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The Canary in the Coal Decline:

Appalachian Household Finance and the Transition from Fossil Fuels*

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March 2025

Abstract

We use individual-level credit data to study how recent declines in Appalachian coal mining affected household finances between 2011 and 2018. Using exogenous variation in electricity sector demand for coal, we find declines in coal demand decreased credit scores and increased financial distress within two years of coal shocks. These effects cannot be explained solely by job losses in coal mine worker households. Credit score declines and financial distress were largest among older individuals and people with lower-middle credit scores. Our results suggest the transition away from fossil fuels may impose meaningful costs on other fossil fuel extraction communities.

Keywords: Coal, household finance, economic transitions

JEL codes: D14, G51, L71, Q52, R11

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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 revenue, and demand for local services. As a result, a transition away from fossil fuels could cause significant financial hardships for people living in regions without comparable alternative sources of employment (Lobao et al (2021); Raimi (2021)). Concerns about the costs to these fossil fuel extraction communities have motivated significant opposition to reducing fossil fuel consumption. 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 such an economic transition: Appalachian coal country.

We explore the magnitude, timing, and distributional 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, respectively, as low-cost fracked natural gas displaced coal in the electricity sector. Coal has historically played a central role in the Appalachian economy. The costs of this economic transition for people living in Appalachia remains an open question, including how fast these costs materialize and whether they are evenly distributed. On the one hand, such large drops in coal mining could cause sizable 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. While this small share could limit the potential negative impacts of the 2011-2018 coal mining decline for Appalachian households on average, certain households and communities may face more severe costs.

We use the New York Fed/Equifax Consumer Credit Panel (CCP), a 5 percent random sample of individuals with credit reports in the United States, 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 our sample. Household finance outcomes such as credit scores, delinquencies, collections, and bankruptcy serve two important roles. First, they provide a snapshot of financial well-being, allowing us to evaluate how people are affected by the decline in coal mining. Second, these measures affect future financial well-being because adverse events on credit reports can limit people's ability to weather negative shocks by making it harder to qualify for new loans (including credit cards, car loans, and mortgages), get jobs, or rent apartments (Ambrose and Diop (2018); Balance, Clifford, and Shoag (2020); Herkenhoff, Phillips, and 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 this 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 in the electricity sector harmed the financial health of people living in Appalachian coal mining counties, decreasing credit scores and increasing financial distress.[2] Our estimates suggest that, if not for the decline in coal demand, 2018 credit scores in these counties would have been nearly 3 points higher on average and about 7 points higher around the subprime threshold. These magnitudes are in line with observed average credit score changes in Appalachia over

[2] We measure credit scores 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.

the sample period and with responses to other large shocks and policies that have underscored that even one-point changes in average credit scores are economically meaningful (Gallagher and Hartley (2017); Brown, Cookson, and Heimer (2019); Argys et al (2020); Dobbie et al (2020); Dettling and Hsu (2021)).

We next consider the dynamics of household finance responses to the coal decline. One might expect shifting coal demand to take time to affect coal production, employment, broader labor markets, and eventually credit outcomes. To better understand the dynamics of the household cost of the coal decline, we use both a distributed lag model and a local projections approach, finding similar magnitude credit score declines as the baseline estimates. We find that the costs of the coal decline transmit to households relatively quickly—with coal demand shocks taking no more than two years (including the year of a shock) to flow through to credit outcomes.

Next, we explore whether these average effects apply evenly or whether some parts of the credit distribution are particularly sensitive to changes in demand for coal. Unconditional quantile regressions indicate that the coal decline primarily reduced lower-middle percentile credit scores. At the 40th percentile, credit scores fell by 7 points, more than double the average effect. With the cutoff for subprime status—which raises borrowing costs and limits access to credit—being at the 42nd percentile (a score of 660), this result indicates that negative impacts on credit scores are largest at precisely the part of the distribution where access to credit is most sensitive to minor credit score movements. Heterogeneity analysis using initial (pre-2011) credit scores indicates that the decline in coal demand had broad-based negative impacts, albeit to varying degrees. Individuals in the bottom half of the pre-period credit score distribution experienced declines across most outcomes we consider. In contrast, individuals with the highest pre-period credit scores experienced relatively modest declines in credit scores and increases in credit utilization but no significant changes in measures of financial distress (delinquency, collections, or bankruptcy). Interacting pre-period credit scores with generation indicators reveals that the main effects are driven largely by Baby Boomers and Generation X, with limited impacts on Millennials.

We then explore the role that income and job losses may play in the declines in household financial well-being in our setting. We begin by examining heterogeneity of credit declines based on the poverty rates where individuals live. We find that people living in Census block groups in the middle of the poverty rate distribution are most affected by the coal decline, which is consistent with our finding that people in the lower-middle part of the credit score distribution are most affected. We also perform back-of-the-envelope analyses to consider whether impacts on coal mine worker households alone might explain our main results. We find that the credit score declines cannot be fully explained by coal mine worker households, suggesting that there are meaningful spillovers from the coal decline into the broader Appalachian economy. Our results provide evidence that, despite coal mining's relatively small share of employment, the coal decline had meaningful credit score effects, including for individuals not directly working in the coal mining industry.

Finally, we investigate the potential role of migration in the response to the coal decline. We confirm via two robustness tests that our main findings do not primarily reflect a migration-driven compositional shift in Appalachia. Next, we perform county-level regressions and find that the coal decline did not change net migration but did reduce churn (the sum of in- and out-migration), potentially suggesting reduced economic activity in the region. We then compare credit score trajectories of individuals who moved out of the Appalachian coal mining region during 2011-2018 versus 2002-2007, when coal demand was strong. We find that, while both groups experienced immediate declines in credit scores upon moving, those who moved during the 2011-2018 coal decline period experienced slower post-move credit score recoveries. We caution that this out-migration analysis is not causal, but the worse credit score trajectory for people leaving Appalachia between 2011 and 2018 could reflect people experiencing job losses or worse economic situations because of the coal decline.

Our paper makes four main contributions. First, we add to the nascent literature examining the costs of energy transitions for households.[3] This literature has primarily used county-level data to examine macroeconomic outcomes in coal mining regions (e.g. Hanson (2023); Krause (2023); Kraynak (2023)). One closely related paper in this literature is Du and Karolyi (2023), which shows that county-level outcomes like employment, wages, and mortgage applications dropped in coal producing counties between 2012 and 2016 relative to non-coal-producing but still resource-rich counties. Our paper adds to this literature by using individual-level panel data and a novel identification strategy based on the electricity sector to estimate average causal effects of the coal decline. Our paper is the first in this literature to focus on household financial outcomes. We leverage the precision of our individual-level data to provide new insights on the financial and economic factors that make this transition more or less severe, including dynamics of coal decline effects, distributional effects, migration responses, heterogeneity, and spillovers. We find that household finance effects vary by age and credit score and materialize quickly, potentially requiring rapid policy responses.

Second, our results add to the literature exploring the effects of large-scale economic transitions in the United States. Our work has similarities to papers that have documented the consequences and costs of increasing import competition from China in the early 2000s (the "China shock") (e.g. Autor, Dorn, and Hanson (2013; 2016; 2021), Pierce and Schott (2016), and Acemoglu et al. (2016)). A particularly relevant analysis is that in Barrot, Loualiche, Plosser and Sauvagnat (2022), who use the CCP to study the effects of China's accession to the World Trade Organization on household finances. They focus on how mortgages can serve as insurance, finding that households in regions with high exposure to import competition took on more debt primarily in the form of mortgages. If the decline in Appalachian coal is the start of a large-scale reorganization of the U.S. energy economy, then it could have similar types of

[3] A related strand of literature examines energy transition costs to firms and investors, showing meaningful implications for asset prices and borrowing costs of exposed firms (Meng (2017); Engle, Giglio, Kelly, Lee, and Stroebel (2020); Bolton and Kacperczyk (2021; 2022); Ilhan, Sautner, and Vilkov (2021); Ivanov, Kruttli, and Watugala (2022); Pástor, Stambaugh, and Taylor (2022); Seltzer, Starks, and Zhu (2022)).

effects as the China shock. Our paper provides evidence that the costs of the decline in Appalachian coal—which emerge quickly—are economically meaningful and particularly pronounced for people in the lower-middle parts of the credit score distribution.

Third, our paper adds to the literature that examines impacts of temporary coal busts in Appalachia on a variety of local outcomes, including disability spending, educational attainment, population growth, entrepreneurship, and local government revenue (see Black, Daniel, and Sanders (2002); Black, McKinnish, and Sanders (2005); Deaton and Niman (2012); Partridge, Betz, and Lobao (2013); Betz et al (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.

Fourth, our paper contributes 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 et al (2020); Dobbie and Goldsmith-Pinkham (2020); Bellon et al (2021); Dettling and Hsu (2021); Blascak and Mikhed (2022); Cookson, Gilje, and Heimer (2022)). This literature has, for example, shown that natural disasters can have significant impacts on household finances (Gallagher and Hartley (2017); Billings, Gallagher, and Ricketts (2022); Beyene (2024)). Our analysis shows that energy transitions also have direct implications for households' financial health.

Our paper provides evidence on how energy transitions could affect other fossil fuel extraction regions in the coming decades. While the geographic and economic context vary by region, our estimates may serve as a lower bound for other resource extraction industries that have a higher share of employment in fossil fuel industries than Appalachia had in the coal industry at the start of our sample. In many cases, similar to coal mining, local economic fortunes are tied to oil extraction, making those communities potentially vulnerable to a decline in oil demand or prices (Decker, Meagan and Upton

(2022); Brown (2021); Brown et al. (2019)). 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). One caveat is that our results are more applicable to those fossil fuel industries that are geographically concentrated, have a long history in a region, and are economically important to their communities. However, many oil extraction communities are similar to coal mining communities, having economically vulnerable populations and a high dependence on the oil industry (Raimi et al. (2022)). The costs for fossil fuel extraction communities, particularly those like Appalachian coal counties that are highly dependent on the prospects of the coal industry, will be increasingly important for policymakers who seek to implement policies to help manage transition costs.

The rest of the paper is organized as follows: Section 1 provides background on Appalachia and the coal industry. Section 2 describes our data. Section 3 discusses our empirical design and identification strategy. Section 4 presents the baseline results along with dynamic analyses. Section 5 examines distributional effects by credit score and the role of age. Section 6 explores the role of income and job losses, while Section 7 examines migration. Section 8 concludes.

1 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 et al (2015), Bollinger, Ziliak, and Troske (2011), Black, McKinnish, and Sanders (2005)). Even when compared with other rural areas in the United States, 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 comparable 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 mid to late 2000s (Energy Information Administration, 2023), 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 3, U.S. coal production and employment declined in recent years because of a reduction in demand from the electricity generation sector that 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 revenue and indirectly through spillovers such as lost service jobs and reduced property and corporate tax revenue (Morris, Kaufman, and Doshi (2019), Welch and Murray (2020)). There are also benefits to reducing coal mining, such as 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.

2 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.

2.1 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 to 2018. Declines in coal production occurred throughout the region.

2.2 Coal consumption

We combine annual data from the publicly available EIA Form 923, which tracks the coal consumed at power plants in the U.S., with National Transportation Atlas Databases 2014 data from the U.S.

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

Department of Transportation's Bureau of Transportation Statistics on the U.S. rail network to generate an exogenous measure of coal demand. We describe this measure in detail in Section 3.

2.3 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 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

[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 four 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.

these variables to assess year-end conditions for individuals relative to that year's coal demand. 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 reflect different types of debt and different phases of financial distress: subprime credit score status, credit utilization, delinquency, third-party collections, and bankruptcy. Table 1 presents summary statistics and shows that, across these indicators, people in our Appalachian sample tend to be worse off than the country as a whole.

Our credit score variable, the Equifax Risk Score, is a proprietary summary measure designed to "help predict the likelihood of a consumer becoming 90 or more days delinquent within 24 months" (Equifax, 2016).[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.

Individuals with subprime credit scores 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 a person's credit score as subprime (Equifax, Federal Reserve Bank of New York, Federal Reserve Bank of St. Louis (2023)).

Credit utilization measures a person's total outstanding balance 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 a \$800 credit card balance has a credit utilization ratio of 80 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

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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.

borrowers. People with prime credit typically use credit cards for consumption, paying off their cards each month. Those with subprime credit tend to use credit cards primarily for debt, carrying a balance from month to month.[9]

Delinquency measures whether people are falling behind on payments to 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.[10,11]

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).[12] These types of bills are not regularly reported to credit bureaus and would not show up in standard measures of delinquency (unlike credit card payments, for example). Instead, these debts typically reach the credit bureaus only once they are in the collections phase.[13]

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[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] We winsorize the delinquent accounts variable at the 99.9th percentile, which caps these observations at 8 delinquent accounts.

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

[13] No standards exist regarding 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).

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, which is very rare.

3 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.

3.1 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 and Cornland (2002); Rubin et al (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).[14] However, this initial influx of natural gas combined-cycle power plants 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 and 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 and McCormack (2019); Coglianese, Gerarden, and Stock (2020)).[15]

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 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

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[14] The construction boom can be seen in Figure 2, which shows the large number of combined cycle natural gas plants built in Appalachia and surrounding states between 2000 and 2008.

[15] Coglianese, Gerarden, and Stock (2020) also consider the role of the Mercury and Air Toxics Standards (MATS) requiring mercury control equipment on coal plants, which 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.

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.[16] We leverage this relationship in our empirical strategy described in the next section.

3.2 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.[17] 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 power plant capacity described in the previous section creates quasi-random variation in changes in demand for coal caused by the subsequent fall in natural gas prices. Power plants typically sell into larger regional electricity markets and their usage depends more on the power plant efficiency characteristics and weather than local economic conditions. As a result, electricity production at power plants is not driven by local economic conditions or household-level credit outcomes.[18]

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

[16] 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.
[17] 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.
[18] Consistent with this assertion, we later show that our results are robust to excluding coal consumption at power plants within 50 miles by rail and to using a radius of 100 or 300 miles for coal demand.

prices would decline starting in 2009 Hanif, Nadeem, Tariq, and Rashi (2022). This predetermined 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.[19] As of 2018, when demand for coal by electricity generators had already fallen significantly, 84 percent of coal mined in the United States 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 that is exogenous to household finances.

3.3 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:

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

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. Because there is serial correlation in the treatment and outcome variables, we include individual (α_i), county (η_c), and year-of-sample (μ_t) fixed effects as well as an individual time trend ($\delta_i t$). Conditional on fixed effects, our estimates of β_2 are identified based on

[19] 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).

the deviations from trends in both credit outcomes and $Coal200_{ct}$. As can be seen in Figure 4, even in the sample averages, there is significant year-to-year variation in our treatment variable. We cluster our standard errors at the county level, the level of our treatment.

Our coefficient of interest, β_2, estimates how an exogenous reduction in coal demand caused by changes in the power sector affects individuals living in active coal mining counties. To facilitate the interpretation of our treatment effects, we rescale our $Coal200_{ct}$ variable by the average annual change in coal demand during our sample window. The β_2 estimate that comes from our rescaled regression shows the changes in individual credit outcomes caused by the average annual decrease in demand for coal.[20]

Our identifying assumption is that, conditional on fixed effects, the outcomes for individuals living in counties with small changes in coal demand in a given year provide a good counterfactual for individuals living in counties with large changes in coal demand, had their demand changed similarly. Given the controls in equation (*1*), we are in essence assuming that the deviations from trend are exogenous and unanticipated. 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 conditional on having the same amount of dose and being in the same time period.[21]

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[20] Specifically, we calculate the sample average annual change in coal burned at power plants within 200 miles of a county by rail, which is a negative value. We then divide the raw level of coal burned at power plants within 200 miles of a county by rail by the annual average change. We caution that rescaled β_2 is not the annual average change in credit scores, but instead should be interpreted as the average effect across our entire time period, including distributed lags, divided by 7, to account for our 7-year sample.

[21] 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.

3.4 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 (IV) 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 demand within 200 miles of a county instead of county-level coal production.

4 <u>Results</u>

4.1 Baseline Results

We find that decreases in demand for local coal cause declines in financial health for people living in active coal mining counties in Appalachia. In Table 3, we present our baseline results from estimating equation (1). In this table and the results throughout the paper, we have rescaled the treatment variable of coal burned within 200 miles by the average annual change in this variable between 2011 and 2018, which was a decline of 4.1 million tons per year in our sample. Rescaling allows us to interpret our coefficients as the average annual change in the outcome variable caused by the coal decline between 2011 and 2018.[22] Multiplying the coefficients by 7 yields an estimate of the average net effect over the 2011 to 2018 timeframe.

Column 1 of Table 3 shows that the average one-year decrease in coal burned within 200 miles of a county caused an average annual 0.386 point credit score decrease for Appalachian coal mining county residents, which translates to about a 2.7 point decrease 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.

Although Table 3 shows that the declines in coal demand had statistically significant effects on credit scores and other household finance outcomes, it is not clear how economically meaningful these effects are. We take three approaches to assess their magnitude. First, Figure 5 contextualizes these effects by showing the actual trajectory of average credit outcomes in our sample between 2011 and 2018 (blue lines) along with the counterfactual 2018 level had the coal decline not occurred (orange dots, shown with 95 percent confidence intervals). Panel (a) suggests our estimated average effect is relatively large given that over the same time period the actual average credit scores had a net increase of 2.9 points (change in

[22] Rescaling does not affect the t-statistics or statistical significance of our estimates.

blue line between 2011 and 2018). Panels (b)-(e) similarly show that the changes in other outcomes caused by the decline in coal mining—as measured by the gap between the counterfactuals (orange dots) and actual levels (blue lines) in 2018—are comparable in magnitude to the actual net observed changes from 2011 to 2018.

Next, we compare our estimates to other shocks studied in the literature. Our average net credit score effect of about 2.7 points is roughly in line with estimated impacts of other economically meaningful shocks on credit scores. For example, Argys et al (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. Our results are also similar in magnitude to the 2-3 point drop in average credit score during the Great Recession (Dorhelm (2021)).

Other papers have found somewhat larger credit score responses from negative shocks. For example, Gallagher and Hartley (2017) find temporary credit score declines of 4 to 7 points when using the CCP to focus on the individuals who resided in the Census blocks that flooded during Hurricane Katrina. In an examination of financial market development in Native American reservations, Brown, Cookson, and Heimer (2019) estimate that growing up in communities without local banking led to 6-to-10-point lower credit scores. Our quantile regression results for credit score declines, detailed in Section 5, find responses similar to these estimates.

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. Figure 5 panel (b) shows that the decline in coal over the course of our sample increased the probability of having subprime status by 1.5 percentage points for the average person. Even relatively small changes in credit score can have large financial consequences if such changes push a person into a higher interest rate on a loan like a mortgage. For example, as of November 2023, for a person buying a median-priced home in Kentucky (a state with counties in our active coal mining sample) with a 20 percent down payment, falling from a FICO score of 660 - 679 to a score of 640 - 659 means paying an extra $18,000 over the life of the loan.[23]

4.1.1 Robustness

Our baseline findings are robust to a variety of alternative specifications. We begin by examining our treatment measure. One concern is that our coal demand measure could reflect other local factors that decrease both local demand for coal and the health of the local economy. To address this concern, in Table 4 we report results when we modify our coal demand variable to only include coal burned between 50 and 200 miles from a county. These results are similar to our baseline results in Table 3, suggesting that local economic activity is not driving our main findings. In Appendix Table A1 we likewise find that using an alternative radius of 100 or 300 miles for our coal demand measure yields qualitatively similar results. In Appendix Table A2 we show that using alternative approaches to turn quarterly outcome data into annual measures yield similar results.

We next consider whether our findings are robust to extending the sample further back in time. Panels (a) and (b) of Table 5 indicate 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, with the exception of delinquent accounts, there are no significant effects during 2002-2007, when coal demand was not declining significantly.

We also explore if there are different treatment effects for parts of Appalachia that have a higher concentration of employment in the coal industry or that are large natural gas producers. Appendix Table A3 shows that there are larger credit score declines for areas that have medium and higher shares of

[23] Home price data from U.S. Census Bureau; https://www.census.gov/quickfacts/fact/table/KY/INC110221. Credit score and interest rate data as of November 2023 from my FICO; https://www.myfico.com/credit-education/calculators/loan-savings-calculator/, November 2023.

employment in the coal industry, suggesting that a larger concentration of coal mine workers results in larger costs from the coal decline. Appendix Table A4 finds that the presence of natural gas production in a county does not reduce the negative consequences of the coal decline. Counties that have medium and high levels of natural gas production show higher costs of the coal decline.

4.2 Dynamic effects of the coal decline

We now examine how quickly the coal decline affected people living in active coal mining counties. In Section 4.1, we estimated the causal effect of the 2011-2018 coal demand decline on average credit scores in Appalachia over the same period. However, that specification does not speak to the dynamics of how long it takes for such declines to affect household financial outcomes. On the one hand, it could take time for declines in demand for coal to translate into cutbacks in coal production, layoffs at mines, and ultimately broader local economic impacts and then further time for these shocks to affect credit scores. On the other hand, coal mines could quickly cut production, which could immediately spill over into the local economy and lead to rapid declines in credit outcomes. In this section we implement two approaches to better understand the dynamics of household finance responses to coal demand shocks.

In our first approach, we add two lags of our coal demand variable to our baseline specification.[24] Table 6 shows the results, which reveal that the decline in coal demand in a given year caused a deterioration in household credit outcomes within the same year. Column 1 indicates that a significant contemporaneous effect on credit scores is followed by a somewhat smaller and marginally less significant effect the following year.[25] The second lag is insignificant and near zero. Subprime status in column 2 follows a similar pattern. In contrast, the contemporaneous effects for the remaining outcomes (credit utilization, delinquent accounts, amount in third-party party collections, and bankruptcy) appear to

[24] Recall that our coal demand coefficient represents deviations from individual-specific time trends, which reduces serial correlation in contemporaneous and lag specifications.
[25] Note that contemporaneous responses could include changes in coal demand in the beginning of a calendar year causing credit to decline later in the calendar year, so that we capture the net effect by the fourth quarter.

be larger and more significant than the lag effects, showing that these negative outcomes mainly manifest within the first year.

In Table 6, below the main coefficient estimates, we also show the estimated three-year cumulative effects over all three coefficients—contemporaneous, first, and second lags. These cumulative effects are generally a bit stronger than our baseline estimates in Table 3, suggesting that the initial effects do not reverse for at least three years.[26] This result may explain why the lag of credit score is significant, as credit scores may decline further when people are unable to fix past credit issues.

To better understand the full dynamics of the coal decline on household finances, our second approach estimates impulse response functions using the panel local projection method (Jordà (2005)). Local projections allow us to dynamically estimate the impact of a negative coal demand shock without the potential for lagged declines in coal demand affecting the contemporaneous treatment variable. Specifically, we estimate

$$\begin{aligned} Y_{i,c,t+h} - Y_{i,c,t-1} = \quad & \beta^h \Delta coal200_{c,t} + \alpha_i^h + \alpha_c^h + \alpha_t^h + \sum_{\substack{\tau=-3, \\ \tau\neq 0}}^{h} \delta^{\tau h} \Delta coal200_{c,t+\tau} \\ & + \sum_{\tau=-3}^{-1} \rho^h \Delta y_{i,t-\tau} + \varepsilon_{c,t+h} \end{aligned} \tag{3}$$

repeatedly for a series of horizons (h) starting with horizon 0 (the contemporaneous effect). For each regression, the outcome is the cumulative change in the dependent variable from baseline period $t-1$ to the horizon period $t+h$. The regressions produce a series of β^h coefficients that trace out the estimated cumulative effects of the treatment at different horizons. The treatment is the one-period change in demand for coal in period t, defined as $\Delta coal200_{c,t} \equiv coal200_{c,t} - coal200_{c,t-1}$. As with our other

[26] The lack of a significant cumulative negative effect on delinquent accounts, which had negative but statistically insignificant point estimates for the lag effects, could reflect that accounts which are closed after going delinquent will no longer show up as delinquencies. This makes the number of delinquent accounts decrease even though individual financial health has not improved.

specifications, the coal variables have been rescaled by the average one-year decline in coal demand between 2011 and 2018 in our sample. The horizon 0 regression is similar to a first difference regression. The specification includes individual fixed effect α_i^h (which controls for individual time trends because the outcome and treatment variables are in differences), county fixed effect α_c^h, time fixed effect α_t^h, three lags and h leads of changes in coal demand, and three lags of one-period changes in the dependent variable. These lags directly control for changes in credit outcomes immediately preceding the shock as well as for subsequent shocks in coal demand that could be serially correlated. Given these controls, the $\Delta coal200_{c,t}$ term serves as a shock that explicitly captures deviations from trends with limited serial correlation. Consistent with our baseline specification, we cluster standard errors by county, which is our level of treatment.

Figure 6 shows the results of estimating the impulse response functions using equation (3). Consistent with our distributed lag findings in Table 6, panel (a) shows that credit scores decline immediately the year of a negative coal demand shock. It shows that credit scores decline further the next year and stay depressed for at least three years after the shock. After three years, confidence intervals widen, which is to be expected given that our treatments only span 2011-2018, thereby limiting sample sizes and statistical power at longer horizons. It is possible that effects reverse by year 4, particularly given the point estimate in year 4 is close to zero. However, the small sample size and wide confidence bands in those years limit our ability to draw conclusions beyond 3 years post-shock. Percent subprime, credit utilization, and amount in third-party collections also show qualitatively similar impulse responses to credit score, though they manifest as increases in negative outcomes. In panel (d), we find a significant increase in delinquent accounts that appears to wane a bit more than the other non-bankruptcy outcomes. We do not find a significant effect on bankruptcy in this specification, which could reflect the relative rarity of bankruptcies.[27]

Both our local projection and distributed lag approaches show that the negative effects of declining coal demand on household financial health appear within the first two years after a negative coal demand shock and do not reverse during our sample window. The approximately two-year time frame for a decline in coal demand to fully affect credit scores suggests that there is both a relatively quick transmission of the coal decline to local economic conditions and from local economic conditions to individual credit scores. We observe two periods of significant declines in coal demand (Figure 4), suggesting that the deterioration in household finances from the coal decline likely occurred both early and late in our sample, with the largest negative effects likely occurring over the 2015-2017 time frame. Moreover, both the distributed lag model and local projection results yield credit score declines similar in magnitude to the baseline estimates. We caution that our findings reflect our empirical setting but may not capture all the potential dynamics of the coal decline. It is possible that the long-run decline in coal demand over the preceding decades has also contributed to declines in the financial health of Appalachian residents, which our exogenous variation of coal demand shocks from the electricity sector will not capture. Despite these caveats, our analysis identifies a channel through which declines in coal demand can quickly harm Appalachian residents.

5 Distributional effects by credit score and age

5.1 Distributional effects by credit score

Having established that decreasing demand for coal leads to worse credit outcomes on average and that effects emerge quickly, we now explore whether these average effects apply evenly or whether some

[27] We model delinquent accounts and bankruptcy somewhat differently here than in Section 4 because of the nature of these variables. The delinquent accounts variable is measured as the net increase in the number of delinquent accounts rather than the net change. This prevents us from measuring the closure of a delinquent account—which may enter collections—as an improvement in financial health. Similar to our baseline regressions, bankruptcy is measured as entry into bankruptcy during the period in question, though it is cumulative for longer horizons.

parts of the credit distribution are particularly sensitive to changes in demand for coal. We take two complementary approaches to answer this question. First, we estimate a heterogeneity analysis in which we group 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 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 between 2007 and 2010, *before* the start of the main sample. Table 7 shows that costs of the coal decline were experienced broadly but in different ways for individuals with high and low initial credit scores. Individuals with the highest pre-period credit scores experienced smaller credit score declines. Although their credit utilization went up and their credit scores went down, they experienced no significant increases in delinquency, collections, or bankruptcy. In contrast, individuals in the bottom half of the pre-period credit score distribution experienced statistically significant adverse responses for all outcomes but delinquency. The differences between the top and the bottom of pre-period credit score distribution likely reflect that low pre-period credit score individuals are already more likely to be on the verge of third-party collections and bankruptcy before being affected by the negative shock of the coal decline.

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

Next, 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 7 shows the impacts of the coal decline are most pronounced at the lower-middle percentiles of the credit score distribution. The 40th percentile, which roughly corresponds to the cutoff for subprime status, exhibits about a 1-point annual decline, which translates to a net 7-point decline between 2011-2018. In contrast, the top and very bottom ends of the distribution do not shift at all. For credit utilization (panel (b)), the responses in the middle-upper end of the distribution 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.

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 not isolated to the bottom, middle, or top 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 of the distribution. This is also the part of the distribution where several points have the greatest potential to make the difference between being able to access credit or having to pay significantly higher interest rates when borrowing.

5.2 Age and credit score

We next consider the role that both age and credit score might play in our results. On average, younger people tend to have lower credit scores because they are still establishing a credit history (Nathe (2021)), which means that the heterogeneity results in Table 7 could reflect age differences. In our setting, younger people are also less likely to have built their careers around coal. Table 8 shows our results when interacting coal treatment with indicators for the generation of people and whether the baseline credit score is in the top or bottom half.[28,29]

The results reveal several insights. First, the coal decline causes no significant credit effects for younger people (Millennials, at most 37 years old in 2018) other than driving up third-party collection amounts for individuals with initially low credit scores. The lack of broader effects for Millennials could reflect their being less exposed to the coal mining sector. Second, the strongest negative credit score effects are among people in Generation X, which suggests that people between their early 30s through early 50s were the most affected overall by the coal decline. Third, Baby Boomers and high credit score Generation Xers are the main groups that significantly increase their credit utilization during the coal decline. At the same time, bankruptcy responses appear to be driven by low credit score Baby Boomers and Generation X members.

6 Role of Income and job losses

Negative income shocks from job losses are likely an important channel through which declines in coal demand affect household finances. In our setting, such shocks can result from jobs lost directly at coal mines, in upstream or downstream enterprises, or in the general labor market. While other papers have found that the coal decline reduced average county-level income (see for example Du and Karolyi (2023) and Kraynak (2023)) and that income is moderately correlated with credit scores (Beer, Ionescu, and Li (2018)), the role of income and job losses in our setting remains an open question. Furthermore, income may play an important role in financial health, as lower income individuals may find it more

[28] 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.

[29] Note that adding 18-24 year olds yields qualitatively similar results, though some results like the Millennial bankruptcy estimate are statistically significant (see Appendix Table A5). However, we exclude individuals under 25 out of concerns that the sample is less representative for younger individuals who are less likely to have established credit histories (resulting in selection bias concerns). Our baseline results are robust to including 18-24 year olds (see Appendix Table A6).

difficult to respond to negative shocks like the coal decline. While our individual-level credit data provide significant advantages in estimating the cost of the coal decline, it is limited to credit records, which do not contain information on employment or income. With this limitation in mind, we perform three sets of analyses exploring the potential role of income and job losses in our setting.

In our first analysis, we examine heterogeneity of credit outcomes by Census block group poverty shares, a local measure of income. Table 9 shows results from a regression in which we interact our main coal demand measure with three poverty bins.[30,31] We find that the negative credit effects of the decline in coal demand were largest for people in the middle bin, which are in block groups where 1999 poverty shares ranged from 10-20 percent. In contrast, credit score responses were insignificant for people living in communities with the highest poverty shares (above 20 percent). The lack of a significant response may reflect that people living in higher poverty areas did not have strong economic ties to the coal mining industry or the labor force in general. Furthermore, they may have already been facing such significant economic hardships that the incremental impact of the coal decline may not have been meaningful for them. The results from this analysis are consistent with our findings in Section 5 indicating that the middle-lower parts of the distribution were most affected by the coal decline.[32]

Our second analysis investigates the potential role of changing income and employment in the credit score decline estimated in Section 4.1. Specifically, we add three time-varying county-level measures of income and employment from the U.S. Bureau of Economic Analysis to our baseline credit score regression. We present these results in Table 10, which shows log of total nonfarm personal income per capita (including categories like rental income and unemployment insurance) in columns 1 and 2, log of

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[30] Our approach is similar to Barrot, et al. (2021), who use zip code level demographics to proxy for individual characteristics.

[31] We use the 2000 Census to capture the share of decennial Census block group residents with income below the poverty line in 1999 because (a) it predates our outcomes and (b) data limitations in the NY Fed / Equifax CCP prevent us from using 2010 Census block groups for our full 2011-2018 sample.

[32] Appendix Table A7, 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.

wage and salary income per capita in columns 3 and 4, and per capita employment in columns 5 and 6. The significant coefficients on wage income and employment in columns 3-6 suggest that the employment mechanism is a channel through which coal demand could affect household finance. These findings are consistent with Du and Karolyi (2023), who find meaningful declines in overall county-level employment and wages in coal-producing counties. However, we find that the coefficients on coal demand in columns 1, 3, and 5 are little changed relative to our baseline results in Table 3, with the coal coefficient being at most 8.5 percent smaller when we include per capita employment in column 5. Taken together, the findings in Table 10 support the idea that income and job losses are a channel through which the coal decline affected people's credit scores. However, we caution that our measures of income and employment are county-level averages and change gradually. This could explain why including them does not have a large effect on the coal decline coefficient.

In our third analysis, we perform back-of-the-envelope calculations to examine whether our average coal decline effects estimated in Section 4.1 can be attributed to job losses. We begin with an extreme case in which households and the local economy experience no spillover effects to determine whether individuals who lost jobs at coal mines can explain our results. Because we are unable to observe either income, employment, or employers of individuals in the CCP, we assume that our CCP sample is proportionally representative of the workforce to estimate that 1,017 individuals in our sample lost jobs at coal mines between 2011 and 2018.[33,34] If the average coal demand decline effects estimated in Table 3 were in fact only experienced by these individuals, then the average credit score decline for people in this group would have been about 494 points between 2011 and 2018. We observe no individuals with credit

[33] Workers at coal mines include office workers, who account for about 3 percent of coal mine workers in Appalachia. Our estimate uses the fact that the number of people working at coal mines in Appalachia dropped from 61,000 to 31,000 between 2011 and 2018 (Mine Safety and Health Adminstration, 2022).

[34] 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 percent of the working population of active coal mining counties in Appalachia.

score drops that large from 2011 to 2018. Therefore, we conclude that the average treatment effects are not coming solely from individuals who lost jobs in the coal mining sector.

We further explore the lost jobs mechanism by considering not only coal mine workers but households with coal mine workers. We assume each individual working for a coal mine shares a household with another equally affected individual. This doubles the estimated number of affected individuals in our sample to 2,034, whose average credit score hits would have been 247 points to explain our full effect. Among the 2,034 individuals with the largest declines in credit scores from 2011-2018, the average decline was 232 points, slightly below 247 points. As a result, we rule out that our estimated drop in credit scores is coming only from households with direct coal mine job losses, suggesting that people outside the coal industry are likely affected.

Our back-of-the-envelope calculations are consistent with other papers that have found that industry-specific negative shocks tend to spill over to jobs in adjacent industries and potentially more broadly as demand for services falls in response to declining local income (e.g. Autor, Dorn, and Hansen (2013; 2021), Autor et al. (2014), Feler and Senses (2017)). Moreover, our findings on employment spillovers outside the coal industry are consistent with Du and Karolyi (2023)'s analysis showing that county-level employment in non-coal sectors is affected by the coal decline. Unfortunately, because we are not able to observe which individuals worked in mining or what the individual counterfactual credit scores would have been if not for the decline in coal, we are unable to extend our back-of-the-envelope analysis to pin down the magnitude of such spillovers. However, by ruling out the extreme cases of no spillovers beyond coal mine worker households, the analysis strongly suggests that the decline in demand for coal caused significant spillovers to the local economy.

6.1 Fragility versus Loss in Economic Opportunity

We now consider the question of whether the effects on credit outcomes are largely driven by a loss in economic opportunity or by fragility in household finances. Household financial fragility can be thought of as a situation where small shocks have large negative financial consequences for households.

Other work using county-level data finds the employment impacts of the coal transition are more pronounced in counties that are more rural, have fewer local bank branches, and have lower economic mobility, suggesting a role for fragility (Du & Karolyi (2023)). Our analysis allows us to compare within- and cross-county heterogeneity. To distinguish between fragility and the loss of economic opportunity as mechanisms we would need individual-level data on income (to identify the sizes of individual shocks) and ideally a measure of precautionary savings (to identify the capacity to absorb shocks). While our individual-level data from credit reports offer many advantages, these data do not include information on income or savings, preventing us from examining fragility directly. However, a few of the analyses in our paper can provide suggestive evidence on the potential role of fragility in our findings.

Both the quartile (Table 7) and quantile regressions (Figure 7) find that people in the middle-lower parts of the credit-score distribution are most affected. Similarly, Table 9 shows the coal decline had no significant credit score effects for people living in Census block groups with poverty shares above 20 percent. A common theme in our findings across our distributional analyses is that the most disadvantaged people in our sample are not necessarily the most affected by the coal decline. This could be for a number of reasons, including that people with the lowest incomes and credit scores may be out of the labor force (e.g. on disability). However, to the extent that fragility is correlated with having low credit scores and living in high poverty areas, our findings suggest that fragility may not be driving our findings. Instead, we may be measuring a response to a negative economic shock that mostly hits people in the lower-middle parts of the income and credit-score distributions.

7 Migration

The results presented so far have focused on how the 2011 to 2018 coal decline affected the financial health of people living in Appalachian coal mining counties. By examining individuals while they lived in Appalachia, we have studied how the coal decline affects places, an important question for policymakers supporting energy communities.[35] However, the decline also affects people. Migration is a potential response to a negative shock like the coal decline. In this section we explore three questions related to migration in the context of the Appalachian coal decline.

First, we investigate whether a compositional shift resulting from migration could be driving our baseline results. We do this with two sets of regressions presented in Table 11. In panel (a), we measure coal demand treatment based on each individual's county in 2010, the location each person was in before the coal decline might have caused them to move into or out of the county. In panel (b), we limit our sample only to individuals who did not move counties between 2011 and 2018. Both sets of results are similar to our baseline, indicating that our main results are not driven by migration.

Second, we consider whether the coal decline affected migration. In Table 12, we show results from regressing county-level net migration (in-migration minus out-migration) and churn (the sum of in- and out-migration) on changes in coal demand. The results indicate that declining demand for coal caused decreases in churn but had no significant effects on net migration. In other words, fewer people moved into the area *and* fewer people moved out, which could reflect a reduction in economic opportunities simultaneously attracting fewer new people to the area and reducing the means to leave.

Finally, we consider how individuals who moved out of Appalachia during the coal decline fared after leaving. This question relates to a recent literature that has used longitudinal data and migration decisions to examine how the characteristics of the place an individual lives affect their well-being or financial decisions (e.g. Brown, Cookson, and Heimer (2019); Jacobsen, Parker and Winikoff (2023); Finkelstein, Gentzkow, and Williams (2021)). For example, Jacobsen, Parker and Winikoff (2023) find that when people move, their bankruptcy rates—which are somewhat dependent on local bankruptcy court rules—converge toward the rates in their new locations, while collections and default outcomes do not. In our setting, we compare the credit score trajectories of individuals who permanently moved out of

[35] The literature that uses aggregate county-level data also examines place-based outcomes. See the discussion in Jacobsen, Parker, and Winikoff (2023) on a similar analysis comparing effects on "people" versus "places."

the Appalachian coal mining region during a "coal decline" period (2011-2018) to individuals who moved out during a "pre-decline" period (from 2002-2007, before the Great Recession). We caution that the coal decline likely changed the timing and composition of out-migration from Appalachia, which limits our ability to draw causal inferences about the impact of the coal decline on movers. The movers analysis that follows should be interpreted as descriptive.[36]

Panel (a) of Figure 8 shows the average credit score of individuals in the quarters before and after their moves out of Appalachia, with separate series for movers in the pre-decline period (2002-2007) and the coal decline period (2011-2018). The vertical line indicates the last quarter before an individual moved out of Appalachia. Panel (a) offers two key insights. First, in both the coal decline and pre-decline periods, individuals' credit scores dropped when they moved. This could reflect a variety of factors including the use of credit to pay for the move or home furnishings, the effects of credit checks for mortgages that can temporarily lower one's credit score, or negative shocks like job losses that precipitated moving and could simultaneously pose other economic difficulties after moving.

Second, the drop in credit scores in Figure 8 panel (a) is more persistent for individuals moving during the coal-decline period.[37,38] While a variety of macroeconomic factors may explain the difference, two potential explanations stand out that are specific to our setting. If people who left Appalachia in the coal-decline period were in worse financial shape going into the move (e.g. having just lost their jobs or with less cash on hand), this could have made it harder to restore their credit. Alternatively, because

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[36] The previous analysis shows that overall mobility declined in this region, which could reflect changes in both desire and means to move.

[37] This is consistent with our finding above that credit outcomes deteriorate even when we assign coal demand treatment based on 2010 locations, an analysis that includes people who have moved out.

[38] In Appendix Figure A2, we compare the trajectories of credit scores for people who moved out of Appalachia between 2011 and 2018 to those who moved out of the Bakken Formation and Mississippi Delta regions. These two regions offer useful comparisons to Appalachia's coal-specific decline. The Bakken region has fossil fuel extraction and experienced economic benefits from the fracking boom during our sample window. People who left this region experienced a temporary drop but an increased slope of future credit score gains. The Delta region allows for comparison to a region that has faced persistent poverty but is not reliant on coal. People in Appalachia had better pre-move credit score trajectories than people in the Mississippi Delta, but similarly sloped trajectories after the move, suggesting that the coal decline could be negatively affecting the people leaving Appalachia's post-migration credit score trajectories.

demand for coal was high during the early period, the average outside opportunity that would entice individuals to leave Appalachia may have been more attractive in the pre-decline period, making it easier to restore credit soon sooner after moving.

Finally, in panel (b) of Figure 8, we examine heterogeneity of post-move outcomes by age at time of move. We find that in the coal-decline period, the post-move credit score decline lasted longer for people who were at least 45 when they moved. Together with our findings in Table 8 showing that older people were more affected by the coal decline, these results suggest that older people were made worse off by the coal decline regardless of whether they stayed in or left the Appalachian coal mining region.

8 Conclusion

In this paper, we showed that the recent decline of coal mining has hurt household finances in Appalachian coal mining communities. These costs materialized quickly (within two years). These negative effects cannot be explained solely by job losses in coal mine worker households, suggesting significant negative spillovers to others living in the region. We find heterogeneity in who is affected by the coal decline. The most affected people are in the middle-lower part of the credit distribution that includes the subprime cutoff, and older workers (Generation X and Baby Boomers) tend to see larger effects than Millennials. We analyze several aspects of migration in this context, finding that the results cannot be explained by compositional changes driven by migration. Descriptive evidence on those who migrate out of coal counties suggests that people who migrated out during the coal decline had worse outcomes than those who migrated out before.

Our paper adds to a growing literature studying the costs of energy transitions and fits more broadly into the literature on large-scale economic transitions in the US. Our paper is the first to examine how a range of household financial outcomes are affected by the coal decline and shows that the costs to households can be economically meaningful. Though our findings focus on Appalachian coal mining communities, they provide insights for the potential costs 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 deterioration in household finances. While the geographic and economic context vary across fossil fuel extraction communities, 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 have implications for policymakers concerned about how energy transitions may affect fossil fuel extraction communities. First, our finding that the costs of the decline in coal mining are not borne solely by households in which a coal mine worker lost their jobs means that policymakers should look beyond the individuals directly affected in fossil fuel extraction communities. Second, the costs of the coal decline that we measure hit household finances within two years, suggesting that a relatively rapid policy response may be needed. Third, our analyses demonstrate that household finance outcomes can serve as a useful tool for monitoring financial well-being of people in affected communities in real time due to how quickly these outcomes respond to coal shocks.

It is important to note that in documenting a specific cost of the reduction of coal, we have not provided 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 from surface mining, which would be reduced with declining coal extraction (Mueller (2022)). A transition away from fossil fuels would have other benefits, including reducing carbon emissions and local air pollution and providing direct positive health benefits for the mining communities themselves (Hernandez-Cortes and Meng (2020); Boyles et al (2017)).

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Tables and Figures

Table 1: Summary statistics

	Active Coal Mining Counties	National Sample
Coal demand and production		
Coal consumed w/in 200 mi by rail (mil short tons)	31.47 (20.44)	.
Total annual coal production (mil. tons)	2.43 (3.82)	.
Total annual employee hours worked (Thous.)	1,017.86 (1,404.89)	.
Number of employees	450.56 (606.50)	.
FRB New York / Equifax CCP data		
Credit score	678.46 (109.06)	686.13 (106.88)
Percent subprime	41.41 (49.26)	38.50 (48.66)
Credit utilization (percent)	39.79 (39.05)	38.93 (38.64)
Delinquent accounts	0.12 (0.71)	0.12 (0.66)
Amt 3rd party (2012 $)	251.59 (1,716.07)	233.10 (2,006.37)
Transition to bankruptcy (percent)	0.39 (6.24)	0.37 (6.05)
Age	44.58 (11.48)	44.68 (11.44)

Source: EIA; Census; NY Fed / Equifax CCP

Note: Standard deviation in parentheses. We define "active coal-mining counties" during 2011-2018 as those with (i) at least one year with non-zero coal production and (ii) at least one year with 10,000 hours or more of total annual employee hours in mining (roughly equivalent to five full-time workers). 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	-0.116^{***}	-60.70^{***}	-30.42^{***}
	(-2.72)	(-3.37)	(-3.02)
Mean of Dep. Var.	2.02	773.11	412.88
Observations	976	976	822
Number of Counties	122	122	119

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 2018. 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	-0.386^{***}	0.233^{***}	0.187^{***}	0.00307^{**}	9.034^{***}	0.0391^{***}
	(-2.79)	(3.98)	(4.39)	(2.40)	(2.83)	(3.40)
Mean of Dep. Var.	680.54	41.02	38.70	0.11	206.63	0.47
Observations	1,498,042	1,498,042	1,078,856	1,518,432	1,545,450	1,597,776
Individuals	228,128	228,128	179,861	221,266	232,841	234,259
Individ w/ Outcome	228,128	124,905	174,808	51,288	101,029	7,523

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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. "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 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	-0.352^{**}	0.208^{***}	0.161^{***}	0.00290^{**}	8.006^{***}	0.0314^{***}
	(-2.59)	(3.62)	(3.63)	(2.26)	(2.69)	(2.78)
Mean of Dep. Var.	680.54	41.02	38.70	0.11	206.63	0.47
Observations	1,498,042	1,498,042	1,078,856	1,518,432	1,545,450	1,597,776
Individuals	228,128	228,128	179,861	221,266	232,841	234,259
Individ w/ Outcome	228,128	125,781	174,995	53,137	102,384	7,877

Source: 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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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. 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 5: 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	-0.444^{***}	0.204^{***}	0.102^{**}	0.00161	6.086^{*}	0.0293^{***}
	(−3.46)	(4.00)	(2.43)	(1.41)	(1.97)	(2.99)
Mean of Dep. Var.	677.16	41.72	42.24	0.12	223.55	0.71
Observations	3,383,302	3,383,302	2,551,169	3,343,974	3,478,857	3,340,346
Individuals	311,073	311,073	264,542	293,237	313,592	306,467
Individ w/ Outcome	311,073	192,847	258,752	104,711	154,857	26,633

(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	-0.461^{**}	0.225^{***}	0.0933^{*}	0.00135	5.576	0.0209^{*}
	(−2.60)	(3.31)	(1.76)	(1.08)	(1.54)	(1.97)
Mean of Dep. Var.	676.90	41.62	42.27	0.11	216.85	0.69
Observations	2,746,657	2,746,657	2,075,121	2,724,395	2,822,822	2,678,608
Individuals	303,505	303,505	256,211	286,909	306,387	300,016
Individ w/ Outcome	303,505	185,301	250,568	92,650	145,505	20,443

(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	−0.300	−0.0438	−0.126	0.00497^{**}	0.816	−0.00749
	(−1.40)	(−0.54)	(−1.33)	(2.50)	(0.09)	(−0.21)
Mean of Dep. Var.	674.01	41.72	45.78	0.12	180.26	1.04
Observations	1,162,537	1,162,537	927,039	1,124,837	1,188,219	994,488
Individuals	214,094	214,094	181,907	203,374	217,017	211,047
Individ w/ Outcome	214,094	114,152	176,586	45,877	78,276	10,451

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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. 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 6: 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	-0.277^{**}	0.146^{***}	0.181^{***}	0.00381^{***}	6.063^{**}	0.0335^{**}
	(-2.37)	(3.11)	(3.86)	(2.86)	(2.26)	(2.40)
Lag Coal tons 200m	-0.222^{*}	0.134^{***}	0.0139	-0.000426	2.011	0.000403
	(-1.97)	(2.62)	(0.32)	(-0.33)	(0.69)	(0.03)
2nd Lag Coal tons 200m	0.0441	0.0424	0.0465	-0.00115	2.860	0.0186
	(0.49)	(0.94)	(1.12)	(-1.03)	(1.18)	(1.43)
Cumulative effect	-0.455**	0.322***	0.242***	0.002	10.934***	0.053***
SE	-2.27	3.70	4.13	1.49	2.71	3.42
Mean of Dep. Var.	683.92	39.93	38.16	0.11	198.36	0.47
Observations	1,393,367	1,393,367	1,011,513	1,414,064	1,436,379	1,520,230
Individuals	217,911	217,911	171,521	212,520	222,858	228,849
Individ w/ Outcome	217,911	119,395	167,155	51,648	98,561	7,788

Source: Census; EIA; NY Fed / Equifax CCP

Notes: Lag of coal demand is a 1 year lag. 2nd lag of coal demand is a 2 year lag. The cumulative effect estimates the net effect from the contemporaneous, one-year lag, and two-year lag. Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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 7: 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 ERS quart	-0.517^{*}	0.361^{***}	0.220	0.00524	18.47^{**}	0.0751^{***}
	(-1.79)	(2.90)	(1.01)	(1.43)	(2.13)	(2.70)
Coal * second ERS quart	-0.598^{**}	0.428^{***}	0.305^{***}	0.00287	5.514	0.0871^{***}
	(-2.35)	(3.02)	(2.86)	(1.25)	(1.47)	(3.33)
Coal * third ERS quart	-0.510^{***}	0.190^{*}	0.208^{***}	0.00292^{*}	0.619	0.00869
	(-2.93)	(1.85)	(3.32)	(1.96)	(0.45)	(0.41)
Coal * top ERS quart	-0.268^{**}	0.102^{***}	0.140^{***}	0.000594	1.026	0.0123
	(-2.23)	(3.09)	(2.75)	(1.19)	(1.43)	(1.47)
Mean of Dep. Var.	686.36	39.15	37.98	0.11	193.08	0.48
Observations	1,338,990	1,338,990	985,549	1,356,272	1,371,606	1,445,728
Individuals	194,635	194,635	158,070	189,390	197,733	202,190
Individ w/ Outcome	194,635	102,862	154,061	45,124	84,529	7,312

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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, 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 8: 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	-0.562^{*}	0.437^{**}	0.294^{**}	0.00173	6.123	0.0914^{***}
	(-1.73)	(2.60)	(2.11)	(0.71)	(0.93)	(2.92)
Coal* High credit score	-0.270^{**}	0.148^{**}	0.150^{**}	0.000492	0.411	-0.00303
	(-2.07)	(2.30)	(2.54)	(0.54)	(0.42)	(-0.19)
Generation X						
Coal* Low credit score	-0.574^{*}	0.446^{***}	0.222	0.00707^{***}	13.13^{**}	0.0788^{**}
	(-1.97)	(2.97)	(1.24)	(2.77)	(2.16)	(2.48)
Coal* High credit score	-0.576^{***}	0.193^{*}	0.220^{***}	0.00301^{**}	0.838	0.0365
	(-3.38)	(1.97)	(3.77)	(2.30)	(0.55)	(1.43)
Millennials						
Coal* Low credit score	-0.164	0.197	0.343	-0.000844	23.55^{**}	0.0628
	(-0.36)	(0.89)	(1.21)	(-0.12)	(2.48)	(1.54)
Coal* High credit score	-0.387	0.208	0.129	0.00492	4.733	-0.0176
	(-1.33)	(1.29)	(0.90)	(1.49)	(1.40)	(-0.44)
Mean of Dep. Var.	686.36	39.15	37.98	0.11	193.08	0.48
Observations	1,338,990	1,338,990	985,549	1,356,272	1,371,606	1,445,728
Individuals	194,635	194,635	158,070	189,390	197,733	202,190
Individ w/ Outcome	194,635	102,862	154,061	45,124	84,529	7,312

Source: EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with (1) generations and (2) credit score bins. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 2018. 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. 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 9: 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	−0.260	0.131	0.386**	0.00268	9.070	0.0397
	(−0.77)	(0.99)	(2.24)	(0.61)	(1.11)	(1.01)
Coal × 0.1 - 0.2 pov share	−0.501**	0.374***	0.193**	0.00363*	9.933***	0.0584**
	(−2.45)	(4.25)	(2.08)	(1.81)	(2.73)	(2.57)
Coal × <0.1 pov share	−0.377***	0.193**	0.176***	0.00257*	5.279**	0.0383***
	(−2.90)	(2.29)	(3.67)	(1.94)	(2.38)	(3.07)
Mean of Dep. Var.	686.90	38.97	37.75	0.11	193.78	0.47
Observations	1,274,696	1,274,696	935,124	1,293,577	1,313,281	1,392,003
Individuals	183,820	183,820	148,566	178,391	187,575	192,425
Individ w/ Outcome	183,820	96,465	144,686	41,733	79,991	6,741

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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, 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 10: Personal income, coal, and credit score

	(1) Credit Score	(2) Credit Score	(3) Credit Score	(4) Credit Score	(5) Credit Score	(6) Credit Score
Coal tons 200m	−0.364**		−0.367***		−0.353**	
	(−2.61)		(−2.63)		(−2.55)	
Nonfarm personal income per capita (log)	7.836	10.18*				
	(1.31)	(1.70)				
Wage and salary income per capita (log)			4.315**	4.921**		
			(1.99)	(2.21)		
Per capita employment					21.19**	27.32**
					(2.05)	(2.49)
Mean of Dep. Var.	680.64	680.64	680.64	680.64	680.64	680.64
Observations	1,491,301	1,491,301	1,491,301	1,491,301	1,491,301	1,491,301
Individuals	227,109	227,109	227,109	227,109	227,109	227,109
Individ w/ Outcome	227,109	227,109	227,109	227,109	227,109	227,109

Source: EIA; NY Fed / Equifax CCP, BEA

Note: Coal tons 200m captures coal (millions of tons) burned within 200 miles of a county centroid by rail. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 2018. Observations are at individual-year level and span 2011-2018. Income variables are in terms of thousands of 2012 U.S. Dollars. County-level per capital income, employment, and population data adjusted to per capita level come from BEA. 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 11: 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)	-0.351^{***}	0.227^{***}	0.210^{***}	0.00241^{**}	8.184^{***}	0.0383^{***}
	(-2.83)	(3.65)	(5.21)	(2.44)	(2.97)	(3.24)
Mean of Dep. Var.	687.12	38.91	37.68	0.11	193.40	0.47
Observations	1,274,527	1,274,527	935,995	1,293,231	1,313,168	1,391,396
Individuals	181,045	181,045	146,997	175,496	184,658	189,418
Individ w/ Outcome	181,045	94,547	143,114	40,683	78,326	6,576

(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	-0.317^{**}	0.195^{***}	0.221^{***}	0.00212^{**}	9.545^{***}	0.0495^{***}
	(-2.21)	(3.12)	(4.96)	(2.08)	(2.78)	(3.94)
Mean of Dep. Var.	686.23	38.81	37.07	0.10	188.60	0.44
Observations	1,058,300	1,058,300	763,044	1,070,996	1,094,412	1,136,814
Individuals	159,931	159,931	125,216	154,174	163,681	165,062
Individ w/ Outcome	159,931	83,776	121,349	33,896	67,960	4,950

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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 12: County-level regression for churn and migration

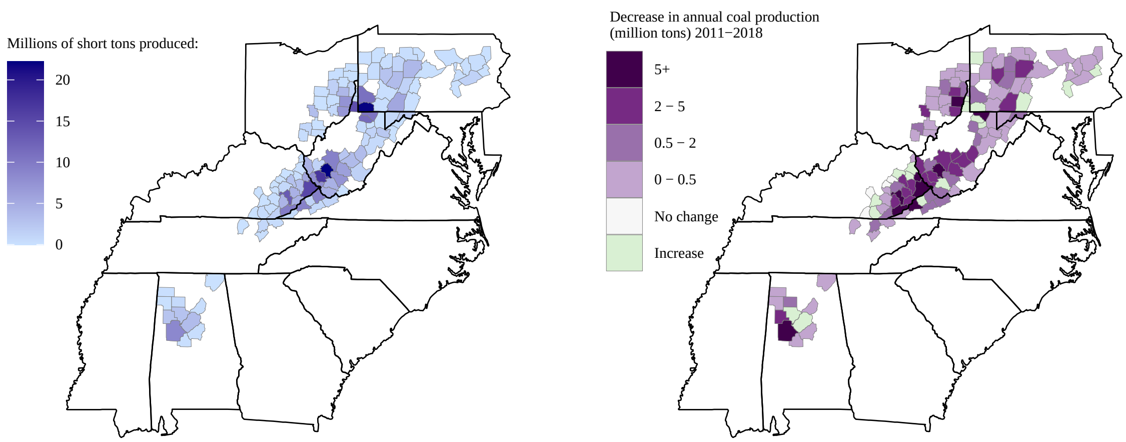
	(1) Net Migration (Percent)	(2) Churn (Percent)
Coal tons 200m	-0.00143	-0.143^{*}
	(-0.02)	(-1.87)
Mean of Dep. Var.	-0.14	4.99
Observations	976	976
Number of Counties	122	122

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 2018. 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.

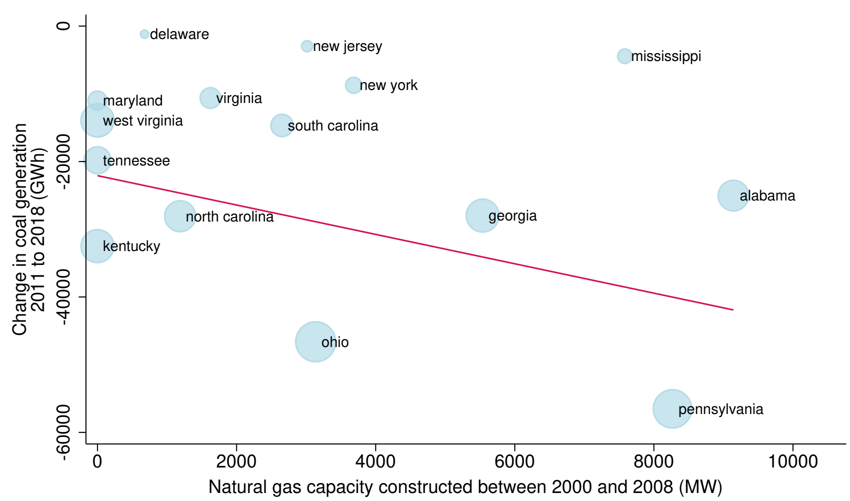
Figure 1: Coal production in Appalachia

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



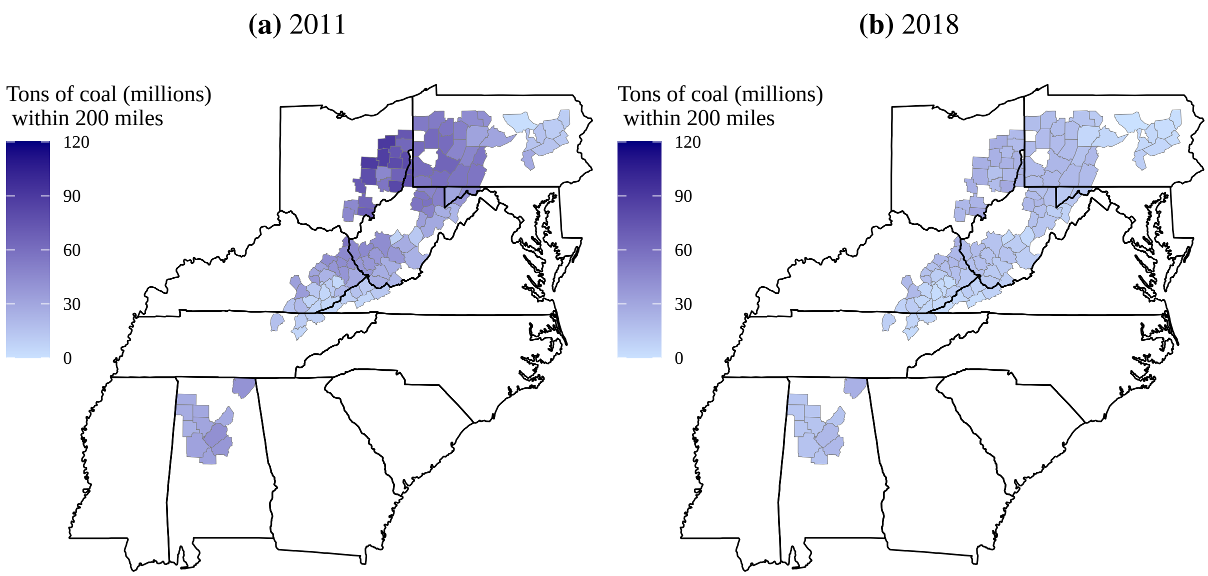
Source: EIA
Counties shown are active Appalachian coal mining counties between 2011 and 2018, our sample period. Defined as: (i) at least one year with non-zero coal production and at least one year with 10,000 hours or more of total annual employee hours in mining (roughly equivalent to five full-time 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.
Size of points reflect 2007 coal generation in gigawatt hours (GWh). Red line is a weighted linear regression showing the correlation between state-level change in coal generation between 2011 and 2018 and natural gas capactiy constructed between 2000 and 2008.

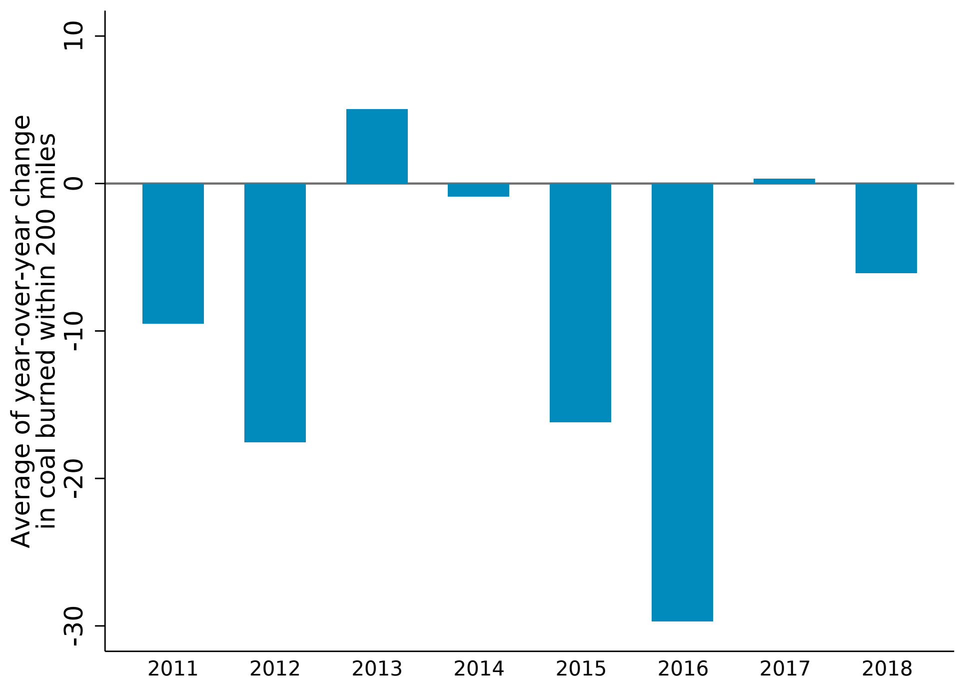
Figure 3: Coal consumed at power plants within 200 miles



Source: EIA

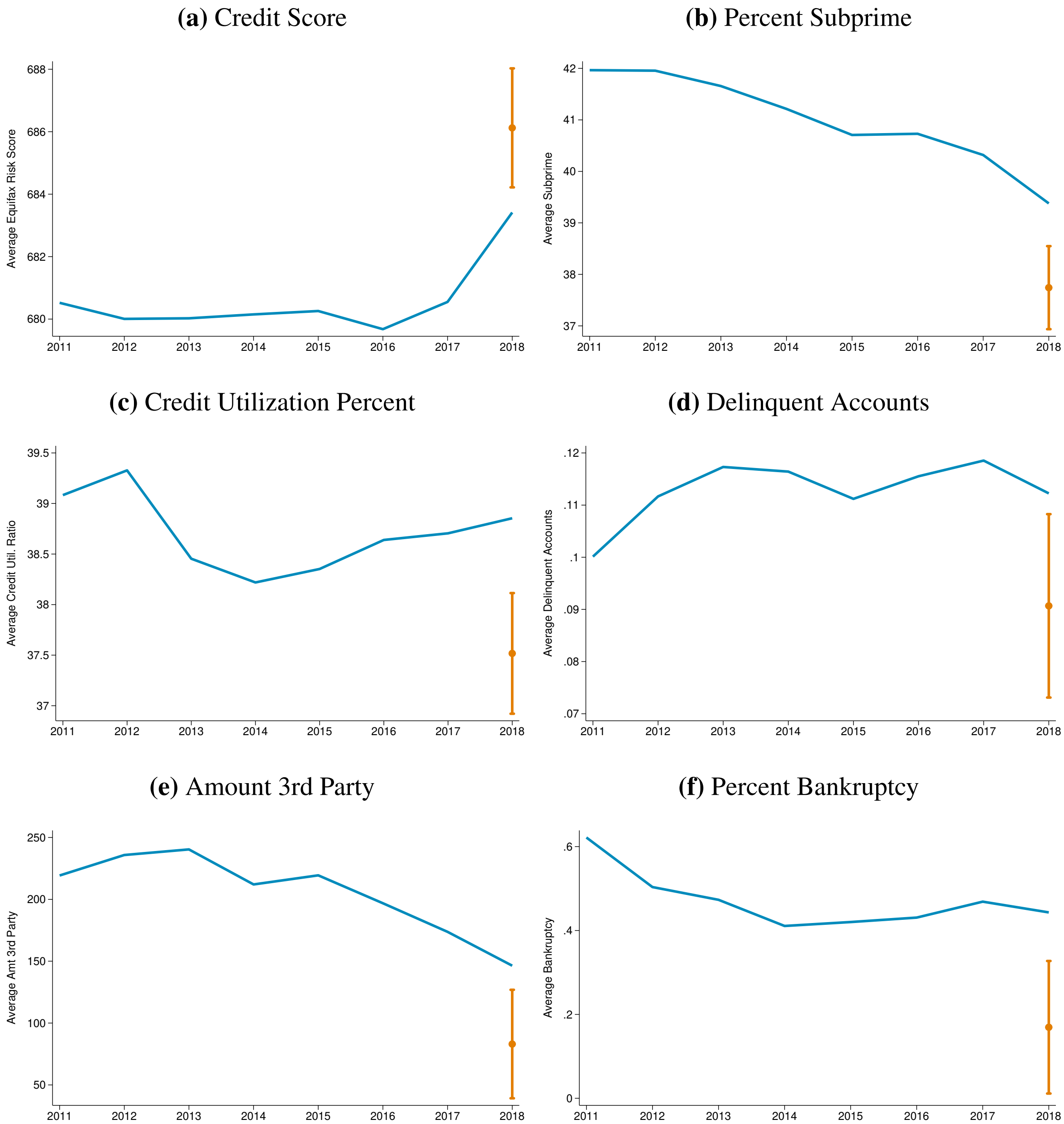
Counties shown are active Appalachian coal mining counties between 2011 and 2018, our sample period. Defined as: (i) at least one year with non-zero coal production and at least one year with 10,000 hours or more of total annual employee hours in mining (roughly equivalent to five full-time workers) 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: Year-to-year variation in coal demand treatment variable



Source: EIA
Bars represent average change in coal demand treatment variable in each year.

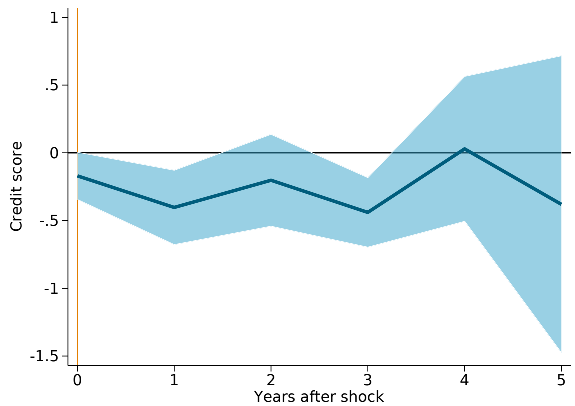
Figure 5: Counterfactual estimate



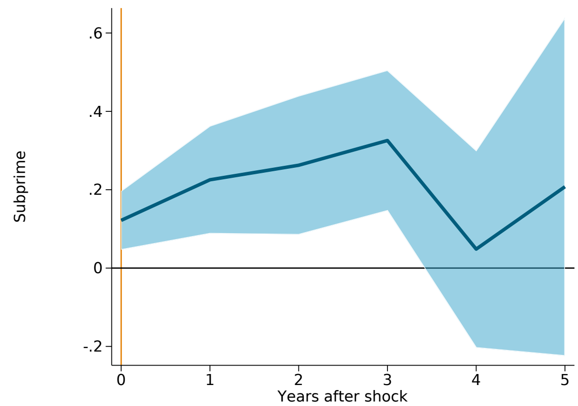
Source: Census; EIA; NY Fed / Equifax CCP
The blue lines depict the outcome variable annual values. The orange dots show counterfactual estimates of the outcomes if coal demanded within 200 miles had remained at 2011 levels. Specifically, for each outcome the distance between the counterfactual and actual levels equals the estimated one-year average response Table 3 multiplied by seven. 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 6: Local projections

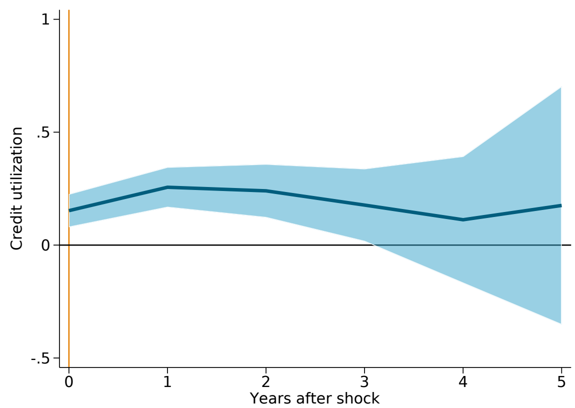
(a) Credit Score



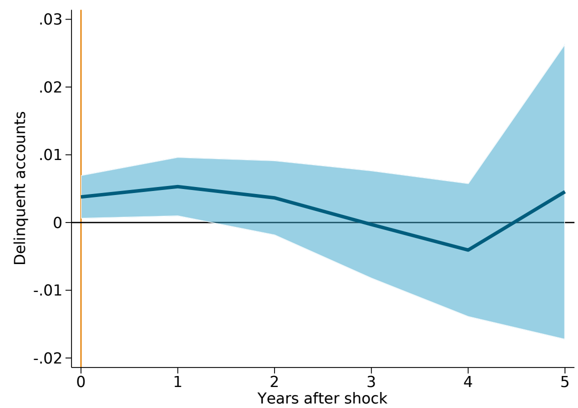
(b) Percent Subprime



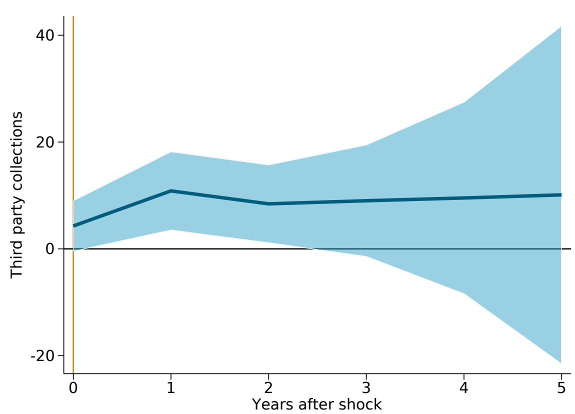
(c) Credit Utilization Percent



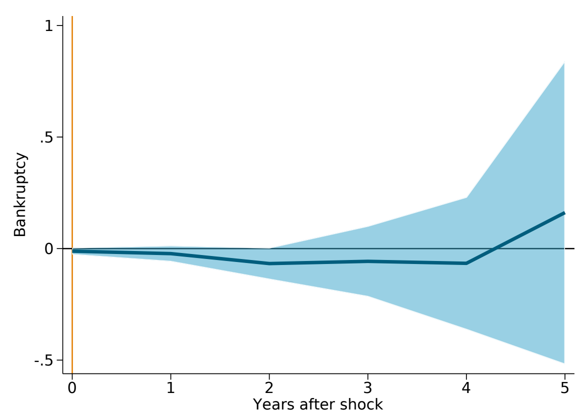
(d) Delinquent Accounts



(e) Amount 3rd Party



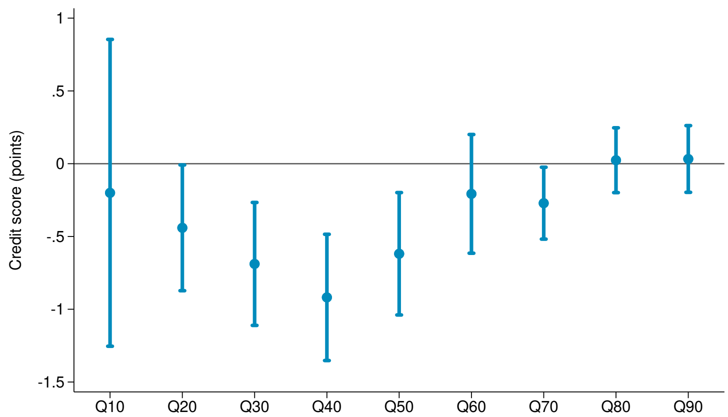
(f) Percent Bankruptcy



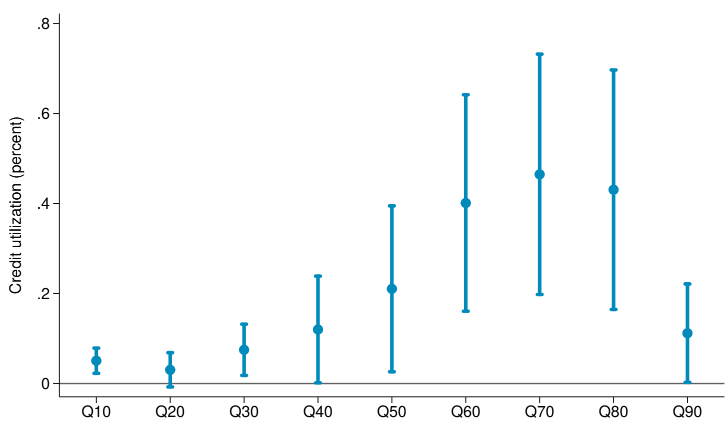
Source: Census; EIA; NY Fed / Equifax CCP
Coefficients and 95 percent confidence intervals from a series of local projections regressions. Coefficients trace out the estimated cumulative effects of the treatment at different time horizons. Treatment is the one-year change in demand for coal in year t. All regressions include individual, county, and year fixed effects. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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.

Figure 7: Quantile regressions

(a) Credit Score



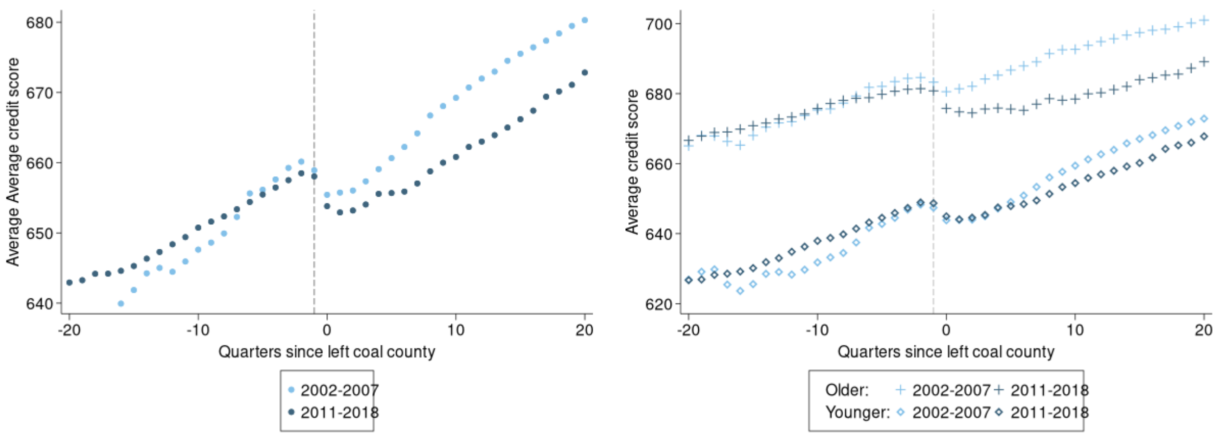
(b) Credit Utilization Percent



Source: Census; EIA; NY Fed / Equifax CCP
Coefficients and 95 percent confidence intervals from a series of unconditional quantile regressions for quantiles 10 - 90. All regressions include individual, county, and year fixed effects as well as linear individual time trends. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 2018. Standard errors are clustered by county.

Figure 8: Credit scores of people who moved out of Appalachia

(a) All movers **(b)** Heterogeneity by age



Source: EIA; NY Fed / Equifax CCP

Note: The points in this chart correspond to the average credit score based on the quarter in relation to when the individual left coal counties. The quarter marked as 0 is the first quarter in which the individual is no longer in an Appalachian coal mining county. The vertical dashed lines indicate quarter -1, the last quarter before the move. For panel (b), age is categorized based on the age of the person the year they move, with individuals who were 45 and younger at that time being designated as "younger." For both panels, the sample only includes individuals who lived in active coal mining counties for at least four consecutive quarters and then made one move out of the region. The panels exclude individuals whose data indicated they moved during quarters with anomalously large number of movers (primarily in the early sample). The timing of these moves was unlikely to be accurate and may introduce significant noise.

Appendix

Table A1: Alternative radii

(a) 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	-0.169^{***}	0.0784^{***}	0.0541^{***}	0.00182^{***}	2.398^{*}	0.0127^{**}
	(-3.82)	(3.89)	(2.75)	(4.27)	(1.70)	(2.13)
Mean of Dep. Var.	680.54	41.02	38.70	0.11	206.63	0.47
Observations	1,498,042	1,498,042	1,078,856	1,518,432	1,545,450	1,597,776
Individuals	228,128	228,128	179,861	221,266	232,841	234,259
Individ w/ Outcome	228,128	125,781	174,995	53,137	102,384	7,877

(b) 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	-0.559^{***}	0.348^{***}	0.181^{***}	0.00499^{***}	12.62^{***}	0.0418^{**}
	(-3.12)	(4.67)	(2.82)	(2.82)	(3.60)	(2.60)
Mean of Dep. Var.	680.54	41.02	38.70	0.11	206.63	0.47
Observations	1,498,042	1,498,042	1,078,856	1,518,432	1,545,450	1,597,776
Individuals	228,128	228,128	179,861	221,266	232,841	234,259
Individ w/ Outcome	228,128	125,781	174,995	53,137	102,384	7,877

Source: Census; EIA; NY Fed / Equifax CCP

Notes: 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). To help with comparison to our other specifications, both coal tons variables are rescaled by the average annual change in coal tons 200m between 2011 and 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. 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 A2: 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)	(6) Percent Bankruptcy
Coal tons 200m	-0.290^{**}	0.203^{***}	0.206^{***}	-0.000151	7.581^{**}	0.0402^{***}
	(-2.41)	(3.97)	(4.00)	(-0.13)	(2.19)	(3.51)
Mean of Dep. Var.	679.64	41.65	39.51	0.11	222.22	0.47
Observations	1,521,557	1,521,557	1,131,227	1,522,429	1,569,394	1,597,754
Individuals	230,114	230,114	187,120	221,287	234,206	234,256
Individ w/ Outcome	230,114	135,249	183,856	78,489	114,192	7,876

(b) Maximum

	(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	-0.309^{**}	0.148^{***}	0.210^{***}	0.000475	12.09^{**}	0.0397^{***}
	(-2.40)	(3.02)	(4.26)	(0.21)	(2.15)	(3.47)
Mean of Dep. Var.	695.62	45.92	47.86	0.24	396.23	0.47
Observations	1,521,490	1,521,490	1,131,189	1,522,376	1,569,376	1,597,742
Individuals	230,104	230,104	187,112	221,284	234,200	234,253
Individ w/ Outcome	230,104	135,239	183,848	78,485	114,186	7,875

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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. "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 A3: 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	-0.288^{*}	0.217^{***}	0.131^{***}	0.00157	6.907^{**}	0.0404^{***}
	(-1.73)	(2.94)	(2.82)	(1.00)	(2.43)	(3.17)
Coal * medium share	-0.665^{***}	0.374^{***}	0.256^{***}	0.00434^{*}	13.14^{*}	0.0365^{*}
	(-3.00)	(4.79)	(3.08)	(1.89)	(1.95)	(1.77)
Coal * large share	-0.594^{**}	0.122	0.505^{***}	0.00909^{***}	13.56^{*}	0.0248
	(-2.59)	(0.71)	(3.04)	(3.61)	(1.89)	(0.59)
Mean of Dep. Var.	680.54	41.02	38.70	0.11	206.63	0.47
Observations	1,498,042	1,498,042	1,078,856	1,518,432	1,545,450	1,597,776
Individuals	228,128	228,128	179,861	221,266	232,841	234,259
Individ w/ Outcome	228,128	125,781	174,995	53,137	102,384	7,877

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. 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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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 A4: 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	-0.275	0.174^{*}	0.205^{**}	0.00380^{**}	-1.770	0.0460^{*}
	(-1.34)	(1.74)	(2.34)	(2.27)	(-0.37)	(1.91)
Medium NG * Coal	-0.528^{**}	0.215^{**}	0.178^{*}	0.00577^{**}	10.84^{***}	0.00871
	(-2.57)	(2.10)	(1.87)	(2.11)	(2.62)	(0.35)
High NG * Coal	-0.381^{*}	0.261^{***}	0.176^{***}	0.00189	11.61^{**}	0.0460^{***}
	(-1.80)	(2.97)	(3.37)	(1.04)	(2.03)	(3.54)
Mean of Dep. Var.						
Observations	1,491,301	1,491,301	1,074,738	1,511,539	1,538,379	1,590,248
Individuals	227,109	227,109	179,148	220,306	231,799	233,207
Individ w/ Outcome	227,109	125,102	174,308	52,898	101,778	7,828

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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 A5: Coal demand interacted with generations and credit score bins (18-64)

	(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	-0.490	0.466^{**}	0.307^{*}	0.00208	6.269	0.0728^{**}
	(-1.46)	(2.51)	(1.94)	(0.84)	(0.94)	(2.28)
Coal* High credit score	-0.324^{**}	0.156^{**}	0.154^{**}	0.000305	0.477	0.0132
	(-2.25)	(2.36)	(2.49)	(0.32)	(0.42)	(0.79)
Generation X						
Coal* Low credit score	-0.641^{**}	0.458^{***}	0.259	0.00710^{***}	13.65^{**}	0.0733^{**}
	(-2.09)	(2.91)	(1.42)	(2.63)	(2.11)	(2.15)
Coal* High credit score	-0.519^{***}	0.209^{**}	0.200^{***}	0.00322^{**}	0.546	0.0464^{**}
	(-2.88)	(2.09)	(3.15)	(2.52)	(0.37)	(2.01)
Millennials						
Coal* Low credit score	-0.0948	0.212	-0.0334	0.00211	20.64^{**}	0.0522^{**}
	(-0.30)	(1.19)	(-0.17)	(0.39)	(2.54)	(2.21)
Coal* High credit score	-0.0441	0.214	0.00375	-0.000189	3.798	-0.0133
	(-0.16)	(1.32)	(0.03)	(-0.06)	(1.25)	(-0.42)
Mean of Dep. Var.	681.03	40.61	38.77	0.11	201.34	0.47
Observations	1,492,455	1,492,455	1,081,120	1,510,687	1,528,846	1,606,343
Individuals	216,269	216,269	174,690	210,546	219,616	224,155
Individ w/ Outcome	216,269	118,458	170,269	52,302	96,305	7,893

Source: EIA; NY Fed / Equifax CCP

Notes: Coal demand within 200 miles is interacted with (1) generations and (2) credit score bins. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 2018. Generations are defined by Pew Research Center: 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. 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 A6: Credit outcomes (18-64)

	(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	-0.351^{**}	0.237^{***}	0.156^{***}	0.00263^{*}	9.289^{***}	0.0397^{***}
	(-2.44)	(3.62)	(3.63)	(1.90)	(2.86)	(3.66)
Mean of Dep. Var.	676.84	41.93	39.13	0.11	208.02	0.45
Observations	1,616,923	1,616,923	1,142,498	1,641,420	1,669,252	1,738,352
Individuals	239,383	239,383	188,812	232,443	243,964	249,113
Individ w/ Outcome	239,383	136,239	183,287	55,629	107,372	7,754

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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. "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.

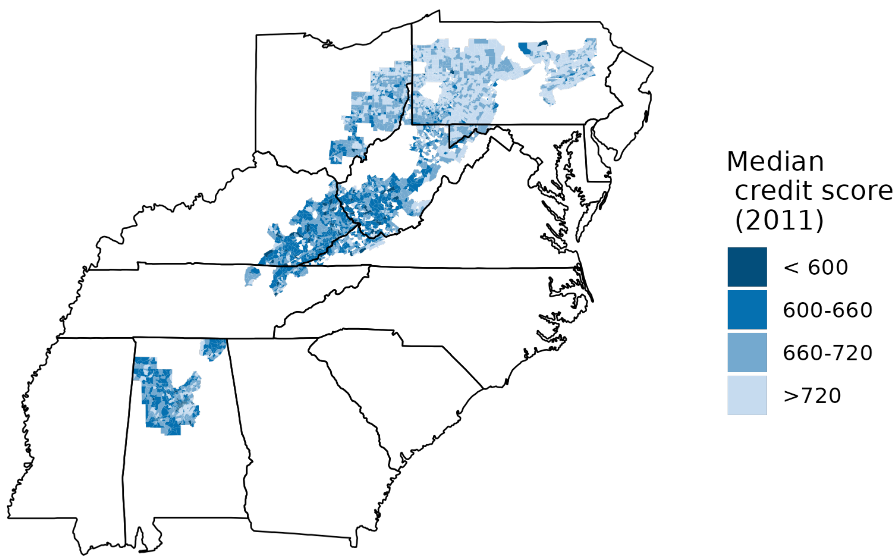
Table A7: Coal demand interacted with 1999 Census block group per capita income

	(1) Credit Score	(2) Percent Subprime	(3) Credit Utilization Percent	(4) Delinquent Accounts	(5) Amt 3rd Party Collections ($ 2012)	(6) Percent Bankruptcy
Coal × $25,000 +	-0.178	0.113	0.146^{*}	0.00146	3.909	0.0248
	(-1.34)	(1.62)	(1.93)	(0.92)	(1.17)	(1.41)
Coal × $20,000-25,000	-0.569^{***}	0.393^{***}	0.286^{***}	0.00441^{**}	10.91^{***}	0.0554^{**}
	(-3.32)	(3.34)	(2.76)	(2.57)	(3.57)	(2.54)
Coal × < $20,000	-0.496^{**}	0.247^{**}	0.227^{**}	0.00433	10.68^{**}	0.0600^{**}
	(-2.02)	(2.56)	(2.14)	(1.42)	(2.23)	(2.35)
Mean of Dep. Var.	686.90	38.97	37.75	0.11	193.79	0.47
Observations	1,274,701	1,274,701	935,120	1,293,583	1,313,287	1,392,011
Individuals	183,821	183,821	148,565	178,392	187,576	192,426
Individ w/ Outcome	183,821	96,466	144,685	41,733	79,992	6,741

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. To help with interpretation, coal tons 200m is rescaled by the average annual change between 2011 and 2018. Treatment coefficients are the average one-year change in the outcome variable caused by the coal decline between 2011 and 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.

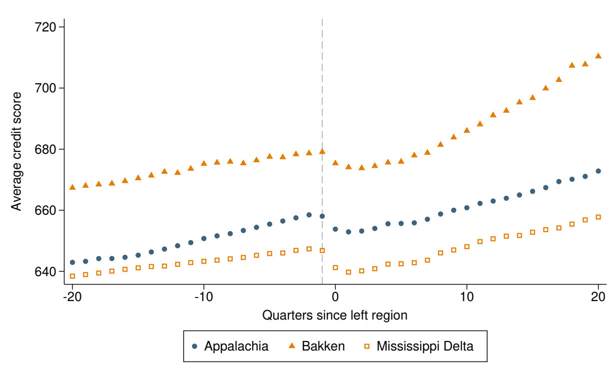
Figure A1: Geographic distribution of credit scores



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: Credit scores of people who moved out of various regions



Source: EIA; NY Fed / Equifax CCP; U.S. Census Bureau, and Delta Regional Authority

Note: The points in this chart correspond to the average credit score based on the quarter in relation to when the individual left coal counties. The quarter marked as 0 is the first quarter in which the individual is no longer in an Appalachian coal mining county. The vertical dashed lines indicate quarter -1, the last quarter before the move. The figure excludes individuals whose data indicated they moved during quarters with anomalously large number of movers (primarily in the early sample). The timing of these moves was unlikely to be accurate and may introduce significant noise.