous to household-level credit outcomes. Alternative measures like county-level coal production might be directly related to credit outcomes. For example, a coal mining company might choose to cut production in their mines where workers have the highest wages, which could be correlated with mine-worker credit outcomes. Second, coal burned within 200 miles captures a good portion of demand for Appalachian coal because transportation costs—which account for about 40 percent of delivered costs—limit the set of electricity generators a given Appalachian mine can economically sell its coal to. Nationally, over 90 percent of U.S. coal is used for electricity generation, and this is particularly true for the coal mined in Appalachia. Third, the size of the coal-to-gas switch was determined by heterogeneity in the amounts of existing natural gas generating capacity for different electricity grids. This leads to cross sectional variation in the coal-to-gas generation shift. Figure 4 shows that the decline in our measure of coal demand coincided with an increasing share in power sourced from natural gas nationally. Thus there is significant spatial variation in our demand measure and there was a broad decline in demand over the course of our sample. We estimate the effects of a decline in coal demand on individual credit outcomes using the following panel fixed effects equation:

$$Y_{ict} = \beta_1 + \beta_2 Coal200_{ct} + \delta_i t + \gamma_i + \eta_c + \mu_t + \varepsilon_{ict}, \quad (1)$$

where Y_{ict} is our outcome of interest for individual i, in county c and year t. Our exogenous measure of the amount of coal burned within 200 miles of county c, $Coal200_{ct}$ is a continuous treatment measure that varies from year to year and county to county. We include individual (γ_i), county (η_c), and year-of-sample (μ_t) fixed effects as well as an individual time trend ($\delta_i t$). We cluster our standard errors at the county level, the level of our treatment.

Our coefficient of interest β_2 estimates the change in individual credit outcomes caused by a change in demand for coal burned at powerplants within 200 miles of a county by rail. It estimates how an exogenous reduction in locally produced coal, caused in this case by changes in the power sector, affects individuals living in active coal mining counties.

Our identifying assumption is that, conditional on fixed effects, the outcomes for individuals living in counties with small changes in coal demand provide a good counterfactual for individuals living in counties with large changes in coal demand, had their demand changed similarly. One potential concern is that the time-varying nature of our treatment could introduce bias in a two-way fixed effects specification. Our main approach is to assume the causal response is homogeneous, which requires that the causal response to more dose (coal demand) is the same across groups conditional on having the same amount of dose and being in the same period. Although this assumption may be appropriate in this setting, it is difficult to prove. We are not aware of an estimator from the two-way fixed effects literature that addresses our situation. The closest is Goodman-Bacon, Callaway, & Sant'Anna (2021). However, their setup requires the specification of treatment dates for each cohort, which our setting does not naturally provide.

Empirical Support for Coal Demand Measure

Our exogenous variation, coal burned within 200 miles using the rail network, captures the demand for coal at the county level. We use this measure because it is determined by preexisting characteristics of the electricity grid unrelated to the credit outcomes of people in Appalachia. Before proceeding to our main results, we examine whether coal burned within 200 miles explains coal production and employment in coal counties. We estimate the following regression:

$$Y_{ct} = \beta_1 + \beta_2 Coal200_{ct} + \eta_c t + \nu_c + \mu_t + \varepsilon_{ct}, \quad (2)$$

where Y_{ct} is now a county-level outcome. In this specification, we include a county-specific time trend ($\eta_c t$) and μ_t is a year fixed effect.

The results in Table 2 show that coal burned at power plants within 200 miles of a county can explain some changes in coal production (column 1), hours worked at coal mines (column 2), and the average number of employees at a coal mine (column 3). Taken together, the results show that our exogenous measure of coal demand explains a portion of the variation in county-level coal production measures.

The strong relationship between coal demand and coal production invites the question as to why we do not instrument for county-level coal production with our coal demand measure. Unfortunately, our coal demand variable is a weak instrument when we reformulate equation (1) as an instrumental variables equation. To avoid a biased IV coefficient, we run our main analysis as a reduced form, which results in an unbiased estimate even when the potential instrument is weak (Chernozhukov & Hansen, 2008). The main disadvantage of using a reduced form approach is the results are interpreted in terms of changes in coal demanded within 200 miles of a county instead of county-level coal production. However, one advantage of our coal demand measure is that we capture the direct effects of the decline of coal demand at powerplants as well as the decline in coal mine production. For example, if a local coal powerplant shuts down and affects the local economy (via tax revenues or layoffs) we will capture that effect even if it does not change the coal mine production of a local county. That could happen if the coal powerplant was buying coal from a different mine on a long-term contract or used a different grade of coal.

IV. **Results**

A. Baseline Results

We generally find that as demand for local coal decreases, individuals living in active coal-mining counties face declines in their financial health. In Table 3, we present our baseline results from estimating equation (1). Column 1 shows that a one-ton decrease in coal burned within 200 miles of a county causes a .0748 point decrease in the Equifax Risk Score for residents. To put this number into context, panel A of Figure 5 shows the average Equifax Risk Score over our sample in blue and a counterfactual 2018 Equifax Risk Score as a red dot, where the latter is the product of our estimated response and the average decrease in coal burned within 200 miles. The figure shows that in the absence of the coal demand decline that occurred between 2011 and 2018, we estimate Equifax Risk Scores would have been about 2 points higher by 2018 (gap between blue line and red dot). This is a relatively large effect given that the actual average Equifax Risk Scores increased about 3 points on net over the same time period (blue line).

Columns 2, 4, and 5 of Table 3 show that declines in demand for local coal also increase credit utilization ratios, amounts in third party collections, and bankruptcy rates. Though the responses are statistically significant, the coefficients appear small. As with Equifax Risk Scores, Figure 5 provides context to our findings. Panel B shows that average credit utilization ratios would have fallen nearly twice as much as they did between 2011 and 2018 if not for the decrease in coal burned within 200 miles of active coal-mining counties. Similarly, in panel D our counterfactual shows the decline in amount in third party collections would have been about two-thirds larger than observed if not for the decline in coal demand. Finally, panel E shows that the decline in new bankruptcies would have been more than twice as large if not for the fall in coal demand.

We do not find evidence that coal declines increase individuals' likelihood of becoming behind on their credit accounts. Column 3 of Table 3 shows the results of estimating equation (1) where the dependent variable is the percent of individuals who have moved from no accounts 60 days past due to at

least one account 60 days past due in a year. The results are not significant, which suggests that annual decreases in coal demand are not causing people to become at least 60 days behind on their accounts.

In Table 3, we focus on changes in financial outcomes contemporaneous with changes in coal demand. However, as some outcomes may take longer to manifest, this specification could be missing important responses that appear with a lag. In Table 4, we present estimates of a distributed lag model version of equation (1). These results show that the decline in Equifax Risk Score and increases in amount in 3rd party collections are even more pronounced a year after a decline in demand for local coal than in the year of the decline itself. In contrast, increases in credit utilization and bankruptcy are primarily contemporaneous to changes in coal demand. While these estimates provide some additional nuance regarding the timing of responses, they are largely consistent with our baseline results shown in Table 3 and Figure 5.

Before turning to examining heterogeneities, we consider two robustness checks. First, we estimate the response of the Equifax Risk Score based on different time frames. In our preferred specifications, we focus on 2011-2018 because we are particularly interested in the time when coal demand was in decline and want to avoid potential confounding factors from the period of the Great Recession. However, the NY Fed / Equifax CCP data allow us to extend our analysis back to 2002. Appendix Table A2 shows estimates of the response of Equifax Risk Scores to demand for coal within 200 miles of active coal-mining counties for three alternative specifications, where column 4 is identical to Table 3, column 1. Because coal demand was rising in the first half of the longer samples, in columns 1 and 2, we use quadratic rather than linear time trends. The results in columns 1 and 2, which differ in terms of whether they include 2008-2010 for the Great Recession, show that the response of Equifax Risk Scores to coal demand shocks is even larger for the longer samples than our main specification, suggesting our estimates may be conservative. Column 3 shows that the relationship in the first part of the sample is not statistically significant, suggesting that the recent decline has been particularly meaningful for Appalachian households.

For our second robustness check, we exclude from our coal demand variable the coal burned within a 50-mile radius of each county, to ensure that we are not simply capturing other local economic phenomena that could be driving both demand for coal and household finance outcomes. These results (shown in Appendix Table A3) are consistent with our estimates in Table 3.

B. *Heterogeneity*

We now examine heterogeneity of outcomes based on a range of individual and local characteristics. Although Appalachia is known for its persistently high rates of poverty, some individuals and areas are worse off than others. We want to understand to what extent the negative financial impacts of declining demand for coal are disproportionately borne by those who were already the most vulnerable or those who were in relatively strong financial positions to begin with. Our approach is to interact $Coal200_{ct}$ in equation (1) with a full set of indicators for a given dimension of heterogeneity as follows:

$$Y_{ictl} = \beta_1 + \sum_{h \in H} \beta_2^h Coal200_{ct} \, \mathbb{I}\{l = h\} + \delta_i t + \gamma_i + \eta_c + \mu_{ht} + \varepsilon_{ict}. \quad (3)$$

Here l reflects which of H bins individual i is in and the term μ_{ht} is a set of year fixed effects for each bin h. These bin-year fixed effects control for broader trends within each group that may not be due to coal demand.

In our first heterogeneity analysis, we show that coal's impact on financial health depends on individuals' overall credit health before the economic shock. In this specification, H is a set of indicators for the quartiles that individual Equifax Risk Scores fall into between 2007 and 2010, *before* the main sample begins. Table 5, column 1 shows that the decline in Equifax Risk Scores caused by decreasing coal demand is broad-based, though the effect is largest for the second quartile and smallest in the top quartile. The relatively low coefficient for the top quartile could be explained by this set of individuals being more resilient against negative shocks (which could explain the relatively high Equifax Risk Scores) or less sensitive to events in the coal industry (if they tend to be older or wealthier.)

Although column 1 of Table 5 shows little heterogeneity in the overall Equifax Risk Score response to declining coal demand, the remaining columns suggests some differences across the quartiles in terms of the primary means through which individuals' financial situations are affected. Columns 2 and 5 together suggest that while individuals in the top two quartiles tend to increase their credit utilization, individuals in the bottom two quartiles are more likely to go bankrupt. These results are consistent with individuals exercising the options available to them in the face of negative financial shocks. Individuals with high baseline Equifax Risk Scores are likely to be able to borrow more on their credit cards up to a point (where they max out and cannot increase their limits further). Those with low baseline Equifax Risk Scores are less likely to have access to additional credit and more likely to already be in default, and thus are more likely to go bankrupt. Individuals in the first quartile on average already have a 90 percent credit utilization ratio, which does not give them much room to increase their utilization. In contrast, in our sample individuals in the 3rd and top quartile utilize 40 and 17 percent of their credit, respectively.

One potential concern is that because younger people tend to have less credit history and lower Equifax Risk Scores, the Table 5 results may reflect heterogeneous responses by age rather than baseline credit. In Table 6, we show that there are some significant generational differences in sensitivity of outcomes to declining coal demand.[14] We find that while Millennials' Equifax Risk Scores, credit utilization ratios, and bankruptcy rates do not respond to declining coal demand, the response of amount in 3rd party collections appears to be driven by Millennials. Taken together, these findings suggest both that the Table 5 results on heterogeneity by baseline Equifax Risk Score are not driven by age profiles—as Millennials do not see a significant response for bankruptcy, ERS, or credit utilization—and that there

[14] We use generational definitions from Pew Research Center (Dimock, 2019). Baby Boomers include individuals born between 1946-1964, individuals in Generation X include those born between 1965-1980, and Millennials are those born between 1981-1996.

are meaningful differences in how the household finances of the generations have been affected by the decline in coal.[15]

We next explore how income profiles of the places that individuals live in may interact with coal demand shocks in terms of affecting credit outcomes. Table 7 shows results from an analysis in which we interact the coal demand measure with the percent of individuals in the Census block group whose income was below the poverty line in 1999.[16] We split the sample into three bins by 1999 poverty share: poverty rates below 10 percent, between 10 and 20 percent, and above 20 percent. We find that although people living in lower poverty areas experience significant declines in Equifax Risk Scores, those living in Census block groups with poverty rates of at least 20 percent on average do not.

One potential explanation for this finding is that people living in high poverty areas may on average already have very low Equifax Risk Scores and may not be in a position to have their credit profiles deteriorate further. Consistent with this explanation, column 2 shows that credit utilization ratios increase significantly for individuals living in high poverty areas. However, in contrast to column 1, this sample is restricted to individuals who have credit limits of at least $100.[17] In column 4, we see that the increase in amount in third party collections is driven by individuals living in areas with the lowest poverty shares. With unpaid medical bills accounting for a large share of third party collections, this finding could reflect differences in access to means-tested aid programs like Medicaid (Consumer Financial Protection Bureau, 2022). We find similar effects for bankruptcy across Census block group poverty shares. Appendix Table A5, in which we group individuals based on the 1999 Census per capita income of the Census block group in which they live, shows qualitatively similar results.

[15] Appendix Table A4 shows that within generations, the responses of individuals in the top and bottom half of the baseline Equifax Risk Score distribution are qualitatively consistent with the results in Table 5. However, it is worth noting that the increase in the amount of third party collections is driven by Millennials with the lowest baseline Equifax Risk Scores.

[16] We use the 2000 Census because it predates our outcomes and because data limitations in the NY Fed / Equifax CCP prevent us from using 2010 Census block groups before 2014.

[17] Note that when we restrict the Equifax Risk Score analysis sample to this same set of individuals, we find that Equifax Risk Scores do decline significantly for individuals living in high poverty areas.

V. **Concluding remarks**

In this paper we show that the decline of coal has already hurt households in Appalachian coal mining communities. The costs of the coal decline are broad based. However, the specific ways in which the negative effects play out vary by individuals' baseline credit health, their stage of life, and their neighborhood income profiles. For example, younger people tend to end up with money in 3rd party collections while older people increase their credit utilization and are more likely to enter bankruptcy. This pattern of results suggests that credit is being used as a buffer against fossil fuel declines, but that younger individuals may not have access to sufficient credit to absorb some of the financial costs.

Although our findings focus on Appalachian coal mining communities, they provide insights for the potential looming transition risks facing other fossil fuel producing communities. If petroleum and natural gas extraction are phased out due to decarbonization policies or market forces, those extraction communities may experience similar reductions in economic conditions. The costs could be higher for those living in more rural and isolated regions that have fewer alternative employment opportunities. Our findings provide insights that credit availability could be used as a buffer against fossil fuel declines. Increased credit availability for younger individuals could help keep some people out of 3rd party collections, although it is likely not sufficient to fully protect the financial health of residents in declining fossil fuel extraction regions. Direct financial assistance is likely the best tool to help financial impacted residents, and our findings suggest the support should be broad-based.

It is important to note that in documenting a specific cost of the reduction of coal, we do not provide a full welfare analysis of a reduction in coal nationally or in local coal communities themselves. Public health and environmental studies have shown that there are also significant benefits from reductions in coal. Older age residents face disproportionate negative health impacts of surface mining, which would be reduced with declining coal (Mueller, 2022). A transition away from fossil fuels would have many

welfare benefits, including mitigating climate change globally, reducing air pollution, and direct positive health benefits for the mining communities themselves (Hernandez-Cortes & Meng, 2020; Boyles, et al., 2017). Historically marginalized communities are more likely to suffer the consequences of climate change, and thus may also benefit more from the transition away from fossil fuels (Hoffman, Shandas, & Pendleton, 2020; Intergovernmental Panel on Climate Change, 2014).

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Table 1: Summary Statistics Table

Variable	Mean	Std. Dev.	Min.	Max.	N
Coal demand and production					
Millions of short tons consumed w/in 200 miles (by rail)	29.85	19.40	0	82	1,445,430
Millions of short tons consumed b/w 50-200m (by rail)	26.40	18.42	0	79	1,442,437
Total annual coal production (mil. tons)	2.40	3.79	0	30	1,267,508
Total annual employee hours worked (Thous.)	987.70	1,348.53	0	7,478	1,267,508
FRB New York / Equifax CCP data					
Age	46.08	11.39	25	64	1,445,430
Equifax Risk Score	679.13	106.29	312	840	1,348,963
Trade 60 DPD	3.85	19.25	0	100	1,445,430
Amt 3rd party (2012 $)	444.91	2,404.88	0	496,996	1,389,499
Bankruptcy	0.47	6.81	0	100	1,444,741
Credit Utilization Ratio	0.48	0.42	0	3	1,007,653
Census block group characteristics					
Household income in 1999 (2012 $)	47,038.69	18,756.33	0	187,389	1,428,507
Per capita income in 1999 (2012 $)	23,733.67	8,924.54	0	114,139	1,428,507
Share of population below poverty line in 1999	0.14	0.11	0	1	1,428,480

Source: EIA; Census; NY Fed / Equifax CCP

Note: Description of the FRB New York / Equifax CCP data variables:

- "Equifax Risk Score" is the average value in the calendar year.
- "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used.
- "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60 days past due (DPD) or worse during the calendar year.
- "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $).
- "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year.

Table 2: First-stage coal production and coal tons demanded

	(1) Coal Production (millions of tons)	(2) Hours (thousands)	(3) Number of Employees
Coal tons 200m	0.123***	66.13***	29.11***
	(2.92)	(4.28)	(4.08)
Mean of Dep. Var.	7.72	2,644.24	1,172.83
Observations	795	795	795
Number of Counties	114	114	114

Source: MSHA; EIA; NY Fed / Equifax CCP

Notes: Coal production is millions of coal tons produced in the county. Hours is thousands of hours worked in the coal industry in that county. Employees is the average number of coal employees working in that county. Coal tons 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Observations are at the calendar year level.

Weights are created by taking the county's pre-period (2007-2010) coal production.

Years included are 2011-2018. Regression includes county and year time trend FE. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table 3: Credit Outcomes

	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal tons 200m	0.0748**	−0.000502***	0.00667	−3.777**	−0.00958***
	(2.58)	(−4.31)	(0.80)	(−2.26)	(−2.92)
Mean of Dep. Var.	679.26	0.48	3.78	450.73	0.49
Observations	1,539,567	1,142,661	1,650,235	1,587,187	1,649,440
Individuals	237,206	191,569	247,349	241,831	247,337
Individ w/ Outcome	237,206	188,259	50,245	118,252	8,593

Source: EIA; NY Fed / Equifax CCP

Note: Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Column headers indicate dependent variables.

- "Equifax Risk Score" is the average value in the calendar year.
- "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used.
- "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year.
- "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $).
- "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year.

"Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table 4: Coal demand distributed lag model

	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal tons 200m	0.0336	-0.000435^{***}	0.00792	-0.498	-0.00752^{**}
	(1.26)	(-3.42)	(0.73)	(-0.37)	(-2.16)
Lag Coal tons 200m	0.0737^{***}	-0.000147	0.00212	-5.101^{***}	-0.00390
	(2.92)	(-1.35)	(0.27)	(-3.03)	(-1.35)
Mean of Dep. Var.	680.90	0.48	3.65	443.90	0.49
Observations	1,486,174	1,106,489	1,591,464	1,530,996	1,591,464
Individuals	231,490	186,731	241,729	236,171	241,729
Individ w/ Outcome	231,490	183,634	49,322	115,722	8,515

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Lag of coal demand is a 1 year lag.

Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Column headers indicate dependent variables. "Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. If table is an interaction, county and year FE are interacted with the different bins. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table 5: Coal demand interacted with baseline Equifax Risk Score quartile

	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal * bottom ERS quart	0.102*	−0.000435	0.0297	−7.212	−0.0160**
	(1.73)	(−1.02)	(1.29)	(−1.60)	(−2.12)
Coal * second ERS quart	0.137**	−0.000334	0.0155	−2.471	−0.0221***
	(2.32)	(−1.34)	(0.75)	(−0.98)	(−3.04)
Coal * third ERS quart	0.0952**	−0.000673***	0.000670	0.675	−0.00347
	(2.38)	(−4.00)	(0.06)	(0.51)	(−0.59)
Coal * top ERS quart	0.0608**	−0.000539***	−0.00814	−0.307	−0.00375
	(2.39)	(−3.40)	(−1.01)	(−0.97)	(−1.61)
Mean of Dep. Var.	685.01	0.47	3.55	423.62	0.51
Observations	1,377,875	1,042,891	1,463,849	1,410,020	1,463,849
Individuals	203,226	168,373	210,669	206,193	210,669
Individ w/ Outcome	203,226	165,703	41,603	97,919	7,923

Source: EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with Equifax Risk Score quartiles. Individuals are placed in quartiles based on their median Equifax Risk Score between 2007 and 2010.

Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Column headers indicate dependent variables. "Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. If table is an interaction, county and year FE are interacted with the different bins. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table 6: Coal demand interacted with generations

	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal * Baby Boomers	0.0794**	−0.000464***	0.00950	−1.431	−0.00624*
	(2.15)	(−3.44)	(1.00)	(−0.76)	(−1.67)
Coal * Generation X	0.0873**	−0.000584***	0.00969	−3.457	−0.0152***
	(2.18)	(−3.69)	(0.72)	(−1.64)	(−2.69)
Coal * Millennials	0.0210	−0.000369	−0.00955	−9.775***	−0.00384
	(0.34)	(−0.99)	(−0.59)	(−2.97)	(−0.63)
Mean of Dep. Var.	679.26	0.48	3.78	450.73	0.49
Observations	1,539,567	1,142,661	1,650,235	1,587,187	1,649,440
Individuals	237,206	191,569	247,349	241,831	247,337
Individ w/ Outcome	237,206	188,259	50,245	118,252	8,593

Source: EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with generations. Generations are defined by Pew Research Center as: Baby Boomers were born between 1946-1964; Generation X were born between 1965-1980; and millenials were born between 1981-1996. Due to age restrictions on our sample (limit to 25-64 year olds), the oldest individuals were born in 1948 and the youngest were born in 1984.

Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Column headers indicate dependent variables. "Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. If table is an interaction, county and year FE are interacted with the different bins. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table 7: Coal demand interacted with percent of Census block group population below the poverty line in 1999

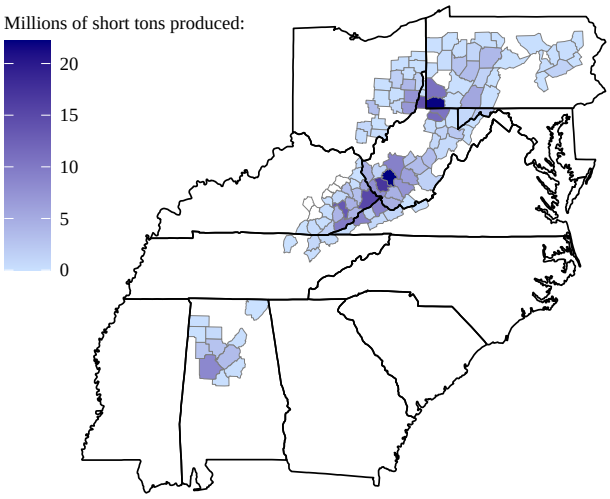
	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal * >20% pov share	0.0344	-0.000758^{**}	0.0213	-1.769	-0.0171^{*}
	(0.47)	(-2.24)	(0.90)	(-0.35)	(-1.87)
Coal * 10 - 20% pov share	0.0835^{**}	-0.000238	0.0194	-1.975	-0.0120^{**}
	(2.16)	(-1.08)	(1.36)	(-0.92)	(-2.27)
Coal * <10% pov share	0.0865^{***}	-0.000585^{***}	-0.00325	-5.110^{***}	-0.0100^{**}
	(2.83)	(-3.00)	(-0.32)	(-3.53)	(-2.46)
Mean of Dep. Var.	684.12	0.47	3.55	434.20	0.50
Observations	1,351,926	1,014,882	1,450,334	1,392,522	1,450,234
Individuals	197,472	162,350	206,165	201,270	206,164
Individ w/ Outcome	197,472	159,694	40,483	96,226	7,523

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with the Census block group's share of population below the poverty line in 1999.

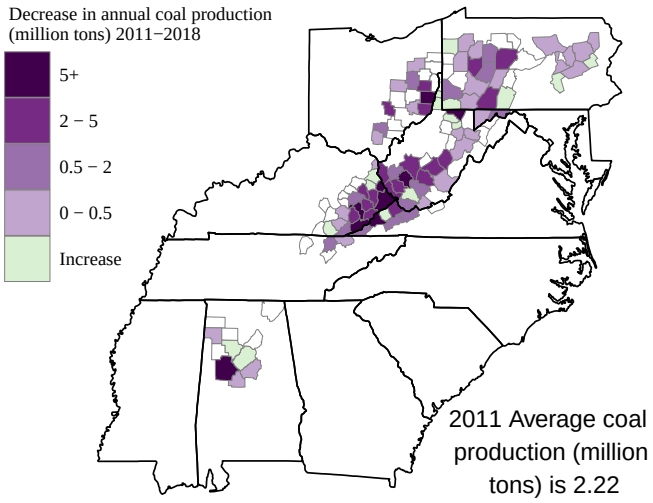
Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Column headers indicate dependent variables. "Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. If table is an interaction, county and year FE are interacted with the different bins. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Figure 1: Coal production in Appalachia (2011)



Source: EIA

Figure 2: Coal decline in Appalachia from 2011 - 2018



Source: EIA

Figure 3: Coal consumed at power plants within 200 miles

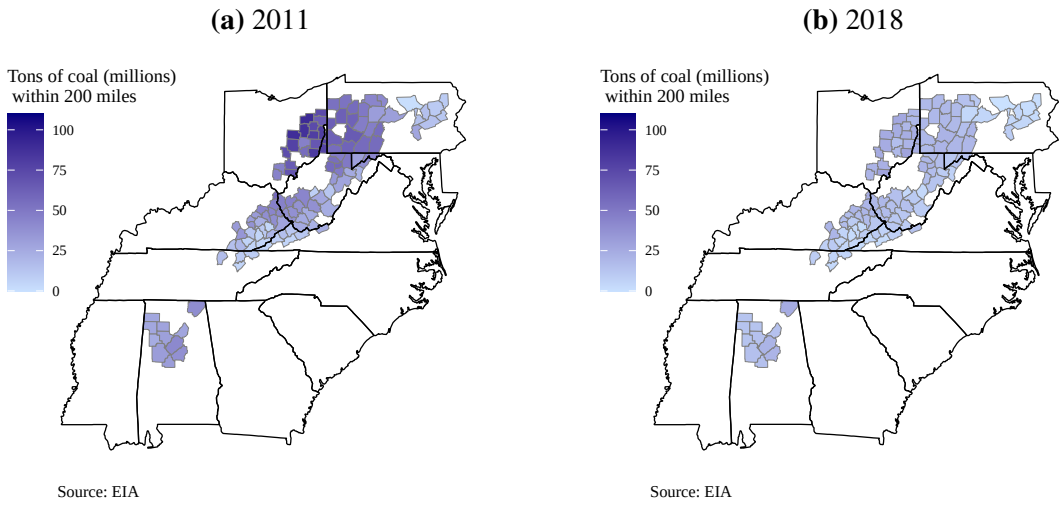


Figure 4: Mean power plant consumption within 200 miles of coal-production counties

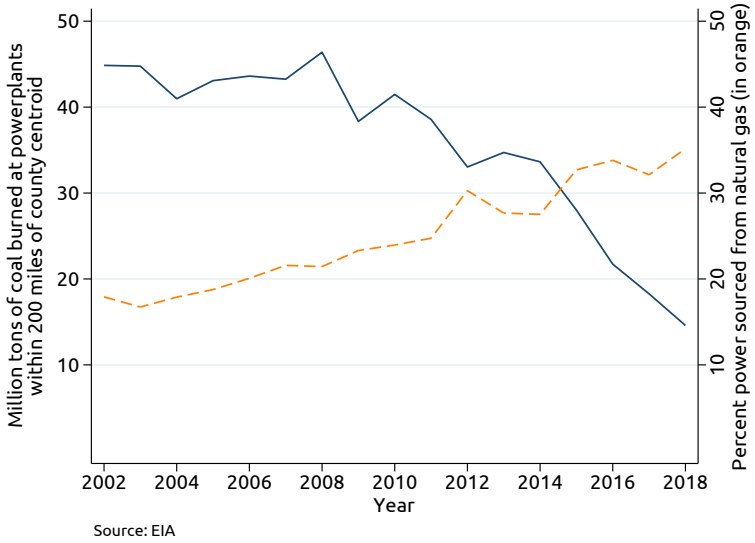
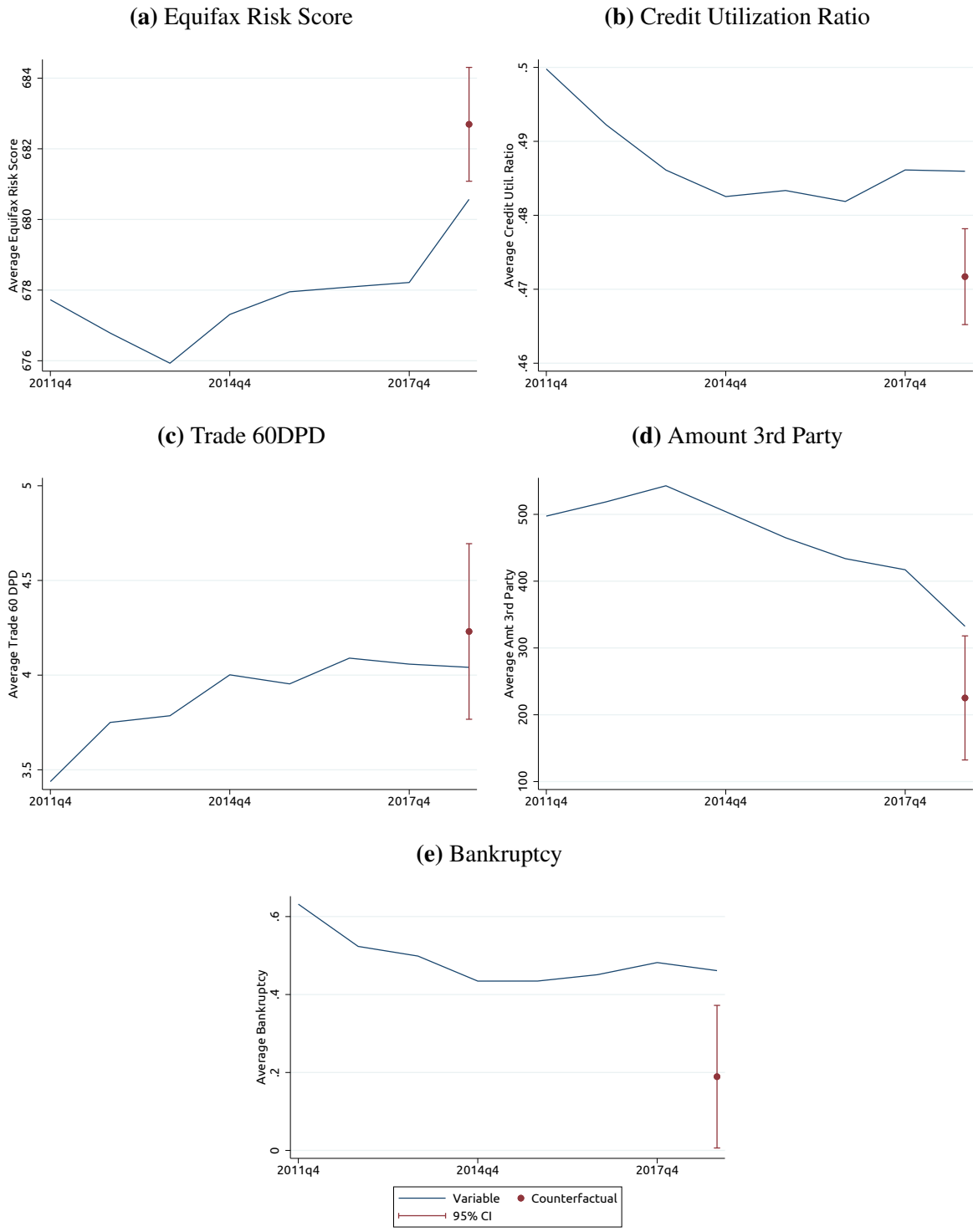


Figure 5: Counterfactual Estimate



The blue line in each plots an annual time series of the dependent variables' average in the regression sample (variable definitions below). The red dot is a back-of-the-envelope estimate of what the variable would have been if coal demanded within 200 miles had not changed between 2011 and 2018. Specifically, for each outcome the distance between the counterfactual and actual levels is equal to the product of (a) the estimated response of that variable to a one-ton change in coal burned within 200 miles as shown in table 3 and (b) the average change between 2011 and 2018 of number of tons of coal burned within 200 miles (a decrease of 28.4 million tons). The 95% confidence intervals are similarly calculated (using the standard errors in table 3).

"Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample.

Appendix A: Main Appendix

Table A1: Percentage of individuals who have ever had each type of debt

Variable	Mean	Std. Dev.	N
Total Balance	0.904	0.295	271,700
Auto Finance	0.416	0.493	271,700
Auto Bank	0.395	0.489	271,700
Bankcards	0.725	0.446	271,700
Consumer Finance	0.355	0.478	271,700
First Mortgage	0.379	0.485	271,700
Home Equity Installment	0.098	0.297	271,700
Home Equity Revolving	0.116	0.320	271,700
Retail Trades	0.571	0.495	271,700
Student Loan	0.242	0.428	271,700
Other Trades	0.216	0.411	271,700

Source: NY Fed / Equifax CCP

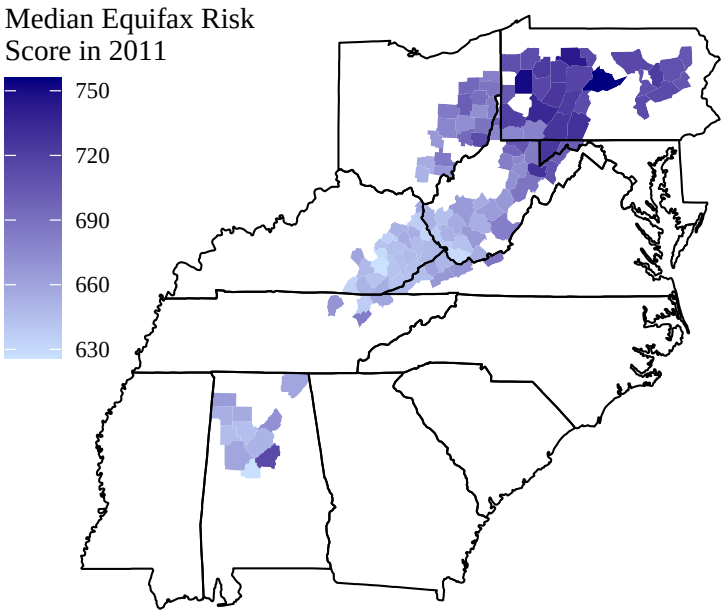
Table A2: Equifax Risk Score across time periods

	Equifax Risk Score			
	(1)	(2)	(3)	(4)
	2002-2018	2002-2007 & 2011-2018	2002-2007	2011-2018
Coal Tons 200m	0.0884***	0.0967**	0.0369	0.0748**
	(2.64)	(2.16)	(0.82)	(2.58)
Mean of Dep. Var.	676.22	676.01	672.13	679.26
Observations	3,421,983	2,789,464	1,230,593	1,539,567
Individuals	309,591	306,776	234,324	237,206

Source: EIA; NY Fed / Equifax CCP

Notes: Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Dependent variable is Equifax Risk Score (calendar year average). All regressions include individual, county, and year FE. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Figure A1: Geographic distribution of Equifax Risk Scores



Source:NY Fed / Equifax CCP

Table A3: Robustness check: Donut coal variable

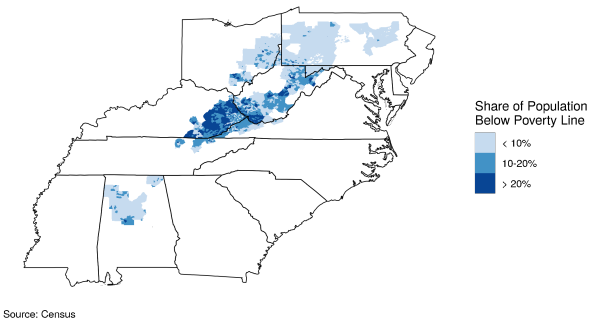
	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal tons 50m-200m	0.0682**	−0.000479***	0.00470	−3.786**	−0.00876**
	(2.26)	(−3.60)	(0.55)	(−2.27)	(−2.49)
Mean of Dep. Var.	679.25	0.48	3.78	450.73	0.49
Observations	1,536,334	1,140,302	1,646,806	1,583,878	1,646,015
Individuals	236,722	191,182	246,846	241,338	246,834
Individ w/ Outcome	236,722	187,877	50,150	117,993	8,575

Source: Census; EIA; NY Fed / Equifax CCP

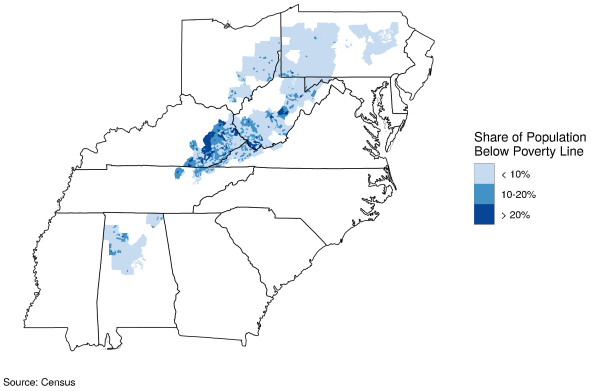
Notes: Coal tons 50m-200m captures million of coal tons burned between 50-200 miles of a county's centroid by rail . Column headers indicate dependent variables. "Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Figure A2: Census Maps

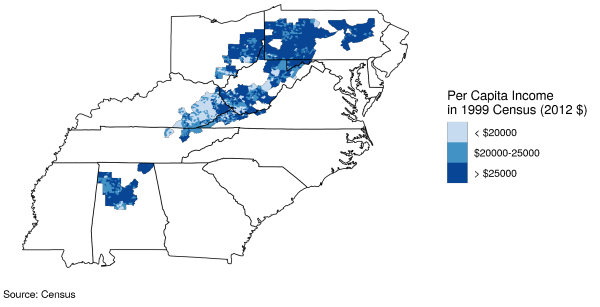
(a) Poverty 2000



(b) Poverty 2010



(c) Per capita income 2000



(d) Per capita income 2010

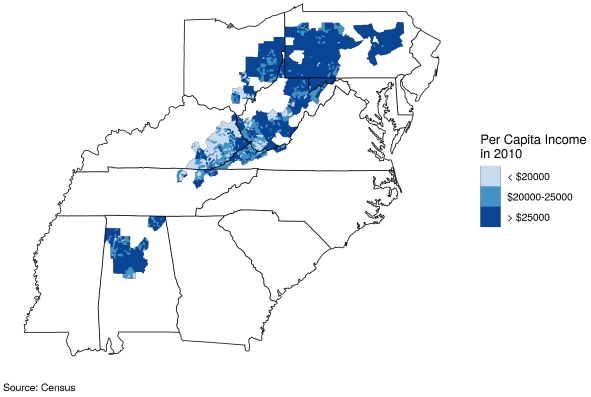


Table A4: Coal demand interacted with generations and Equifax Risk Score (ERS) bins

	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal * Baby Boomers * Low ERS	0.150**	−0.000340	0.0332*	−2.217	−0.0184**
	(2.05)	(−0.95)	(1.81)	(−0.57)	(−2.54)
Coal * Baby Boomers * High ERS	0.0613*	−0.000524***	−0.00732	−0.199	−0.000629
	(1.92)	(−3.00)	(−0.87)	(−0.20)	(−0.17)
Coal * Generation X * Low ERS	0.0916	−0.000294	0.00961	−4.673	−0.0211**
	(1.52)	(−0.98)	(0.43)	(−1.48)	(−2.43)
Coal * Generation X * High ERS	0.107***	−0.000798***	0.0100	0.568	−0.00917
	(2.75)	(−4.97)	(0.86)	(0.68)	(−1.39)
Coal * Millennials * Low ERS	0.0255	−0.000511	0.0306	−12.08**	−0.0121
	(0.26)	(−0.72)	(0.86)	(−2.34)	(−1.23)
Coal * Millennials * High ERS	0.0671	−0.000269	−0.0500	0.153	0.00201
	(0.83)	(−0.78)	(−1.66)	(0.08)	(0.21)
Mean of Dep. Var.	685.01	0.47	3.55	423.62	0.51
Observations	1,377,875	1,042,891	1,463,849	1,410,020	1,463,849
Individuals	203,226	168,373	210,669	206,193	210,669
Individ w/ Outcome	203,226	165,703	41,603	97,919	7,923

Source: EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with (1) generations and (2) Equifax Risk Score (ERS) bins. Generations are defined by Pew Research Center as: Baby Boomers were born between 1946-1964; Generation X were born between 1965-1980; and millenials were born between 1981-1996. Due to age restrictions on our sample (limit to 25-64 year olds), the oldest individuals were born in 1948 and the youngest were born in 1985. Low and high Equifax Risk Score bins determined by individual's median ERS score between 2007-2010.

Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Column headers indicate dependent variables. "Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. If table is an interaction, county and year FE are interacted with the different bins. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A5: Coal demand interacted with Census block group per capita income in 1999 (2012 $)

	(1) Equifax Risk Score	(2) Credit Utilization Ratio	(3) Trade 60 DPD per 100 people	(4) Amt 3rd Party ($ 2012)	(5) Bankruptcy per 100 people
Coal * $25000 +	0.0713**	−0.000480**	0.00209	−4.850***	−0.0101*
	(2.03)	(−2.50)	(0.16)	(−2.99)	(−1.78)
Coal * $20000-25000	0.0985**	−0.000608***	0.00256	−3.391	−0.0118**
	(2.43)	(−3.59)	(0.18)	(−1.38)	(−2.19)
Coal * < $20000	0.0661	−0.000475**	0.0192	−3.217	−0.0147**
	(1.33)	(−2.06)	(1.01)	(−1.34)	(−2.27)
Mean of Dep. Var.	684.12	0.47	3.55	434.20	0.50
Observations	1,351,925	1,014,880	1,450,334	1,392,522	1,450,234
Individuals	197,472	162,350	206,165	201,270	206,164
Individ w/ Outcome	197,472	159,694	40,483	96,226	7,523

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with the Census block group's per capita income in 1999 (2012 $). Coal 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Column headers indicate dependent variables. "Equifax Risk Score" is the average value in the calendar year. "Credit Util. Ratio" variable uses bankcard and retail trade balances and credit limits in its calculation and the max value for the calendar year is used. "Trade 60DPD" is the percentage of individuals who have transitioned from all accounts current to at least one account 60DPD (or worse) during the calendar year. "Amt 3rd Party" is the individual's maximum dollar amount in 3rd party collections in the calendar year (2012 $). "Bankruptcy" is the percentage of individuals who have entered bankruptcy (either Ch7 or Ch13) in that calendar year. "Individuals" refers to the number of individuals included in the regression (i.e. have nonmissing values for the dependent variable). "Individuals with outcome" refers to the number of individuals who ever have at least a trade 60 days past due, positive amount in 3rd party collections, a bankruptcy flag, or a working credit utilization ratio greater than zero in our sample. Years included are 2011-2018. All regressions include individual, county, and year FE as well as linear individual time trends. If table is an interaction, county and year FE are interacted with the different bins. Standard errors clustered at the county level. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.