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THE CANARY IN THE COAL DECLINE:
APPALACHIAN HOUSEHOLD FINANCE AND THE TRANSITION FROM FOSSIL FUELS

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ABSTRACT

The energy transition away from fossil fuels, despite its substantial overall climate benefits, presents significant transition risks for communities historically built around the fossil fuel industry. This paper uses the decline in the Appalachian coal industry between 2011 and 2018 to understand how individuals are harmed by a reduction in local fossil fuel extraction activity. We use individual-level credit data and exogenous variation in coal demand from the electricity sector to identify how the coal mining industry's decline affected the finances of Appalachian households. We find that the decline in demand for coal caused broad-based negative impacts, decreasing credit scores and increasing credit utilization, delinquencies, amounts in third party collections, bankruptcy rates, and the number of individuals with subprime status. These effects were broad based and cannot be explained solely by individuals who lost coal mining jobs. Individuals with the lowest pre-period credit scores were more likely to end up in financial distress and experienced a greater deterioration in credit scores. Quantile regressions show that the drop in credit scores from the coal decline was most pronounced between the 30th and 50th percentiles of the credit score distribution. Our results provide evidence that people living in fossil fuel extraction regions are likely to experience declines in financial well-being from the energy transition even if they do not directly work in the affected industry.

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Meeting international climate goals will require the US to greatly reduce its consumption of fossil fuels. The fossil fuel industry has played a central role in a variety of regional economies, including Appalachia, Wyoming, North Dakota, West Texas, the Gulf Coast, and western Pennsylvania. In these areas, fossil fuel extraction provides employment, tax revenues, and demand for local services. As a result, the energy transition away from fossil fuels could cause significant financial hardships for people living in regions without comparable alternative sources of employment, a transition risk for these communities (Lobao, et al., 2021; Raimi, 2021). Despite substantial overall benefits from reducing fossil fuel consumption, concerns about the costs of the energy transition to these fossil fuel extraction communities have motivated political opposition. However, empirical evidence on these potential costs is limited. This paper fills that gap by examining the costs to individuals living in a region already feeling the effects of the energy transition: Appalachian coal country.

We explore the effects of the coal decline in Appalachia between 2011 and 2018, a period when Appalachian coal production and employment dropped by 40 and 49 percent as low-cost fracked natural gas displaced coal in the electricity sector. Coal has historically played a central role in the Appalachian economy and the costs of this energy transition for people living in Appalachia remains an open question. On the one hand, such large drops in coal mining could cause sizeable declines in local incomes and strain household finances. On the other hand, by 2011 coal mining accounted for only 2 percent of employment in active coal mining counties. This small share could limit the potential negative impacts of the 2011-2018 coal mining decline for Appalachian households.

We use the New York Fed/Equifax Consumer Credit Panel (CCP), a 5 percent random sample of individuals with credit reports in the US, to study the effects of the transition away from coal mining on household finances in Appalachia. The individual-level panel data in the CCP track the same people throughout the decline in coal mining we study. Household finance outcomes like credit scores, delinquencies, collections, and bankruptcy serve two important roles. First, they provide a snapshot of people's financial well-being, allowing us to evaluate how people are affected by the decline in coal mining. Second, these measures affect future financial health because adverse events on credit reports can limit people's ability to weather negative shocks by making it harder to qualify for future loans (including credit cards, car loans, and mortgages), get jobs, or rent apartments (Ambrose & Diop (2018); Balance, Clifford, & Shoag (2020); Herkenhoff, Phillips, & Cohen-Cole (2021); Seikel (2022); Consumer Financial Protection Bureau (2020; 2022)).

A major challenge when estimating the causal effect of declines in coal mining on people in mining communities is that changes in coal production may be endogenous. For example, a coal mining company may cut production first in mines where workers have the highest wages, which could be correlated with local household finances. We overcome the endogeneity challenge by constructing a novel variable to proxy for demand for local coal production that measures how much coal is consumed annually at power plants within 200 miles (by rail) of active coal-mining counties. This variable reflects demand for locally produced coal because (a) the majority of Appalachian coal is consumed by the electricity sector and (b) the high cost of transporting coal limits the set of plants a given mine can sell its coal to without incurring losses. The measure is plausibly exogenous because during our sample the amount of coal burned at power plants was driven in part by preexisting electricity generation infrastructure that enabled some electric utilities to switch from coal to gas generation more than others when natural gas prices fell due to fracking.

We find that declines in coal demand driven by exogenous changes in the electricity sector harmed the financial health of people living in Appalachian coal-mining counties, decreasing credit scores and increasing measures of financial distress.[3] A back-of-the-envelope estimate suggests that the 2018 average credit score in our sample would have been nearly 3 points higher if not for the decline in coal demand. This magnitude is in line with analyses of other large shocks and policies, which underscore that

[3] We measure credit score using the Equifax Risk Score, which is a proprietary credit score similar to other credit scores used in the industry. It is designed to predict the likelihood of a consumer becoming 90 or more days delinquent within 24 months.

even one-point changes in average credit scores are economically meaningful (Gallagher & Hartley (2017); Argys, Friedson, Pitts, & Tello-Trillo (2020); Dobbie, Goldsmith-Pinkham, Mahoney, & Song (2020); Dettling & Hsu (2021)). We also show that our results cannot be fully explained by coal miners who lost their jobs between 2011 and 2018, meaning the decline in coal mining affected individuals outside the coal industry.

We next examine heterogeneous effects along the credit score distribution. First, we do a heterogeneity analysis using initial (pre-2011) credit scores, finding that the decline in coal demand negatively affected a broad swath of residents to varying degrees. Individuals in the bottom half of the pre-period credit score distribution experienced declines across all outcomes we consider. In contrast, individuals with higher pre-period credit scores experienced relatively smaller credit score declines and credit utilization increases and no significant increases in measures of financial distress (delinquency, collections, or bankruptcy). Second, we estimate unconditional quantile regressions and find that the coal decline primarily reduced credit scores in the 30^{th} to 50^{th} percentiles. The cutoff for subprime status—which raises borrowing costs and limits access to credit—is at the 42^{nd} percentile (a score of 660). At the 40^{th} percentile, credit scores fell by 7 points, more than double the average effect, pushing people's credit scores even further away from reaching prime status. Taken together, our results show that the effect of the decline in coal mining extends beyond coal mine workers and causes significant deterioration in financial health for vulnerable individuals.

Our paper makes three main contributions. First, we add to the finance literature examining transition risks caused by a shift away from fossil fuels. Most of these papers have focused on the costs to firms and investors, showing that the energy transition has meaningful implications for asset prices and borrowing costs of exposed firms (Meng (2017); Engle, Giglio, Kelly, Lee, & Stroebel (2020); Bolton & Kacperczyk (2021; 2022); Ilhan, Sautner, & Vilkov (2021); Ivanov, Kruttli, & Watugala (2022); Pástor, Stambaugh, & Taylor (2022); Seltzer, Starks, & Zhu (2022)). We complement this work by analyzing transition risks for households already facing consequences of a long run decline in coal using credit data. Other work examining household effects of this longer run decline in coal uses shift-shares to county-level data to examine economic dynamics in coal mining regions (Autor, Dorn, & Hanson (2021); Hanson (2023); Krause (2023)). We add to this work by applying a novel identification strategy to individual-level household finance data to find not only average causal effects of the coal decline but also spillovers and distributional implications within coal mining regions.

Second, our paper adds to the literature that examines impacts of temporary coal busts on a variety of local outcomes, including disability spending, educational attainment, population growth, entrepreneurship, and local government revenues (see Black, Daniel, & Sanders (2002); Black, McKinnish, & Sanders (2005); Deaton & Niman (2012); Partridge, Betz, & Lobao (2013); Betz, Partridge, Farren, & Lobao (2015); Welch and Murray (2020). These papers use county-level data and find that temporary coal busts, which have been a common part of the coal industry's boom and bust cycles, have had significant impacts on Appalachian coal communities. However, the current long-run decline of the coal industry may limit the insights that studies of pre-2011 Appalachia can provide for those concerned about a more permanent transition away from coal and other fossil fuels.

Third, our paper adds to the literature showing how household finances respond to a range of shocks such as minimum wage laws, the shale boom, and loss of access to health insurance (Argys, Friedson, Pitts, and Tello-Trillo (2020); Dobbie and Goldsmith-Pinkham (2020); Dettling and Hsu (2021); Blascak and Mikhed (2022); Cookson, Gilje, andHeimer (2022)). This literature includes some work at the nexus of climate and household finances that examines how households are affected by natural disasters, a dimension of physical climate risk (Gallagher & Hartley (2017) ; Billings, Gallagher, & Ricketts (2022)). Our analysis shows that the energy transition also has direct implications for households' financial health.

Our paper provides evidence on how the energy transition may affect other fossil fuel extraction regions in the coming decades. While the geographic and economic context vary by region, our findings demonstrate that negative impacts can be broad-based. We should not expect the economic costs of decarbonization to be limited to the workers in fossil fuel extraction industries. Our estimates may serve as a lower bound because for fossil fuel regions that have a higher share of employment in fossil fuel industries than Appalachia had in the coal industry during our sample. For example, as of 2018, mining activity represented 13 percent of total employment in the region covering the Permian Basin oil fields of Texas (Federal Reserve Bank of Dallas, 2022; Bureau of Economic Analysis, 2022). While the benefits of the energy transition are immense, the costs for other fossil fuel extraction communities will be increasingly important for policymakers who seek to implement equitable policies and manage transition costs.

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 may be particularly vulnerable to a transition away from coal because it 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). 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). 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). 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).

Although U.S. coal production quantities did not start to decline until the early 2000s, Appalachian 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 further reduced Appalachian coal mining employment by inducing a shift to low-sulfur coal mined in the Powder River Basin in Montana and Wyoming, which is more capital intensive than the generally higher-sulfur coal found in Appalachia (Carlson, Burtraw, Cropper, and Palmer (2000)).

As we describe in more detail in Section III, US coal production and employment declined in recent years because of a reduction in demand from the electricity generation sector, which was driven by technological developments. Despite the recent declines, coal remains a potentially important economic and cultural force in Appalachia (Lewin, 2019). Efforts to reduce carbon emissions involve further reducing coal consumption and may have important implications for the region. 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 spillovers such as lost service jobs and reduced property and corporate tax revenues (Morris, Kaufman, & Doshi, 2019; Welch & Murray, 2020). There are also benefits to reducing coal mining like decreases in environmental degradations from strip mining and improved health conditions. Such benefits are important considerations for policymakers but are not in the scope of our analysis. Instead, this paper focuses on a major cost of the decline of the Appalachian coal sector: the negative impact on household finances.

II. **Data**

We combine data on coal production at mines, coal consumption at electric power plants and credit outcomes to study how changing coal demand has impacted individuals living in coal mining communities. We describe each of these data sources below.

Coal mining

We study Appalachian 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 reported 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). We use the EIA's designations of Appalachian mining basins to identify counties in Appalachia. We then drop Allegheny County, PA, which contains Pittsburgh, because it is very large and urban, has low per capita coal activity, and is generally not representative of the Appalachian region overall.[4]

In our sample, average annual county coal production is 2.4 million tons, with about 1 million hours of coal labor (about 500 full-time workers, Table 1). Figure 1 shows cross-sectional variation in coal production in our sample region. Panel A shows variation in coal production at the start of our sample in 2011 and Panel B shows variation in the decline in production during our sample period from 2011-2018. Declines in coal production occurred in regions with both high and low levels of initial production.

Coal consumption

We combine annual data from the publicly available EIA Form 923, which tracks the coal consumed at power plants in the US, with National Transportation Atlas Databases 2014 data from the U.S. Department of Transportation's Bureau of Transportation Statistics on the US rail network to generate an exogenous measure of coal demand. We describe this measure in detail in Section III.

Household finance

We use the NY Fed / Equifax Consumer Credit Panel (CCP) to analyze how coal declines have impacted individual-level household finance outcomes. This dataset is a nationally representative 5

[4] Our results are broadly robust to including Allegheny and to dropping additional relatively urban counties.

percent anonymized random sample of adults with Social Security numbers and a credit history.[5] An individual-level panel, this data set contains 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 each individual lives (at the Census block level), their age, credit score (measured by the Equifax Risk Score), and outcomes like bankruptcies and outstanding debts. We start our sample in 2011 to limit potential confounding factors from the Great Recession.

To focus our sample on individuals likely to have significant exposure to local economic conditions in active coal-mining counties, we include people of working age (25 to 64 years old) who live in active coal-mining counties in Appalachia.[6] With the exception of bankruptcy—for which we use a flag that indicates entry to bankruptcy—the variables we consider measure stocks (as opposed to flows) which provide snapshots of financial health at specific points in time. We use fourth quarter observations for these variables to assess what condition the coal demand that occurred over the course of a year has left individuals in by the end of that year. Our sample includes about 1.5 million individual-year observations and over 225,000 unique individuals. We examine each person's credit score (measured by Equifax Risk Score), a summary of overall credit health, and five variables that capture different phases of financial

[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. However, the CCP sample includes people who have no active credit accounts if they (i) have third party collections or a public record item such as a bankruptcy or (ii) have closed accounts or accounts where 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 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 have passed away.

distress and different types of debt: subprime credit score status, credit utilization, delinquency, third party collections, and bankruptcy.

Our credit score variable, the Equifax Risk Score, is a proprietary summary measure designed to predict the likelihood of a consumer becoming 90 or more days delinquent within 24 months.[7] We observe substantial geographic variation in credit 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). Credit scores in our sample range from 296 to 841. Table 1 shows in the left column that the mean credit score in our sample is 680, a bit below the national mean of 686 in the right column

People with credit scores below a certain level are considered to have subprime credit scores. Individuals with subprime credit are more likely to be denied access to new loans, charged higher interest rates, be unable to raise their borrowing limits, and end up in default. We apply a credit score threshold of 660 points to define subprime status (Equifax, Federal Reserve Bank of New York, Federal Reserve Bank of St. Louis (2023)). Table 1 shows that 38 percent of observations in our sample have subprime credit scores, which is similar to the national average.

Credit utilization measures how high a person's total outstanding balance is as a percentage of their combined credit limit across all their credit cards (including those issued by banks and retailers). For example, a person with a $1,000 credit limit and $800 credit card balance has a credit utilization ratio of 80 percent. The mean credit utilization ratio in our sample is 39 percent. Some individuals owe *more* than their limit after accumulating interest on their balances, leading to credit utilizations above 100 percent.[8]

Credit utilization can measure different things for different types of borrowers. People with prime credit typically use credit cards for consumption, paying off their cards each month. Those with subprime

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[7] The Equifax Risk Score is similar to the FICO scores generated by the three main credit agencies.
[8] We top code credit utilization at 300%, which is relatively rare, as we assume larger numbers are mostly due to errors (either with unreasonably small credit limits or unreasonably large balances). For this variable, we drop observations with credit limits below $100.

credit tend to use credit cards primarily for debt, carrying a balance from month to month.[9] Previous work examining cash windfalls shows that prime borrowers increase credit utilization (consistent with increased consumption), while subprime borrowers decrease credit utilization (consistent with paying down debt) (Cookson, Gilje, & Heimer, 2020). Therefore, our analyses of distributional effects for people with higher and lower credit scores can help distinguish likely changes in consumption from changes in debt.

Delinquency measures whether people are falling behind on making payments on credit accounts like mortgages, auto loans, and credit cards. When a person misses a payment, their lender typically reports the missed payment to credit agencies. We add up the total number of delinquent accounts, including those that are 60, 90, 120, or more days past due.[10] We winsorize the delinquent accounts variable at the 99.9th percentile, which caps these observations at 8 delinquent accounts.

While credit utilization and delinquency are only observed for people with traditional credit accounts, third party collections include a broader set of people with accounts not regularly reported to credit bureaus. This variable allows us to measure outcomes for a population with less access to traditional credit, which may be important in our low-income setting. People owe money to third party debt collectors when their original creditors sell their debt to a collection agency. Around two thirds of third party collections accounts have historically been attributable to medical bills, utility bills, or telecommunications bills (Consumer Financial Protection Bureau, 2014).[11] 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

[9] The CCP data does not allow us to differentiate between an individual who rolls over balances from month to month and incurs interest payments and one who pays off their credit card every month.
[10] We do not include "severe derogatory" accounts in our delinquent accounts measure.
[11] Reporting rules have changed over time. For example, many medical debts were removed from credit reports in 2017.

are in the collections phase.[12] The mean third party collections amount in our sample is around $241 (USD 2012), which is about one-third above the national average.

Finally, we analyze bankruptcy, the most severe measure of financial distress in our analysis. Bankruptcy (either Chapter 7 or Chapter 13) is the final stage for a borrower who is in default and unable to pay their debts. We use an indicator for entry into bankruptcy in a given calendar year. Although entry into bankruptcy is rare, with just 0.5 percent of observations entering bankruptcy per year (see Table 1), about 3.5 percent of individuals in our analyses enter bankruptcy at some point during our sample.

III. Empirical design

In this section we describe the novel identification strategy we use to estimate the causal impacts of reductions in coal demand on Appalachian household finance outcomes. Our goal is to estimate the impact of declines in coal production on the finances of people living in active Appalachian coal mining counties. One challenge is that declines in production may not be randomly distributed across counties, raising concerns about endogeneity. For example, a coal mining company may cut production first in mines where workers have the highest wages, which could be correlated with mine workers' household finances. Alternatively, the least productive mines may pay the lowest wages and could be first to see production cuts, resulting in the opposite correlation. To get around this challenge, we introduce an identification strategy based on (i) the electricity sector's broader shift from coal to natural gas caused by the fracking boom and (ii) the locations of natural gas generators that were in place when natural gas prices dropped starting in 2009.

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[12] No standards exist as to when a debt must be reported to credit bureaus as being 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).

Basis of Identification: Electricity sector's shift from coal to natural gas

Two technological advances in the energy sector contributed to the market-driven decline in coal demand in the electricity sector. First, technological advances lowered construction costs of natural gas generators by as much as 35 percent in the 1990s (Colpier & Cornland, 2002; Rubin, Azevedo, Jaramillo, & Yeh, 2015). This contributed to a boom in natural gas plant construction in the early 2000s, which more than tripled the natural gas capacity between 2000 and 2008 (U.S. Department of Energy, 2022).[13] However, this initial influx of natural gas combined cycle powerplants did not drive immediate large declines in coal generation because natural gas prices climbed to relatively high levels between 2000 and 2008.

Second, technological advances in natural gas extraction caused the fracking boom starting around 2009, which quickly drove down the cost of natural gas. Natural gas prices dropped by nearly 50 percent from an average of $6.02/MMBTU between 2000 and 2008 to an average of $3.27/MMBTU between 2011 and 2018 (U.S. Department of Energy, 2022). Utilities that had the natural gas capacity to do so took advantage of the declining natural gas prices by changing the dispatch order of electricity grids, leading to declines in coal generation (Cullen & Mansur, 2017). The relationship between natural gas prices and the decline in coal has been well documented in the literature, which shows that natural gas prices (rather than environmental regulations) were responsible for the decline in coal generation (Linn & McCormack, 2019; Coglianese, Gerarden, & Stock, 2020).[14]

Figure 2 shows the relationship between the shift away from coal and the construction of natural gas capacity in Appalachian and neighboring states. The horizontal axis shows the natural gas generation

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[13] The construction boom can be seen in appendix figure A3, which shows the large number of combined cycle natural gas plants built in Appalachia and surrounding states between 2000 and 2008.
[14] Coglianese, Gerarden, and Stock (2020) also consider the role of The Mercury Air Toxic Standard (MATS), which required mercury control equipment on coal plants, was proposed in 2012, and went into effect April 2016. Coglianese, Gerarden, and Stock (2020) estimate that MATS was not a large factor in the coal decline, causing a reduction of 0.6 percent of total 2014 coal production.

capacity that was completed between 2000 and 2008. The vertical axis shows the change in coal generation during our 2011 to 2018 sample. The size of each dot reflects the amount of coal generation in each state in 2007 (before the Great Recession-induced declines in total electricity generation), showing that some states burned a lot of coal in 2007 (e.g., Ohio and Pennsylvania) while others burned relatively little (e.g., New York and Mississippi). The red line shows the fitted line from a linear regression of excess natural gas capacity in 2007 on the change in coal generation between 2011 and 2018 weighted by 2007 coal generation. It shows a negative relationship (p value of .11 based on 15 observations), demonstrating that declines in coal generation were associated with a state having more available natural gas capacity before natural gas prices started to drop after 2008 due to fracking.[15] We leverage this relationship in our empirical strategy described in the next section.

Empirical strategy

To capture the market-driven decline in coal from the rise of natural gas, we construct a new measure of coal demand at the county level: the amount of coal burned at electricity generators within 200 miles of an active coal mining county measured via the rail network.[16] We use this measure for three reasons. First, unlike other measures such as coal production, our coal demand measure is exogenous to household-level credit outcomes. The 2000-2008 expansion of natural gas powerplant capacity described in the previous section creates quasi-random cross-sectional variation in changes in demand for coal caused by the subsequent fall in natural gas prices. Powerplants typically sell into larger regional electricity markets and their usage depends more on the powerplant efficiency characteristics and weather

[15] Electric utilities continued to build natural gas generators after 2009 to take advantage of the lower prices. Our identification strategy leverages generators built before 2009 because those decisions were predetermined with respect to the low-cost natural gas in our sample window.

[16] Our approach to calculating rail distances relies on similar principles to the calculations in Preonas (2023). We are grateful to Louis Preonas for providing us with relevant code.

than local economic conditions. As a result, electricity production at powerplants is not driven by local economic conditions or household-level credit outcomes.[17]

Second, our coal demand measure captures differences in the coal mining decline across areas within Appalachia. As Figure 2 shows, not every state in the surrounding region saw uniform declines in coal generation. Some regions had excess natural gas generation capacity available to take advantage of the unexpectedly low natural gas prices starting in 2009. Importantly, the planning and construction of these natural gas plants, which can take several years, was completed before it was known that natural gas prices would decline starting in 2009 (Hanif, Nadeem, Tariq, & Rashid, 2022). This pre-determined natural gas generation capacity caused cross-sectional spatial heterogeneity in the extent of the coal-to-gas switch. Some regions with more preexisting natural gas capacity were able to shift more towards natural gas while others were not. Figure 3 shows the variation across counties in our coal demand measure at the beginning and end of our sample.

Third, 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 sells its coal to.[18] As of 2018, when demand for coal by electricity generators had already fallen significantly, 84 percent of coal mined in the US was used for electricity generation (U.S. Energy Information Adminstration, 2019). Taken together, our measure of coal demand within 200 miles of a coal county captures variation in coal demand caused by the electricity sector which is exogenous to household finances.

[17] Consistent with this assertion, Appendix Table A2 shows that our results are robust to excluding coal consumption at powerplants within 50 miles by rail and to using 100 or 300 mile radii for coal demand.
[18] Coal mined in the Powder River Basin in Wyoming and Montana is shipped longer distances to generators around the US. Relative to the coal mined in Appalachia, this Powder River Basin coal has a lower sulfur content, making it more valuable to power plants needing to comply with sulfur dioxide regulations in the Clean Air Act (Carlson, Burtraw, Cropper, & Palmer (2000).

Estimating Equation

We estimate the effects of our measure of the decline in coal demand on individual credit outcomes using the following panel fixed effects equation:

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

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 (α_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 demand for coal mined in a county caused 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 approach is to assume that the causal response to more “dose” (change in coal demand) is the same across counties conditional on having the same amount of dose and being in the same time period.[19]

[19] 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 via rail, captures the demand for coal at the county level. We use this measure because it is exogenous on account of being determined by preexisting characteristics of the electricity grid unrelated to the contemporaneous credit outcomes of people in Appalachia. Before proceeding to our main results, we validate our approach by examining whether coal burned within 200 miles explains coal production and employment in coal counties. We estimate the following regression:

$$Y_{ct} = \gamma_1 + \gamma_2 Coal200_{ct} + \eta_c t + \nu_c + \mu_t + \varepsilon_{ct}, \quad (2)$$

where Y_{ct} is a county-level outcome. This specification includes a county-specific time trend ($\eta_c t$) as well as fixed effects at the county (ν_c) and year (μ_t) levels.

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 coal mines (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 regression, 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.

IV. **Results**

A. Baseline Results – Average Effects

We find that decreases in demand for local coal cause declines in financial health for people living in active coal-mining counties. In Table 3, we present our baseline results from estimating equation (1). Column 1 shows that a one million ton decrease in coal burned within 200 miles of a county causes an average 0.096 point decrease in the credit score for Appalachian coal mining county residents. During our sample the average change in coal burned within 200 miles was a decline of 28.5 million tons. To provide more context, panel A of Figure 4 shows the average credit score over our sample in blue and a counterfactual 2018 credit score as a red dot, where the gap between the two is the product of our estimated response and the average decrease in coal burned within 200 miles. Overall credit health improved during our sample period, increasing average credit scores over the course of this period of national economic recovery from the Great Recession (Federal Reserve Bank of New York, 2014). However, Figure 4 shows that in the absence of the coal demand decline that occurred between 2011 and 2018, average credit scores would have been nearly 3 points higher in 2018 (gap between blue line and red dot). This is a relatively large effect given that over the same time period the actual average change in credit scores was a 0.64 point increase (change in blue line between 2011 and 2018).

Columns 2-6 of Table 3 show that declines in coal demand increased subprime shares, credit utilization ratios, delinquencies, amounts in third party collections, and bankruptcy rates. Panels B-E of Figure 4 provide context to our findings, showing that these other credit outcomes would have been better in the absence of the coal mining decline. The changes caused by the decline in coal mining, as measured by the gap between the counterfactuals and actual levels in 2018, are comparable in magnitude to the net observed changes from 2011 to 2018.

As we show in the Appendix, these baseline results are generally robust to using alternative radii for the demand measure, extending the sample further back (Table A4), and alternative treatment of movers

(Table A6). When using alternative approaches to turn quarterly outcome data into annual measures, all results are robust except for delinquency (Table A3).[20]

Interpretation and Context for Baseline Results

We conduct a back-of-the-envelope calculation to understand if the average treatment effects for all of Appalachia found in Table 3 could be driven by direct job losses by coal miners, or if the costs of the coal decline are felt by others in the community. Between 2011 and 2018, the number of coal miners in Appalachia dropped from 61,000 to 31,000 (Mine Safety and Health Adminstration, 2022). Assuming that coal miners are proportionally represented in our CCP sample, we approximate that over 1,100 individuals in our CCP sample were coal miners that lost their jobs between 2011 and 2018.[21] If the costs of the coal decline were only experienced by those who lost coal mining jobs, it would require these miners to experience average credit score drops of about 470 points between 2011 and 2018. We observe no individuals with credit score drops of at least 470 points from 2011 to 2018, which shows that the average treatment effects are not coming solely from individuals who lost jobs in the coal-mining sector.

Our findings are roughly in line with analyses of the impacts of other economically meaningful shocks on credit scores. Argys, Friedson, Pitts, & Tello-Trillo (2020) estimate that a one-time disenrollment of roughly 10 percent (135,000 individuals) of Tennessee's Medicaid recipients resulted in an average 2.8 point decline in the credit score of an individual living in the median county. The paper uses the same CCP data and a similar county-level dose shock to our paper and finds a similar change in average credit scores. Gallagher & Hartley (2017) also use the CCP to study the effects of hurricane Katrina on household credit outcomes. They find that individuals residing in flooded Census blocks saw

[20] Specifically, we find that with the exception of the delinquency finding, our baseline results are robust to using mean or maximum quarterly levels rather than the year-end level.

[21] Proportional representation is supported by the CCP's random sampling procedure (Lee & van der Klaauw, 2010). The CCP is randomly selected from adults with a credit report. Our estimation sample focuses on adults between the ages of 25 and 64. To account for the difference in the sample population, we adjust our estimates to account for the working-age population using the American Community Survey. We find that our working age CCP population includes around 3.5% of the working population of active coal-mining counties in Appalachia.

their credit scores temporarily decline by 4 to 7 points for about a year and a half after Hurricane Katrina. Our results are also similar in magnitude to the 2 to 3 point drop in average credit score during the Great Recession (Dorhelm (2021).

To further understand the economic significance of our estimates, we consider the additional cost of having a subprime credit score for individuals trying to access credit. We find that the probability of having subprime status increased by 1.5 percentage points for the average person. For example, according to Optimal Blue Mortgage Market Indices, in December of 2018, the average interest rate on a 30-year fixed rate mortgage was about 4.85 percent for individuals with FICO scores above 740.[22,23] In contrast, with a subprime FICO score below 680, the average interest rate on the mortgage would have been about 5.35 percent, representing a 50-basis point premium.[24,25]

B. Distributional Effects

Having established that decreasing demand for coal leads to worse credit outcomes on average, we now explore whether these average effects apply evenly or whether groups or parts of the distribution are particularly sensitive to changes in demand for coal. We take two complementary approaches to answer this question. First, we run a heterogeneity analysis in which we estimate the effects of the decline in coal demand for different groups of individuals based on their pre-period credit scores. This analysis estimates whether people with different credit scores *before* the start of our sample were affected differently by the

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[22] While the CCP data do not contain FICO scores, the FICO score is based on the same credit characteristics as the credit score that we use.
[23] See Optimal Blue, 30-Year Fixed Rate Conforming Mortgage Index: Loan-to-Value Greater Than 80, FICO Score Greater Than 740 [OBMMIC30YFLVGT80FGE740], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/OBMMIC30YFLVGT80FGE740, January 4, 2023.
[24] In this example, on a 30-year loan with a principal of $200,000, the low FICO score borrower would pay about $61 (or 6 percent) more for their monthly payment, and a total of about $22,000 (12 percent) more in interest over the life of the loan, illustrating how having lower credit scores like credit score can affect borrowing costs in meaningful ways.
[25] See Optimal Blue, 30-Year Fixed Rate Conforming Mortgage Index: Loan-to-Value Greater Than 80, FICO Score Less Than 680 [OBMMIC30YFLVGT80FLT680], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/OBMMIC30YFLVGT80FLT680, January 4, 2023.

coal decline. Second, we estimate quantile regressions to understand how declining coal demand affected people along different points of the credit score distribution *during* our sample, regardless of what scores they had before the sample.

Starting with our heterogeneity analysis, we modify equation (1) by interacting the $Coal200_{ct}$ treatment variable with a set of indicators that reflect which quartile an individual's average credit score was in between 2007 and 2010, *before* the start of the main sample. Table 4 shows that costs of the coal decline were experienced broadly but in different ways for individuals with high and low pre-baseline credit scores. Individuals with higher pre-period credit scores experienced relatively smaller credit score declines and credit utilization increases and no significant increases in the measures of financial distress shown in columns 4-6 (delinquency, collections, or bankruptcy). In contrast, individuals in the bottom half of the pre-period credit score distribution experienced declines across all of our outcomes. The differences between the top and the bottom of the pre-period credit distribution likely reflect that low pre-period credit score individuals are already more likely to be on the verge of delinquency, 3rd party collections, and bankruptcy before the coal decline in our sample begins.

For subprime status, the point estimate is the largest for the second quartile, which reflects that the subprime threshold is within the range of credit score values in the second quartile, meaning people in this group start out closest to potentially changing subprime status. The bottom quartile is also more likely have a subprime credit score when coal demand decreases, which in practice often translates to these individuals being less likely to improve their credit scores sufficiently to rise above subprime status. Somewhat surprisingly, individuals in the top quartile show a small but significant increase in the percent subprime, which would require a large drop in credit scores given that the lowest pre-period credit score for the top quartile is 769 points.

Before discussing quantile regression results, we note that the findings above are not driven by differences in age, a potential concern because younger people tend to have lower credit scores (Nathe (2021)). Appendix Table A1, which shows results by generation and whether the baseline credit score is in the top or bottom half, yields qualitatively similar results.[26] For example, within generation, the delinquency, third party collections, and bankruptcy result are driven by those in the bottom half of the pre-period credit score distribution.

We complement our baseline credit score analysis with quantile regressions to analyze whether certain parts of the credit score distribution are more sensitive to the decline in coal.[27] We estimate unconditional quantile regressions following Firpo, Fortin, & Lemieux (2009) and Maclean, Webber, & Marti (2014). This approach allows us to estimate whether, for example, the lower percentiles of the credit score distribution face larger declines than the higher percentiles. In contrast to heterogeneous treatment effects by baseline credit scores, this approach does not require us to classify people into bins before treatment.[28]

Our quantile regression results show that the coal decline effects are not uniform across the distribution. Plotting quantile regression point estimates, panel A of Figure 5 shows the impacts of the coal decline are most pronounced for the 30th, 40th, and 50th percentiles of the credit score distribution (with the 40th percentile roughly corresponding to the cutoff for subprime). The top end of the distribution does not shift at all, while the 70th and 20th percentiles show modest declines. For credit utilization (panel B), although there are broad-based statistically significant responses, the responses in the middle-upper end of the distribution (50th – 80th percentiles) are much larger than at the tails. Credit utilization is a key factor in determining credit score: People with high credit utilization tend to have lower credit scores. Therefore, the parts of the distribution for which we observe credit score effects roughly correspond to the parts of the distribution for which we observe the strongest credit utilization effects.

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[26] 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.

[27] We do not perform quantile regressions for the subprime and bankruptcy outcomes because they are binary or for amount in third party collections because it has a large share of observations equal to zero.

[28] We use the rifhdreg package in Stata to estimate unconditional quantile regressions with our full set of fixed effects.

In summary, we find that although the credit outcomes through which individuals are affected vary, deterioration in financial health due to declining coal demand is broad-based and not isolated to the top, bottom, or middle of the distribution based on initial credit scores. However, when we examine how the distribution itself is affected, we find that our average results appear to be driven by a significant downward shift of the mid-lower portion (30^{th} – 50^{th} percentiles) of the distribution.

C. Other specifications

Before concluding, we briefly describe additional specifications which we include in the appendix. These specifications show robustness results when using alternative radii for the demand measure (Table A2), approaches for translating quarterly credit report data to annual measures (Table A3), time frames (Table A4), and treatment of movers (Table A6). The appendix also includes results on movers (Table A5), intertemporal dynamics (Table A7), and explore heterogeneity by income profile of place of residence (Tables A8 and A9), baseline county coal employment shares (Table A10), and natural gas extraction (Table A11).

V. <u>Conclusion</u>

In this paper, we showed that the recent decline of coal mining has hurt household finances in Appalachian coal mining communities. These costs are broad-based and cannot be explained solely by coal miners who have lost their jobs, suggesting that there are significant negative spillovers to others living in the region. We further find that the specific ways in which the decline in coal mining negatively affected individuals varied across the credit score distribution and based on individuals' baseline credit health.

Though 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 fossil fuel 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 higher shares of workers in the fossil fuel extraction industry or fewer alternative employment opportunities.

Our results also have policy implications for those concerned about how the energy transition may affect fossil fuel extraction communities. First, our finding that the costs of the decline in coal mining are not borne solely by coal mine workers who have lost their jobs means that policymakers should look beyond the directly affected individuals in fossil fuel extraction communities. Second, our analyses demonstrate that household finance outcomes are responsive to local declines in fossil fuel extraction and can serve as a useful tool for monitoring outcomes in affected communities in real time.

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 significant benefits from reducing coal activities. For example, older 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 reducing carbon emissions and local air pollution, and providing direct positive health benefits for the mining communities themselves (Hernandez-Cortes & Meng, 2020; Boyles, et al., 2017).

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Tables and Figures

Table 1: Summary Statistics Table

Variable	**Active Coal Mining Counties**	**National Sample**
Coal demand and production		
Millions of short tons consumed within 200 miles by rail	31.64	
	(20.49)	
Total annual coal production (mil. tons)	2.42	
	(3.82)	
Total annual employee hours worked (Thous.)	1,016.19	
	(1,402.95)	
Number of employees	450.06	
	(605.85)	
FRB New York / Equifax CCP data		
Credit score	680.35	686.13
	(108.69)	(106.88)
Percent subprime	37.99	38.50
	(48.54)	(48.66)
Credit utilization (percent)	39.04	38.93
	(39.07)	(38.64)
Delinquent accounts	0.11	0.10
	(0.59)	(0.58)
Amount in 3rd party collections (2012 $)	241.06	184.12
	(1,628.93)	(851.11)
Transition to bankruptcy (percent)	0.49	0.45
	(6.95)	(6.73)
Age	46.08	44.68
	(11.37)	(11.44)

Source: EIA; Census; NY Fed / Equifax CCP

Note: Standard deviation in parentheses. Credit score is the fourth quarter value. Subprime is defined as having a credit score below 660. Credit utilization percent is based on bankcard and retail trade balances and credit limits. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due in the fourth quarter. Amount in 3rd party collections reflects the fourth quarter amount. Bankruptcy equals 1 if individuals transition into chapter 7 or 13 bankruptcy in a year.

Table 2: Relationship between coal tons demanded and coal production measures

	(1) Coal Production (millions of tons)	(2) Hours (thousands)	(3) Number of Employees
Coal tons 200m	0.122***	65.49***	29.11***
	(3.04)	(4.45)	(4.08)
Mean of Dep. Var.	7.55	2,585.22	1,172.95
Observations	928	928	793
Number of Counties	116	116	113

Source: MSHA; EIA; NY Fed / Equifax CCP

Notes: Observations are at county-year level. Coal tons 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. The sample spans 2011-2018. Regressions are weighted by each county's 2007-2010 coal production, and include county and year fixed effects as well as county time trends. Standard errors are clustered by county. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table 3: Credit Outcomes

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 200m	0.0963***	−0.0588***	−0.0467***	−0.000741**	−2.228***	−0.00949***
	(2.88)	(−4.04)	(−4.80)	(−2.28)	(−2.83)	(−2.89)
Mean of Dep. Var.	680.47	41.05	38.73	0.11	206.87	0.49
Observations	1,496,899	1,496,899	1,077,830	1,498,174	1,544,365	1,622,370
Individuals	227,860	227,860	179,609	228,553	232,590	237,964
Individ w/ Outcome	227,860	125,664	174,748	52,979	102,358	8,261

Source: EIA; NY Fed / Equifax CCP

Note: Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades.Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table 4: Coal demand interacted with baseline credit score quartile

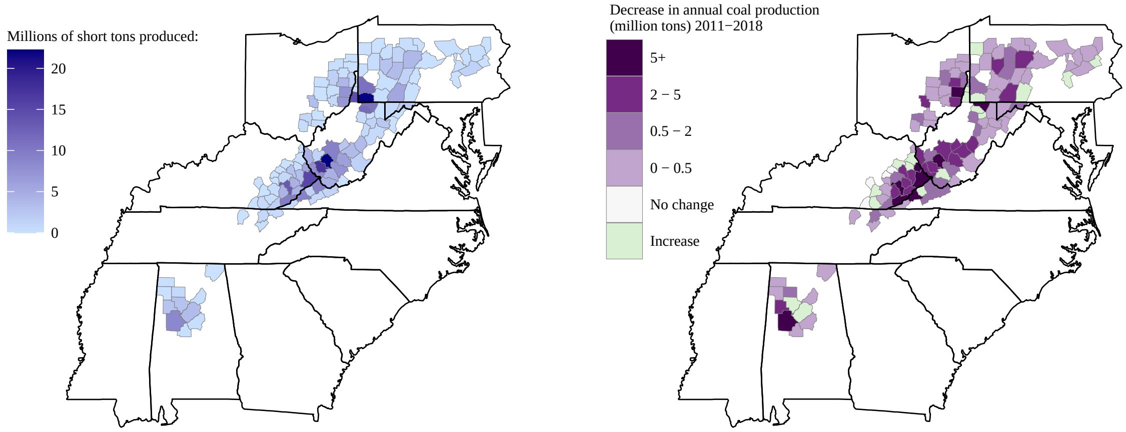
	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal × bottom credit score quart	0.131**	−0.0781***	−0.0638	−0.00162**	−4.360**	−0.0159**
	(2.05)	(−2.69)	(−1.44)	(−2.02)	(−2.00)	(−2.08)
Coal × second credit score quart	0.146**	−0.123***	−0.0534**	−0.000399	−1.460*	−0.0224***
	(2.22)	(−3.23)	(−2.12)	(−0.67)	(−1.77)	(−3.07)
Coal × third credit score quart	0.108**	−0.0344	−0.0594***	−0.000521	0.0105	−0.00312
	(2.44)	(−1.34)	(−3.75)	(−1.43)	(0.03)	(−0.53)
Coal × top credit score quart	0.0719**	−0.0306***	−0.0374***	−0.000192	−0.243	−0.00381
	(2.38)	(−4.19)	(−3.03)	(−1.44)	(−1.34)	(−1.65)
Mean of Dep. Var.	686.28	39.18	38.00	0.11	193.24	0.51
Observations	1,339,211	1,339,211	985,515	1,336,295	1,371,842	1,439,276
Individuals	194,714	194,714	158,096	194,835	197,819	202,251
Individ w/ Outcome	194,714	102,894	154,082	45,035	84,563	7,612

Source: EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with credit score quartiles. Individuals are placed in quartiles based on their median credit score between 2007 and 2010. Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects, county and year FE interacted with the different bins, and linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

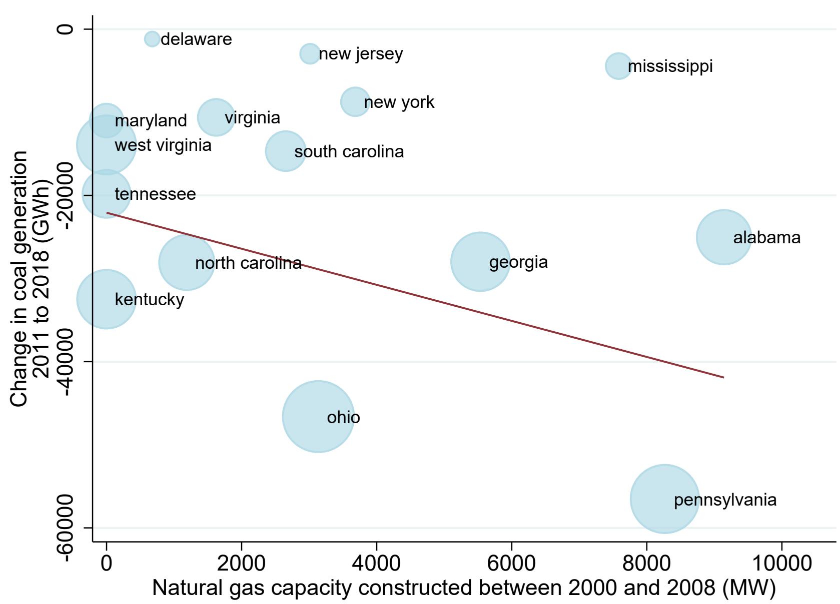
Figure 1: Coal production in Appalachia

(a) 2011 production **(b)** Decline from 2011 to 2018



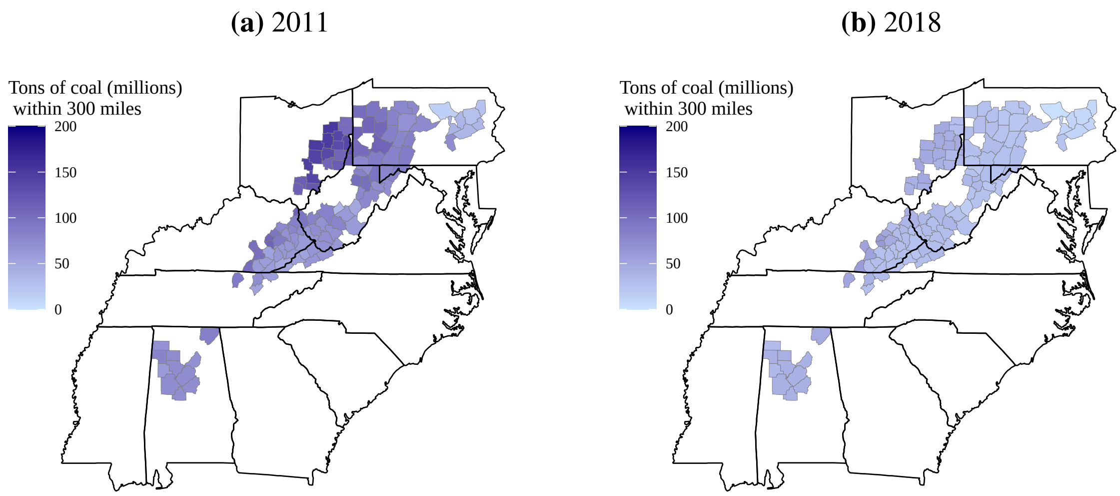
Source: EIA
Counties shown are active Appalachian coal mining counties between 2011 and 2018, our sample period. Defined as: (i) at least one year with non-zero coal production and at least one year with 10,000 hours or more of total annual employee hours in mining (roughly equivalent to five full-time workers) according to the Energy Information Administration (EIA) and (ii) U.S. Mine Safety and Health Administration (MSHA). Counties are considered in Appalachia if they are within the EIA-designated Appalachian mining basins.

Figure 2: Relationship between decline in coal generation and excess natural gas capacity



Source: EIA. Points in figure are weighted by 2007 coal generation.

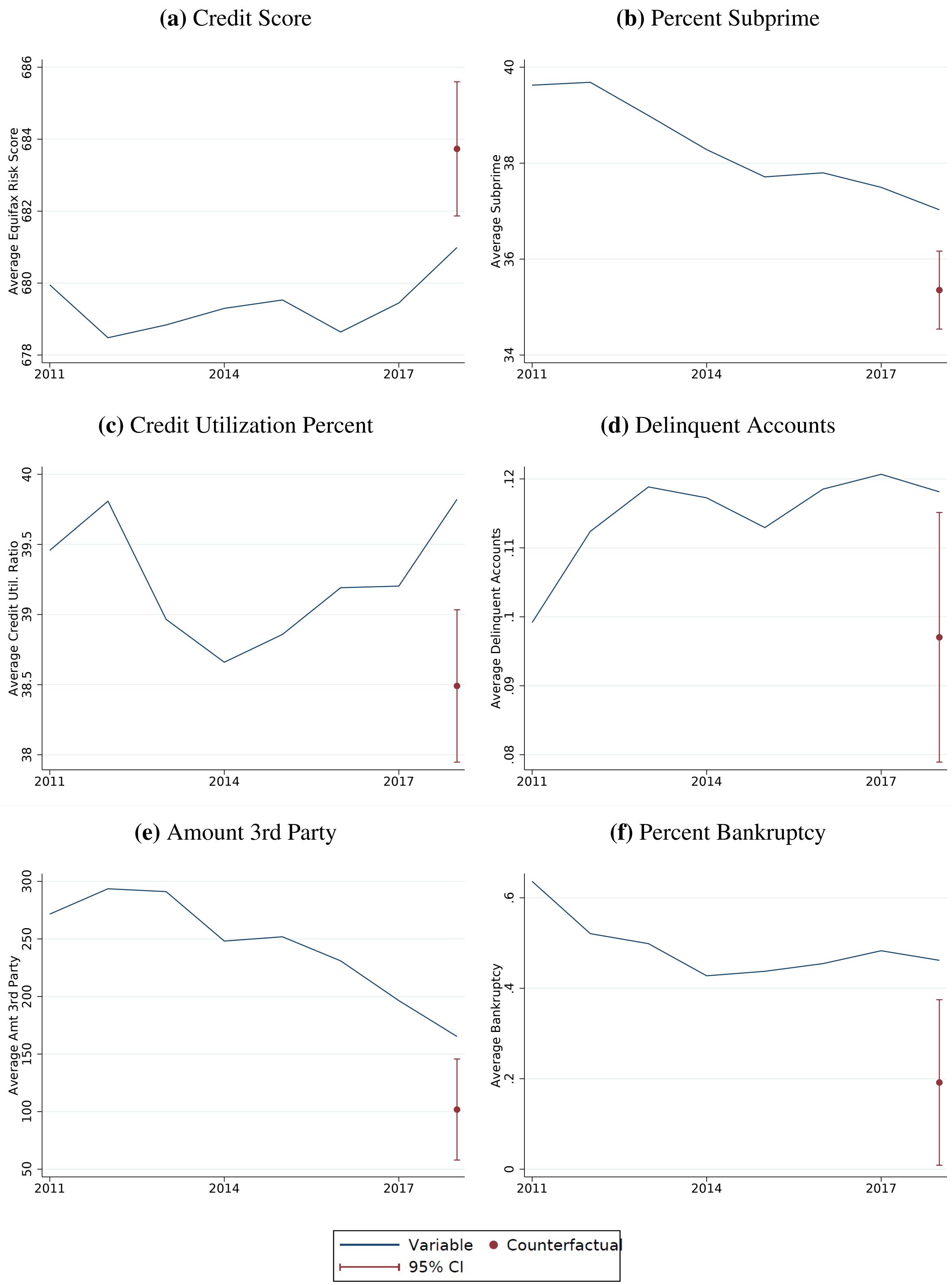
Figure 3: Coal consumed at power plants within 200 miles



Source: EIA

Counties shown are active Appalachian coal mining counties between 2011 and 2018, our sample period. Defined as: (i) 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 Energy Information Administration (EIA) and (ii) U.S. Mine Safety and Health Administration (MSHA). Counties are considered in Appalachia if they are within the EIA-designated Appalachian mining basins.

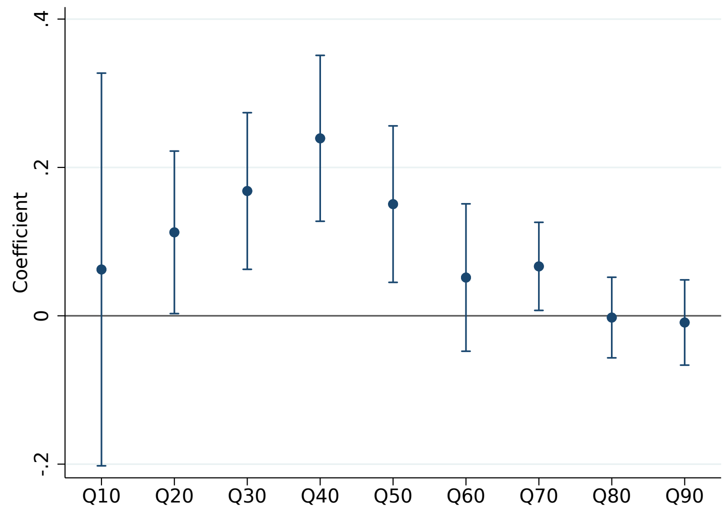
Figure 4: Counterfactual Estimate



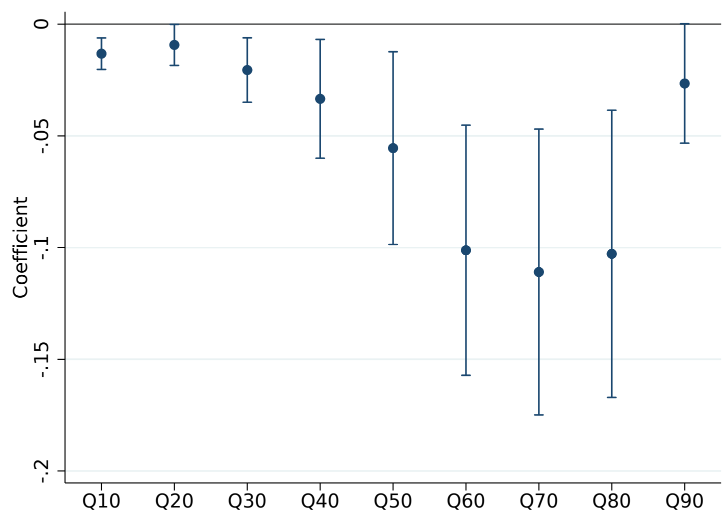
Source: Census; EIA; NY Fed / Equifax CCP
The blue lines depict the outcome variable average annual values. The red dots show counterfactual estimates of the outcomes if coal demanded within 200 miles had remained at 2011 levels. Specifically, for each outcome the distance between the counterfactual and actual levels equals the product of (a) the estimated response of the 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). Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy.

Figure 5: Quantile regressions

(a) Credit Score



(b) Credit Utilization Percent



Source: Census; EIA; NY Fed / Equifax CCP
This figure shows point estimates from quantile regressions with 95 percent confidence intervals.

Appendix

A1. Robustness to alternative radii for coal demand measure

In our analyses we use a 200-mile radius (by rail) when calculating the coal burned at powerplants to measure demand for local coal. We now consider alternative radii for our treatment measure. In Appendix Table A2, panel A, we show that our results are robust to excluding from our coal demand variable the coal burned within a 50-mile radius of each county. This ensures that we are not simply capturing other local economic phenomena that could be driving both demand for coal and household finance outcomes. In Panels B and C, we measure demand based on coal burned within 100 and 300 miles, finding similar qualitative results to our main specification in Table 3. One must take care in comparing the point estimates, as the average treatment value changes as we vary how large of a radius we use.

A2. Use of quarterly credit report data for annual outcomes

In our analyses we use observations from the fourth quarter for our non-bankruptcy variables in order to combine the quarterly credit report data from the CCP with our annual treatment variable. We use the fourth quarter values, which provide snapshots of people's financial health at the end of the year, to assess how the treatment that occurred over the course of a year has affected individuals on net. Appendix Table A3 uses the annual mean (Panel A) and annual maximum (Panel B) of our credit outcomes and finds similar results with the exception of delinquent accounts.

A3. Robustness to alternative time samples

We estimate the response of credit scores 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 Great Recession. However, the NY Fed / Equifax CCP data allow us to extend our analysis back to 2002. Appendix Table A4 shows estimates of the response of credit scores to demand for coal within 200 miles of active coal-mining counties for three alternative specifications. Because coal demand was rising in the first half of the longer samples, in panels A and B, we control for quadratic rather than linear individual time trends. The results in panels A and B, which differ in terms of whether they include 2008-2010 for the Great Recession, show that the response of credit scores to coal demand shocks is even larger for the longer samples than our main specification. The remaining outcome variables show qualitatively similar results, although a few are not statistically significant. Panel C shows that the relationship in the first part of the sample is not statistically significant on its own, suggesting that the recent decline has been particularly meaningful for Appalachian households.

A4. The role of individuals who move counties

One concern is that by focusing on people who live in active coal-mining counties in Appalachia while they are living there, our results may reflect a compositional shift if higher credit profile individuals move out of the region in response to the loss of coal activity. Although this would still mean that the average financial health of residents in the region we study has declined, such a compositional shift could occur even if on an individual basis people are no worse off financially. We perform two analyses that show that moving does not play a significant role in our results. First, county-level regressions in column 1 of Table A5 show that the decline in coal demand does not cause changes in net migration. Column 2 shows, however, that churn (in migration plus out migration) decreases as demand for coal declines, which could reflect a less dynamic labor market. Second, our baseline results are robust to using the counties where individuals lived in 2010 to determine treatment and to restricting our sample to individuals who did not move counties between 2011 and 2018 (see Appendix Table A6).

A5. Intertemporal dynamics

In our main results, we focus on changes in financial outcomes contemporaneous with changes in coal demand. However, as some outcomes may take longer to manifest, our main specification could be missing important responses that appear with a lag. Adding a one-year lag of coal demand to our baseline specification (see Appendix Table A7), shows that there may be some meaningful lagged effects, particularly for credit scores and subprime status. Furthermore, for all of our outcomes, the estimated net effects over the two years are slightly larger than our contemporaneous effects, suggesting our baseline results may be somewhat conservative.

A6. Heterogeneity by income profiles of place of residence

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. We use poverty rates to understand how the socioeconomic status of a neighborhood affects credit outcomes for people living there.[29] 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.

Table A8 shows results from a regression in which we interact the coal demand measure with three bins based on the share of Census block group residents with income below the poverty line in 1999.[30] We find that although people living in lower poverty areas (less than or equal to 20 percent poverty rate) experience significant credit score declines, those living in Census block groups with poverty rates of at least 20 percent on average do not.[31]

One potential explanation for this finding is that people living in high poverty areas may on average already have very low credit scores and may not be in a position to have their credit profiles deteriorate further. Consistent with this explanation, column 3 shows that credit utilization ratios increase significantly for individuals living in high poverty areas. However, in contrast to column 1, this sample is

[29] 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.

[30] 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.

[31] Appendix Table A9, 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.

restricted to individuals who have credit limits of at least $100. When we restrict the credit score analysis sample to this same set of individuals, we find that the credit score result becomes larger and statistically significant for individuals living in high poverty areas. Column 5 shows that the increase in the amount in third party collections is driven by individuals living in areas with relatively low 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).

A7. Coal employment shares and natural gas activity

Two channels that could amplify or ameliorate the impacts of declining coal demand on household finance are baseline coal employment share and natural gas extraction activity. Because employment is a key channel through which declining demand for coal may affect household finances, one might expect that the response to coal demand changes might be larger in counties with a higher initial share of employment in coal mining. In Appendix Table A10 we show that counties with medium and high baseline (2010) coal employment shares have the largest credit score responses. However, individuals in low baseline coal employment share counties are also affected negatively by coal demand declines, experiencing significant increases in likelihood of subprime status, credit utilization, third party collections, and bankruptcy.

We also consider the role that outside employment options in the natural gas sector might play in the costs of the coal decline. Appendix Table A11 conducts a heterogeneity analysis using 2010 natural gas production to group counties into low, medium, and high producing counties. The results show that the medium and high natural gas counties generally show the largest responses to the coal decline, which suggests that the extraction of natural gas in a county is not significantly offsetting the negative effects of the decline in coal production. This finding is consistent with the observation that workers in natural gas often come from outside as natural gas companies do not tend to hire coal workers.

Table A1: Coal demand interacted with generations and credit score bins

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Baby Boomers						
Coal* Low credit score	0.134*	−0.115***	−0.0580*	−0.000506	−1.528	−0.0190**
	(1.73)	(−2.77)	(−1.69)	(−0.75)	(−1.00)	(−2.62)
Coal* High credit score	0.0712**	−0.0317**	−0.0422***	−0.000189	−0.114	−0.000493
	(2.03)	(−1.99)	(−2.84)	(−0.85)	(−0.47)	(−0.13)
Generation X						
Coal* Low credit score	0.148**	−0.114***	−0.0478	−0.00170***	−3.152**	−0.0206**
	(2.16)	(−3.08)	(−1.24)	(−2.75)	(−2.12)	(−2.37)
Coal* High credit score	0.115***	−0.0426*	−0.0597***	−0.000432	−0.0456	−0.00900
	(2.68)	(−1.77)	(−4.09)	(−1.30)	(−0.13)	(−1.37)
Millennials						
Coal* Low credit score	0.0324	−0.0428	−0.0766	0.000229	−5.748**	−0.0129
	(0.31)	(−0.76)	(−1.15)	(0.13)	(−2.39)	(−1.29)
Coal* High credit score	0.106	−0.0520	−0.0288	−0.00117	−0.962	0.00202
	(1.43)	(−1.26)	(−0.89)	(−1.48)	(−1.11)	(0.21)
Mean of Dep. Var.	686.28	39.18	38.00	0.11	193.24	0.51
Observations	1,339,211	1,339,211	985,515	1,336,295	1,371,842	1,439,276
Individuals	194,714	194,714	158,096	194,835	197,819	202,251
Individ w/ Outcome	194,714	102,894	154,082	45,035	84,563	7,612

Source: EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with (1) generations and (2) credit score 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 credit score bins determined by individual's median credit score between 2007-2010.

Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A2: Coal demand interacted with percent of Census block group population below the poverty line in 1999

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal * >0.2 pov share	0.0697	−0.0378	−0.125***	−0.000512	−2.114	−0.0165*
	(0.84)	(−1.20)	(−3.41)	(−0.50)	(−1.01)	(−1.80)
Coal * 0.1 - 0.2 pov share	0.125***	−0.0880***	−0.0348*	−0.000896	−2.433**	−0.0123**
	(2.70)	(−3.99)	(−1.67)	(−1.54)	(−2.58)	(−2.30)
Coal * <0.1 pov share	0.0930***	−0.0515***	−0.0436***	−0.000631**	−1.672***	−0.00993**
	(2.98)	(−2.82)	(−4.09)	(−2.02)	(−3.23)	(−2.45)
Mean of Dep. Var.	685.42	39.49	37.98	0.11	197.10	0.50
Observations	1,315,717	1,315,717	960,505	1,316,235	1,355,803	1,427,777
Individuals	189,992	189,992	153,042	190,523	193,809	198,552
Individ w/ Outcome	189,992	100,749	149,048	43,569	83,511	7,272

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 tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects, county and year FE interacted with the different bins, and linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A3: Coal demand interacted with 1999 Census block group per capita income

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal * $25000 +	0.0637*	−0.0426***	−0.0301***	−0.000353	−1.276	−0.00998*
	(1.73)	(−2.77)	(−2.63)	(−0.93)	(−1.56)	(−1.75)
Coal * $20000-25000	0.137***	−0.0827***	−0.0713***	−0.000777*	−2.578***	−0.0120**
	(3.27)	(−3.36)	(−3.45)	(−1.74)	(−3.37)	(−2.21)
Coal * < $20000	0.111*	−0.0638***	−0.0657**	−0.00123*	−2.828**	−0.0144**
	(1.85)	(−2.83)	(−2.52)	(−1.85)	(−2.26)	(−2.22)
Mean of Dep. Var.	685.42	39.49	37.98	0.11	197.10	0.50
Observations	1,315,715	1,315,715	960,501	1,316,233	1,355,802	1,427,776
Individuals	189,992	189,992	153,042	190,523	193,809	198,552
Individ w/ Outcome	189,992	100,749	149,048	43,569	83,511	7,272

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 tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A4: Alternative time periods

(a) Full time period (2002-2018)

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 200m	0.110***	−0.0506***	−0.0240**	−0.000417	−1.561**	−0.00532**
	(3.41)	(−3.86)	(−2.53)	(−1.62)	(−2.09)	(−2.14)
Mean of Dep. Var.	677.12	41.73	42.27	0.12	223.44	0.74
Observations	3,387,297	3,387,297	2,555,459	3,407,982	3,482,948	3,604,176
Individuals	310,520	310,520	264,240	311,263	313,054	314,765
Individ w/ Outcome	259,881	142,569	202,152	59,579	114,613	9,293

(b) Time period with gap (2002-2007, 2011-2018)

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 200m	0.115**	−0.0551***	−0.0218*	−0.000410	−1.463*	−0.00320
	(2.60)	(−3.26)	(−1.80)	(−1.39)	(−1.69)	(−1.14)
Mean of Dep. Var.	676.87	41.63	42.29	0.12	216.81	0.72
Observations	2,750,012	2,750,012	2,078,734	2,761,110	2,826,235	2,929,465
Individuals	303,155	303,155	256,103	303,886	306,042	308,141
Individ w/ Outcome	254,452	139,473	197,398	58,253	112,394	9,094

(c) 2002-2007

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 200m	−0.00833	0.0122	0.0152	−0.000584	0.219	0.0115
	(−0.19)	(0.49)	(0.64)	(−1.24)	(0.10)	(1.06)
Mean of Dep. Var.	674.03	41.70	45.78	0.12	179.84	1.03
Observations	1,162,769	1,162,769	927,707	1,170,867	1,188,450	1,210,990
Individuals	213,930	213,930	181,771	215,305	216,873	218,469
Individ w/ Outcome	167,224	82,563	128,124	35,357	68,579	6,237

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Coal tons 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. Years included are labeled in the subheadings. 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 A5: Alternative radii

(a) Coal demand measured as coal burned within 50-200 miles

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 50m-200m	0.0939^{***}	-0.0573^{***}	-0.0437^{***}	-0.000775^{**}	-2.101^{***}	-0.00856^{**}
	(2.66)	(−3.75)	(−3.89)	(−2.16)	(−2.65)	(−2.44)
Mean of Dep. Var.	680.47	41.05	38.73	0.11	206.87	0.49
Observations	1,496,899	1,496,899	1,077,830	1,498,174	1,544,365	1,622,370
Individuals	227,860	227,860	179,609	228,553	232,590	237,964
Individ w/ Outcome	227,860	125,664	174,748	52,979	102,358	8,261

(b) Coal demand measured as coal burned within 100 miles

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 100m	0.142^{***}	-0.0699^{***}	-0.0426^{***}	-0.00142^{***}	-2.226^{*}	−0.00839
	(3.85)	(−3.93)	(−2.62)	(−3.74)	(−1.85)	(−1.58)
Mean of Dep. Var.	680.47	41.05	38.73	0.11	206.87	0.49
Observations	1,496,899	1,496,899	1,077,830	1,498,174	1,544,365	1,622,370
Individuals	227,860	227,860	179,609	228,553	232,590	237,964
Individ w/ Outcome	227,860	125,664	174,748	52,979	102,358	8,261

(c) Coal demand measured as coal burned within 300 miles

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 300m	0.0743^{***}	-0.0476^{***}	-0.0233^{***}	-0.000622^{***}	-1.731^{***}	-0.00498^{**}
	(3.20)	(−5.07)	(−2.84)	(−2.68)	(−3.80)	(−2.01)
Mean of Dep. Var.	680.47	41.05	38.73	0.11	206.87	0.49
Observations	1,496,899	1,496,899	1,077,830	1,498,174	1,544,365	1,622,370
Individuals	227,860	227,860	179,609	228,553	232,590	237,964
Individ w/ Outcome	227,860	125,664	174,748	52,979	102,358	8,261

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. Coal tons 100m captures million of coal tons burned within 100 miles of a county's centroid by rail. Coal tons 300m captures million of coal tons burned between 300 miles of a county's centroid by rail. The coal demand average for 200m was 31.76 (million tons), the coal demand average for 100m was 11.23 (million tons), the coal demand average for 300m was 59.95 (million tons). Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. 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 A6: Coal demand distributed lag model

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 200m	0.0698**	−0.0426***	−0.0453***	−0.000878**	−1.569**	−0.00744**
	(2.34)	(−3.52)	(−3.89)	(−2.35)	(−2.19)	(−2.15)
Lag Coal tons 200m	0.0486*	−0.0340**	−0.00621	0.000263	−0.816	−0.00383
	(1.69)	(−2.44)	(−0.52)	(0.91)	(−1.28)	(−1.33)
Cumulative effect	0.118***	-0.077***	-0.051***	-0.001*	-2.385***	-0.011***
	(2.76)	(-4.05)	(-4.37)	(-1.74)	(-2.60)	(-3.26)
Mean of Dep. Var.	682.15	40.51	38.46	0.11	202.75	0.49
Observations	1,446,534	1,446,534	1,045,783	1,447,260	1,491,332	1,567,614
Individuals	223,013	223,013	175,688	223,665	227,897	233,480
Individ w/ Outcome	223,013	122,674	171,090	52,329	100,731	8,228

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Lag of coal demand is a 1 year lag. The cumulative effect estimates the net effect from the contemporaneous and one-year lag. Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A7: County-level regression for churn and migration

	(1) Net Migration (Percent)	(2) Churn (Percent)
Coal tons 200m	0.0434	0.114***
	(1.13)	(3.22)
Mean of Dep. Var.	-0.27	4.60
Observations	928	928
Number of Counties	116	116

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Coal tons 200m captures millions of coal tons burned within 200 miles of a county centroid by rail. For this table, an individual is considered to have moved if they are in one county for at least four consecutive quarters immediately after being in another county for at least another four consecutive quarters. "Net Migration (Percent)" equals the percent of the individuals in a county that moved into the county minus the percent that moved out. "Churn (Percent)" equals the sum of the percentages of the individuals in a county that moved into and out of that county.

Table A8: Sensitivity of results to alternative approaches to treating movers

(a) Coal tons burned within 200 miles based on counties where individuals lived in 2010

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 200m (2010 FIPS)	0.0870***	−0.0578***	−0.0504***	−0.000620**	−2.023***	−0.0101***
	(2.86)	(−3.85)	(−5.09)	(−2.54)	(−3.01)	(−3.33)
Mean of Dep. Var.	686.98	38.96	37.71	0.11	193.51	0.49
Observations	1,286,804	1,286,804	945,593	1,287,270	1,325,583	1,395,996
Individuals	182,653	182,653	148,453	183,160	186,261	190,870
Individ w/ Outcome	182,653	95,496	144,551	41,083	79,101	6,906

(b) Sample restricted to individuals who did not move counties between 2011 and 2018

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal tons 200m	0.0859***	−0.0507***	−0.0557***	−0.000528**	−2.313***	−0.0129***
	(2.72)	(−3.55)	(−5.21)	(−2.28)	(−2.89)	(−3.77)
Mean of Dep. Var.	686.59	38.67	37.03	0.10	186.85	0.45
Observations	1,068,798	1,068,798	771,894	1,070,579	1,104,963	1,168,746
Individuals	161,296	161,296	126,479	161,882	165,057	169,692
Individ w/ Outcome	161,296	84,252	122,594	34,076	68,310	5,239

Source: EIA; NY Fed / Equifax CCP

Note: Coal tons 200m (2010 FIPS) in Panel A captures millions of coal tons burned within 200 miles of a county centroid by rail, where the county centroid is based on the individual's county of residence in 2010. Coal tons 200m in Panel B captures millions of coal tons burned within 200 miles of a county centroid by rail, where the sample is restricted to individuals who did not change counties of residence from 2011 to 2018. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A9: Coal demand interacted with pre-period coal employment share

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal * low share	0.0590	-0.0521^{***}	-0.0326^{**}	-0.000137	-1.866^{**}	-0.00892^{**}
	(1.35)	(−2.82)	(−2.52)	(−0.39)	(−2.26)	(−2.02)
Coal * medium share	0.165^{***}	-0.0798^{***}	-0.0523^{***}	-0.00132^{***}	-1.930	-0.00892
	(4.02)	(−4.95)	(−3.11)	(−2.64)	(−1.27)	(−1.41)
Coal * large share	0.134^{**}	-0.0284	-0.119^{***}	-0.00207^{***}	-2.947^{*}	-0.00972
	(2.39)	(−0.71)	(−3.12)	(−3.17)	(−1.72)	(−0.88)
Mean of Dep. Var.	680.47	41.05	38.73	0.11	206.87	0.49
Observations	1,496,899	1,496,899	1,077,830	1,498,174	1,544,365	1,622,370
Individuals	227,860	227,860	179,609	228,553	232,590	237,964
Individ w/ Outcome	227,860	125,664	174,748	52,979	102,358	8,261

Source: MSHA; EIA; NY Fed / Equifax CCP

Notes: Pre-period coal shares calculated by county level coal employment in 2010 divided by the total number of employed individuals in 2010. Bins are balanced by county. The low share includes counties with coal shares less than 0.0042, the medium share includes counties with coal shares between 0.0042 and 0.03, and the large shares includes counties with coal shares greater than 0.03.

Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A10: Coal demand interacted with pre-period natural gas production

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Low NG * Coal	0.0699	-0.0360	-0.0464^{**}	-0.000968^{***}	0.599	-0.00966
	(1.46)	(−1.58)	(−2.33)	(−2.66)	(0.48)	(−1.54)
Medium NG * Coal	0.127^{**}	-0.0582^{**}	-0.0361^{*}	-0.00119^{*}	-2.879^{***}	-0.000198
	(2.39)	(−2.26)	(−1.69)	(−1.69)	(−3.00)	(−0.03)
High NG * Coal	0.0985^{*}	-0.0702^{***}	-0.0505^{***}	-0.000533	-3.040^{**}	-0.0126^{***}
	(1.90)	(−3.22)	(−4.15)	(−1.10)	(−2.13)	(−3.33)
Mean of Dep. Var.	680.47	41.05	38.73	0.11	206.87	0.49
Observations	1,496,899	1,496,899	1,077,830	1,498,174	1,544,365	1,622,370
Individuals	227,860	227,860	179,609	228,553	232,590	237,964
Individ w/ Outcome	227,860	125,664	174,748	52,979	102,358	8,261

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with county's natural gas production in 2010.

Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Table A11: Alternative Year-Level Measures of Financial Health Based on Quarterly Credit Outcomes

(a) Average

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)
Coal tons 200m	0.0730**	−0.0693***	−0.0494***	0.0000494	−1.737**
	(2.51)	(−4.25)	(−3.99)	(0.17)	(−2.12)
Mean of Dep. Var.	679.63	40.57	39.52	0.11	220.90
Observations	1,517,581	1,517,581	1,128,964	1,522,424	1,563,536
Individuals	229,655	229,655	186,703	230,650	233,757
Individ w/ Outcome	229,655	126,862	183,441	78,173	114,013

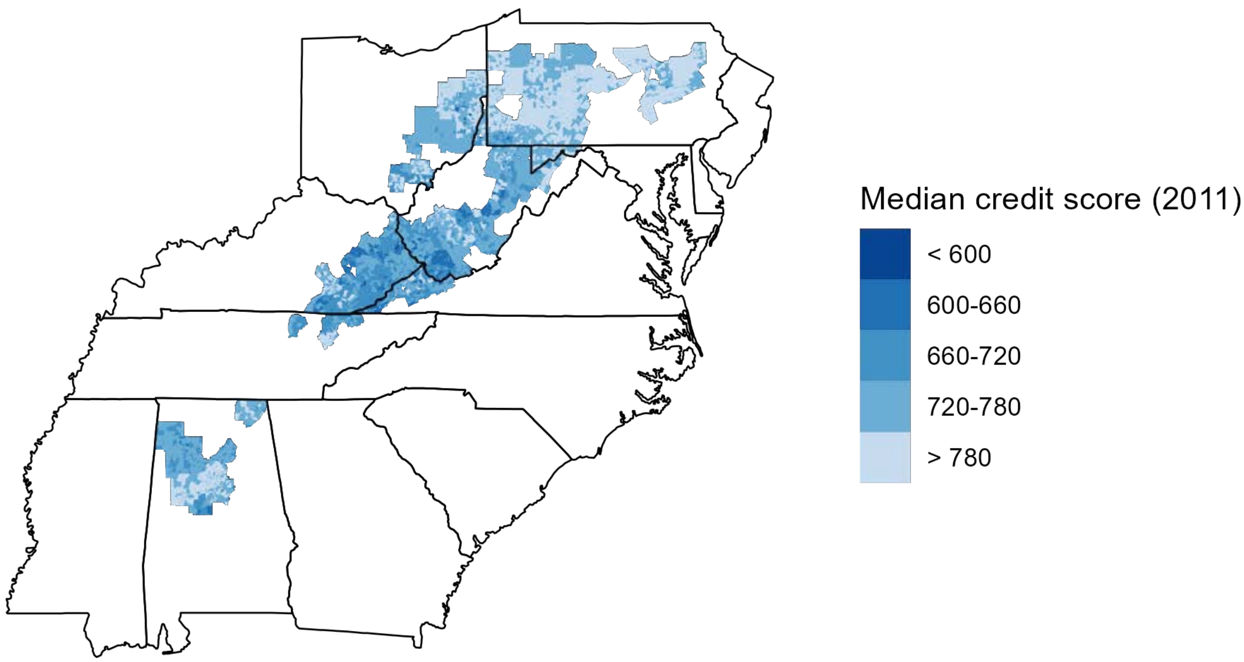
(b) Maximum

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)
Coal tons 200m	0.0758**	−0.0384***	−0.0506***	−0.000122	−3.071**
	(2.14)	(−3.18)	(−4.38)	(−0.23)	(−2.24)
Mean of Dep. Var.	662.20	45.93	47.88	0.24	394.35
Observations	1,517,515	1,517,515	1,128,921	1,522,388	1,563,532
Individuals	229,637	229,637	186,694	230,642	233,750
Individ w/ Outcome	229,637	134,923	183,432	78,169	114,006

Source: EIA; NY Fed / Equifax CCP

Note: Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. Observations are at individual-year level and span 2011-2018. Subprime equals 1 when credit score is below 660. Credit utilization percent is based on bankcard and retail trades. Delinquent accounts is the total number of accounts that are 60, 90, 120 or more days past due. Bankruptcy equals 1 when individuals transition into chapter 7 or 13 bankruptcy. "Individuals with outcome" shows the number of individuals who at some point had a non-zero observation. All regressions include individual, county, and year fixed effects as well as linear individual time trends. Standard errors are clustered by county. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Figure A1: Geographic distribution of credit scores

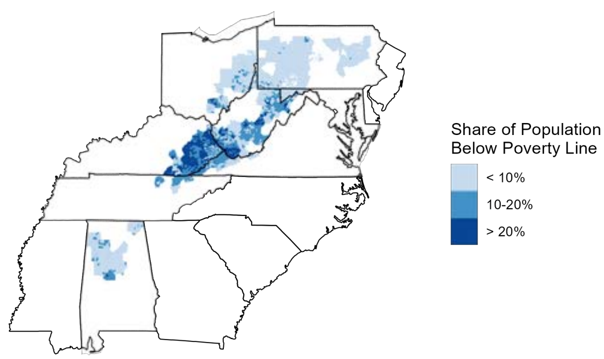


Source: NY Fed / Equifax CCP

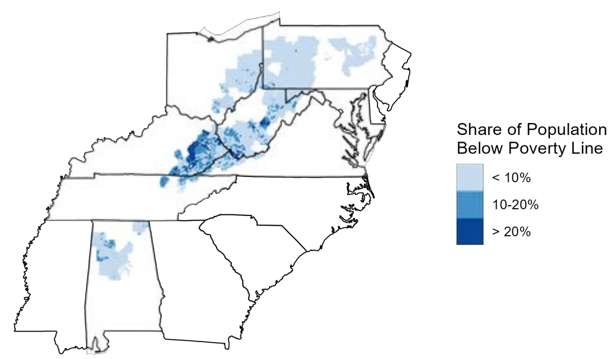
Note: This figure shows the median credit score observed at the Census Block group level. Counties shown are active Appalachian coal mining counties between 2011 and 2018, our sample period. Defined as: (i) at least one year with non-zero coal production and at least one year with 10,000 hours or more of total annual employee hours in mining (roughly equivalent to five full-time workers) according to the Energy Information Administration (EIA) and (ii) U.S. Mine Safety and Health Administration (MSHA). Counties are considered in Appalachia if they are within the EIA-designated Appalachian mining basins.

Figure A2: Census Maps

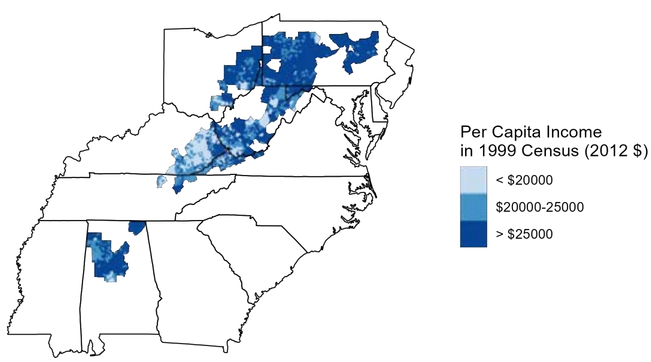
(a) Poverty 2000



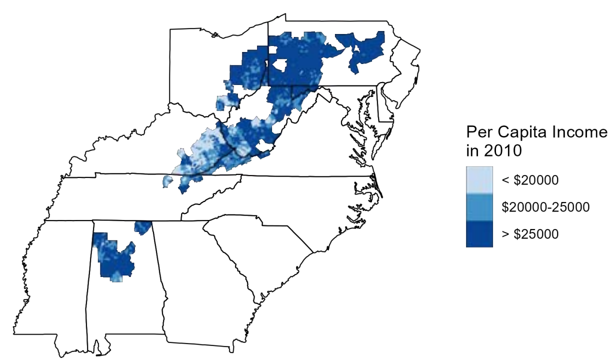
(b) Poverty 2010



(c) Per capita income 2000

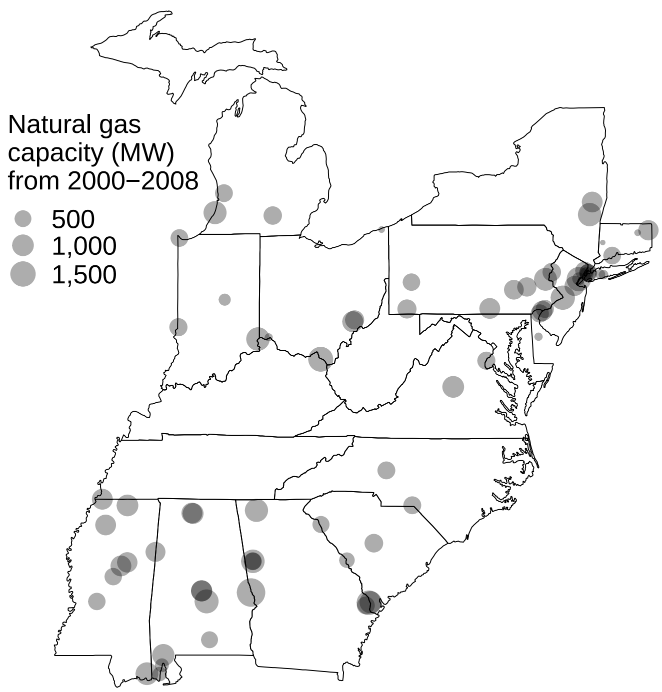


(d) Per capita income 2010



Source: Census.
Note: This figure shows the median credit score observed at the Census Block group level. Counties shown are active Appalachian coal mining counties between 2011 and 2018, our sample period. Defined as: (i) 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 Energy Information Administration (EIA) and (ii) U.S. Mine Safety and Health Administration (MSHA). Counties are considered in Appalachia if they are within the EIA-designated Appalachian mining basins.

Figure A3: Natural gas plants



Source: Form EIA-861M data from the U.S. Energy Information Administration.