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Selective Migration and Regional Decline: Evidence from Coal Country

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The most recent version of this paper can be found here.

Abstract

Why do regions decline? This paper explores how adverse shocks in one period affect regional adjustment to subsequent shocks, emphasizing the role of selective migration. I leverage differential exposure to coal's decline and variation in proximity to historical employment shifts to study this process of regional decline in Appalachia. The consequences of the 2007–2017 coal shock were more acute in counties that experienced larger declines in college-educated adults due to exogenous labor demand shifts in the 1980s. These findings indicate that the adverse effects of shocks can accumulate over time, leaving certain regions differentially vulnerable to new challenges.

Keywords: labor-market adjustment, population mobility, regional inequality, human capital, energy transition

JEL Codes: E24, J20, J60, L72, Q30, R10

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1 Introduction

As certain regions serve as engines of economic opportunity, why are others trapped in a state of persistent decline? The consequences of adverse shocks in one generation often persist into the next, potentially weakening a community's capacity to adapt to new challenges. This paper examines one mechanism through which regions decline: selective migration. By inducing selective migration (i.e., reducing the human capital endowment) in affected communities, adverse shocks may differentially influence how places adjust to shocks in future periods. I study this phenomenon in the context of the ongoing transition away from carbon-intensive energy sources. Large-scale declines in demand for coal have had differential effects across places, driven by the geographic concentration of industry activity and the legacy of historical shocks that altered the population composition and economic trajectory of exposed places. Understanding how historical shocks shape the adjustment to contemporary industry contractions offers broader insights into the mechanisms driving regional economic decline.

In this paper, I present a graphical version of a spatial equilibrium model that describes how adverse shocks in one period reverberate into the next. The model implies that adverse shocks will negatively influence the skill composition of exposed communities, and this selective migration stifles economic activity such that future generations are more vulnerable to subsequent adverse shocks. I apply the model's hypotheses in Appalachia's coal country, which has been subject to recurrent adverse local shocks resulting from macroeconomic shifts in demand for coal throughout history. Between 2007 and 2017, coal mining employment declined by nearly 50 percent in Appalachia, largely thanks to the sudden introduction of cheap natural gas made available by hydraulic fracturing technology, which rapidly altered the electricity-generating landscape as well as the terms of trade for communities that specialized in coal mining (Kolstad, 2017; Linn and McCormack, 2019; Coglianese et al., 2020). This recent episode is, however, dwarfed by the decline in Appalachian coal employment that occurred during the 1980s. Driven by falling coal and oil prices, improvements in mining technology, and the introduction of more accessible Western coal reserves, this historical coal bust led to large increases in transfer payments and negative spillovers into other employment sectors, among other adverse economic consequences (Black et al., 2002, 2003, 2005a).

Importantly, these two major, unexpected declines in demand for coal (i.e., "coal shocks") occurred amidst the backdrop of expansions and contractions in other industries which differentially affected places based on the regional concentration of industry employment. I exploit variation in county-level exposure to these employment shifts to investigate how the region adjusted to the contemporary (2007–2017) coal shock, and then estimate the extent to which this adjustment process can be explained by the persistent consequences of historical shocks on the human capital endowment of affected communities. I first leverage a Bartik shift-share instrument to examine how Appalachian communities adjusted to the 2007–2017 coal shock along various employment and population margins. I estimate that a 1 standard deviation increase in the coal shock reduces county-level employment by 5 percent, reduces the working-age adult population by 2.4 percent, and reduces the employment rate by 1.5 percentage points. Population losses are larger among the college-educated, and this selective migration grows over progressively longer time horizons. Average earnings losses are driven by the most immobile group of residents, such that the incidence of the demand shock likely falls on residents who remain in exposed communities.

I next estimate the extent to which employment and population adjustments to the 2007–2017 coal shock depend on a place's history of selective migration. The identification strategy is based on the insight that the gravity structure of trade and the bilateral nature of migration decisions mean that places more proximate to growing economies are relatively more attractive for better-educated workers. Exploiting differential spatial proximity to employment shocks in other labor markets during the 1980s, I predict the magnitude of selective migration in each Appalachian county during the 1980–1990 decade. Re-estimating the effect of the recent coal shock across counties with varying historical migration flows reveals that places with greater historical declines in college-educated adults experienced substantially larger adjustment costs resulting from the 2007–2017 coal shock. The employment, population, and earnings adjustment to the coal shock are between 2 and 4 times larger in the quartile of counties with the greatest levels of selective migration predicted by employment shocks in preceding periods. This result is robust to different methods of predicting migration flows, controlling for historical employment shocks, alternative definitions of selective migration, and other specification choices. Consistent with the model describing how the consequences of adverse shocks persist across generations, I present evidence that selective migration suppresses business formation in subsequent periods. By altering the population and economic trajectory of exposed places, adverse shocks reinforce a process of decline, making certain regions more vulnerable to the consequences of subsequent shocks.

This paper contributes to several strands of literature. First, it provides new insights into the persistent effects of labor demand shocks and one of the mechanisms underlying regional decline.

A growing body of research considers the transitional costs of sectoral reallocation, examining the effects of labor demand shocks on various outcomes including earnings, health, marriage rates, and migration. Population mobility from under-performing areas is an important re-equilibrating force following employment shocks (Blanchard and Katz, 1992). However, increasingly sluggish migration adjustments over time may deepen persistent regional income disparities (Amior and Manning, 2018; Zabek, 2024), pushing communities to adjust along other margins, such as reduced employment, lower wages, and greater reliance on government transfer payments (e.g., Molloy et al., 2011; Dao et al., 2017; Amior and Manning, 2018; Charles et al., 2019; Notowidigdo, 2020).[1] Still, internal migration remains an important channel through which workers arbitrage real wage differentials across place, and this is especially true for better-educated workers (Topel, 1986; Bound and Holzer, 2000; Glaeser and Gyourko, 2005; Wozniak, 2010).[2] The selectivity of population mobility has helped drive broader patterns of diverging economic performance across regions (Long, 1988; Diamond, 2016; Ganong and Shoag, 2017; Autor, 2019).

I contribute to this literature by exploring how exogenously driven declines in human capital endowments — i.e., brain drain — shape the capacity for places to adjust to future shocks. To the extent that the stock of human capital is important to the trajectory of local economic activity (Glaeser et al., 1995; Glaeser, 2005; Bollinger et al., 2011; Gennaioli et al., 2014; Islam et al., 2015; Fluegge, 2022; Gagliardi et al., 2023), selective migration induced by shocks in one period may weaken a place's capacity to recover from shocks in the future. A closely related paper is Gagliardi et al. (2023), which shows that manufacturing hubs with higher initial college shares recovered more rapidly from deindustrialization. While their focus is on contemporaneous heterogeneity in human capital at the onset of decline, I emphasize its historical origins — showing how earlier shocks shaped the skill composition of local labor markets and influenced the adjustment to later shocks. In doing so, I provide new evidence on how selective migration reinforces regional decline and long-run spatial divergence.

Second, this paper contributes to the growing body of research on the economic consequences of energy transitions. Compared to the extensive literature on shocks to manufacturing employment caused by import penetration and other macroeconomic shifts (e.g., Autor et al., 2013;

[1] Evidence of the secular decline in internal migration and possible explanations for low rates of mobility, including migration frictions and local ties, is offered by Mincer (1978); Molloy et al. (2011, 2014); Alesina et al. (2015); Molloy et al. (2017); Huttunen et al. (2018); Coate et al. (2019) and Zabek (2024).

[2] Numerous explanations for the selectivity of migration have been forwarded, including variation in the receipt of government transfers and the returns to migration across types of worker (e.g., Sjaastad, 1962; Autor, 2019; Notowidigdo, 2020).

Acemoglu et al., 2016; Pierce and Schott, 2016; Charles et al., 2019; Gagliardi et al., 2023), research on energy transitions remains relatively limited, despite that the clean energy transition is poised to reshape labor markets on a much larger scale. Recent studies document the economic and fiscal consequences of coal's decline — including reductions in earnings (Colmer et al., 2024; Rud et al., 2024), lower tax revenues (Morris et al., 2019; Raimi et al., 2023), reduced household-level financial health (Blonz et al., 2023), and increased reliance on government transfers (Autor et al., 2021; Hanson, 2022) — but the broader regional adjustment process remains poorly understood.[3] This paper examines how a comprehensive set of regional economic outcomes responded to coal's recent collapse, extending early research on the 1980s coal bust (Black et al., 2002, 2005a,b) to consider how the effects of industry contractions can accumulate over time. Because coal mining employment is geographically concentrated in relatively remote regions with limited alternative opportunities, the labor market adjustments in these areas may differ markedly from those observed in manufacturing hubs. By estimating the regional adjustment costs of coal's collapse and linking past and present episodes of sectoral decline, this paper provides insights into the long-term vulnerabilities of energy-dependent regions and previews the challenges that may emerge as fossil fuel industries continue to contract.

The remainder of the paper is organized as follows. Section 2 clarifies major data sources and provides a brief background on Appalachia's coal industry. In section 3, I present a graphical version of a model delivering predictions about how shocks influence the population composition and economic trajectory of exposed places. Section 4.1 documents the county-level adjustment costs associated with the 2007–2017 coal shock. In section 4.2, I examine the extent to which these adjustment costs differ based on selective migration in historical periods. Section 5 concludes.

2 Data and economic setting

Data on employment, industry composition, population, and government transfer receipt are compiled at the county level for 413 counties in Appalachia over the 2007–2017 period. The definition of Appalachia used in this paper follows the regional boundaries defined by the Appalachian Regional Commission (ARC). I supplement these contemporary data with a smaller set of county-level characteristics going back to 1980. After clarifying major data sources, I describe Appalachia's coal industry and population composition in historical context.

[3] Other recent research on the economic consequences of coal's collapse in Europe include Aragón et al. (2018); Brey and Rueda (2024), and Haywood et al. (2024).

2.1 Data on economic conditions and population characteristics

Publicly available employment data by industry or occupation often suppress employment values for sparsely populated counties, and there are no publicly available datasets that have fully informative data on coal mining employment at the county level. To address this, I construct a dataset of county-level economic and population statistics from a variety of sources, including the Mine Safety and Health Administration (MSHA), County Business Patterns (CBP), the Census Bureau, and the Bureau of Economic Analysis (BEA).

County-level coal mining employment statistics for the 2007–2017 period are constructed from mine-level employment data from MSHA's Mine Data Retrieval System. These mine-level statistics are aggregated to the county based on the county in which the mine operates.[4] County-level coal mining employment for earlier periods is defined as the sum of all employment in SIC code 12 or NAICS code 2121 based on data from the County Business Patterns (CBP) and imputed by Eckert et al. (2020).[5] Both the CBP- and MSHA-based definitions of coal mining employment capture only workers directly employed in the coal mining industry.

Annual, county-level population counts by age group over the 1980 to 2017 period are based on the intercensal estimates produced by the U.S. Census Bureau. Other county-level population characteristics are retrieved from the American Community Survey (ACS) 5-year samples and Decennial Censuses.[6] Statistics derived from these sources include place of birth (foreign-born share), the female share of the workforce, and the number and share of college-educated adults.[7]

Statistics on county-wide employment and income for years 1980 through 2017 are primarily drawn from the Bureau of Economic Analysis (BEA) Regional Economic Accounts.[8] Industry-specific employment counts are retrieved from the Quarterly Census on Employment and Wages (QCEW). The Census Bureau's Business Dynamics Statistics program (BDS) is used to estimate

[4]Specifically, I combine the annual "Employment Production Data set" with the "Mines" dataset to link mine employment to the appropriate county. Total mine-level employment in the MSHA is defined as the mean quarterly average employee count.

[5]The MSHA data begin in 2000. For the historical period, I use county-level industry-based employment data imputed from CBP datasets by Eckert et al. (2020). County-level coal mining employment is frequently suppressed in recent CBP datasets because of the change from SIC to NAICS industry classifications, and thus the imputed values are less reliable for this recent period.

[6]Characteristics for years 2007 and 2017 are based on the ACS 2005–2009 and ACS 2015–2019 samples, respectively. Characteristics for years 1980 and 1990 are based on the Decennial Census.

[7]I report summary statistics on median household income, racial composition (white share), and the homeownership rate derived from the ACS, as well as poverty and Supplemental Nutrition Assistance Program (SNAP) receipt from the Census SAIPE program. These characteristics are not considered in the central analysis.

[8]BEA data are not available for seven independent Virginia cities in the ARC region, which are omitted from the analysis.

the number of new business establishments in each county going back to 1980. I supplement the data described above with a county-level dataset on employment for all U.S. counties at the 3-digit NAICS code derived from the CBP. The CBP provides employment data in highly detailed industry categories, though specific counts in less populous places are often suppressed. I thus rely on the imputed values presented by Eckert et al. (2020).[9]

2.2 Economic setting: Appalachia's coal country

While representing only a small fraction of the total United States workforce, coal mining has long played an integral role in the economies of many Appalachian communities. Due to the spatial concentration of coal deposits and the secular shifts in demand for the commodity, many coal-dependent communities have been subject to recurrent demand shocks across generations — sometimes referred to as the "boom and bust" cycle that commonly characterizes economies dependent upon traditional industries (Black et al., 2005b,a; Marchand, 2012; Betz et al., 2015; Allcott and Keniston, 2018; Aragón et al., 2018). Appalachia — which includes all of West Virginia and parts of 12 other states — presents an informative empirical setting in which to examine local demand shocks, selective migration, and regional decline due to its historical dependence on this legacy industry and the persistent poverty afflicting many of its communities (Harrington, 1962; Eller, 2008; Ziliak, 2012). In 1964, President Lyndon B. Johnson visited Martin County, Kentucky — where coal accounted for over half of county earnings and the poverty rate exceeded 60 percent — to promote his "unconditional war on poverty." The following year, the ARC was established as a federal agency to help bring the region into socioeconomic parity with the rest of the United States through grant programs that support infrastructure and workforce development projects, among other activities.

Over the past several decades, coal mining employment declined by over two-thirds nationally, with these declines driven by the same Appalachian communities where poverty, joblessness, premature mortality, and other indications of economic and social distress have persisted since ARC's founding. Table 1 compares population and economic characteristics in 2007 across counties outside of Appalachia (column 1), inside of Appalachia (column 2), and coal counties within

[9] The CBP datasets provide detailed, county-level employment statistics for most counties, with specific data suppression flags that indicate the employment size class of the workforce in a given industry when the exact number is withheld to avoid disclosure. Since many counties are sparsely populated, many industry-employment counts are suppressed in the CBP databases. The Eckert et al. (2020) dataset includes imputed values for these suppressed cells for all industries using a straightforward imputation process, detailed in the paper.

Table 1: Summary Statistics (2007)

	(1) Outside Appalachia	(2) Appalachia	(3) Appalachian coal counties
Baseline covariates			
College share of adults	27.93	20.55	15.69
	(9.88)	(8.53)	(6.71)
Female share of workforce	46.90	46.82	46.44
	(2.20)	(1.84)	(1.79)
Foreign-born share of population	13.06	3.74	1.20
	(10.85)	(4.43)	(0.92)
Additional statistics			
Employment rate (per person ages 20–64)	79.48	70.35	63.36
	(23.12)	(20.08)	(18.36)
Median household income ($1000s)	61.94	49.00	41.78
	(15.50)	(10.51)	(7.43)
White share	64.24	85.02	92.41
	(21.35)	(12.96)	(8.14)
Share of pop 60 years and older	17.20	20.07	21.15
	(4.09)	(3.82)	(2.89)
Homeownership rate	66.27	72.78	73.77
	(10.87)	(5.21)	(5.28)
Poverty rate	12.87	14.75	18.51
	(5.17)	(4.67)	(6.37)
SNAP recipiency rate (per 100 people)	9.00	11.26	15.82
	(5.24)	(5.14)	(7.89)
Gov. transfers ($1000s) per capita	6.62	7.66	9.10
	(1.55)	(1.71)	(1.39)
Observations	2,668	413	65

Author's calculations based on data from ACS, SAIPE, and BEA. All statistics are population-weighted. Shares and rates are multiplied by 100 unless otherwise noted. Statistics derived from the ACS are estimates from the 2005–2009 5-year ACS samples. All other statistics are based on 2007 estimates. Appalachia includes 413 counties defined by the Appalachian Regional Commission with non-missing BEA data. The coal counties in column 3 include with at least 0.537 percent of the adult population employed in coal mining in 2007. The 0.537 percent cutoff reflects the median coal share among counties with any coal mining employment in 2007.

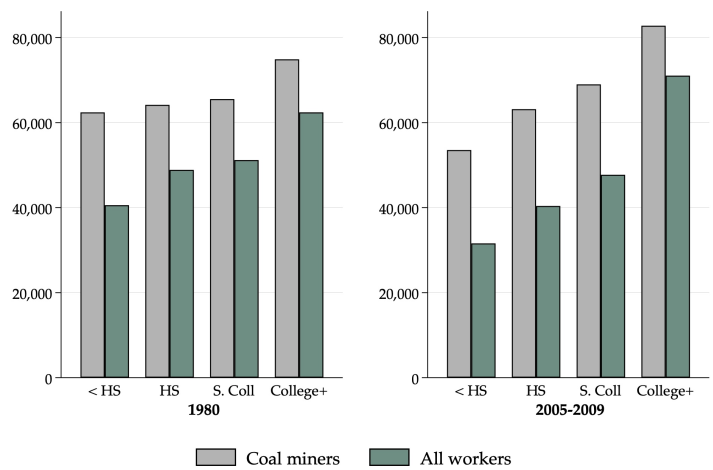
Appalachia (column 3).[10] Appalachian counties host relatively older populations with low levels of college attainment, and high shares of non-Hispanic whites and native-born residents. Before coal's recent decline, Appalachian counties had lower employment rates, lower incomes, higher poverty rates, and higher rates of public assistance than the rest of the United States, with these qualities intensified in Appalachia's coal regions. The average poverty rate in Appalachian coal counties was 43 percent higher than outside of Appalachia, and the SNAP recipiency rate was 75 percent higher. Across a range of characteristics, Appalachia's coal regions fare poorly compared

[10]For exposition purposes, I define a county as a coal county in Table 1 if its coal mining employment share of the adult population in 2007 was at least 0.537 percent. This cutoff reflects the median coal share among counties with any coal employment in 2007.

to others.

Coal mining has traditionally offered relatively high wages to workers with relatively low levels of educational attainment, providing a critical source of labor income in these distressed communities. Figure 1 compares median (2017 inflation-adjusted dollars) earnings among full-time, male workers ages 20–64 in Appalachia to those working in the coal mining industry, while Figure 2 shows the relative educational composition of these groups of workers, based on data from the 1980 Census and the 2005–2009 ACS. At all levels of educational attainment, coal mining delivers relatively higher wages. In the 2005–2009 ACS sample, the median wage for full-time, male coal miners was about 37 percent more than that for all full-time, male workers in Appalachia. That the coal industry offers such a large wage premium suggests that job loss in the industry might be particularly consequential for communities built around the resource, which lack robust industrial sectors to absorb displaced workers.

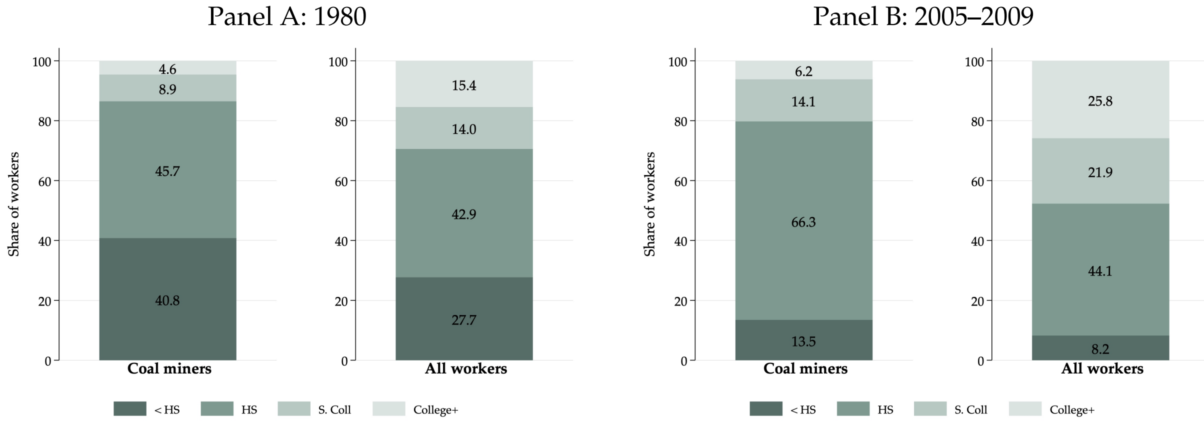
Figure 1: Median annual wages of male workers in Appalachia by educational attainment



Notes: Author's calculations based on the 1980 Census and 2005–2009 ACS, retrieved from IPUMS. The sample is restricted to male workers ages 20–64 in Appalachian counties reporting working at least 40 weeks at an average of 35 hours per week, and reporting earning at least the minimum hourly wage ($3.10 in 1980 and $5.85 in 2007), adjusted to a 40 week, 35-hour-week schedule. Earnings are adjusted to 2017 dollars using the CPI-U. Coal miners refers to all workers reporting working in the coal mining industry.

The economic divides documented in Table 1 intensified in the decade that followed alongside large-scale declines in demand for coal. Appalachia lost over 23,000 coal mining jobs between 2007 and 2017, reflecting a 43 percent loss in industry employment. At the same time, the population of Appalachia's most coal-dependent counties declined rapidly. The top half of Appalachia's coal-dependent counties (in terms of the coal share in 2007) lost nearly 75,000 residents over the

Figure 2: Educational attainment of male workers in Appalachia



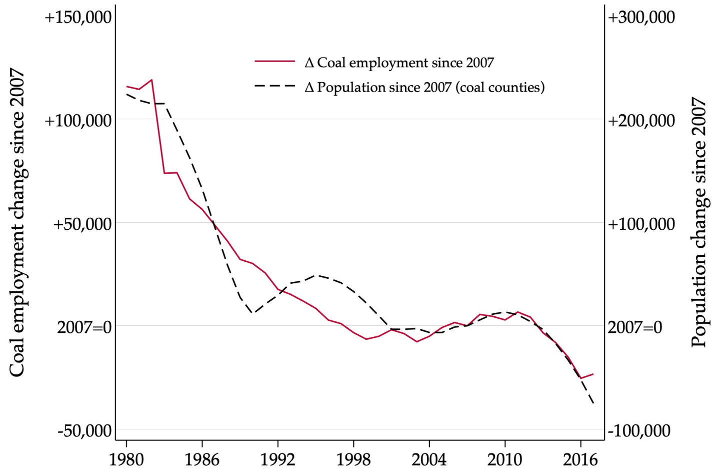
Notes: Author's calculations based on the 1980 Census and 2005–2009 ACS, retrieved from IPUMS. The sample is restricted to male workers ages 20–64 in Appalachian counties reporting working at least 40 weeks at an average of 35 hours per week, and reporting earning at least the minimum hourly wage ($3.10 in 1980, and $5.85 in 2007), adjusted to a 40 week, 35-hour-week schedule. Coal miners refers to all workers reporting working in the coal mining industry.

decade, reflecting a 2.7 percent decline. This recent decline succeeded a period of relative stability following a large-scale coal "bust" during the 1980s. Figure 3 depicts the change in annual population and coal mining employment in Appalachia over the 1980–2017 period, with values indexed to 2007 levels, demonstrating the extremely tight relationship between coal mining employment and population in coal-dependent communities that has persisted in this region for several decades. Over the 37-year period, coal mining employment fell by about 140,000 jobs (an 82 percent decline), while the total population in the top half of coal-dependent Appalachian counties fell by nearly 300,000 over the same period (a 10 percent decline).[11]

Notably, this population loss was highly selective, characterized by larger declines in young and better-educated residents. The selectivity of population change in Appalachia's coal communities was more pronounced than in other Appalachian regions, although there was substantial heterogeneity across coal regions. Appendix Figure A1 shows the distribution across counties of population changes between 1980 and 2007 expressed in deviation from the U.S. mean, separately for the top 50% of Appalachian coal-dependent counties (in teal) and all Appalachian counties (in gray). Counties to the left of zero experienced relative declines in the population category between

[11] While the decline in coal mining employment in the 1980s resulted from falling coal prices, improvements in coal mining technology, and the introduction of more accessible Western coal reserves, the more recent decline in Appalachian coal mining employment is largely attributable to technological advances in hydraulic fracturing that has made cheap natural gas more widely available (Kolstad, 2017; Linn and McCormack, 2019; Coglianese et al., 2020). Coglianese et al. (2020) estimate that 92 percent of the total decline in coal production between 2008 and 2016 could be attributed to the decline in natural gas prices relative to coal.

Figure 3: Population and coal mining employment, Appalachian counties



Notes: Coal mining employment in years 2000-onward is calculated based on mine-level statistics from the Mine Safety and Health Administration (MSHA). Coal mining employment in years prior to 2000 is calculated based on County Business Patterns (CBP) data imputed by Eckert et al. (2020). The red line captures the change in coal mining employment in all Appalachian counties between 2007 (employment $sim54$ thousand) and the year indicated. The dashed black line represents the change in the aggregate annual population in 65 Appalachian coal counties between 2007 (population $\sim$ 2.7 million) and the year indicated. These 65 counties are those in which at least 0.537 percent of the adult population was employed in coal mining in 2007. The 0.537 percent cutoff reflects the median coal share among counties with any coal mining employment in 2007.

1980 and 2007 compared to the U.S. average. Appalachia's most coal-dependent counties experienced larger relative losses in their adult populations (ages 20–64) during this period leading up to the 2007–2017 coal shock, and these losses were more selective than in Appalachia as a whole. Appalachian coal counties are heavily concentrated in the leftmost bins of the figure, such that these counties were becoming older and less educated compared to the rest of Appalachia and America. However, there exists dispersion in the degree of selective migration, even within Appalachian coal regions. Investigating the extent to which the consequences of the contemporary coal shock are influenced by historical changes in human capital endowments is a central goal of the analysis that follows.

3 A model of coal shocks

Recent shifts in coal demand have impacted all of Appalachia's coal communities, but places may vary in their capacity to adjust due to historical episodes that shaped their initial conditions. This section introduces a high-level, graphical version of a spatial equilibrium model that illustrates how adverse shocks in one generation can reverberate into the next. The model is detailed in Appendix Section B. It follows the work of Rosen (1974, 1986); Roback (1982); Blanchard and Katz (1992), and basic labor demand and supply models that incorporate heterogeneous types of workers (Diamond, 2016; Notowidigdo, 2020). Here, I outline the model's basic setup, broader intuition, and major predictions.

3.1 Setup

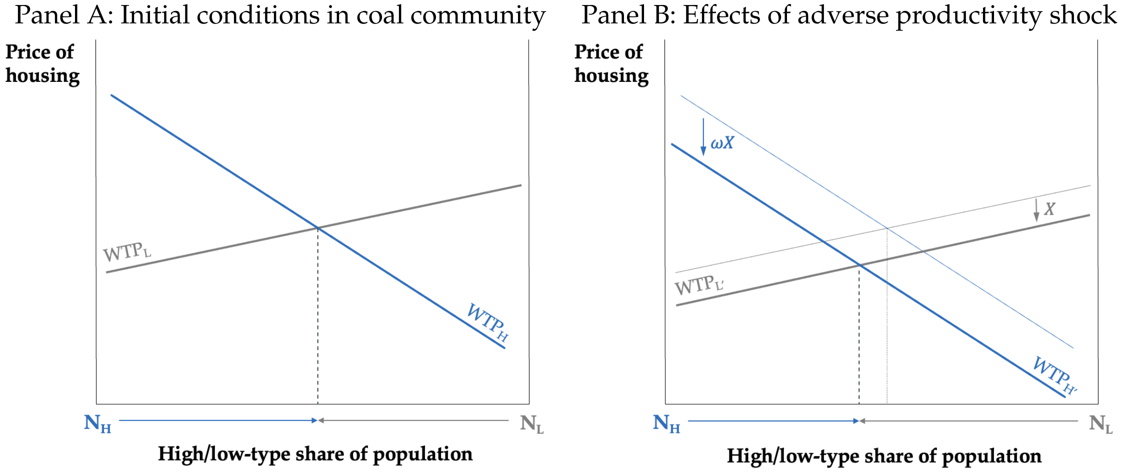
There are two "types" of workers in the economy: high (H) and low (L). High-type workers are relatively more productive than low-type workers, and thus they receive low-type workers' wages scaled by the efficiency parameter ω, where $\omega > 1$. Workers choose to live in either a coal community or elsewhere, and there are a total of N^H high-type and N^L low-type workers living in the coal community. Each worker consumes one unit of a fixed housing stock within a place, such that the number of housing units in the coal community is equal to the number of workers ($N^H + N^L$). Because there is one market for housing, high and low types pay the same price in equilibrium. High- and low-type workers' willingness to pay (WTP) for housing is dictated by the wages they receive in the coal community as well as their local amenity preferences.

Each place has many firms in one of two industries: coal (C) and non-coal (NC). Both coal and non-coal firms hire from the same pool of local high- and low-type workers, and thus firms in both industries pay the same wage (W^*) for an effective unit of labor in equilibrium, where an effective unit of labor is one unit of labor from a high-type worker or one unit of labor from a low-type worker scaled by the efficiency parameter, ω. An important feature of the model is that the number of local non-coal firms is increasing in the number of high-type workers in the preceding period. This connection reflects the well-documented relationship between human capital, entrepreneurship, and firm creation found in the literature (e.g., Lucas, 1988; Acemoglu and Angrist, 2000; Moretti, 2004; Gennaioli et al., 2013; Chatterji et al., 2014). Here, high-type workers function as entrepreneurs that give birth to new, non-coal firms in subsequent periods.

3.2 First-period shock and selective migration

Panel A of Figure 4 displays the initial conditions in the coal community. The number of high-type workers increases rightward from the lower left corner, while the number of low-type workers increases leftward from the lower right corner. The bottom axis is fixed. It reflects the total population in the coal community ($N^H + N^L$), which is equal to the number of housing units. The price of housing is determined by the intersection of high- and low-type WTP, where both WTP lines are downward-sloping from their respective axes.

Figure 4: A first-period shock and selective migration



Notes: Panel A describes the initial conditions in the coal community. The number of high types is increasing from left to right and the number of low types is increasing from right to left, with the total population fixed by the X-axis. The Y-axis describes the price of housing. WTP_H (WTP_L) describes the WTP for housing among high (low) types. Panel B describes the impacts of an adverse productivity shock in the coal community. This shock produces a downward shift in WTP_H that is equal to the downward shift in WTP_L, scaled by the high-type efficiency parameter, ω.

Panel B of Figure 4 illustrates the consequences of an adverse productivity shock in the coal community, which reduces the wages of both high- and low-type workers. This wage reduction shifts the WTP for housing inward for both types. Because high types are relatively more efficient than low types, their WTP declines by a greater amount, with the reduction in low-type WTP, X, scaled by the efficiency parameter ω. This produces selective migration, reducing the equilibrium number of high-types living in the coal community. Consequently, the migration response influences the resulting population composition (N^H/N^L) to include relatively fewer high types, as depicted by the leftward shift in the dotted line intersecting the bottom axis.[12]

3.3 Second-period shock

That an adverse shock can produce selective migration is a relatively standard prediction in many spatial equilibrium models, and is borne out in many empirical settings (e.g., Topel, 1986; Bound and Holzer, 2000; Moretti, 2011; Notowidigdo, 2020). How does this influence the consequences of future shocks? Here, I describe the model predictions regarding how a first-period shock influences firm composition, as well as how this shift in firm composition affects the wage conse-

[12]Because migration decisions respond to wages and amenities influenced by the shock, the resulting population composition (N^H/N^L) is an endogenous parameter.

quences of a subsequent, second-period shock.

Figure 5 displays the labor demand conditions in a coal community. The number of effective units of coal (non-coal) labor in the community is L_C (L_{NC}). On the bottom axis, L_C increases rightward from the lower left corner, and L_{NC} increases leftward from the lower right corner. Equilibrium wages W^* are determined by the intersection of the downward-sloping labor demand curves for coal and non-coal labor. Because firm entry in the non-coal sector is increasing in the lagged supply of high-type workers, a first-period shock that induces selective out-migration reduces the number of non-coal firms in the following period. This, in turn, lowers both the level and elasticity of non-coal labor demand – effectively pivoting the demand curve downward, as shown by the shift from the thinner to the thicker purple line in Figure 5.[13]

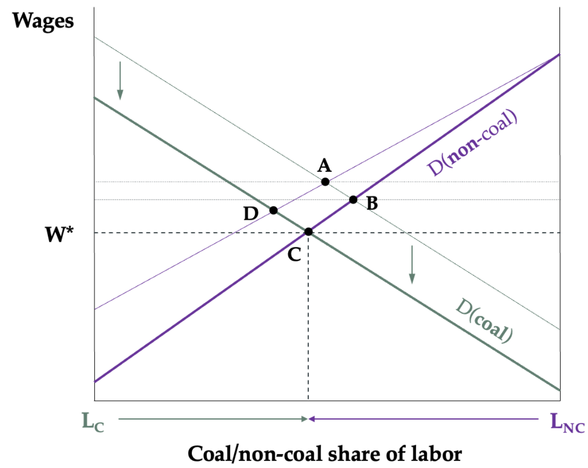
Suppose that the coal industry experiences an adverse shock in a subsequent period. Figure 5 displays this as an inward, level shift in the labor demand curve for coal, from the thinner to the thicker green line. This inward shift reduces equilibrium wages W^* and reduces the coal share of total labor. The figure illustrates how selective migration induced by a first-period shock alters the wage adjustment to a second-period coal shock. In a community with a higher initial skill share and a flatter non-coal labor demand curve (i.e., in the absence of the first-period shock), equilibrium wages would adjust from point A to point D. In contrast, the steeper the non-coal labor demand curve produced by a lower skill share amplifies the wage adjustment to the second-period coal shock, as shown by the larger change from point B to point C.

The spatial equilibrium model, graphically depicted here and detailed in Appendix Section B, produces two major results that are relevant to understanding selective migration, regional decline, and the consequences of recurrent shocks. First, adverse shocks produce selective migration, which affects the relative population sizes of high- and low-skilled labor. Allowing educational attainment to serve as a crude proxy for different types, adverse shocks will yield local population loss, with larger losses among better-educated (i.e., high-type) workers. Second, the consequences of adverse shocks will be more severe in places exposed to shocks in preceding periods, thanks to the selective migration induced by preceding shocks and the effect that selective migration has on subsequent economic activity. This implies that shocks can have long-term consequences on the evolution of places via their effect on the flow of human capital.[14] In the context of Appalachia's

[13]With fewer non-coal firms, labor demand declines and becomes less responsive to wages, resulting in a downward pivot (i.e., steeper slope) of the demand curve.

[14]This is consistent with other work indicating that the stock of human capital is important to regional economic growth (Glaeser et al., 1995; Glaeser, 2005; Gennaioli et al., 2014; Islam et al., 2015; Gagliardi et al., 2023).

Figure 5: Selective migration, labor demand, and a second-period shock



Notes: Figure describes the labor demand conditions in the coal community. The number of coal labor units is increasing from left to right and the number of non-coal labor units is increasing from right to left. The Y-axis describes wages for an effective unit of labor. D(non-coal) and D(coal) reflect demand curves for non-coal and coal labor. Thinner lines depict labor demand in the absence of a first-period shock. The pivot from the thinner to the thicker purple line reflects reduced firm entry in the non-coal sector, which is increasing in the lagged supply of high-type labor. The shift from the thinner to the thicker green line reflects a second-period adverse coal shock, which directly lowers demand for coal labor. Point A identifies initial equilibrium wages, W^*. Point B identifies W^* following a pivot in demand for non-coal labor caused by a first-period shock which reduced the number of high types. Point C identifies W^* following the new coal shock, and point D identifies W^* following the new coal shock in the absence of the initial shock and hence in the absence of pivoting demand for non-coal labor.

coal country, certain communities may be more vulnerable to the consequences of the contemporary decline in demand for coal because they were exposed to shocks in preceding periods which reduced the stock of human capital.

4 Regional adjustment to coal shocks

In this section, I first consider the adjustment costs associated with a single-period coal shock. This analysis leverages differential county-level exposure to the 2007–2017 coal shock to estimate the effect of declining demand for coal on county-level employment, population counts, and the employment-population ratio. Next, I exploit variation in spatial proximity to historical employment shifts to understand how selective migration in preceding periods influences the consequences of the contemporary coal shock.

4.1 Adjustment to a single-period shock

4.1.1 Empirical approach

To understand the county-level adjustment to a single-period coal shock in terms of its effect on employment, population mobility, and other outcomes, I estimate the following long-difference equation (Griliches and Hausman, 1986):

$$\Delta y_j^{2007\text{-}17} = \beta_0 + \beta_1 \Delta Coal_j^{2007\text{-}17} + \beta_2 \left(\mathbf{1}[Coal_j^{2007} > 0]\right) + \mathbb{X}_j'\gamma + \delta_s + \varepsilon_j \tag{1}$$

where $\Delta y_j^{2007\text{-}17}$ is county j's long-difference change in outcome y between 2007 and 2017. The main independent variable of interest, $\Delta Coal_j^{2007\text{-}17}$, is -1 times the change in the coal mining employment share of the population ages 20–64 over the same period. I refer to the change in the coal share as the coal shock throughout.[15] The observed change in the coal share is multiplied by -1 for ease of interpretation, such that a larger decline in the coal share implies a larger coal shock. In equation 1, I include a dummy variable indicating whether the county had any coal employment at the beginning of the period ($\mathbf{1}[Coal_j^{2007} > 0]$) and state fixed effects, δ_s.[16] A vector of county-level controls $\mathbb{X}_j'$ includes the initial share of the adult population with a college degree, the share of the population that is foreign-born, and the female share of the adult workforce (ages 20–64). Coal is concentrated in regions with different population characteristics which may be predictive of outcome trajectories. These controls capture other potential determinants of outcomes that might be correlated with the initial coal share. Omitting covariates in the estimation of equation 1 does not alter the conclusions, and controlling for a richer set of county-level characteristics (e.g., the manufacturing share of employment and the population age distribution) also produces similar results. The coefficient β_1 measures the responsiveness of the outcome of interest to changes in the local coal mining employment share of the adult population over the decade, such that a positive (negative) β_1 implies that the outcome increases (decreases) with a larger shock.

I consider a range of outcomes $\Delta y_j^{2007\text{-}17}$ that capture various county-level margins of adjustment to the coal shock. I focus on the change in the natural log of employment, the change in the natural log of working-age adults (ages 20–64), and the change in the employment-population ra-

[15] The conclusions are quantitatively similar when defining the shock as the change in the coal share of employment, as well as the change in the coal share of the consistent (2007) population.

[16] One concern is that coal is highly spatially concentrated, and heavily so in Eastern Kentucky and West Virginia, such that large declines in coal mining employment would coincide with state-level regulations or policies that would also influence outcomes. The inclusion of state fixed effects absorbs these idiosyncratic state-level policies. The conclusions are robust to omitting state fixed effects and alternative levels of geographic controls (e.g., division).

tio, defined as the number of employees per working-age adult.[17] Employment counts are based on total wage and salary employment from the BEA and the number of working-age adults is derived from Census estimates.[18] In the appendix, I consider several other outcomes, including changes in earnings and changes in population counts by sex and education.

I estimate equation 1 for the 413 counties served by the ARC with non-missing data in all years of analysis.[19] Of these 413 counties, 129 (31 percent) had any coal mining employment in 2007. Appendix Table A1 reports summary statistics for the primary independent variables in this analysis. The population-weighted mean coal shock (x100) was 0.38 (implying a decline in the coal share of 0.38pp) and the standard deviation was a change of 1.6pp. The distribution of the coal shock has a long right tail: counties at the 95$^{\text{th}}$ and 99$^{\text{th}}$ percentiles experienced declines of 1.6pp and 6.9pp, respectively. All regressions are weighted by the initial county population to minimize measurement error driven by sparsely populated areas. In practice, weighting has little effect on the estimates.[20]

Estimating equation 1 using ordinary least squares (OLS) could yield biased estimates of the causal effect of the coal shock for several reasons. Unobservable, idiosyncratic factors may simultaneously reduce (or increase) county-level economic indicators and draw individuals out of the coal sector, producing a spurious association between the change in the coal share and the economic indicator. An environmental disaster, such as the historic 2022 flood in Eastern Kentucky, might reduce coal mining activity and prevent employment in other sectors, producing a downward bias in the OLS coefficient. Counties actively diversifying their workforce by providing educational investments and tax credits for new businesses might draw workers away from coal mining and into other, more productive industries, producing an upward bias in the OLS coefficient. To address this, I exploit the fact that changes in coal demand are macroeconomic in

[17]The primary independent variable is defined such that a 1-unit change in the coal shock reflects a 0.01pp change in the coal share. Thus, the coefficient estimate for all outcome variables that are expressed as the change in the natural log can be interpreted as the effect of a 1pp change in the coal share, without multiplying by 100, as is typical for log-transformed outcome variables. Outcome variables that are expressed as changes in shares are also defined such that 1 unit reflects a 0.01pp change. Thus, the coefficient estimates for these outcomes can also be interpreted directly as the effect of a 1pp change in the coal share.

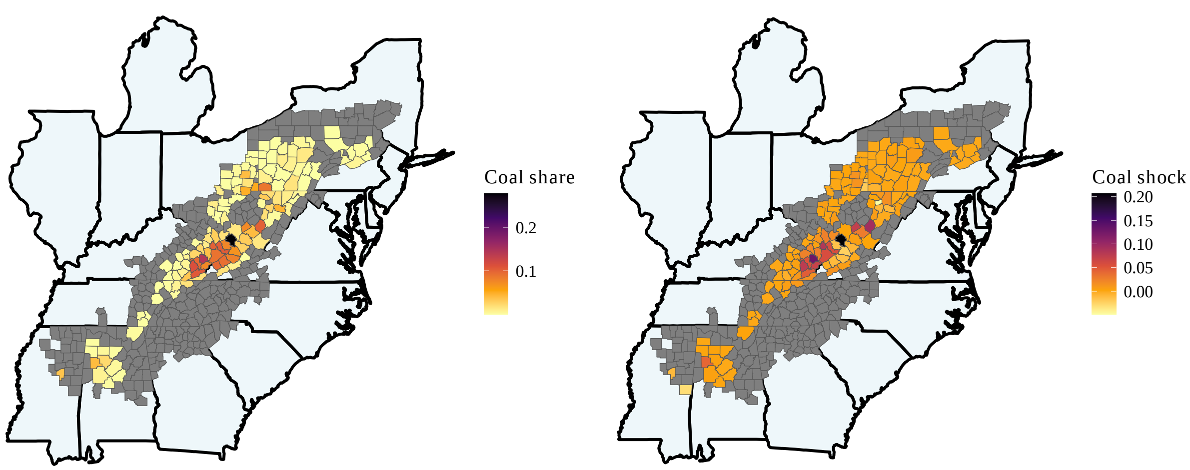
[18]Wage and salary employment excludes sole proprietorships, partnerships, and tax-exempt cooperatives. The conclusions are broadly similar when including these forms of employment.

[19]The ARC-defined region serves as a natural geographic setting to examine the coal shock, as it has been subject to common policy interventions since the ARC's foundation. However, it does include several relatively urban, non-coal areas that may serve as poor counterfactuals for the less dense and distressed coal communities in Central Appalachia. The results are insensitive to omitting these areas.

[20]All specifications report robust (heteroskedasticity-consistent) standard errors, following the approach used in related work with similar instruments (Charles et al., 2019) Clustering by state is unreliable with only 13 clusters. While recent work recommends exposure-robust standard errors in shift-share designs (e.g., Borusyak et al., 2025), clustering at the commuting zone level yields similar inference.

nature, and yet certain counties are differentially exposed to these fluctuations thanks to existing coal infrastructure (i.e., comparative advantage due to the spatial concentration of coal reserves). Specifically, I instrument for the local coal shock $\Delta Coal_j^{2007\text{-}17}$ with the initial (2007) coal mining share of the adult population (ages 20–64), $Coal_j^{2007}$. The interaction between regional variation in comparative advantage, or "exposure," and the national sectoral shock serves as the identification strategy.[21] The left panel of Figure 6 displays a heat map of $Coal_j^{2007}$ across Appalachian counties, while the right panel displays a heat map of the local coal shock, $\Delta Coal_j^{2007\text{-}17}$. As seen in the figure, coal employment was heavily concentrated in Eastern Kentucky and West Virginia, which subsequently experienced the largest declines in coal employment over the 2007–2017 period.[22]

Figure 6: Coal share in 2007 ($Coal_j^{2007}$) and subsequent coal shock ($\Delta Coal_j^{2007\text{-}17}$)



Notes: The coal share $Coal_j^{2007}$ is defined as the coal employment share of the working-age adult population in 2007. The coal shock $\Delta Coal_j^{2007\text{-}17}$ is the change in the coal share between 2007 and 2017, multiplied by -1. Coal employment is calculated based on mine-level statistics from the Mine Safety and Health Administration. Adult population is defined as the population ages 20–64 and is based on Census estimates. Shaded area includes 413 Appalachian counties, where grey indicates that the county hosted no coal mining employment in 2017.

This IV approach is akin to a Bartik industry shift-share instrument, where the initial coal share of the adult population serves as the "share," or county-level exposure to the labor demand shock (Bartik, 1991). The "shift" is the national change in demand for coal, largely influenced by the emergence of cheap natural gas made available by hydraulic fracturing technology (Linn and McCormack, 2019; Coglianese et al., 2020; Davis et al., 2022).[23] Because this shift is macroeconomic

[21] Because there is only one industry, the instrument used here is effectively identical to a leave-one-out shift-share instrument that multiplies the initial share by the common shock, as in Autor et al. (2021)

[22] The first-stage F-statistic on the 2007 coal share is 22.

[23] Environmental regulations increasing the cost of producing coal-fired energy and weak international demand both amplified waning demand for coal.

in nature and thus common to all counties, the initial shares drive the variation necessary for identification (Goldsmith-Pinkham et al., 2020). The exclusion restriction requires that having a highly coal-dependent workforce at the beginning of the period does not affect a county's expected outcomes except through its relationship with declining coal mining shares in the subsequent decade, conditional on observables. This is impossible to test for explicitly, but one indirect test of the exclusion restriction is to examine whether the instrument predicts outcome changes during a period of relative stability in demand for coal. Appendix section D details this falsification test, offering evidence that the 2007 coal share is quite predictive of outcome changes during the period of coal's sectoral decline (2007–2017), but not during the placebo period in which demand for coal is relatively stable (1997–2007).[24] The results presented in this paper are additionally robust to controlling for lagged population changes, lagged coal shares, spatial spillovers, and instrumenting for the local coal shock with a county-level measure of initial coal endowment, predating any experience with coal mining.

4.1.2 Employment and population adjustment to a single-period shock

Table 2 presents the baseline coefficient estimates of β_1 from equation 1 reflecting the relationship between the 2007–2017 coal shock and the change in total employment (Panel A), the change in the working-age adult population (Panel B), and the employment-adult population ratio (Panel C). The point estimates in column 1 are produced using OLS, while the estimates in columns 2 through 5 instrument for the coal shock with the initial (2007) coal share. I initially present a parsimonious specification with no controls. The employment and population estimates in column 2 are larger in magnitude than the OLS estimate in column 1, which is consistent with several hypotheses about the nature of idiosyncratic declines in coal employment at the local level. For example, if declines in coal employment result from economic diversification efforts and the growth of other industries, this would produce a positive correlation between coal shocks and local labor demand that would bias OLS estimates toward zero.

The estimates in column 3 incorporate state fixed effects and those in column 4 control for baseline county-level covariates including the initial share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable

[24]Further, the interaction of the initial coal share with the price of relevant competing commodities (oil and gas) predicts outcomes over the periods in which coal is in decline, while this interaction does a poor job of predicting outcomes during the relatively stable periods of coal demand. These tests indicate that the coal share influences outcomes through its interaction with macroeconomic factors, but does not predict outcomes during periods of stability, conditional on observables.

indicating whether the county had positive coal employment at the beginning of the period. The specification in column 5 additionally controls for the county's initial manufacturing share of employment, the share of natural gas produced by the county in 2007, and the 2007-level share of the population ages 0-19, 20-39, and 40-59.[25] These additional controls do not substantively change the point estimates.[26] I refer to the specification in column 4 as the baseline.

Table 2: Employment and population adjustment to single-period coal shock, 2007–2017

	(1)	(2)	(3)	(4)	(5)
	OLS		IV		
Panel A: Δln(wage and salary employment) 2007-2017					
Coal shock, 2007–2017	-3.30***	-4.60***	-3.77***	-3.24***	-3.45***
	(0.45)	(1.13)	(0.88)	(0.74)	(0.80)
Panel B: Δln(population ages 20–64) 2007-2017					
Coal shock, 2007–2017	-1.48***	-3.29**	-2.14**	-1.42**	-1.44**
	(0.37)	(1.28)	(0.88)	(0.63)	(0.61)
Panel C: Δ employment:population ratio, 2007-2017					
Coal shock, 2007–2017	-0.82***	-0.50*	-0.78***	-0.97***	-1.07***
	(0.14)	(0.28)	(0.23)	(0.23)	(0.23)
State FE			✓	✓	✓
Baseline controls				✓	✓
Additional controls					✓
First-stage F-stat		26.52	24.29	22.48	24.55
Observations	413	413	413	413	413

All regressions are weighted by initial (2007) county population. Robust standard errors are in parentheses. Baseline controls include the initial share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Additional controls include the manufacturing share of employment, the share of natural gas produced by the county, and the share of the population ages 0-19, 20-39, and 40-59. The coal shock is defined as -1 times the change in the coal employment share of the adult population (ages 20–64). I instrument for the coal shock in columns 2-5 with the coal share in 2007. The first-stage F-stat on the instrument is reported in the second row from the bottom. Outcome variables are retrieved from the BEA Regional Economic Accounts.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The point estimates in column 4 indicate that a 1-unit change in the coal shock (a 1pp decline in the coal share of the population ages 20–64) yields a 3.2 percent decline in employment, a 1.4 percent decline in the population ages 20–64, and nearly a 1pp decline in the employment-population ratio (i.e., the employment rate). The decline in employment exceeds what would

[25]The manufacturing share is based on the imputed CBP data from Eckert et al. (2020). Natural gas production is retrieved from the USDA Economic Research Service (ERS) "County-level onshore oil and natural gas production in the lower 48 States, 2000-11". Population age shares are based on Census estimates.

[26]The conclusions drawn from Table 2 are robust to additionally controlling for commuting flows between adjacent coal counties, indicating that these adjustment costs persist after accounting for potential spillovers from proximate coal activity.

be expected from population loss alone.[27] Moreover, the magnitude of the employment decline exceeds what might be explained by direct job losses in the coal sector alone, particularly given its modest size in most counties.[28]

To interpret the magnitude of these changes, consider the effect of a 1-standard deviation (SD) increase in the coal shock (1.6pp). This implies a reduction in employment of over 5 percent, a 2.4 percent reduction in the size of the working-age adult population, and a 1.5pp reduction in the employment rate.[29] That employment counts and employment rates decline with local demand shocks is consistent with a broader body of work documenting the regional adjustment costs associated with shocks in other industries, like manufacturing. At the same time, population mobility appears to be a particularly important margin of adjustment in Appalachian coal regions compared to these other settings, where researchers often document null or very modest population responses in contemporary settings (Autor et al., 2013; Charles et al., 2019; Faber et al., 2022). This scholarship tends to conclude that population mobility is an increasingly sluggish adjustment mechanism (Molloy et al., 2011; Partridge et al., 2012; Dao et al., 2017; Jia et al., 2023; Olney and Thompson, 2024). Appendix Table A2 reveals that the adjustment to coal shocks in Appalachia has remained quite consistent over time, with the 1980–1990 coal shock producing similar employment and population effects as the 2007–2017 shock.[30] Although population mobility can help attenuate the overall wage and employment rate impacts of local demand shocks (Blanchard and Katz, 1992), it can also reduce human capital endowments, tax revenues, and influence other local characteristics which may amplify the risks associated with subsequent shocks.

4.1.3 Selective migration and other adjustments

In line with other work documenting the selective nature of migration responses (Bound and Holzer, 2000; Glaeser and Gyourko, 2005; Wozniak, 2010; Amior and Manning, 2018; Notowidigdo, 2020), the population response to coal shocks is larger among college-educated adults. Table 3

[27]To attribute the entire 3.2% employment decline to the 1.4% decline in population, one would need to assume that every single individual reflected in the population decline was employed and that the employment rate was only 40 percent.

[28]This may indicate negative spillover effects in other industries, consistent with Black et al. (2005a). I explore this possibility in Appendix Section E.

[29]The population-weighted mean employment rate in 2007 across all 413 Appalachian counties was 70 percent (Table 1), so this reflects a very modest decline in the employment rate.

[30]The regression specification used to produce the estimates in Appendix Table A2 is analogous to that used to produce Table 2, but with 1980-level covariates, 1980 population weights, and the 1980 coal share as an instrument for the 1980–1990 coal shock. The average coal county had a much higher coal share in 1980 than in 2007, and thus a 1-unit coal shock reflects a smaller percent change in the historical period than the contemporary period. Thus, the smaller coefficients in the historical period do not necessarily imply a smaller adjustment.

displays the IV estimates for the effect of the 2007–2017 coal shock (panel A) and 1980–1990 coal shock (panel B) on adult (ages 25 and older) population counts by educational attainment. Panel A distinguishes male versus female population responses, revealing that population declines in response to the 2007–2017 coal shock are largest among men with at least a college degree (column 4), while the response among men and women with less than a high school degree is statistically indistinguishable from zero (column 2). Over the decade, a 1-unit (1pp) increase in the coal shock yields a 3.1 percent decline in the college-educated male population and a slightly less precise 0.29pp decline in the share of adult men with a college degree.

To account for lagged mobility responses, Panel B of Table 3 displays the effect of the historical (1980–1990) coal shock on population mobility across progressively longer time horizons. The first row reveals that the 1980–1990 coal shock reduces the head counts of better-educated adults, but not by a large enough magnitude to change the skill composition of the adult population. Subsequent rows reveal that the selectivity of population mobility grows over progressively longer time horizons. A 1-unit (1pp) increase in the 1980–1990 coal shock reduces the college share of the adult population by about 0.22pp over the 1980–2007 period, and it reduces the aggregate college-educated headcount by about 3.2 percent by 2007. Thus, by the time the contemporary coal shock unfolds, Appalachia's coal communities were much smaller and less educated than in the absence of the 1980s coal bust.

Other work has documented a wide range of consequences of local demand shocks, including reduced earnings and income (Davis and von Wachter, 2011; Colmer et al., 2024; Rud et al., 2024), increased reliance on disability insurance and other transfer payments (Black et al., 2002, 2003; Jacobsen and Parker, 2016; Charles et al., 2019; Hanson, 2022), and impacts on the housing market (Zabel, 2012; Notowidigdo, 2020). Appendix Section E explores several of these other forms of labor market adjustments. In addition to reducing employment and population counts, the 2007–2017 coal shock reduced total and average earnings. With aggregated, county-level data, it is impossible to distinguish the extent to which changes in average earnings are driven by simultaneous changes in the population composition. Larger local employment losses among the most productive workers will mechanically reduce average earnings. While compositional shifts in the population are a contributing factor, earnings losses are concentrated among relatively immobile groups of workers (less-educated men). This is consistent with other work using individual-level data to document relatively large earnings impacts from various shocks (Topel, 1990; Jacobson et al., 1993; Walker, 2013; Rud et al., 2024), and provides suggestive evidence that average earnings

Table 3: Adult (ages 25 and older) population change by sex and educational attainment, 2007–2017 and 1980–1990 coal shock

	(1) Δ College share of adults	(2) Δ ln(adults w/ less than high school)	(3) Δ ln(adults w/ HS or some college)	(4) Δ ln(adults w/ college degree or more)
Panel A: 2007–2017 coal shock				
Δ **Male** adult population				
Coal shock, 2007–2017	-0.29*	0.64	-0.64*	-3.11**
	(0.15)	(0.77)	(0.37)	(1.40)
Δ **Female** adult population				
Coal shock, 2007–2017	-0.04	0.57	-1.31**	-1.59
	(0.11)	(0.95)	(0.59)	(1.04)
Panel B: 1980–1990 coal shock				
Δ Adult population, **1980–1990**				
Coal shock, 1980–1990	-0.03	-0.12	-0.61**	-0.74*
	(0.04)	(0.21)	(0.25)	(0.45)
Δ Adult population, **1980–2000**				
Coal shock, 1980–1990	-0.14**	-0.21	-1.29***	-2.23***
	(0.06)	(0.40)	(0.48)	(0.62)
Δ Adult population, **1980–2007**				
Coal shock, 1980–1990	-0.22***	-0.79	-1.46**	-3.23***
	(0.08)	(0.57)	(0.59)	(0.81)
State FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	413	413	413	413

All regressions are weighted by initial (2007 or 1980) county population and include state fixed effects and controls for the initial (2007 or 1980) share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. The coal shock is defined as -1 times the change in the coal employment share of the adult population (ages 20–64) over the 2007–2017 (Panel A) or 1980–1990 (Panel B) period. I instrument for the coal shock with the coal share in 2007 (Panel A) or 1980 (Panel B). Outcome variables in Panel A describe the 2007–2017 change in the population ages 25 and older by sex and educational attainment, based on ACS 5-year estimates (2005–2009 and 2015–2019). Outcome variables in Panel B describe the change in the population ages 25 and older by educational attainment, based on decennial Census estimates (1980, 1990, and 2000) and the ACS 5-year estimates (2005–2009). Each row in Panel B defines the outcome over a different time horizon: 1980–1990, 1980–2000, and 1980–2007.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

declines are not solely driven by mechanical compositional changes in the workforce. Appendix Section E additionally demonstrates that employment losses extend beyond the mining industry. The 2007–2017 coal shock reduced employment in certain service sectors relatively more reliant on local demand, suggesting the adverse coal shocks might trigger de-agglomeration forces in exposed communities.

The result that the 2007–2017 coal shock reduces local employment and population counts is robust to alternative identification strategies and definitions of the coal shock. Appendix sections F and G detail these alternative specifications. In Appendix section F, I instrument for the 2007–2017 coal shock with a measure of county-level coal endowments that predates any economic experience with the industry. This exercise produces largely similar point estimates as the baseline specification, supporting the notion that the baseline estimates are driven by differential exposure to coal's sectoral collapse. In Appendix Section G, I examine the role of spatial spillovers across counties, accounting for potential indirect effects of the coal shock on neighboring labor markets.

4.2 Selective migration and a second-period shock

4.2.1 Identification strategy

The model presented in this paper implies that an adverse shock may be more consequential in places that experienced selective migration, or greater brain drain, resulting from shocks in preceding periods. In this section, I explore whether the adjustment costs associated with the contemporary coal shock differ based on a place's history of selective migration. Because the underlying population composition is endogenous to local economic conditions, I leverage differential exposure to plausibly orthogonal labor demand shocks occurring during the 1980s to isolate the exogenous component of selective migration. These shocks created uneven push and pull dynamics for high-skilled workers in coal communities. I detail this identification strategy below.

The spatial concentration of coal deposits introduces an additional challenge: serial correlation in exposure to coal shocks across time makes this setting less suitable for the standard local projections-style approach commonly used to estimate impulse response functions (Jordà, 2005, 2023).[31] Instead, I identify selective migration from preceding shocks by leveraging the fact that the 1980s coal bust occurred amidst the backdrop of orthogonal expansions and contractions in other industries which differentially affected places based on the regional concentration of industry employment. This approach is motivated by the insight that local employment and wages are influenced both by local industry productivity and — in the case of spatial spillovers — industry productivity in proximate labor markets. The bilateral nature of migration decisions implies that the population adjustment to shocks depends both on the direct impact of the local demand shock

[31] A local projections-style approach in this setting would require that shocks are independent across time, but coal shocks are serially correlated. The same geographic concentration of coal activity that made certain counties highly exposed to the 1980s coal bust also made them disproportionately exposed to the 2007–2017 coal shock. Because earlier shocks fundamentally altered baseline conditions – through mechanisms like selective migration – that shape the observed impacts of later shocks, I cannot credibly identify heterogeneity in selective migration between the two periods based on the historical coal shock alone.

as well the indirect impact of demand shocks in proximate locations, with the relative strength of the relationship between two locations dictated by the gravity structure of trade (Adão et al., 2019; Redding, 2022; Borusyak et al., 2022b; Olney and Thompson, 2024). In this setting, selective migration can emerge thanks to the "push" of the historical coal shock, which is common across coal counties, as well as the "pull" of historical labor demand shocks in proximate markets, which vary in intensity across coal communities.

To operationalize this approach, I define selective migration as the change in the natural log of the college-educated adult population, and I predict selective migration driven by exogenous shocks over the 1980–1990 period ($\Delta\widehat{college_j}^{1980\text{-}90}$) by estimating the following:

$$\Delta college_j^{1980\text{-}90} = \tau_0 + \tau_1 Prox_j^{1980} + \tau_2 Coal_j^{1980} + \tau_3 \left(\mathbf{1}[Coal_j^{1980} > 0]\right) + \mathbb{X}_j'\gamma + \delta_s + \varepsilon_j \tag{2}$$

where $\Delta college_j^{1980\text{-}90}$ is the observed change in county j's (log) adult population with a college degree or more between 1980 and 1990.[32] The variable $Prox_j^{1980}$ reflects county j's proximity to labor demand shocks in all other U.S. counties during the 1980s. Specifically, it is the gravity-weighted predicted employment change in all other U.S. counties $j' \neq j$ (i.e., the sum of Bartik employment shocks in each other county j' weighted by the distance between county j and j'):[33]

$$Prox_j^{1980} = \sum_{j'} \omega_{jj'}^{1980} \times \Delta Z_{j'}^{1980\text{-}90} \tag{3}$$

where $\omega_{jj'}^{1980}$ is a weight that describes the distance between county j and county j',[34] and $\Delta Z_{j'}^{1980\text{-}90}$ is the 1980–1990 employment shock in other county j' predicted by a standard, Bartik-style leave-one-out shift-share instrument (Bartik, 1991; Blanchard and Katz, 1992; Notowidigdo, 2020).[35]

[32]This analysis predicts changes in the number of college-educated adults, capturing selective migration in absolute terms. Robustness checks further examine the change in the share of college-educated workers.

[33]The sample used to estimate equation 2 includes only Appalachian counties, but non-Appalachian counties are included in the construction of $Prox_j^{1980}$.

[34]$\omega_{jj'}^{1980}$ is defined as:

$$\omega_{jj'}^{1980} \equiv \frac{P_{j'} D_{jj'}^{-\delta}}{\sum_k P_k D_{jk}^{-\delta}} \tag{4}$$

where $P_{j'}$ reflects the initial-period (1980) population in county j', $D_{jj'}$ reflects the distance between counties j and j', and δ is the trade-cost elasticity which, as in Autor et al. (2021), I set equal to 5. The conclusions are insensitive to the specific trade-cost elasticity used here. Additionally, using initial-period migration networks or commuting flows as weights rather than the distance-based measure does not alter the conclusions.

[35]$\Delta Z_{j'}^{1980\text{-}90}$ is defined as:

$$\Delta Z_{j'}^{1980\text{-}90} = \sum_{k \in K} s_{j'k}^{1980} \times \Delta emp_{-j'k}^{1980\text{-}90} \tag{5}$$

In equation 2, $Coal_j^{1980}$ reflects the coal share of the adult population in 1980, which determines a county's exposure to the historical decline in demand for coal. As in equation 1, $\mathbb{X}_j'$ represents the initial (1980) share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree, $\mathbf{1}[Coal_j^{1980} > 0]$ is a dummy variable indicating whether the county had positive coal employment in 1980, and δ_s reflects state fixed effects. The inclusion of the 1980 coal share, control variables, and state fixed effects improves precision but does not alter the qualitative conclusions of this exercise.

I estimate equation 2 using the sample of 413 Appalachian counties, weighting observations by 1980 population counts, and then predict $\Delta\widehat{college_j}^{1980\text{-}90}$ for each county to arrive at the selective migration predicted by exogenous shocks.[36] The intuition for this approach is that an individual's migration decisions depend on the economic circumstances in their local labor market and the economic circumstances in related labor markets which influence local economic activity. Certain regions are well-positioned for industrial expansions because of their initial industry mixes, and more proximate communities are better positioned to gain from these plausibly exogenous demand shifts. Visually, the major ingredient in equation 2 and the resulting predicted selective migration can be seen in Figure 7. Panel A displays a heat map of the (standardized) values for $Prox_j^{1980}$ across Appalachia, where darker shading indicates closer proximity to (predicted) employment growth. Panel B of Figure 7 displays the (standardized) values for $\Delta\widehat{college_j}^{1980\text{-}90}$, where darker shading indicates larger increases in the predicted change in the college-educated population over the 1980s. Those counties with the lightest shading are those with predicted losses in the college-educated adult population over this decade.

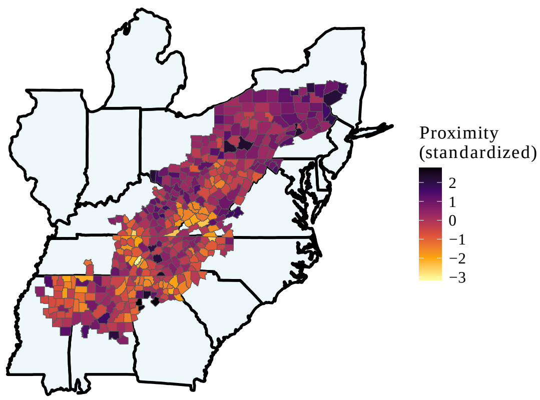
To assess whether the adjustment costs associated with the 2007–2017 coal shock depend on a place's history of selective migration induced by shocks, I bifurcate counties into two groups based on $\Delta\widehat{college_j}^{1980\text{-}90}$ and compare the employment and population adjustment to the 2007–2017 coal shock across these two groups of counties. I define counties in the lowest quartile of $\Delta\widehat{college_j}^{1980\text{-}90}$ (i.e., those with greater selective migration or brain drain) as $migr_j = 1$, and the remainder as $migr_j = 0$. There is nothing special about the bottom quartile versus other potential cutoffs (e.g., the bottom tercile or bottom half), and the conclusions are robust to alternative grouping methods and incorporating a continuous measure of predicted selective migration, detailed

where $s_{j'k}^{1980}$ is the fraction of county j' employment in 3-digit industry k in 1980 (the "share"), and $\Delta emp_{-j'k}^{1980\text{-}90}$ reflects the growth rate of industry k from 1980 to 1990 in all counties except county j' (the "shift"). I use the CBP-imputed industry-employment counts provided by Eckert et al. (2020) to produce $\Delta Z_{j'}^{1980\text{-}90}$.

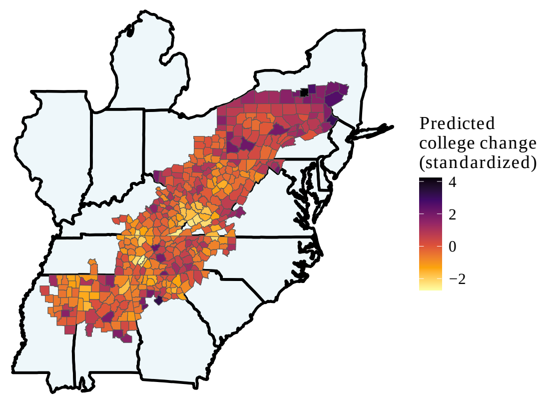
[36]The first-stage F-statistic on $Prox_j^{1980}$ in equation 2 is 14.9.

Figure 7: Proximity to employment growth and predicted population change

Panel A: Proximity to predicted 1980s employment growth



Panel B: Predicted change in college-educated adults, 1980—1990



Notes: Panel A reflects the (standardized) values for the variable $Prox_j^{1980}$, calculated as described in text. This variable captures a county's gravity-weighted proximity to other counties' predicted employment growth over the 1980–1990 decade. Darker shading reflects counties that are closer in proximity to regions with (predicted) employment growth. Panel B reflects the (standardized) values for the $\Delta\widehat{college}_j^{1980\text{-}90}$ variable, calculated as described in text. This variable reflects the predicted change in the college-educated adult population (ages 25 and older) in a county between 1980 and 1990. Darker shading reflects counties with larger predicted increases in the number of college-educated adults. Lighter shading implies that counties hold low or negative values for the change in the college-educated population over this decade.

in Section 4.2.3. I then re-estimate a modified version of equation 1 for the contemporary period (2007–2017), interacting the coal shock $\Delta Coal_j^{2007\text{-}17}$ with a dummy variable indicating whether county j was in the selective migration group ($migr_j = 1$) or not ($migr_j = 0$):

$$\begin{aligned}\Delta y_j^{2007\text{-}17} = \alpha_0 + \alpha_1 \left(\Delta Coal_j^{2007\text{-}17} \times \mathbf{1}[migr_j = 0]\right) + \alpha_2 \left(\Delta Coal_j^{2007\text{-}17} \times \mathbf{1}[migr_j = 1]\right) \\ + \alpha_3 \left(\mathbf{1}[Coal_j^{2007} > 0]\right) + \mathbb{X}_j'\gamma + \delta_s + \varepsilon_j\end{aligned} \tag{6}$$

As in equation 1, I include a vector of initial (2007) county-level controls $\mathbb{X}_j'$ (the share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree), a dummy for having coal employment in 2007 $\mathbf{1}[Coal_j^{2007} > 0]$, state fixed effects δ_s, and I instrument for $\Delta Coal_j^{2007\text{-}17}$ with $Coal_j^{2007}$. Observations are again weighted by the initial (2007) county population, although the conclusions are insensitive to the weighting scheme. Comparing the coefficient estimates α_1 and α_2 provides a comparison of the effect of the 2007–2017 coal shock on the change in outcome y across groups of counties with more or less selective migration induced by historical shocks. Notably, because the vector of controls $\mathbb{X}_j'$ includes the initial (2007) share of adults with a college degree, this approach reveals differential responses to the 2007–2017 coal shock conditional on the initial skill composition of the population.

4.2.2 Selective migration and adjustment to the 2007–2017 coal shock

Table 4 presents the central point estimates of α_1 and α_2 from equation 6 for seven different outcomes across Appalachian counties. I consider employment, population, and various county-wide measures of earnings and income adjustments to the 2007–2017 coal shock. The point estimates in the first row represent these adjustment costs for the 310 Appalachian counties for which $migr_j = 0$, with lower levels of selective migration in the 1980s resulting from historical shocks. The point estimates in the second row represent these adjustment costs for the remaining 103 Appalachian counties, where $migr_j = 1$. The point estimates in each column are produced from a single regression.

Table 4: Historical selective migration and adjustment to the 2007–2017 coal shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Change in outcome over 2007–2017 period						
	ln(wage & salary employment)	ln(pop ages 20–64)	emp: population ratio	ln(wages & salaries)	ln(wages & salaries per emp)	ln(pers. income)	ln(pers. income per capita)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-2.22***	-0.67*	-0.86***	-3.26***	-1.04**	-0.46	0.08
	(0.54)	(0.35)	(0.26)	(0.89)	(0.47)	(0.45)	(0.51)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-4.92***	-2.65***	-1.15***	-7.82***	-2.90***	-3.35***	-1.62***
	(1.15)	(0.80)	(0.44)	(1.73)	(0.78)	(0.89)	(0.57)
Controls	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓
P-val($\alpha_1 = \alpha_2$)	0.033	0.022	0.558	0.020	0.038	0.004	0.021
Observations	413	413	413	413	413	413	413

All regressions are weighted by initial county population and include state fixed effects and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. Controls include the initial (2007) share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree. $migr_j = 1$ if county j is in the bottom quartile of Appalachian counties in terms of the predicted change in college-educated adults (ages 25+) between 1980 and 1990, as described in text, and $migr_j = 0$ otherwise. I instrument for the 2007–2017 coal shock with the coal share in 2007. Outcome variables are defined in changes over the 2007–2017 period, and are retrieved from the BEA Regional Economic Accounts. The p-value refers to the p-value testing the equality of the point estimates on Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$ and Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$.
*** p<0.01, ** p<0.05, * p<0.1

The estimates in Table 4 indicate that the adverse consequences of the 2007–2017 coal shock are magnified in counties that experienced more selective migration predicted by historical shocks. The point estimates in column 1 indicate that the effect of the 2007–2017 coal shock on the number of employees is over twice as large in counties for which $migr_j = 1$ (a 1-unit increase in the coal shock yields nearly a 5 percent decline in employment) compared to other Appalachian counties (a 2.2 percent decline). The effect of the 2007–2017 coal shock on the working-age adult population (column 2) is nearly four times larger in this selective migration group of counties. A 1-unit increase in the coal shock suppresses the employment rate (column 3) by 1.15pp in the $migr_j = 1$ group, compared to 0.86pp for other Appalachian counties, although the difference in these estimates is not statistically distinguishable from zero. Total county-level earnings (column 4) fall by nearly 8 percent in the $migr_j = 1$ quartile, an adjustment more than double the magnitude of the remaining Appalachian counties (3.26 percent). Wages per employee (column 5) fall by nearly 3 times as much in the $migr_j = 1$ quartile, and this group of counties experiences the only statistically detectable decline in personal income (column 6) and personal income per capita (column 7) in response to the 2007–2017 coal shock. While wage and income effects are likely driven to some extent by simultaneous compositional shifts in the population, declines in these measures reflect real declines in economic activity and a shrinking of the local tax base, which may have residual consequences for residents who remain. For nearly all outcomes, I can reject that the coefficient on the 2007–2017 coal shock is the same for the two groups of counties.[37]

By controlling for the initial share of adults with a college degree, Table 4 reveals differential responses to the 2007–2017 coal shock conditional on the initial skill composition of the population. This complements research documenting the importance of the stock of human capital in shaping economic activity (Glaeser et al., 1995; Glaeser, 2005; Gennaioli et al., 2014; Gagliardi et al., 2023) by highlighting the importance of human capital flows.[38] These findings suggest that coal's recent decline imposed significantly larger adjustment costs on counties that experienced greater selective migration following historical shocks. Shifts in human capital endowments resulting from shocks in one period may weaken a community's capacity to adjust to subsequent shocks, leading to a more sluggish recovery in areas shaped by adverse historical experiences.

[37]Note that a 1pp coal shock reflects a much smaller percentage change in the coal share in counties in the $migr_j = 1$ quartile compared to other Appalachian coal counties. The population-weighted average 2007 coal employment share of the working-age-adult population was 3.83 percent for coal counties in the bottom quartile, compared to 0.66 percent in other coal counties. Thus, the estimates in Table 4 likely understate the differences in adjustment costs when the shock is defined to reflect similar magnitudes of employment change. The estimated effect of the coal shock in the $migr_j = 1$ quartile is also much larger if expressed in terms of a 1-SD increase, as the standard deviation of the 2007–2017 coal shock was much larger for the $migr_j = 1$ quartile (3.08pp) versus other coal counties (1.28pp).

[38]There is a strong empirical relationship between these flows and later stocks: the correlation coefficient between the predicted decline in college-educated adults during the 1980s ($\Delta \widehat{college}_j^{1980\text{-}90}$) and the 2007 college share is 0.60. While this raises a potential concern that the 2007 control vector ($\mathbb{X}'_j$) includes post-treatment variables, the conclusions are robust to omitting these controls.

4.2.3 Selective migration and adjustment to shocks: Robustness to alternative specifications

Employment shifts in one period might be correlated with employment shifts in subsequent periods, such that proximity to employment shifts in other counties in the 1980s ($Prox_j^{1980}$) is associated with proximity to employment shifts in subsequent decades, which could affect contemporary outcomes in important ways. Thus, the differential consequences of the contemporary coal shock observed in Table 4 could reflect differential exposure to more recent (non-coal) employment shocks which are correlated with $Prox_j^{1980}$. In Appendix Table A3, I use alternative specifications to estimate equation 6 for the three primary outcome variables (employment, population, and employment rate changes), although the conclusions are similar when considering a wider range of outcomes. These alternative specifications (i) directly control for historical exposure to shocks, (ii) isolate the selective migration predicted by $Prox_j^{1980}$, and (iii) redefine selective migration based on the change in the college-educated share of the adult population.

The estimates in Panel A of Appendix Table A3 follow the primary specification described above, adding controls for $Prox_j^{1980}$ and $Coal_j^{1980}$ to equation 6 in all even-numbered columns. These controls absorb the legacy consequences of exposure to historical shocks, including spatial proximity to other affected regions and direct exposure to past coal declines. In Panel B, I re-estimate $\Delta\widehat{college}_j^{1980\text{-}90}$ using only $Prox_j^{1980}$, omitting $Coal_j^{1980}$, $\mathbf{1}[Coal_j^{1980} > 0]$, $\mathbb{X}_j'$, and δ_s from the estimation of equation 2. This specification isolates the variation in predicted selective migration driven by proximity to external labor demand shocks, rather than by historical coal conditions. This helps address the concern that persistent coal-sector characteristics could confound the relationship between historical and recent coal declines.[39] In Panel C, I define $\Delta\widehat{college}_j^{1980\text{-}90}$ as the predicted change in the college-educated *share* of the adult population over the 1980–1990 decade. The magnitude of the point estimates is quite stable across all three panels. That is, the differential adjustment costs observed in Table 4 across places with more or less selective migration cannot be explained by the legacy of spatially proximate shocks nor the direct effect of historical coal shocks. They are also not solely the result of general declines in adult population counts which are correlated with losses in college-educated adults, as controlling for lagged population or employment changes does not alter the conclusions drawn from Tables 4 and A3. Thus, the adjustment to the contemporary coal shock is larger in places where prior shocks eroded local human capital endowments, conditional on the simultaneous decline in population counts.[40]

[39]The correlation between $Coal_j^{1980}$ and $Prox_j^{1980}$ is extremely weak, with a correlation coefficient of 0.028.

[40]Appendix Table A4 confirms that the main conclusions hold when using only 1980 covariates or omitting the

Additionally, Appendix Figure A2 and Appendix Table A5 show that the main conclusions are robust to using a continuous measure of predicted selective migration and to alternative definitions of the selective migration group. Appendix Figure A2 plots the relationship between the predicted change in the number of college-educated adults (ages 25+) between 1980 and 1990 (x-axis) and the estimated effect of the 2007–2017 coal shock (y-axis). The effect of the coal shock is estimated using a modified version of equation 1 that adds as regressors $\Delta\widehat{college}_j^{1980\text{-}90}$ and its interaction with $\Delta Coal_j^{2007\text{-}17}$. The upward-sloping pattern indicates that the negative effects of the coal shock are largest in counties with lower predicted growth in college-educated adults — consistent with the idea that selective migration may amplify the adjustment costs of future shocks. Appendix Table A5 demonstrates that the estimated heterogeneity in adjustment costs is stable across alternative binary definitions of the migration group, using cutoff points at the bottom half, third, and fifth of the distribution of predicted changes in college-educated adults.

Spatially proximate shifts in employment demand could affect the skill composition of Appalachian coal counties beyond the 1980s. Further, industries that experienced employment booms (or busts) in the 1980s may have continued to expand or contract in subsequent decades. To account for this, I repeat the exercise above, but I predict the change in the number of college-educated adults over a longer time horizon — between 1980 and 2007 — and I use this predicted value, $\Delta\widehat{college}_j^{1980\text{-}07}$, to bifurcate counties. Again, I define counties as $migr_j = 1$ or $migr_j = 0$ based on whether they are in the bottom quartile of this predicted value. I use the same specification to predict the change in the number of college-educated adults between 1980 and 2007 as in equation 2, but I add two additional terms to the right-hand side of the equation: the proximity to predicted employment growth between 1990 and 2000 ($Prox_j^{1990}$), and the proximity to predicted employment growth between 2000 and 2007 ($Prox_j^{2000}$). These variables are defined analogously to $Prox_j^{1980}$ detailed by equation 3.[41]

The estimates produced using this strategy are reported in Appendix Table A6. This approach yields similar results to those reported in Table 4. As before, the conclusions drawn from Appendix Table A6 are qualitatively similar after controlling for $Prox_j^{1980}$, $Prox_j^{1990}$, and $Prox_j^{2000}$,

control vector entirely. This addresses concerns that including 2007-era controls may condition on variables potentially influenced by earlier selective migration.

[41]The weight remains the same in the construction of these new proximity variables, as defined in equation 4. The only change is to $\Delta Z_{j'}$, which is defined over the relevant period (1990–2000 or 2000–2007). For example, $Prox_j^{1990} = \sum_{j'} \omega_{jj'}^{1980} \times \Delta Z_{j'}^{1990\text{-}2000}$, and $\Delta Z_{j'}^{1990\text{-}2000} = \sum_{k \in K} s_{j'k}^{1990} \times \Delta emp_{-j'k}^{1990\text{-}2000}$. Thus, $Prox_j^{1990}$ reflects the proximity to predicted employment growth in the 1990s, and $Prox_j^{2000}$ reflects the proximity to predicted employment growth between 2000 and 2007.

and $Coal_j^{1980}$ (displayed in even-numbered columns), indicating that differential proximity to historical employment shifts is not driving the differential effect of the 2007–2017 coal shock across the two groups of counties. Both approaches yield the same conclusion: The adjustment costs associated with the contemporary coal shock are more acute in counties that experienced larger declines in college-educated adults in decades prior due to exogenous, historical demand shifts.

4.3 Mechanisms: The role of business formation

What mechanisms drive the relationship between selective migration and resilience to shocks? The model indicates that "high-type" workers — those who are better-educated or more productive — facilitate economic activity by driving the establishment of new firms. Selective migration diminishes the stock of these workers, stifling entrepreneurial activity and hindering local non-coal firm growth in subsequent periods. Consistent with other research documenting the relationship between the population composition and entrepreneurial activity, the model predicts that this reduced stock of high-type workers leads to fewer new firm entries, thereby exacerbating the consequences of future adverse shocks.

While other mechanisms are also likely at play, this section presents evidence of the mechanism implied by the model.[42] There is a strong relationship between the change in the number of college-educated adults in the 1980s and the number of new business establishments in subsequent periods. The Census Bureau's Business Dynamics Statistics (BDS) program offers annual measures of new, net, and gross flows of establishments and job creation by county. To understand the relationship between a changing college-educated population and the rate of establishment entry, I estimate the following equation:

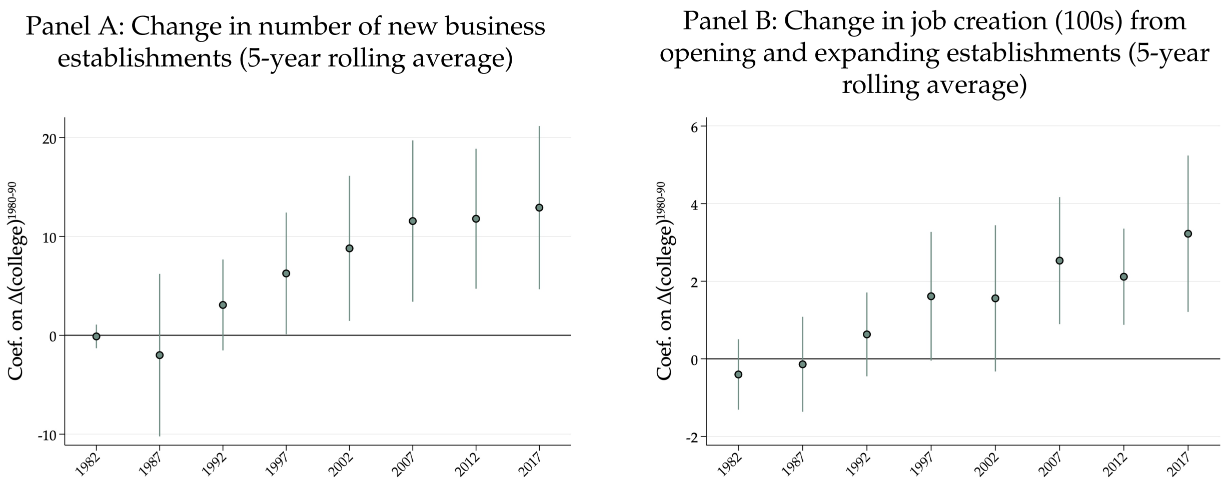
$$\Delta est_j^{1980-t} = \beta_0 + \beta_1 \Delta college_j^{1980\text{-}90} + \beta_2 Coal_j^{1980} + \beta_3 \left(\mathbf{1}[Coal_j^{1980} > 0]\right) + \mathbb{X}_j'\gamma + \delta_s + \varepsilon_j \quad (7)$$

where Δest_j^{1980-t} is the change in the number of new business establishments between 1980 and year t. I define the number of new business establishments in year t as the rolling average in the 5-year window around year t to purge idiosyncratic annual fluctuations in business entry. The primary independent variable $\Delta college_j^{1980\text{-}90}$ is the observed 1980 –1990 change in county j's (log) adult population with a college degree or more. I instrument for $\Delta college_j^{1980\text{-}90}$ with

[42] For example, business formation may also reflect consumer market access or increased demand for local services rather than entrepreneurship alone. While I am unable to distinguish between these channels, the evidence is consistent with the model and existing work documenting the role of human capital in entrepreneurship and business formation (e.g., Glaeser et al., 2010; Doms et al., 2010).

the proximity variable $Prox_j^{1980}$ defined in equation 3 to isolate the change attributable to exogenous employment shocks in proximate labor markets. These population-weighted regressions also control for the 1980 coal share of the working-age-adult population $Coal_j^{1980}$, a dummy variable $\mathbf{1}[Coal_j^{1980} > 0]$ indicating whether the county had any coal employment in 1980, a vector of 1980 county-level covariates $\mathbb{X}_j'$ (foreign-born share of population, female share of employment, and the share of adults with a college degree), and state fixed effects δ_s. I conduct a separate regression each period 1980–t for $t \in \{1982, 1987, ..., 2017\}$.

Figure 8: Change in college-educated adults in the 1980s and establishment entry and job creation, 1980 to 2017



Notes: Sample includes only Appalachian counties. Each marker reflects the coefficient estimate and 95 percent confidence interval of a separate regression for each time difference between 1980–1982 and 1980–2017. The dependent variable in Panel A is the change in the number of new establishments between 1980 and the year depicted on the horizontal axis. The dependent variable in Panel B is the change in the number of new jobs (in 100s) created by new and expanding business establishments between 1980 and the year depicted on the horizontal axis. Both dependent variables are divided by 100 for ease of interpretation. The primary independent variable is the change in the natural log of the college-educated adult population (ages 25 and older) in the 1980s, which is instrumented for with a variable that depicts a county's proximity to predicted employment growth over the 1980–190 decade, described in text. All regressions are weighted by initial county population and include state fixed effects, 1980 county-level covariates (foreign-born share of population, female share of employment, and the share of adults with a college degree), a control for the share of the adult population (ages 20–64) employed in coal mining in 1980, and a dummy variable for having any coal employment in 1980.

The coefficient estimates and 95 percent confidence intervals for these 8 separate regressions are presented in Panel A of Figure 8. While the instrumented change in the number of college-educated adults in the 1980s has no immediate impact on the rate of new business entry, this relationship manifests over progressively larger time horizons. The point estimate reflected by the rightmost coefficient in Panel A indicates that, by 2017, a 1 percent increase (decline) in the college-educated population in the 1980s is associated with an increase (decline) in the rate of business entry of about 13 new establishments per year compared to 1980 levels. The relationship between the number of college-educated adults and firm entry is not solely driven by a mechanical relationship between population size and business activity: These results are qualitatively similar if one defines the primary independent variable as the change in the college-educated *share* of the adult population between 1980 to 1990, rather than the change in the aggregate number of college-educated adults.

Establishments vary substantially in size and scope for generating local economic activity. An establishment that employs two workers might have a lesser capacity to influence a community's economic trajectory than one employing several hundred workers. The BDS provides annual estimates of the number of jobs created by opening and expanding establishments, which provides a proxy for the magnitude of firm entrants' size. Defining the outcome variable as the change in the number of new jobs created (in 100s) by opening and expanding establishments between 1980 and year t demonstrates a similar pattern, as reflected in Panel B of Figure 8.[43] The point estimate reflected by the rightmost coefficient in Panel B indicates that, by 2017, a 1 percent increase (decline) in the college-educated population in the 1980s is associated with an increase (decline) of nearly 330 new jobs per year by opening and expanding establishments compared to 1980 levels of job creation. Broadly, this evidence is consistent with the mechanism implied by the model: firm growth in future periods depends on skill endowments affected by shocks in the current period. Again, because the vector of controls in equation 7 includes the initial (1980) *stock* of human capital in terms of the share of adults with a college degree, these results indicate that *flow* of human capital might be independently important to the evolution of local economic activity.

5 Conclusion and discussion

Local labor demand shocks can fundamentally alter the skill composition of affected areas via selective migration, with greater net out-migration among more skilled or college-educated adults (Topel, 1986; Bound and Holzer, 2000; Glaeser and Gyourko, 2005; Wozniak, 2010). While out-migration from under-performing areas is an important regional adjustment mechanism, shock-induced changes in local human capital endowments may make certain communities more vulnerable to future economic challenges. This paper demonstrates how these forces may contribute to broader patterns of regional decline and thus amplify underlying spatial inequality.

I consider this phenomenon in the context of Appalachia's coal country. Declines in demand

[43] I again define the number of new jobs as the rolling average within a 5-year window of year t.

for coal between 2007 and 2017 reduced county-level employment, population, earnings, and income. Both aggregate and average earnings and total personal incomes declined, consistent with other literature documenting large community- and individual-level consequences of regionally concentrated shocks (e.g., Blanchard and Katz, 1992; Black et al., 2005a; Autor et al., 2013, 2014; Amior and Manning, 2018; Colmer et al., 2024; Rud et al., 2024). Unlike other settings, population mobility in Appalachia remains relatively responsive to deteriorating labor market conditions. These migration responses are highly selective, such that adverse shocks reduce human capital endowments in affected communities. Consistent with a model linking selective migration to longer-run economic trajectories, I find that the adjustment costs resulting from the 2007–2017 coal shock were more acute in counties that experienced greater degrees of selective migration in preceding periods. I document one potential mechanism behind this pattern: by reducing the number of college-educated residents, historical shocks may suppress later business formation, shaping how regions respond to future disruptions. While other mechanisms may also play a role, the results underscore the lasting importance of human capital flows in regional adjustment.

These findings have implications for how economists and policymakers understand local adjustment costs in declining labor markets and the consequences of large-scale shifts in the economic and energy landscape going forward. The evidence presented here indicates that the selectivity of population mobility following employment shifts can have long-term consequences on the capacity of remaining residents to adjust to new economic challenges. While migration is an important indication that certain individuals are adjusting to adverse shocks, relatively immobile, less-educated residents remaining in affected communities may suffer greater consequences as a result of historical population adjustments. Retaining, building, or attracting a relatively skilled workforce might improve places' capacity to adapt to new economic challenges (Bollinger et al., 2011; Black and Sanders, 2012; Kahn, 2012; Islam et al., 2015), and potentially slow or reverse the process of regional decline.

The ongoing transition away from fossil fuels will likely exacerbate these challenges. This paper quantifies the population and economic loss in places most exposed to this energy transition, showing that the self-reinforcing process of decline fueled by the exit of better-educated workers has left communities with lesser capacity to adjust to recent challenges. Recurrent shocks to coal employment have reshaped the demographic and economic structure of affected regions, likely elevating the risks associated with the energy and economic shifts ahead. While quantifying adjustment costs is a critical first step in identifying appropriate transition assistance, further research is needed to evaluate what interventions might be most effective at mitigating long-term economic distress in historically coal-dependent and other fossil fuel-reliant communities.

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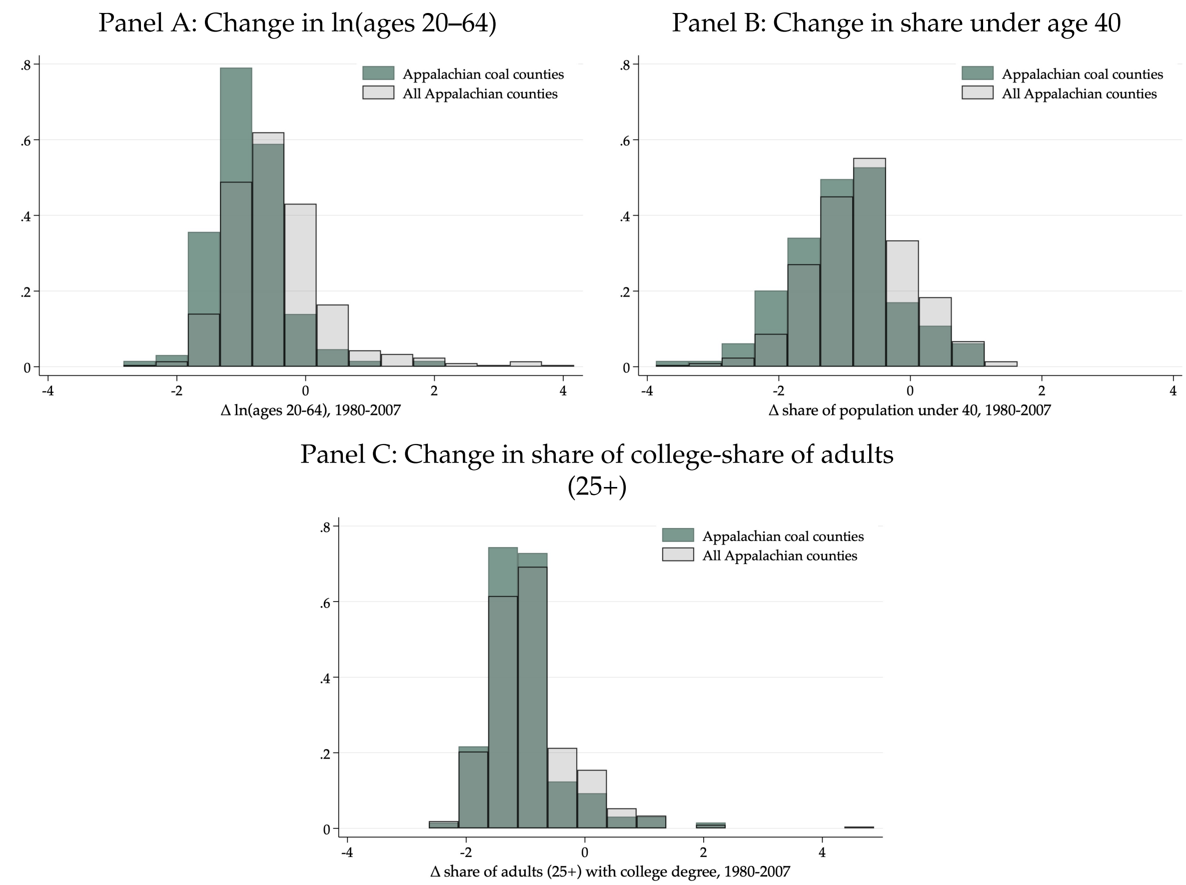
Appendix

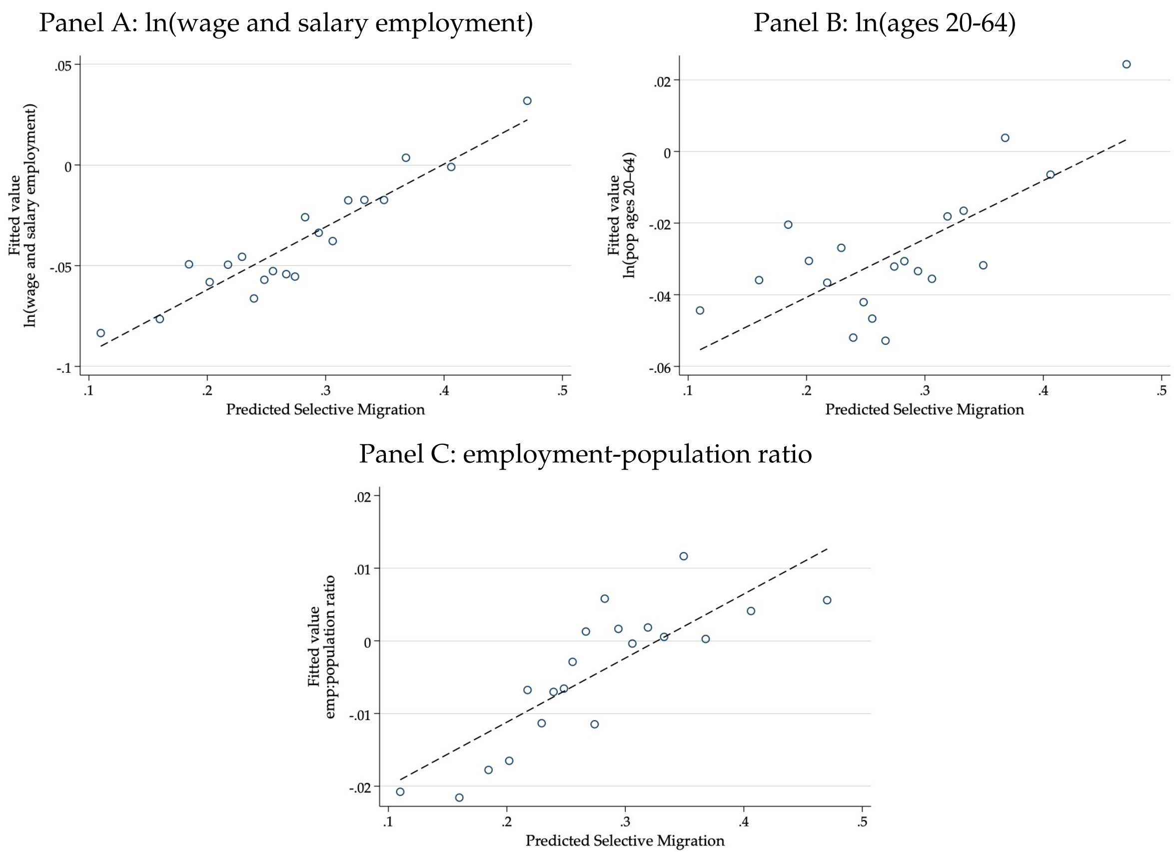
A Appendix Figures and Tables

Figure A1: Distribution of population change in Appalachia, 1980–2007



Notes: The county-level change in the variable of interest between 1980 and 2007 is expressed in deviation from the population-weighted U.S. average. Appalachian coal counties include those in which at least 0.537 percent of the adult population was employed in coal mining in 2007 (N=65). The 0.537 percent cutoff reflects the median coal share among counties with any coal mining employment in 2007. 1980-level characteristics are based on estimates produced from the 1980 Census. Population counts in 2007 are based on the intercensal estimates produced by the U.S. Census. Educational attainment in 2007 is based on estimates from the 2005–2009 ACS.

Figure A2: The 2007–2017 coal shock and a continuous measure of historical selective migration



Notes: Each panel presents a binned scatter plot of the relationship between predicted selective migration (x-axis) and the estimated effect of the 2007–2017 coal shock (y-axis). The x-axis reflects quantiles of the predicted change in the number of college-educated adults (ages 25+) between 1980 and 1990 ($\Delta\widehat{college_j}^{1980\text{-}90}$). The y-axis reflects quantiles of the fitted values from an OLS regression of the change in the outcome described between 2007 and 2017 on the change in the coal share over the same period $\Delta Coal_j^{2007\text{-}17}$, predicted selective migration $\Delta\widehat{college_j}^{1980\text{-}90}$, and the interaction of $\Delta Coal_j^{2007\text{-}17}$ and $\Delta\widehat{college_j}^{1980\text{-}90}$. All regressions are weighted by initial county population and include state fixed effects, a dummy variable indicating whether the county had positive coal employment at the beginning of the period, and baseline controls: the 2007 foreign-born population share, female employment share, and college-educated share. The fitted values represent the marginal effect of the coal shock at different levels of predicted selective migration.

Table A1: Summary statistics for coal shock variables

	(1) Mean	(2) SD	(3) p50	(4) p75	(5) p95	(6) p99
Coal shock variables, 2007–2017						
Coal share, 2007	0.97	2.43	0.18	0.78	4.94	10.40
-1×Δ Coal share, 2007-17	0.38	1.60	0.04	0.22	1.59	6.91
Observations: 129						
Coal shock variables, 1980–1990						
Coal share, 1980	2.74	5.17	0.56	2.87	13.66	28.13
-1×Δ Coal share, 1980-90	1.33	3.00	0.23	1.30	5.91	20.26
Observations: 169						

Coal share refers to the coal employment share of the population ages 20–64. The sample includes Appalachian counties with positive coal employment in 2007 (2007–2017 statistics) or 1980 (1980–1990 statistics). Statistics are weighted by initial (2007 or 1980) county population. All variables have been multiplied by 100 for ease of interpretation.

Table A2: Employment and population adjustment to single-period coal shock, 1980–1990

	(1)	(2)	(3)	(4)	(5)
	OLS		IV		
Panel A: Δln(wage and salary employment) 1980–1990					
Coal shock, 1980–1990	-3.10***	-3.21***	-2.33***	-2.22***	-2.92***
	(0.36)	(0.39)	(0.31)	(0.41)	(0.44)
Panel B: Δln(population ages 20–64) 1980–1990					
Coal shock, 1980–1990	-1.49***	-1.74***	-0.97***	-0.90***	-1.42***
	(0.24)	(0.30)	(0.19)	(0.24)	(0.30)
Panel C: Δ employment:population ratio, 1980–1990					
Coal shock, 1980–1990	-0.94***	-0.90***	-0.73***	-0.46***	-0.49***
	(0.11)	(0.13)	(0.13)	(0.16)	(0.16)
State FE			✓	✓	✓
Baseline controls				✓	✓
Additional controls					✓
F-stat		67.47	67.50	60.52	61.05
Observations	413	413	413	413	413

All regressions are weighted by initial (1980) county population. Robust standard errors are in parentheses. Baseline controls include the initial (1980) share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Additional controls include the initial (1980) share of the population ages 0-19, 20-39, and 40-59. The coal shock is defined as -1 times the change in the coal employment share of the adult population (ages 20–64) over the 1980–1990 period. I instrument for the coal shock in columns 2-5 with the coal share in 1980. The first-stage F-stat on the instrument is reported in the second row from the bottom. Outcome variables are retrieved from the BEA Regional Economic Accounts.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3: Historical selective migration and adjustment to the 2007–2017 coal shock, alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in outcome over 2007–2017 period					
	ln(wage & salary emp)		ln(pop ages 20–64)		emp:population ratio	
Panel A: Primary specification						
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-2.22***	-2.21***	-0.67*	-0.14	-0.86***	-1.12***
	(0.54)	(0.57)	(0.35)	(0.24)	(0.26)	(0.24)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-4.92***	-4.10***	-2.65***	-1.64***	-1.15***	-1.14***
	(1.15)	(0.84)	(0.80)	(0.48)	(0.44)	(0.39)
P-val($\alpha_1 = \alpha_2$)	0.033	0.090	0.022	0.006	0.558	0.967
Panel B: Predict $\Delta\widehat{college}_j^{1980\text{-}90}$ using only $Prox_j^{1980}$						
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-2.44***	-2.48***	-0.84**	-0.37	-0.91***	-1.16***
	(0.51)	(0.56)	(0.41)	(0.33)	(0.23)	(0.21)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-5.07***	-4.17***	-2.75***	-1.66***	-1.11**	-1.07**
	(1.39)	(0.99)	(0.98)	(0.53)	(0.52)	(0.47)
P-val($\alpha_1 = \alpha_2$)	0.072	0.168	0.065	0.039	0.716	0.856
Panel C: Define $\Delta\widehat{college}_j^{1980\text{-}90}$ based on 1980–1990 change in college share of adult pop						
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-2.40***	-2.37***	-0.84**	-0.37	-0.89***	-1.09***
	(0.48)	(0.49)	(0.39)	(0.27)	(0.22)	(0.20)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-5.61***	-4.71***	-3.05**	-1.89**	-1.21**	-1.21**
	(1.76)	(1.26)	(1.22)	(0.73)	(0.60)	(0.53)
P-val($\alpha_1 = \alpha_2$)	0.073	0.110	0.076	0.045	0.594	0.845
Baseline controls	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Controls for lagged exposure		✓		✓		✓
Observations	413	413	413	413	413	413

All regressions are weighted by initial county population and include state fixed effects and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. Baseline controls include the initial (2007) share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree. Specifications in even-numbered columns include controls for both $Prox_j^{1980}$ and $Coal_j^{1980}$. In Panel A, $migr_j = 1$ if county j is in the bottom quartile of Appalachian counties in terms of the predicted change in college-educated adults (ages 25+) between 1980 and 1990, as described in text, and $migr_j = 0$ otherwise. The approach to bifurcate counties in Panel B is analogous to A, except $\Delta\widehat{college_j^{1980-90}}$ is predicted using only $Prox_j^{1980}$. The approach to bifurcate counties in Panel C is analogous to A, except I predict the change in the college *share* of the adult population between 1980 and 1990 using the approach in equation 2. I instrument for the 2007–2017 coal shock with the coal share in 2007. Outcome variables are defined in changes over the 2007–2017 period, and are retrieved from the BEA Regional Economic Accounts. The p-value refers to the p-value testing the equality of the point estimates on Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$ and Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$.
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Historical selective migration and adjustment to the 2007–2017 coal shock, alternative controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in outcome over 2007–2017 period					
	ln(wage & salary emp)		ln(pop ages 20–64)		emp:population ratio	
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-2.64***	-2.10***	-1.13*	-0.54	-0.78***	-0.85***
	(0.60)	(0.53)	(0.60)	(0.40)	(0.25)	(0.24)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-5.68***	-4.51***	-3.67***	-2.47***	-0.95**	-1.08**
	(1.60)	(1.27)	(1.36)	(0.93)	(0.47)	(0.51)
1980 controls		✓		✓		✓
State FE	✓	✓	✓	✓	✓	✓
P-val($\alpha_1 = \alpha_2$)	0.080	0.076	0.091	0.054	0.741	0.669
Observations	413	413	413	413	413	413

All regressions are weighted by 1980 county population and include state fixed effects and a dummy variable indicating whether the county had positive coal employment in 1980. Robust standard errors are in parentheses. Specifications in even-numbered columns include controls for the 1980 share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree. Following the primary specification, $migr_j = 1$ if county j is in the bottom quartile of Appalachian counties in terms of the predicted change in college-educated adults (ages 25+) between 1980 and 1990, as described in text, and $migr_j = 0$ otherwise. Outcome variables are defined in changes over the 2007–2017 period, and are retrieved from the BEA Regional Economic Accounts. The p-value refers to the p-value testing the equality of the point estimates on Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$ and Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$.
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Historical selective migration and adjustment to the 2007–2017 coal shock, alternative cutoffs

	(1)	(2)	(3)
	Change in outcome over 2007–2017 period		
	ln(wage & salary emp)	ln(pop ages 20–64)	emp: population ratio
Panel A: $migr_j = 1$ **if bottom 50% of** $\Delta\widehat{college}_j^{1980\text{-}90}$			
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-1.65**	-0.28	-0.78***
	(0.67)	(0.24)	(0.30)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-5.11***	-2.76***	-1.20***
	(1.07)	(0.71)	(0.42)
P-val($\alpha_1 = \alpha_2$)	0.005	0.001	0.399
Panel B: $migr_j = 1$ **if bottom 33% of** $\Delta\widehat{college}_j^{1980\text{-}90}$			
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-1.71***	-0.37*	-0.77***
	(0.56)	(0.20)	(0.29)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-5.32***	-2.84***	-1.24***
	(1.15)	(0.79)	(0.44)
P-val($\alpha_1 = \alpha_2$)	0.004	0.003	0.350
Panel C: $migr_j = 1$ **if bottom 20% of** $\Delta\widehat{college}_j^{1980\text{-}90}$			
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$	-2.36***	-0.78**	-0.90***
	(0.51)	(0.38)	(0.24)
Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$	-5.02***	-2.72***	-1.12**
	(1.30)	(0.91)	(0.48)
P-val($\alpha_1 = \alpha_2$)	0.053	0.044	0.671
Baseline controls	✓	✓	✓
State FE	✓	✓	✓
Observations	413	413	413

All regressions are weighted by initial county population and include state fixed effects and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. Baseline controls include the initial (2007) share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree. In Panel A, $migr_j = 1$ if county j is in the bottom half of Appalachian counties in terms of the predicted change in college-educated adults (ages 25+) between 1980 and 1990, as described in text, and $migr_j = 0$ otherwise. In Panel B, $migr_j = 1$ if county j is in the bottom third of Appalachian counties in terms of this predicted change, and $migr_j = 0$ otherwise. In Panel C, $migr_j = 1$ if county j is in the bottom fifth of Appalachian counties in terms of this predicted change, and $migr_j = 0$ otherwise. I instrument for the 2007–2017 coal shock with the coal share in 2007. Outcome variables are defined in changes over the 2007–2017 period, and are retrieved from the BEA Regional Economic Accounts. The p-value refers to the p-value testing the equality of the point estimates on Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 0]$ and Coal shock$^{07\text{-}17}$ $\times$ $\mathbf{1}[migr_j = 1]$.
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Historical selective migration and adjustment to the 2007–2017 coal shock, based on 1980–2007 population changes

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in outcome over 2007–2017 period					
	ln(wage & salary emp)		ln(pop ages 20–64)		emp:population ratio	
Coal shock$^{07\text{-}17} \times \mathbf{1}[migr_j = 0]$	-2.22***	-2.49***	-0.52**	-0.41*	-0.95***	-1.13***
	(0.28)	(0.34)	(0.22)	(0.22)	(0.15)	(0.16)
Coal shock$^{07\text{-}17} \times \mathbf{1}[migr_j = 1]$	-5.22***	-4.47***	-3.17***	-1.63**	-1.02*	-1.24**
	(1.44)	(1.20)	(1.06)	(0.72)	(0.58)	(0.60)
Baseline controls	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Controls for lagged exposure		✓		✓		✓
P-val($\alpha_1 = \alpha_2$)	0.037	0.097	0.014	0.082	0.902	0.847
Observations	413	413	413	413	413	413

All regressions are weighted by initial county population and include state fixed effects and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. Baseline controls include the initial (2007) share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree. Specifications in even-numbered columns include controls for $Prox_j^{1980}$, $Prox_j^{1990}$, $Prox_j^{2000}$, and $Coal_j^{1980}$, defined in text. $migr_j = 1$ if county j is in the bottom quartile of Appalachian counties in terms of the predicted change in college-educated adults (ages 25+) between 1980 and 2007, and $migr_j = 0$ otherwise. The change in college-educated adults is estimated following a modified version of equation 2 that includes $Prox_j^{1990}$ and $Prox_j^{2000}$. I instrument for the 2007–2017 coal shock with the coal share in 2007. Outcome variables are defined in changes over the 2007–2017 period, and are retrieved from the BEA Regional Economic Accounts. The p-value refers to the p-value testing the equality of the point estimates on Coal shock$^{07\text{-}17} \times \mathbf{1}[migr_j = 0]$ and Coal shock$^{07\text{-}17} \times \mathbf{1}[migr_j = 1]$.
*** p<0.01, ** p<0.05, * p<0.1

B A spatial equilibrium model of coal shocks

This section details the spatial equilibrium model depicted graphically in the primary text. The model demonstrates how the evolution of local economic activity is dependent upon the number of "high-type" (i.e., more productive) workers in the local economy and the implications of this for the relative severity of shocks occurring in subsequent generations. The major prediction is that the negative consequences of adverse shocks — in terms of wages and population head counts — are more pronounced in places that have already been exposed to shocks in generations prior.

B.1 Setup

B.1.1 Labor supply and wages

Let there be two types of workers in the economy: high (H) and low (L). Each worker chooses to live in one of two local labor markets: a coal community or elsewhere. There are a total of H high-type and L low-type workers in the whole economy and a total of N^H high-type and N^L low-type workers living in the coal community. Each worker inelastically supplies one unit of labor to his local labor market and consumes one unit of housing, such that the number of housing units in the coal community (S) is equal to the number of workers ($N^H + N^L$).[1]

Workers consume only housing, a tradable (numeraire) good, and receive utility from a vector of local amenities, A. Let high types living elsewhere receive reservation utility $\overline{U}^H$, and low types living elsewhere receive reservation utility $\overline{U}^L$, where $\overline{U}^H > \overline{U}^L$. Workers choosing to live in the coal community receive utility in a single time period according to the following concave utility function (omitting time subscripts):

$$U(W,P,A) = \begin{cases} \alpha(W - P - W_0) + W_0 + A_i & W - P \geq W_0 \\ W - P + A_i & W - P < W_0 \end{cases}$$

where W is the worker's wage, P is the price of housing, A_i is a worker-specific amenity parameter, and W_0 is defined such that $W - P > W_0$ for all high types and $W - P < W_0$ for all low types. All high types living in the coal community earn wages $W = W^H$ and all low types earn wages

[1]The simplifying assumption of fixed housing stock is made to make the model analytically tractable by enabling closed-form solutions, focusing attention on changes in skill composition. While this abstraction does not reflect long-run population dynamics, the empirical analysis captures actual population decline and complements the model by quantifying the effects of selective out-migration.

$W = W^L$. I assume that $\alpha < 1$, such that there is a decreasing marginal utility to income.[2] The amenity parameters are distributed in the population, where low types have amenity parameters $A_i \sim \text{Unif}(m^L, M^L)$ and high types have amenity parameters $A_i \sim \text{Unif}(m^H, M^H)$. Let ε^L and ε^H be the values of the amenity parameter for the marginal low- and high-type resident of the coal county, respectively.

Let there be two types of tradable industries, $k \in \{c, d\} = \{\textit{Coal, Non-coal}\}$. There are F_c firms in the coal industry and F_d firms in the non-coal industry within the coal community. Revenue is identical for firms within each industry. A firm in the type k industry hiring n^H high-type workers and n^L low-type workers in a single time period makes revenue (omitting time subscripts):

$$\theta_k b(E) - a(E)^2 \tag{8}$$

where $a > 0$, $b > 0$, and $\theta_k > 0$ is a place-specific productivity parameter for the industry of type $k \in \{c, d\}$.[3] The term $E = n^L + \omega n^H$ reflects the firm's effective labor, in which the parameter $\omega > 1$ captures the fact that high types are relatively more efficient than low types.

Firms have no market power and therefore hire where the marginal revenue product is equal to the wage. Because firms in the coal and non-coal industries hire from the same pool of workers, they pay the same wages for workers of the same type. That implies that the wage for high types (W^H) is equal to the efficiency parameter times wages for low types (ωW^L). I solve for wages in terms of labor supply and relevant production parameters in Appendix C.

In equilibrium, the marginal worker of either type is indifferent between the coal community and elsewhere. The static equilibrium is thus characterized by the menu of local wages (W^L, W^H), local housing prices (P), local population head counts (N^L, N^H) and amenity cutoff parameters (ε^H, ε^L) such that demand for high-type labor equals supply of high-type labor, demand for low-type labor equals supply of low-type labor, and demand for housing equals supply of housing. The seven equations that characterize these seven equilibrium parameters are detailed in Appendix C.

B.1.2 Evolution of firms

In any given period t, the number of firms is fixed, but I allow for the *evolution* of firms to be dictated by the existing population composition. More explicitly, I assume that the number of

[2] I also assume that workers do not save and are myopic in their knowledge of local wage and productivity changes.

[3] θ is the only parameter in the production function that is place-specific.

firms in the non-coal industry F_d is constrained by the number of high types in the local labor market. Firms evolve proportionately to the number of high types and the pre-existing stock of non-coal-industry firms. Specifically, let the number of firms in the non-coal industry in the local community in period $t+1$ be increasing in the number of high-type workers in period t:

$$F_{d,t+1} = \delta F_{d,t} + \gamma N_t^H \tag{9}$$

where N_t^H is the number of high types at time t, $\gamma > 0$ reflects the local "entrepreneurship" or "birth" rate, and $0 < \delta < 1$ captures the death rate of existing firms in the non-coal industry.[4] That γ is assumed to be greater than zero implies that more (fewer) high types at time t leads to more (fewer) firms in period $t+1$.

B.2 Coal shocks and the evolution of economic activity

Here, I explore the consequences of shocks to the coal industry. Section B.2.1 considers the evolution of wages and population head counts with respect to a shock to productivity in the coal industry occurring between period t and period $t+1$ (a "first-period" shock). In section B.2.2, I consider the impact of a "second-period" coal shock occurring between period $t+1$ and period $t+2$, and illustrate how the consequences of this second-period shock — in terms of the evolution of wages and population head counts — are more severe if the community experienced a coal shock in the first period. This differential severity stems from the impact of shocks on the composition of the population. In reducing the number of high types, first-period shocks alter the path of firm growth, which magnifies the consequences of local productivity shocks in subsequent periods.

B.2.1 First-period shocks

Let a shock to the coal industry occurring between period t and period $t+1$ affect local productivity in the coal industry according to the following:

$$\theta_{c,t+1} = \theta_{c,t} + \Delta\theta_{c,t} \tag{10}$$

[4] The γ parameter might be thought of as capturing the rate at which high types establish new firms in the non-coal industry (hence, "entrepreneurship" rate).

An adverse (negative) productivity shock implies that $\Delta < 0$. How does this coal shock influence local wages and population sizes?

Proposition 1. *Wages for low (W^L) and high (W^H) types are increasing, the number of high types (N^H) is increasing, and the number of low types (N^L) is decreasing linearly in $\Delta\theta_{c,t}$. A negative shock to productivity in the coal industry between period t and $t+1$ ($\Delta < 0$) thus reduces wages, reduces the number of high types, and increases the number of low types living in the affected community. The number of non-coal firms F_d is also increasing in $\Delta\theta_{c,t}$, such that a community that experienced a negative shock to θ_c will have fewer non-coal firms in subsequent periods than an identical community that experienced no shock.*

Proof. See Appendix C.3.

Proposition 1 describes the evolution of wages and population head counts with respect to a coal shock occurring between period t and $t+1$. Such a shock decreases low- and high-type wages, decreases the number of high-type workers, and increases the number of low-type workers. The evolution of firms dictated by equation 9 implies that a lower number of high types (a lower value of N^H) will produce a lower value of F_d, such that a shock that reduces the value of N^H in period $t+1$ will lower the value of F_d in period $t+2$. Note additionally that a suppressed value of $\theta_{c,t}$ is not in and of itself relevant to the severity of $\theta_{c,t}$-type shocks, as wages and population head counts are linear with respect to coal shocks.

B.2.2 Second-period shocks

A second-period shock to the coal industry occurring between period $t+1$ and $t+2$ is defined analogously to a first-period shock occurring between period t and $t+1$:

$$\theta_{c,t+2} = \theta_{c,t+1} + \Delta\theta_{c,t+1} \tag{11}$$

Do the effects of a second-period coal shock depend on whether a community experienced a first-period shock? To answer this question, consider two communities: Community j and Community l. They are identical in period t. Between period t and period $t+1$, Community j suffers a negative productivity shock to its coal industry. Between period $t+1$ and period $t+2$, both Community j and Community l suffer coal shocks of identical magnitudes. How do the effects of the second-period shock in Community j (which experienced a first-period shock) and Community l (which did not) compare?

Proposition 2. *Wages for low (W^L) and high (W^H) types increase, the number of high types (N^H) increases, and the number of low types (N^L) decreases by more in $\Delta\theta_{c,t+1}$ in a community which experienced a shock in the preceding period than an otherwise identical community. A negative shock to productivity in the coal industry between period $t+1$ and period $t+2$ ($\Delta < 0$) thus has a larger impact — in terms of its effect on local wages and population head counts — in Community j (which also experienced a first-period shock) than Community l (which did not).*

Proof. See Appendix C.3.

Proposition 2 indicates that the consequences of a coal shock will be more severe (i.e., larger in magnitude) in places exposed to adverse shocks in preceding periods relative to places with no history of coal shocks. This differential severity stems from the impact of the preceding (first-period) shock on the number of high types, and thus the number of non-coal-industry firms, in the affected community. Because Community j arrives at the more recent (second-period) coal shock with fewer firms in the non-coal industry than an otherwise identical Community l, wages and population head counts are more responsive to the shock. This differential severity does *not* stem from differences in the *level* of productivity in the coal industry at the beginning of the period ($\theta_{c,t+1}$). Rather, it is explained by differences in the number of firms in the non-coal industry at the time of the shock.

C Model expressions and proofs

Below are the primary mathematical expressions excluded in the main text. I first solve for low-type wages and show that high-type wages can be written in terms of low-type wages. Next, I outline the seven equations that characterize the static equilibrium. I then detail the components of the central parameters N^H, N^L, W^H, and W^L, the partial derivatives of W^L and N^H with respect to θ_c, and the cross-partials of W^L and N^H with respect to θ_c and F_d.

C.1 Solving for wage

High-type wages (W^H) are equal to the efficiency parameter (ω) times low-type wages (W^L), as

$$\begin{aligned}
W^H =& \frac{\partial}{\partial n^H}(-a(n^L + \omega n^H)^2 + \theta_c b(n^L + \omega n^H)) \\
&= \omega(-2a(n^L + \omega n^H) + \theta_d b) \\
&= \omega(\frac{\partial}{\partial n^L}(-a(n^L + \omega n^H)^2 + \theta_c b(n^L + \omega n^H))) \\
&= \omega W^L.
\end{aligned}$$

Wage W^L is given by solving for the wage at which everyone is hired. At wage W^L for low types and ωW^L for high types, coal firms hire until:

$$W^L = \frac{\partial}{\partial W^L}(-a(n^L + \omega n^H)^2 + \theta_c b(n^L + \omega n^H)) = -2a(n^L + \omega n^H) + \theta_c b$$

Rearranging this expression, each firm in the coal industry hires such that:

$$n^L + \omega n^H = \frac{1}{2a}(\theta_c b - W^L)$$

Symmetrically, each firm in the non-coal industry hires such that:

$$n^L + \omega n^H = \frac{1}{2a}(\theta_d b - W^L).$$

Aggregating across all firms:

$$N^L + \omega N^H = \frac{1}{2a}(F_c(\theta_c b - W^L) + F_d(\theta_d b - W^L)),$$

where N^L and N^H represent the total population of low and high types in the local labor market, respectively.

C.2 Characterizing the static equilibrium

The seven equations that characterize the seven equilibrium parameters (W^L, W^H, P, N^L, N^H, ε^H, and ε^L) are expressed below:

1. $P = \frac{1}{\alpha}(W_0 + \varepsilon^H - \overline{U}^H) + W^H - W_0$ (High-type marginal utility is equal to his reservation

utility.)

2. $P = W^L + \varepsilon^L - \overline{U}^L$ (Low-type marginal utility is equal to his reservation utility.)
3. $N^H = H(\frac{M^H - \varepsilon^H}{M^H - m^H})$ (The number of high-type workers is determined by the amenity cutoff above which high-types stay in the coal community.)
4. $N^L = L(\frac{M^L - \varepsilon^L}{M^L - m^L})$ (The number of low-type residents is determined by the amenity cutoff above which low-types stay in the coal community.)
5. $N^L + N^H = S$ (Housing prices are such that every unit of housing is occupied.)
6. $N^L + \omega N^H = \frac{1}{2a}(F_c(\theta_c b - W^L) + F_d(\theta_d b - W^L)$ (Wages as derived earlier.)
7. $W^H = \omega W^L$ (Wages as derived earlier.)

The detailed expressions for N^H, N^L, W^H, and W^L are outlined below:

- N^H: The number of high types in a local labor market is written $N^H = A/B$, where:

$$\begin{aligned} A = H(-2a\alpha LS(\omega - 1) + F_c L(-\alpha(-b\theta_c\omega + b\theta_c + M^L - \overline{U}^L + W_0) \\ +M^H - \overline{U}^H + W_0) + F_d L(-\alpha(-b\theta_d\omega + b\theta_d + M^L - \overline{U}^L + W_0) \\ +M^H - \overline{U}^H + W_0) + \alpha F_c S(M^L - m^L) + \alpha F_d S(M^L - m^L)) \end{aligned}$$

and

$$B = 2a\alpha HL(\omega - 1)^2 - (F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H))$$

- N^L: The number of low types in a local labor market is written $N^L = A/B$, where:

$$\begin{aligned} A = L(-2a\alpha HS(\omega - 1)\omega \\ +F_c H(-\alpha(-b\theta_c\omega + b\theta_c + M^L - \overline{U}^L + W_0) + M^H - \overline{U}^H + W_0) \\ +F_d H(-\alpha(-b\theta_d\omega + b\theta_d + M^L - \overline{U}^L + W_0) + M^H - \overline{U}^H + W_0) \\ +F_c S(m^H - M^H) + F_d S(m^H - M^H)) \end{aligned}$$

and

$$B = (F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H)) - 2a\alpha HL(\omega - 1)^2$$

- W^H: High-type wages are written $W^H = A/B$, where:

$$
\begin{aligned}
A = \omega(-2a(HL(\omega-1)(-\alpha(M^L - \overline{U}^L + W_0) + M^H - \overline{U}^H + W_0) \\
+\alpha HS\omega(M^L - m^L) + LS(M^H - m^H)) \\
-b(F_c\theta_c + F_d\theta_d)(\alpha H(m^L - M^L) + L(m^H - M^H)))
\end{aligned}
$$

and

$$
B = 2a\alpha HL(\omega-1)^2 - (F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H))
$$

- W^L: Low-type wages are written $W^L = A/B$, where:

$$
\begin{aligned}
A = -2a(HL(\omega-1)(-\alpha(M^L - \overline{U}^L + W_0) + M^H - \overline{U}^H + W_0) \\
+\alpha HS\omega(M^L - m^L) + LS(M^H - m^H)) \\
+b(F_c\theta_c + F_d\theta_d)(\alpha H(m^L - M^L) + L(m^H - M^H))
\end{aligned}
$$

and

$$
B = 2a\alpha HL(\omega-1)^2 - (F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H))
$$

C.3 Proofs

C.3.1 Proof of Proposition 1

Proof. A negative shock to coal is realized as a decrease in θ_c between period t and $t+1$ ($\Delta < 0$). Differentiating the primitive expressions with respect to θ_c shows that $\frac{\partial N^H}{\partial \theta_c} > 0$ and $\frac{\partial W^L}{\partial \theta_c} > 0$, such that low-type wages and high-type population head counts decline with declines in coal productivity. Because $W^H = \omega W^L$, it follows that $\frac{\partial W^H}{\partial \theta_c} = \omega \frac{\partial W^L}{\partial \theta_c}$, and therefore $\frac{\partial W^H}{\partial \theta_c} > 0$,. Further, as $N^H + N^L = S$, it follows that $\frac{\partial N^L}{\partial \theta_c} = -\frac{\partial N^H}{\partial \theta_c}$.

Thus, $\frac{\partial N^H}{\partial \theta_c} > 0$, $\frac{\partial N^L}{\partial \theta_c} < 0$, $\frac{\partial W^L}{\partial \theta_c} > 0$, and $\frac{\partial W^H}{\partial \theta_c} > 0$, indicating that a decrease in θ_c between period t and $t+1$ ($\Delta < 0$) decreases N^H, increases N^L, and decreases W^L and W^H. That is, the adverse shock reduces the number of high types, increases the number of low types, and reduces both high- and low-type wages. The linearity of wages and population head counts with respect to coal shocks is illustrated by $\frac{\partial^2 N^H}{\partial \theta_c^2} = \frac{\partial^2 W^L}{\partial \theta_c^2} = 0$. The full expressions for these derivatives and cross-partials are in Appendices C.3.3 and C.3.4. □

C.3.2 Proof of Proposition 2

Proof. In period $t+1$, there are only two primitives in which Community j and Community k differ: θ_c and F_d. Both of these primitives are lower in Community j than Community k. The relative severity of the effect of the shock in the two communities is determined by the relative magnitude of $\frac{\partial W^L}{\partial \theta_c}$ and $\frac{\partial N^H}{\partial \theta_c}$. As before, these relationships determine the corresponding partials of W^L and N^L by the linear equations $W^H = \omega W^L$ and $N^L + N^H = S$. Because the second-order derivatives with respect to θ_c are zero (shown in the proof to Proposition 1), the differences in the relative severity are explained by the cross-partial $\frac{\partial^2}{\partial \theta_c \partial F_d}$.[5] Taking these derivatives and examining the expressions shows that $\frac{\partial^2 N^H}{\partial \theta_c \partial F_d} < 0$ and $\frac{\partial^2 W^L}{\partial \theta_c \partial F_d} < 0$. By extension, $\frac{\partial^2 N^L}{\partial \theta_c \partial F_d} > 0$ and $\frac{\partial^2 W^H}{\partial \theta_c \partial F_d} < 0$. The full expressions for these derivatives and cross-partials are in Appendices C.3.3 and C.3.4.

□

C.3.3 Derivatives with respect to θ_c

- $\frac{\partial W^L}{\partial \theta_c} = A/B$, where:

$$A = bF_c(\alpha H(m^L - M^L) + L(m^H - M^H))$$

and

$$B = (F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H)) - 2a\alpha HL(\omega - 1)^2$$

- $\frac{\partial N^H}{\partial \theta_c} = A/B$, where

$$A = -\alpha bF_c HL(\omega - 1)$$

and

$$B = (F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H)) - 2a\alpha HL(\omega - 1)^2$$

C.3.4 Cross-partials with respect to θ_c and F_d :

- $\frac{\partial^2 W^L}{\partial \theta_c \partial F_d} = A/B$, where:

$$A = -bF_c(\alpha H(m^L - M^L) + L(m^H - M^H))^2$$

[5] Proposition 1 indicates that a suppressed value of $\theta_{c,t}$ is not in and of itself relevant to the severity of $\theta_{c,t}$-type shocks.

and

$$B = \left((F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H)) - 2a\alpha HL(\omega - 1)^2\right)^2$$

- $\frac{\partial^2 N^H}{\partial \theta_c \partial F_d} = A/B$, where:

$$A = \alpha b F_c HL(\omega - 1)(\alpha H(m^L - M^L) + L(m^H - M^H))$$

and

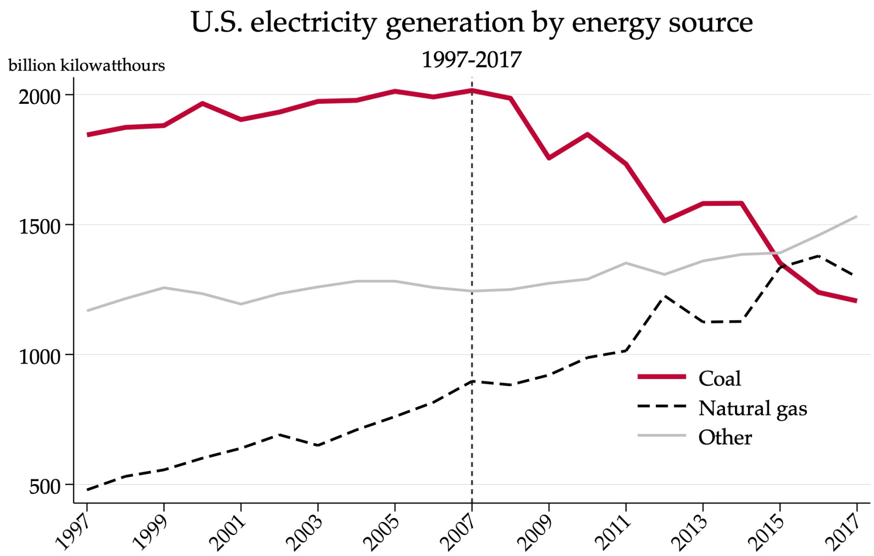
$$B = \left((F_c + F_d)(\alpha H(m^L - M^L) + L(m^H - M^H)) - 2a\alpha HL(\omega - 1)^2\right)^2$$

D Indirect evidence of exclusion restriction assumption

The primary empirical approach leverages a county's exposure to the coal shock by instrumenting for changes in the coal share of the adult population with the coal share at the beginning of the period. The assumption is that the initial coal share is exogenous to expected outcomes, only influencing subsequent changes in employment, population, and other outcomes via its relationship with shocks to coal demand. While impossible to test for directly, one indirect test of this exclusion restriction is to examine whether the instrument predicts outcome changes during a period of relative stability in demand for coal. That is, were there no legacy consequences of historical shocks, the county coal share should predict changes in outcomes when coal is in decline, but not during periods of relative stability. While demand for coal has fluctuated over the past several decades, the industry enjoyed relatively steady demand in the period directly preceding the contemporary coal shock. Figure D3 shows that electricity generation from coal was remarkably flat between 1997 and 2007, but then fell by about 40 percent in the decade that followed, just as natural gas generation increased by a similar magnitude.

I exploit this relatively stable period of coal demand in one indirect test of the exclusion restriction. Table D7 reports the relationship between $Coal_j^{2007}$ and changes in outcome variables, in both the period of declining coal demand (2007–2017) and the relatively stable decade leading up to the contemporary analysis (1997–2007). Panel A (2007–2017) reflects the standard reduced-form relationship between the instrument and outcomes of interest, while Panel B (1997–2007) offers a falsification test between the instrument and outcomes that should not be influenced by the 2007 coal share if this instrument were as good as randomly assigned. All regressions are population-weighted and include controls for the share of the adult population with a college

Figure D3: U.S. electricity generation by energy source



Notes: Figure based on data retrieved from the EIA. "Other" includes generation from nuclear, renewables, and petroleum and other. Values are based on generation from power plants with at least 1-megawatt electric generating capacity.

degree, the share of the population that is foreign-born, the female share of the adult workforce (ages 20–64), a dummy indicating any coal employment at the start of the period, and state fixed effects. Odd-numbered columns control for 2007-level characteristics (based on the 2005–2009 ACS estimates) and weight by 2007 population. Even-numbered columns control for 2000-level characteristics (based on the decennial Census) and weight by 1997 population.

The point estimates in Panel A of Table D7 indicate that the instrument strongly predicts outcome changes during the period of declining national coal demand. A 1pp increase in the coal share predicts a 1.7 percent decline in wage and salary employment, a 0.8 percent decline in the population ages 20–64, a 0.5pp decline in the employment share of the adult population, a 2.7 percent decline in wages and salaries, and nearly a 1 percent decline in wages per employee over the 2007–2017 period. While the 2007 coal share predicts pre-period declines in the working-age adult population, it has much less predictive power over trends in other outcomes during the placebo period from 1997 to 2007 (Panel B), a time when coal mining employment was relatively stable in Appalachia. Indeed, it predicts a slight increase in the employment-population ratio in the years prior to the contemporary coal shock. That counties with heavier coal shares were experiencing waning population counts prior to the contemporary coal shock is consistent with

Table D7: Reduced form and falsification tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Δln(**emp**)		Δln(**ages 20-64**)		Δ **emp:pop ratio**		Δln(**wages**)		Δln(**wages/emp**)	
Panel A: Contemporary coal shock (Δ 2007-2017)										
Coal share, 2007	-1.73***	-1.75***	-0.76***	-0.78***	-0.52***	-0.51***	-2.66***	-2.69***	-0.93***	-0.94***
	(0.30)	(0.28)	(0.20)	(0.19)	(0.17)	(0.17)	(0.51)	(0.49)	(0.25)	(0.24)
Panel B: Placebo period (Δ 1997-2007)										
Coal share, 2007	-0.26	-0.11	-0.67**	-0.66***	0.21*	0.28**	-0.46	-0.29	-0.20	-0.18
	(0.35)	(0.27)	(0.26)	(0.21)	(0.12)	(0.11)	(0.44)	(0.37)	(0.14)	(0.14)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls base year	2007	2000	2007	2000	2007	2000	2007	2000	2007	2000
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	413	413	413	413	413	413	413	413	413	413

All regressions include state fixed effects and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. The coal share refers to the coal mining share of the working-age adult population in 2007. Controls in even- (odd-) numbered columns include the 2007- (2000-) level share of the population that is foreign-born, the female share of employment, and the share of adults with a college degree. Regressions in even- (odd-) numbered columns are weighted by 2007 (1997) population. Outcomes are based on estimates from the BEA Regional Economic Accounts. Outcomes in Panel A are defined over the 2007–2017 period, while those in Panel B are defined over the 1997–2007 period.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

the persistent consequences of historical shocks on population mobility, but the increase in the employment rate is inconsistent with a secular decline in economic activity. Still, one might be concerned that the effect of the contemporary coal shock is biased upward by the legacy effects of historical events. The conclusions are insensitive to controlling for lagged population changes, controlling for lagged (e.g., 1980 level) coal shares, and matching coal counties to non-coal counties based on population pre-trends.

E Adjustment to a single-period shock: Additional outcomes

Table E8 displays the baseline IV estimates of the effect of the 2007–2017 coal shock on the change in (log) wages and salaries (column 1), wages and salaries per wage and salary employee (column 2), total personal income (column 3) and personal income per capita (column 4). All outcomes are based on estimates produced by the BEA Regional Economic Accounts. The point estimate in column 1 indicates that a 1-unit (1pp) increase in the coal shock reduces total wages and salaries by nearly 5 percent, or about 50 percent more than the fall in total employment (3.24 percent). Consistent with this, average wages and salaries (per wage and salary employee) fall by 1.74 percent. This could reflect both compositional shifts in the employed population, with the most productive or highest-paid employees exiting the local workforce, as well as declines in the wages of incumbent employees. Without individual-level data, I am unable to distinguish between these two forces, although other work using administrative tax data has shown that declines in demand for coal produced large declines in individual earnings (Colmer et al., 2024; Rud et al., 2024).

Table E8: Earnings and income adjustment to coal shock, 2007–2017

	(1) Δln(wages & salaries)	(2) Δln(wages & salaries per employee)	(3) Δln(personal income)	(4) Δln(personal income per capita)
Coal shock, 2007–2017	-4.98***	-1.74***	-1.55**	-0.56*
	(1.06)	(0.42)	(0.61)	(0.31)
State FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	413	413	413	413

All regressions are weighted by initial (2007) county population and include state fixed effects and controls for the initial share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. The coal shock is defined as -1 times the change in the coal employment share of the adult population (ages 20–64). I instrument for the 2007–2017 coal shock with the coal share in 2007. Outcome variables are defined over the 2007–2017 period and are retrieved from the BEA Regional Economic Accounts. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

At the same time, Table E8 shows that total personal income falls by only 1.55 percent (column 3), and personal income per capita falls by 0.56 percent (column 4), following a 1-unit (1pp) increase in the coal shock. That total incomes fall by less than total wages suggests that non-wage income becomes a more important component of total income. That is, households may rely more on transfer payments, non-wage earnings, and other forms of income to buffer total income losses. Again, I am unable to distinguish the extent to which declines in average earnings result from mechanical changes in the population composition using the aggregated county-level data. However, that things like transfer payments (e.g., SSDI) become a more important component of total income would be consistent with other research demonstrating the responsiveness of transfer receipt to economic conditions and labor demand shocks (Black et al., 2002, 2003; Autor and Duggan, 2003; Autor et al., 2014; Hanson, 2022).

The evidence presented in Table E9 indicates that the average earnings losses documented in Table E8 are unlikely to be driven entirely by compositional shifts in the population. It explores differential earnings consequences of the 2007–2017 coal shock by sex and educational attainment, where median earnings for full-time workers ages 25 and older are based on ACS 5-year estimates.[6] The outcome variable is defined as the change in the natural log of median earnings for the sex-education category indicated. The point estimates indicate that less-educated men experience the largest declines in earnings, while the changes in earnings for other sex-education categories are statistically indistinguishable from zero. A 1-unit increase in the coal shock yields a 3.57 percent decline in earnings among men with less than a high school degree, a 2.4 percent decline in earnings among men with exactly a high school degree, and a statistically imprecise 1.4 percent decline in earnings among men with a college degree. For these patterns to be driven entirely by the mechanical effect of population composition changes, it would need to be the case that only the highest wage male workers with lesser levels of education are leaving the local workforce, but the estimates in Table 3 revealed that population responses were largest among better educated male workers. That the largest (and only detectable) wage adjustments come from the most immobile group of workers is instead consistent with Topel (1986), where positive productivity shocks generate wage gains for the least geographically mobile group of workers: those who are older and less educated. It is also consistent with Borjas (2006), who demonstrates that internal migration among native workers weakens the wage impact of immigrant in-migration. Here, internal migration of more educated workers might mollify the adverse wage consequence of local productivity shocks.

Table E10 reports the effect of the coal shock on employment in other industries based on data from the QCEW.[7] Examining the 1970s coal boom and subsequent 1980s coal bust, Black et al. (2005a) find that the 1980s shock yielded declining employment and earnings in construction, services, and retail. Table E10 indicates that the contemporary coal shock does not have a statistically distinguishable effect on employment in goods-producing industries (which include construction) once natural resources and mining employment are omitted, but the direction and magnitude of the coefficient implies potentially large negative spillovers on these industries.[8]

[6]The number of observations varies across columns, as the Census does not produce earnings estimates for certain sex-education categories in counties with very small base populations.

[7]Employment is calculated by industry Super Sector in the QCEW High-Level dataset. More details on these groupings, as well as their corresponding NAICS codes, can be found at https://www.bls.gov/cew/classifications/industry/high-level-industries.htm. Industry-level employment counts are suppressed by the QCEW for confidentiality purposes in certain cases. I estimate the effect of the coal shock on the change in log industry employment for all counties with non-missing values for employment counts in both 2007 and 2017. I omit the change in employment in information and financial activities from Table E10, as both industries compose a relatively insubstantial fraction of total county employment for most counties in the analysis.

[8]The employment total in column 2 is defined as all goods-producing employment less employment in natural resources and mining, consisting of employment in construction and manufacturing.

Table E9: Earnings change by sex and educational attainment, 2007–2017

	(1)	(2)	(3)	(4)
	∆ln(median earnings), 2007–2017			
	All full-time workers ages 25 +	Workers w/ less than high school	Workers w/ HS degree	Workers w/ college degree
Panel A: ∆ln(median earnings), Male				
Coal shock, 2007–2017	-2.26***	-3.57*	-2.44***	-1.42
	(0.68)	(1.87)	(0.58)	(1.23)
State FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	412	404	412	401
Panel B: ∆ln(median earnings), Female				
Coal shock, 2007–2017	-0.05	2.29	-0.29	-1.14
	(0.41)	(1.84)	(0.58)	(1.21)
State FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	412	378	411	403

All regressions are weighted by initial (2007) county population and include state fixed effects and controls for the 2007 share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. The coal shock is defined as -1 times the change in the coal employment share of the adult population (ages 20–64). I instrument for the 2007–2017 coal shock with the coal share in 2007. Outcome variables describe the change in the natural log of median annual earnings by sex and educational attainment for full-time workers ages 25 and older, based on estimates produced from the ACS 5-year surveys (2005–2009 and 2015–2019).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The coal shock produces substantial negative spillover effects in some service-producing industries, particularly those more reliant on local demand. A 1-unit (1pp) increase in the coal shock yields a 2.4 percent decline in ”trade, transportation, and utilities” (which includes both wholesale and retail trade) and a 1.6 percent decline in leisure and hospitality, indicating that shocks to coal mining employment adversely affect employment opportunities in other sectors. This aligns with research showing that industries more dependent on local demand are more vulnerable to demand shocks in other local industries (Moretti, 2011; Aragón and Rud, 2013; Mian and Sufi, 2014). Conversely, demand for some other service-oriented industries, such as health services, might be less elastic to local shocks. Indeed, the null effect on education and health might indicate that demand for things like healthcare services is relatively insulated from the adverse spillover

Table E10: Spillover effects of the 2007–2017 coal shock: Employment changes in other industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Goods-producing ind			**Service-producing** ind			
	All goods	Non-NR	All service	TTU	Prof.	Ed & health	LH
Coal shock, 07-17	-9.88***	-4.57	-1.43*	-2.43**	-2.51	0.25	-1.61**
	(2.64)	(2.90)	(0.80)	(0.97)	(3.02)	(0.74)	(0.82)
Controls	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓
Observations	406	406	410	413	391	409	407

All regressions are weighted by initial (2007) county population and include state fixed effects and controls for the initial share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. Robust standard errors are in parentheses. The coal shock is defined as -1 times the change in the coal employment share of the adult population (ages 20–64). I instrument for the 2007–2017 coal shock with the coal share in 2007. Outcome variables are defined over the 2007–2017 period and are retrieved from the QCEW. Non-NR refers to employment in all goods-producing industries *less* employment in natural resources and mining (i.e., construction and manufacturing). TTU refers to trade, transportation, and utilities, and prof. refers to professional and business services. LH refers to leisure and hospitality.
*** p<0.01, ** p<0.05, * p<0.1

effects of local demand shifts in other industries.[9] Broadly, these results suggest that adverse coal shocks might trigger de-agglomeration forces in local economies, with potentially broader and more lasting negative effects for exposed communities.

F Adjustment to a single-period shock: Robustness

Instrumenting for the contemporary coal shock ($\Delta Coal_j^{2007\text{-}17}$) with the coal share in the initial period ($Coal_j^{2007}$) leverages variation in initial coal shares and an exogenous national, sectoral shock (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022a). The exclusion restriction assumption might be particularly strong in the context of Appalachia's coal industry, as a central motivation of this investigation is that some places that are highly coal-dependent in the contemporary period might have been shaped by historical experiences in ways that affect their recovery from shocks. In light of this, I consider several alternative instruments for $\Delta Coal_j^{2007\text{-}17}$ that are plausibly more exogenous to expected outcomes in the contemporary period. All have relatively weaker first stages than the instrument used in the primary analysis and thus yield slightly noisier estimates, but the direction and magnitude of coefficients support the central findings.

[9]This is supported by anecdotal evidence that demand for health workers has increased in many communities hit hardest by declining coal employment. See, for example, https://www.nytimes.com/2019/09/14/us/appalachia-coal-women-work-.html.

First, I use the estimated county-level coal reserves per capita to instrument for the coal shock. The intuition behind this approach is that a place's comparative advantage in the coal industry depends upon its natural resource endowment. This endowment predates any economic activity in a county, such that initial coal reserves only influence a place's economic and population trajectory by generating differential exposure to changes in demand for the resource. County-level data on initial coal reserves (in millions of short tons) is available for only four states in the Appalachian region (West Virginia, Kentucky, Ohio, and Pennsylvania).[10] I limit the sample to the 193 Appalachian counties in these four states and I instrument for the 2007–2017 coal shock with estimated (original) county-level coal reserves, divided by the total population at the beginning of the period (2007).[11] I use the original reserves rather than an estimation of remaining reserves both because this measure is consistently estimated across the four states, and because this measure is purged of a county's history with coal mining, which could potentially influence expected outcomes. This instrument will be valid if having large per-capita coal endowments is not predictive of outcomes except through its influence on the change in the coal share of the population. Given that the endowment of this resource substantially predates the empirical setting, it is plausible that coal reserves provide an exogenous source of variation in exposure to the contemporary shift in demand for coal.

The estimates produced when instrumenting for $\Delta Coal_j^{2007\text{-}17}$ with the initial coal reserves per capita on this four-state sample are similar in magnitude to those from the baseline analysis, as seen by comparing the coefficients represented by the blue circles and gray boxes in Figure F4, which reflect the estimates from the baseline specification and those produced by instrumenting for $\Delta Coal_j^{2007\text{-}17}$ with initial reserves per capita, respectively. Figure F4 also reports the estimates when instrumenting for the contemporary coal shock with the coal reserves per capita using the 1980 population size as the base. These estimates are reflected by the red circles. The standard errors are slightly larger when instrumenting for the coal shock with initial reserves per capita, as the instrument itself has a weaker first stage than the initial coal share used in the primary analysis.[12] While the estimates are slightly less precisely estimated exploiting initial coal endowments

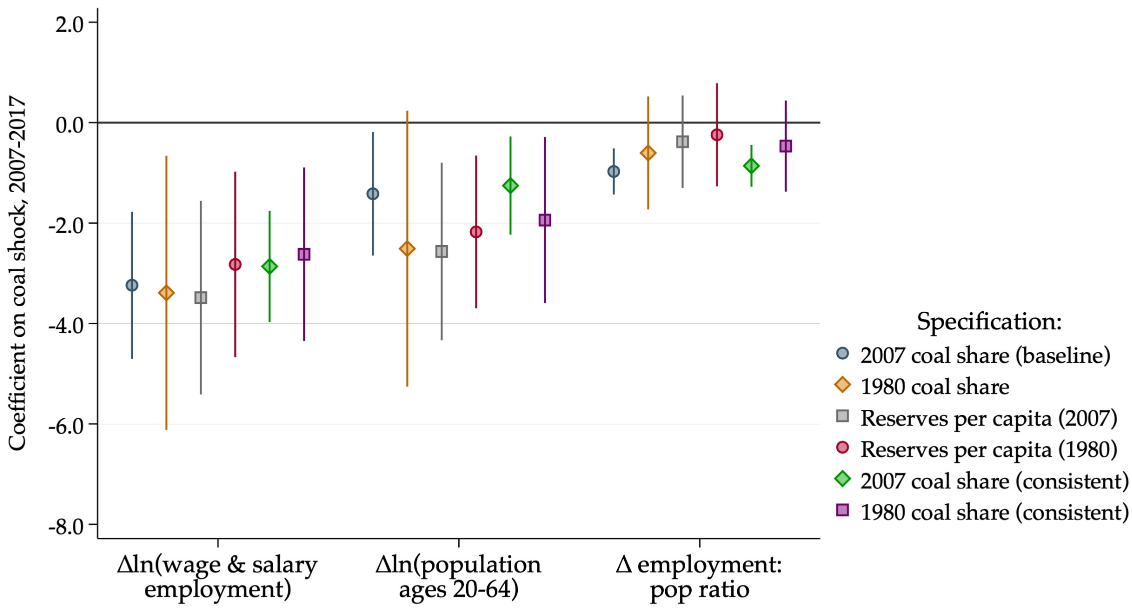
[10] These four states form the basis of the analysis in Black et al. (2002, 2003, 2005a), which use the value of coal reserves as the exogenous source of variation when analyzing the 1970s coal boom and 1980s coal bust.

[11] Initial coal reserves are all estimates based on geological surveys, provided by various state agencies. Initial reserves in Ohio counties were retrieved from Sorrell and Spahr (2016a,b) and Wright and Erber (2018). Kentucky reserves were retrieved from Association (2010), Pennsylvania reserves from Edmunds (1972), and West Virginia reserves from West Virginia Office of Miners' Health Safety and Training (2009).

[12] The first stage F-statistic when instrumenting for the 2007–2017 coal shock with the reserves per capita (in 2007) is just over 10.

as the driving source of variation, the coefficients produced using this strategy are quantitatively and qualitatively similar to those in the main analysis.

Figure F4: Effect of contemporary coal shock: Alternative instruments



Notes: Figure reflects the coefficient on the 2007–2017 coal shock in different specifications described in the legend. All regressions are weighted by population and include state fixed effects, initial (2007) county-level covariates, and a dummy variable for having any coal employment in 2007. The 2007 coal share (baseline) specification instruments for $\Delta Coal_j^{2007\text{-}17}$ with the 2007 coal share, $Coal_j^{2007}$. The 1980 coal share specification instruments for $\Delta Coal_j^{2007\text{-}17}$ with the 1980 coal share, $Coal_j^{1980}$. Reserves per capita specifications instrument for $\Delta Coal_j^{2007\text{-}17}$ with initial coal reserves per capita, where capita is defined by either the 2007 or 1980 population, indicated in the legend. The sample for these two specifications includes only Appalachian counties in West Virginia, Kentucky, Ohio, and Pennsylvania. The primary independent variable in the final two specifications is defined as the change in the coal employment share of the (consistent) 2007 population, instrumented by the 2007 coal share $Coal_j^{2007}$ or 1980 coal share $Coal_j^{1980}$ as indicated by the legend.

Given that the degree of coal mining in a county is largely dependent on the (immobile) natural endowment of the resource, counties that were more dependent on coal mining in 2007 were also highly dependent on the industry in 1980. The 1980 coal mining employment share could be a strong and (plausibly) more exogenous instrument for the change in the contemporary coal share, given that the 2007 coal share is, in part, dictated by the experiences with the 1980 coal shock. While the coal share in 2007 is highly correlated with the coal share in 1980, the latter provides a weak instrument for $\Delta Coal_j^{2007\text{-}17}$ (the first-stage F-statistic on $Coal_j^{1980}$ is only 3). Still, the coefficients produced using this instrument are largely similar to those from the baseline specification. They are reflected by the orange diamonds in Figure F4. Ultimately, the relative weakness of this instrument favors using the more contemporary coal share, but the results are broadly similar across specifications.

Finally, if the coal shock reduces local population sizes, this will influence the denominator of the primary independent variable. If population declines are much larger than coal mining employment declines — perhaps due to negative spillovers into other industries — the coal employment share of the adult population may appear to increase despite declining coal employment. To address this, I redefine the coal shock to purge the variable of any contemporaneous change in the working-age-adult population over the 2007–2017 period. In the final two specifications in Figure F4, the primary independent variable is defined as the change in the coal mining employment share of the initial (2007) working-age adult population:

$$\Delta Coal_j^{2007\text{-}17} = \frac{emp_{coal,j}^{2017} - emp_{coal,j}^{2007}}{adult_j^{2007}} \tag{12}$$

As before, I multiply this value by -1. The coefficients represented by the green triangles in Figure F4 are produced by instrumenting for $\Delta Coal_j^{2007\text{-}17}$ as defined in equation 12 with the 2007 coal share, $Coal_j^{2007}$. Those represented by the purple squares are produced by instrumenting for $\Delta Coal_j^{2007\text{-}17}$ as defined in equation 12 with the 1980 coal share, $Coal_j^{1980}$.

The conclusions drawn from these alternative specifications are largely similar to those drawn from the baseline specification.[13] This is true across a wider range of outcome variables than those reflected in Figure F4. Using alternative instruments and definitions of the coal shock reveals that counties adjust to declining demand for coal via reduced employment, reduced population counts, and a range of other adjustment processes.

G Addressing spatial spillovers

Appalachian counties are small geographic units, and labor market shocks in one county may have spillover effects into neighboring units. Neighboring counties may receive displaced coal workers searching for new jobs, or they may experience reduced demand for local goods and services resulting from the proximate shock. In this case, these observations may be contaminated by the indirect effects of the coal shock. I consider these potential spillover effects in three ways. First, I exclude from the analysis all counties that border coal counties, but do not have any coal employment themselves, based on coal employment counts in 2007. This approach omits these control observations that may be contaminated by neighboring counties' exposure to the coal shock. Sec-

[13] Defining the coal shock as the change in the coal share of employment produces similar results.

ond, I construct a control variable that captures exposure to coal shocks in neighboring places based on the commuting flows between counties. This control variable $Commute_j^{2007}$ for county j is defined as:

$$Commute_j^{2007} = \sum_{j' \in adjacent} Coal\ employment_{j'}^{2007} \times \varsigma_{j'} \tag{13}$$

where the weight on the 2007 coal employment in county j', $\varsigma_{j'}$, is defined as:

$$\varsigma_{j'} = \frac{Commuters_{jj'}^{2000}}{Commuters_j^{2000}}$$

Thus, I multiply $Coal\ employment_{j'}^{2007}$, the 2007-level coal mining employment in an adjacent county j', by the share of total commuters in county j who commuted from j to j' in 2000 ($\varsigma_{j'}$) and sum this value over all counties j' adjacent to county j.[14]

Third, I control for the spatial proximity of county j to other counties $j' \neq j$ with high exposure to coal shocks:

$$ProxCoal_j^{2007} = \sum_{j'} \omega_{jj'} \times Coal_{j'}^{2007} \tag{14}$$

Where $\omega_{jj'}$ is defined exactly as in equation 4 and $Coal_{j'}^{2007}$ is the coal mining employment share of the adult population (ages 20–64) in 2007 in other county j'. Thus, $ProxCoal_j^{2007}$ reflects the gravity-weighted coal share in all other counties. As discussed in Adão et al. (2019), the indirect spillover effects of shocks in other labor markets likely attenuate the direct impact of local shocks in a general equilibrium setting. Relatedly, Borusyak et al. (2022b) show that, because workers' location decisions depend on economic conditions in both their origin and potential destination locations, conventional migration regressions are misspecified by omitting shocks in relevant destination labor markets. This control variable is meant to capture these considerations.

The first column of Table G11 reports the baseline IV coefficient estimates of the effect of the 2007–2017 coal shock on the change in total employment (Panel A), the change in the working-age adult population (Panel B), and the employment-adult population ratio (Panel C). These are identical to the estimates in column 4 of Table 2. Column 2 applies the same baseline specification to the restricted sample, omitting adjacent, non-coal counties. These estimates are similar to those from the baseline specification, indicating that the indirect effects in neighboring, non-coal counties do not substantially affect the estimates. In column 3, I add to the baseline controls the

[14] County-to-county commuting flow data are estimates reported by the U.S. Census, based on the 2000 Census.

Table G11: Employment and population adjustment to single-period coal shock, 2007–2017

	(1)	(2)	(3)	(4)
Panel A: Δln(wage and salary employment) 2007-2017				
Coal shock, 2007–2017	-3.24***	-3.23***	-3.27***	-2.56***
	(0.74)	(0.77)	(0.78)	(0.50)
Panel B: Δln(population ages 20–64) 2007-2017				
Coal shock, 2007–2017	-1.42**	-1.52**	-1.35**	-0.78**
	(0.63)	(0.69)	(0.63)	(0.34)
Panel C: Δ employment:population ratio, 2007-2017				
Coal shock, 2007–2017	-0.97***	-0.89***	-1.09***	-1.01***
	(0.23)	(0.25)	(0.24)	(0.23)
State FE	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓
Control for $Commute_j^{2007}$			✓	
Control for $ProxCoal_j^{2007}$				✓
Sample	Baseline	Restricted	Baseline	Baseline
Observations	413	300	413	413

All regressions are weighted by initial (2007) county population. Robust standard errors are in parentheses. Baseline controls include the initial share of the population that is foreign-born, the female share of employment, the share of adults with a college degree, and a dummy variable indicating whether the county had positive coal employment at the beginning of the period. The variable $Commute_j^{2007}$ captures commuting relationships to adjacent counties' coal employment. The variable $ProxCoal_j^{2007}$ captures a distance-weighted measure of proximity to other coal counties. The construction of these two variables is described in the text. The baseline sample is that used in the primary analysis. Restricted removes all counties that border coal counties, but have no coal employment themselves. The coal shock is defined as -1 times the change in the coal employment share of the adult population (ages 20–64). I instrument for the coal shock with the coal share in 2007. Outcome variables are retrieved from the BEA Regional Economic Accounts.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

variable $Commute_j^{2007}$. Again, these parameters are similar to the baseline estimates. Column 4 controls for $ProxCoal_j^{2007}$. Consistent with Adão et al. (2019), accounting for a county's exposure to shocks in all relevant labor markets produces attenuated coefficient estimates for employment and population changes. This attenuation likely occurs because the gravity-weighted proximity measure captures spillover effects from all relevant counties, rather than being limited to those that are directly adjacent. In contrast, controlling for adjacent commuting relationships only accounts for direct neighbor-to-neighbor spillovers, which appear less consequential in driving the estimated effects. However, the overall patterns remain intact, and the conclusions drawn from the central analysis are robust to these spatial spillover adjustments.