From the Ground Up:
Labor Demand and Intergenerational Mobility in the US

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Abstract

Intergenerational mobility varies widely across the United States, and recent research has sought to understand why. This article considers the effects of large labor demand shocks on this geographic inequality. I show that the fracking boom and increased import competition led to substantial changes in upward mobility for the 1980-82 birth cohort, largely driven by changes at the bottom of the income distribution. The mobility and income gains are primarily realized by men from low-income backgrounds. Between 10-15 percent of the spatial variation of absolute upward mobility in the U.S. can be explained by fracking intensity and trade competition alone.

JEL: E24, J23, L71, R12, R58

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I Introduction

Belief in the "American Dream", the ideal that a person's achievement is not limited by the conditions of their birth, is an enduring national ethos. However, there are stark differences in average outcomes across the United States. The probability that a child reaches the top fifth of the national income distribution if they were born to parents in the bottom fifth is 9.5 percent in Pittsburgh, but only 5.1 percent in Cincinnati, a city of similar size only a four and a half hour drive to the west. In a world where parental income played no role in determining children's income, the probability of ending up in the top income quintile conditional is mechanically 20 percent, so these differences are substantial.

Chetty et al. 2014 provides the most well-known measures of intergenerational mobility in the U.S., using administrative tax data for the 1980-82 birth cohort to document substantial spatial disparities in mobility. Figure 1 Panel A maps "absolute upward mobility"[1] across commuting zones (CZs)[2], which measures the relative success of a child born to poor parents in a specific CZ. Formally, this measure can be interpreted as the average spot in the national income distribution a member of the 1980-82 birth cohort reaches if they are born to parents at the 25^{th} percentile of the national *parental* income distribution. These data come from the Opportunity Atlas, a highly cited project by both academics and the popular press which documents spatial inequality in the United States.

While much of the discussion of these place-based disparities have focused on segregation, education, family stability, and social capital (Chetty et al., 2014; Chetty et al., 2018), I consider the role of large labor demand shocks that impacted the children identified in the Opportunity Atlas as they were reaching adulthood. Unlike previous cohorts, this group entered the labor market as two large changes were reshaping opportunities for men in America: China's entry into the World Trade Organization (WTO) and the fracking boom. Increased import competition with Chinese goods contributed to the fall of manufacturing employment from a relatively stable 18 million over the previous decades to just 12 million nearly 10 years later. Meanwhile, the creation of new techniques to extract oil and natural gas allowed previously inaccessible reserves led to a production boom. Bartik et al, (2019) estimate that local households have an annual willingness-to-pay of \$1300-\$1900 to allow fracking, even accounting for amenities losses.

1. Increases in absolute mobility represent better outcomes for children born to poorer parents relative to the national average outcomes of similar children. Absolute mobility does not rise because more well-off children in that area are doing worse.

2. Commuting zones are aggregations of counties meant to approximate local labor markets. Tolbert and Sizer (1996) use county-to-county commuter flows to construct geographic boundaries which typically encompass four counties, and on average include just under 400,000 individuals.

The main channel through which local labor demand affects mobility, especially in the short-term, is wage earnings and employment. In Figure 1 Panel B, I report the change in the employment-to-population ratio from 2000 to 2012, where employment is restricted to only looking at natural resource extraction and manufacturing. This exercise is a simple test of the correspondence between both labor demand shocks and absolute mobility. The similarity of this map to the absolute mobility map is correlational, but suggests that changes to local labor markets could have downstream effects on mobility. Both shocks represent natural experiments, where some communities, like those in Western Pennsylvania near Pittsburgh and North Dakota enjoyed the boost in economic activity while being relatively insulated from Chinese competition. On the other hand, communities such as Cincinnati in the Rust Belt experienced a sizeable negative shock to manufacturing employment, and were unaffected by the fracking boom due to uncontrollable geological factors.

Crucially for the mobility measures from the Opportunity Atlas, parent's household income is measured from 1996-2000, before fracking technologies were adopted, and before new tariff rates were permanently established. Children's household income is measured from 2011-2012, during which time all shale plays had begun using fracking technologies and production was undergoing large and sustained growth, as summarized in Figure 2 Panel A. Conversely, we can see an immediate, sharp decline in manufacturing employment that bottomed out in 2011 in Figure 2 Panel B. This timing means that parents were unable to take advantage of fracking jobs while the children were entering young adulthood (15-20 years old), meaning their income for the subsequent mobility measures was unaffected by either shock. Children, however, were largely able to benefit directly from the boom or be hurt by the bust in their early adulthood (30-32 years old), when their income is measured.

Using variation in fracking potential driven by exogenous geological variation, I find that, on average, areas of the country which benefit from the fracking boom are more upwardly mobile. Specifically, children born to low-income parents in boom areas are 2.4 percentage points higher in the national income distribution than their peers, who on average reach the 44^{th} percentile. This figure is similar to the aggregate effects on earnings (and employment) attributable to the fracking boom using a panel of all US counties from 1996 to 2012. These effects are entirely concentrated among boys. Boys born to low-income parents in areas that would experience a fracking boom can expect almost 10 percent higher individual incomes than similar children who grow up elsewhere. The changes are even more substantial in the opposite direction for the manufacturing bust than the fracking boom; though this effect is driven by across state rather than within state variation.

Chetty et al. 2014 argue that since spatial differences in mobility track closely with social factors like college attendance, minority prevalence, and teen birthrates, mobility may be primarily driven by community-level behavior and culture rather than labor market conditions in adulthood. To get a sense for how the boom and bust compare with social characteristics like segregation and marriage rates, I show using a variance decomposition exercise that geological factors amenable to fracking (despite being localized) explain roughly 5 percent of the national variation in mobility rates for children born to low-income parents, comparable to the amount explained by the fraction of Black residents. Exposure to Chinese import competition explains almost double the national variation. Within areas that actually had fracking production, this geological variation is the third largest explanatory factor of absolute mobility, behind marriage rates and commuting times. I also confirm that these results are not driven by differences in pre-existing conditions across boom and bust areas.

These results point towards the importance of labor market characteristics for explaining the spatial heterogeneity in mobility documented by the Opportunity Atlas. While social factors clearly play a large role, these two labor market shocks to low-skill male employment rival common measures in the literature in terms of explanatory power. While the Opportunity Atlas focuses on non-labor market characteristics of place, other work, including Katz and Kearney (2006) and Autor (2010), have highlighted the role that skill-biased technological change and declining opportunities play for low- and middle-income workers, suggesting instead that local labor markets are a crucial factor in shaping achievement. My work complements these papers, showing that variation in labor demand for low-income workers has intergenerational consequences, implying that declining opportunities may compound on each other over time.

Another strand of literature has explored the social and family formation impacts of the fracking boom (Kearney and Wilson, 2018) and the manufacturing bust (Autor et al., 2019). Black et al. (2013) found that marriage and fertility increased during the coal boom of the 1970's, while Autor et al. (2019) find the opposite changes followed manufacturing job destruction in response to Chinese competition. These findings imply that the social conditions which can aid or hamper mobility are, at least in part, downstream of labor market opportunities. I add to this literature by directly studying the changes in mobility that occurred in the wake of these booms and busts. In particular, I highlight the unequal geographic effects of Chinese import competition, complementing Fort et al. (2018), who emphasized that *prior* to 2000, manufacturing employment had been growing in the South Atlantic.

Finally, my results point to the potential effectiveness of place-based policies that spur labor demand. Kline and Moretti (2014) and Bartik (2020) argue for the efficacy of interventions which target labor demand in local labor markets. In related work, Kline and Moretti (2014) document the long-run benefits of regional development programs by documenting the effects of the Tennessee Valley authority. My paper contributes to this literature by documenting how geographically concentrated shocks like the fracking boom can have sustained and substantial consequences for local economies, which particularly benefit individuals from disadvantaged backgrounds.

II The Fracking Boom and Manufacturing Bust

Hydraulic fracturing or "fracking" refers to a set of technologies and techniques used to extract oil and natural gas from shale plays, which are dense, fine-grained rock formations that trap hydrocarbons within small, dispersed pockets. To extract these reserves well operators inject a highly pressurized slurry of water and particulate matter into a wellbore. The water "fractures" the rock trapping the oil and natural gas, and the small particulates wedge the newly formed cracks open. Since the reserves are often diffuse and spread throughout the shale, fracking wells are drilled horizontally so large amounts of the surrounding shale can be fractured at once. This is in contrast to traditional wells, which are drilled vertically over large, dense hydrocarbon deposits.

Prior to improvements in wide-scale directional drilling and hydraulic fracturing, producers largely assumed shale play reserves were unusable. Fracking technological changes led private, academic, and government researchers to reassess the U.S.'s proved reserves, defined as the amount of hydrocarbons that can be recovered from deposits with a "reasonable level of certainty". Demonstrating the revisions caused by these changes, Figure 3 shows the more than 2-fold increase in proved reserves as estimated by the U.S. Energy Information Administration (EIA) from 2000 to 2019. These increases match the spread of fracking technologies around the country (shown in Figure 2 Panel A), as new shale plays were surveyed and shown to be amenable to fracking techniques.

Shale plays are large formations, the Marcellus shale in particular stretches from West Virginia to New York and encompasses over 100,000 square miles. Figure 4 Panel A overlays the boundaries of major US shale plays with the Opportunity Atlas mobility measure, where the Marcellus shale play in particular traces the contours of the most upwardly mobile parts of Pennsylvania and West Virginia. There is substantial variation both within and across shale plays in the viability of fracking, which is determined by the size of the hydrocarbon reserves, the density of the surrounding rock, and other factors. This is reflected in the spatial variation of actual production[3] shown in Appendix Figure A.2. Exploiting the variation in actual production driven these exogenous geological factors will allow me to causally identify the effects of the fracking boom, as discussed in detail in Section IV.

II.A Measuring Chinese Import Competition

Figure 2 Panel B shows the immediate, sustained drop in manufacturing employment in the U.S. between 2000 and 2001. Pierce and Schott (2016) document that the fall in manufacturing employment was concentrated in industries heavily exposed to Chinese import competition as a result of the permanent normalization of trade relations with China in October 2000. Prior to normalization of trade relations, which was conditional on China's entry into the World Trade Organization (WTO) at the end of 2001, tariffs on Chinese goods were conditional on annual approval from Congress.

The Smoot-Hawley Tariff Act, passed by Herbert Hoover in 1930 as a protectionist measure over the stringent protests of economists and business executives like Henry Ford, set the second highest level of tariff rates in U.S. history. These rates were automatically applied to products from non-market economies (including China). However, starting in 1974 with the passage of the Trade Act, the U.S. president could grant lower, normalized tariff rates to non-market economies, subject to renewal each year by congressional vote. Although this special exemption status was granted to Chinese goods each year from 1980 to 2001, the process was contentious,[4] and there was considerable uncertainty over whether the much higher Smoot-Hawley rates would come back into effect. Pierce and Schott (2016) and Handley and Limao (2017) both connect the removal of this uncertainty upon China's entry into the WTO to the large decline in U.S. manufacturing employment and nearly one-third of the rise in China's export growth.

I aggregate these industry-level tariff changes to the CZ-level by weighting the difference between the two rates by the 1990 share of employment in each industry (discussed further in Section IV). Figure 4 Panel B plots this tariff exposure measure, which indicates that the traditional manufacturing heartland of the Rust Belt and the South Atlantic were hardest

3. I calculate the total fracking production of each CZ using well-level data(disused in Section *III.A*)
4. From 1990-1992, the House voted to repeal the exemption on Chinese goods, but were overruled by the Senate.

hit by Chinese competition. A growing literature has used this spatial variation to explain negative social changes such as rises in crime (Che et al., 2018), falls in marriage (Autor et al., 2019), along with declines in standard measures of economic security including relative increases in household debt (Barrot et al., 2018).

III Data

While all of the data I consider exist at the county level, for the main results I focus on commuting zones (CZs), a choice motivated by two concerns. First, due to sample limitations placed on the data in order to ensure more accurate measurements, a much larger fraction of the data from the Opportunity Atlas are missing for smaller, rural counties than for commuting zones.[5] Secondly, Feyrer et al. (2017) document substantial geographic spillovers as a result of the fracking boom, where localities adjacent to fracking counties also saw employment and wage growth. In part, this is likely due to the increased demand for trucking jobs; the operations of just a single well can involve hundreds of commercial truck trips (Goodman et al., 2017) to haul the water and particulate matter needed for hydraulic fracturing.[6] By aggregating the data to commuting zones, I am better able to capture the potential beneficiaries of increased fracking production, although all the results are robust to focusing on the county-level measures, as shown in the Appendix.

III.A Fracking Data

The EIA provides shape files defining every known shale play, which I use to identify counties that have any fracking potential. I obtained well-level production data on the near-universe of operational wells from Enverus, a private oil and gas software company, through their academic outreach initiative. These data include information on total monthly production, the latitude/longitude of each well, and the orientation of the wellbore, which I use to identify fracking wells.[7] Data on the actual timing of fracking adaption is from Bartik et al. (2019), who scrape this information from local news sources.

5. This is because Chetty et al. 2014 places restrictions on the number of tax returns used to estimate the mobility measure, requirements which are less likely to be met in these counties.

6. Several law firms in Texas (https://www.daxgarzalaw.com/blog/fracking-and-oilfield-trucking-dangers/) and Pennsylvania (https://www.rosenbauminjuryfirm.com/practice-areas/fracking-accidents-damages/fracking-related-truck-and-transportation-accidents/) even specialize in fracking related vehicle accidents.

7. I follow Kearney and Wilson (2018) and Feyrer et al. (2017) by defining any well with a non-vertical orientation as a "fracking well". For all the analysis here, I do not consider the Antirim Shale in Michigan or the Montery Shale in California. As of 2011, the official EIA estimates of shale oil and natural gas reserves do not consider either of these locations, nor has a fracking start time been identified for either shale play prior to 2013.

III.B Mobility Data

The measures of intergenerational mobility are taken from Chetty et al. 2014, and are calculated from restricted-access federal income tax records. The persistence of intergenerational income can be summarized by the rank-rank slope, which can be estimated by fitting a line through the position of children relative to the position of their parents in their respective income distributions. A flatter rank-rank slope implies that children's income is less dependent on their parent's income (less income persistence). Chetty et al. 2014 calculate this relationship for each county and commuting zone in the country using parent and children positions in the national income distribution.[8] Variation in income persistence across the U.S. is shown in Appendix Figure A.1, where it seems that children's income is most determined by their parents in the South and parts of the Rust Belt.

The intercept of the rank-rank relationship is equal to the expected outcome of a child born to parents at the bottom of the parental income distribution. This value characterizes an absolute measure of mobility, where higher values imply that low-income children born in a specific area are more likely to be better off in absolute terms than their peers born elsewhere. The intercept (absolute mobility) and the slope (income persistence) give parsimonious descriptions of mobility across different areas of the country.

Chetty et al. 2014 focus on measuring intergenerational mobility for the 1980-1982 birth cohort (hereafter referred to as "children"). Parents are the individual(s) who have claimed the children as dependents. Parental income is averaged from 1996-2000, when the children were 15-20 years old. Children's income is averaged from 2011-2012, when the children were 30-32 years old. Figure 2 emphasizes that the parental income, in terms of when it is calculated for either mobility measure should be unaffected by either shock. Conversely, children's income is measured after all major shale plays adopted fracking at the height of the boom, after the substantial declines in manufacturing employment opportunities had already taken place.

III.C County/Commuting Zone Characteristics

I take yearly, county-level population estimates from the National Cancer Institute's Surveillance, Epidemiology and End Results (SEER) Program, which are updated annually

8. Income is measured at the household level, and includes labor earnings, capital income, unemployment insurance, Social Security, and disability benefits. All income measures are pretax.

to account for migration. Data on a variety of county-level characteristics including labor force participation and marriage rates are obtained from the US Census Bureau's 1990 Decennial Census. I also use data on the number of firms, total employment, and wages from the Quarterly Census of Employment and Wages (QCEW). The QCEW is produced by the US Bureau of Labor Statistics, which aggregates data from approximately 95% of employers in the country at the county-sector level.

Since shale plays are subterranean rock formations of relatively no economic value before advancements in fracking technology, we may expect there to be minimal differences between shale and non-shale areas. However, shale plays can only form in large geological depressions (called basins), and in areas where large quantities of organic-matter have accumulated, which may have shaped local development.[9] I consider a variety of different baseline characteristics which may vary across shale and non-shale regions in Table 1. The sign of the correlation of each variable with absolute upward mobility is reported in parentheses next to the variable name. Shale CZs seem positively selected in terms of their non-shale counterparts. However, Appendix Table A.1 shows that the most productive fracking counties are somewhat negatively selected.

Places with large domestic manufacturing employment, may differ from one another for a wide variety of reasons. Although this is somewhat ameliorated by the fact that I am using variation in tariff rates set in 1930 to scale the intensity of the manufacturing shock, Table 2 shows that there are non-insubstantial baseline differences between commuting zones that were more or less impacted by the China trade shock. Human capital measures in particular seem to be lower in heavily impacted CZs, and the broader negative selection may be explained by so called "domestic offshoring", where manufacturing shifted to the South Atlantic region prior to 2000 in search of lower wages (Fort et al., 2018). I explore the sensitivity of my results to the inclusion of these controls in Section V, and specifically try to gauge the explanatory power of each shock from other factors in Section *V.A*.

IV Empirical Strategy

While the previous literature has focused on correlations between social characteristics that describe childhood environment and intergenerational mobility, I focus on the fracking

9. This organic material is compressed by heat and pressure over millions of years, and is transformed into fossil fuels. These same factors can lead to the formation of more traditional oil deposits (as in Texas) or coal veins (as in Pennsylvania and West Virginia).

boom and the manufacturing bust, two oppositely signed labor demand shocks which affected the 1980-82 birth cohort in young adulthood. I first consider a simple exposure measure that is similar to the correlations explored in Chetty et al. 2014 as a benchmark, and then shift to identifying exogenous variation that affects the magnitude of each shock in a reduced-form analysis.

A basic measure of exposure to the fracking boom is the presence of a shale play beneath a CZ. While this comparison ignores the intensive margin of production, it does give a sense for the average mobility effects of any fracking potential. Additionally, I also include a broad measure of Chinese import exposure which does not account for the differential industry effects: whether or not a county is above the median level of manufacturing employment share in 1990. The following regression is just a formalization of a visual inspection of the differences in mobility across the U.S. shown in Figure 1:

$$y_g = \alpha + \beta * \mathbb{1}\{\textit{Any Shale Play}_g\} + \rho * \mathbb{1}\{\geq \textit{Median 1990 Manu. Employment}_g\} + \epsilon_g \quad (1)$$

where y_g is a measure of intergenerational mobility in CZ g. $\mathbb{1}\{\textit{Any Shale Play}_g\}$ indicates that a CZ g is, in whole or in part, above any shale play. ϵ_g is a hetroskedasticity robust error term, clustered at the state level. The above regression, while informative, suffers from two broad issues. The first is that there is substantial heterogeneity in both fracking production and manufacturing employment, which are not captured by these basic measures. Second, these estimates may suffer from omitted variable bias, due to differences in other factors important for mobility shown in Table 1 and Table 2.

IV.A Variation in Fracking Intensity

Actual fracking production is likely endogenous with respect to local labor market characteristics; for example, more economically advantaged areas may be better positioned to adopt the new technologies that enabled the fracking boom. On the other hand, the value of land is cheaper in rural areas, and there may be fewer political impediments to drilling. In fact, Table A.1 shows that, while not being substantially different from low-production shale CZs, high productivity shale CZs are slightly negatively selected in terms of characteristics that are correlated with upward mobility. To isolate variation in fracking intensity based only on plausibly exogenous, geographic variation in fracking amenability over time, I create a measure of simulated fracking production by estimating the following equation:

$$ln(new\ value_{gt} + 1) = \alpha_g + \sum_{\tau=2001}^{2012} \sum_{j=1}^{J} \theta_{\tau j} * \mathbb{1}\{CZ\ g\ over\ shale\ play\ j\} * \mathbb{1}\{t = \tau\} + \upsilon_{gt} \quad (2)$$

where $ln(new\ value_{gt} + 1)$ is the (real, \$2010) dollar value of oil and natural gas from wells drilled in location g in year t. θ_{tj} captures the average effect of being over shale play j, and allows this effect to vary over time as both prices and technologies evolve. I also control for time-invariant location characteristics via α_g. I can then use this predicted values to calculate simulated production as follows:

$$sim.new\ value_{gt} = exp\left(\widehat{\alpha}_g + \sum_{\tau=2001}^{2012} \sum_{j=1}^{J} \widehat{\theta}_{\tau j} * \mathbb{1}\{CZ\ g\ over\ shale\ play\ j\} * \mathbb{1}\{t = \tau\}\right) - 1 \quad (3)$$

For all my results, I divide this measure by the 1990 population to calculate the simulated value of production per capita in thousands of dollars. To capture the effects of the total exposure to the fracking boom, I use the total value of simulated production in place g from 2001 to 2012 in all the cross-sectional regressions. The correlation between simulated and actual production is 0.73, and I map the simulated production measure in Appendix Figure A.2.

IV.B Variation in Chinese Import Competition

The simple indicator of counties with an initially high manufacturing share is likely endogenous with respect to both local labor market conditions and polices, as discussed in Section *II.A*. To leverage plausibly exogenous variation in Chinese import exposure, I follow Pierce and Schott (2016) by exploiting the difference in tariff rates between the normalized, WTO rates that were permanently applied to Chinese goods in 2001 and the much higher Smoot-Hawley Tariff Act rates, which were set in 1930. Since these tariffs are set for specific industries (4-digit SIC codes) I follow Pierce and Schott (2016) by constructing a CZ-level weighted average measure of exposure as follows:

$$WTO\ Gap_g = \sum_i \frac{Employment_{ig}^{1990}}{Employment_g^{1990}} * (Smoot\text{-}Hawley\ Rate_i - WTO\ Rate_i) \tag{4}$$

where g indexes place and i indexes industries. $WTO\ Gap_g$ is an employment weighted measure of Chinese import competition, as captured by the difference between protectionist and free-trade tariff schemes.[10] To represent the effects of the WTO gap visually, I first rank all US counties based on the above measure. Next, I plot the manufacturing employment to working age population ratio against this rank, and fit a polynomial through the data for each year. I show a select number of years in Figure 5, where we can see a strong, stable linear relationship between manufacturing employment and the WTO Gap in the three years prior to China's entry into the WTO, and an immediate decline across all counties in the following three years. This drop is sustained, and largest for the most exposed counties by 2012.

IV.C Reduced Form Analysis

I then estimate the reduced-form relationship between the total exposure to simulated fracking production on mobility using the following specification:

$$y_g = \alpha + \beta \sum_{2000}^{2012} sim.new\ value_g + \rho WTO\ Gap_g + X_g'\Omega + \epsilon_g \tag{5}$$

where each independent variable to have a mean of zero and a standard deviation of 1. β captures the effect of a standard deviation shift in simulated fracking production on the different mobility measures. I also include the $WTO\ Gap_g$, the employment-weighted measure of tariff changes discussed in Section II, to identify areas with larger shares of workers who were more likely to face job-losses as a result of industry-level competition with cheaper Chinese imports. In all regressions I include the characteristics of places discussed in Chetty et al. 2014 as being the most strongly correlated with the absolute upward mobility measure (represented by represented by X_g') shown in Table 1. However, because these controls are not exogenous with respect to parental location decisions, I also report estimates without controls.

10. Employment counts at the county-industry level are available from the US County Business Patterns Database. Pierce and Schott (2016) provide the change in tariff rates at the industry-level as a result of China's entry into the WTO.

V Results

Table 3 and Table 4 show results from Equation (1) and Equation (5). Income persistence is the slope of the rank-rank relationship in each CZ, while absolute mobility is the average income rank of children born to parents at the 25^{th} percentile of the income distribution.[11] While declines in income persistence may be driven by worse outcomes for children born to high-income parents, a rise in absolute mobility at a given income level measures how well children do relative to similar peers.

Across all specifications, exposure to fracking potential increases absolute upward mobility. Exposure to a shale play, independent of actual production, leads to a 1.7-5.6 percent increase in absolute upward mobility from the national average. CZs that are above the median level of manufacturing employment experience a much larger mobility fall, but this relationship is no longer significant and is much smaller in magnitude when controls are included. However, the more detailed level of Chinese import exposure used in Columns 4-6 show that the manufacturing bust led to substantial declines in mobility, although again this effect is mediated by the inclusion of controls and state fixed effects. Specifically, an SD shift in the measure of import competition leads to a 0.6-5 percent decline in upward mobility. In the specification with controls and state fixed effects, a standard deviation shift in exposure to either shock leads to similar changes in absolute upward mobility. We observe much larger effect sizes at the county-level, as shown in Appendix Table A.4 potentially because the independent variables are measured with more precision.[12]

Unlike absolute mobility, the fracking boom does not have a robust effect on income persistence, with all specifications implying very small effects of either shale exposure or simulated production. While fracking jobs are concentrated among low-skill workers (Cascio and Narayan, 2015) Feyrer et al. (2017) found substantial positive spillovers into other local industries. Additionally, Hornbeck and Moretti (2018) find that homeowners benefit substantially from local total factor productivity shocks due to increased housing prices.[13] However, we see that the manufacturing bust led income to be more persistent. Autor et al. (2019) found that the Chinese import competition led to sustained losses in earnings across the income distribution, albeit with greater magnitude losses occurring at lower incomes. Additionally, Corak and Piraino (2011) found substantial intergenerational transmission of

11. Absolute mobility then is the slope of the rank-rank relationship multiplied by 25, and added to the intercept. In this sense, absolute mobility incorporates both the mean outcomes of children born to parents at the absolute bottom of the income distribution (the intercept), and degree to which parental income translates to better child outcomes (the rank-rank slope).

12. This is true especially for simulated production: there is substantial within-CZ heterogeneity in fracking potential.

13. Bartik et al. (2019) found that housing prices increased by 5.7 percent in boom counties, and the local willingness to pay for fracking was $2,500 annually, per household.

manufacturing employers - if the manufacturing bust limited the job finding potential of children from poorer households more dramatically, this is consistent with increasing income persistence.

I show the effect size of a standard deviation shift in each independent variable in Appendix Figure A.3 and Appendix Figure A.4. In terms of absolute mobility, the effect size of both shocks is comparable to a standardized shift in the high school dropout rate (the most important education-related mobility correlate) and the social capital index.[14] In terms of relative mobility, a standardized shift in import competition causes the largest change aside from the percent of single of mothers in a CZ.

V.A ANCOVA Analysis

While it is clear that both shocks led to substantial changes in absolute mobility, we may wonder how these effects compare with non-labor market factors known to be important for mobility, such as education and marriage rates. For the sake of comparisons, I focus on similar factors to those discussed in Chetty et al. 2014. First, I report analysis of covariance (ANCOVA) results, which decompose the variance of the mobility measures into variance explained by fracking, variance explained by other covariates, and residual variance.

Figure 6 shows the results of the ANCOVA decomposition for the lower 48 states. The symbols correspond to estimates of partial η^2, which is the share of the variance of the outcome of interest attributable to a specific covariate (the share of the R^2 explained). The bands represent 95 percent confidence intervals. The sign of the correlation with the outcome of interest is reported in parentheses next to each variable. Figure 6 Panel A shows that roughly 5 percent of the variation in absolute mobility can be explained by the fracking measure, while 10 percent can be explained by the China trade measure. This proportion is very similar to the amount of variation explained by the percent of black residents and the value of the social capital index.

The single largest factor in explaining absolute mobility is the percent of single mothers. This is partially mechanical, since the mobility measures are calculated using household income. Additionally, a large body of research has documented that children growing up outside a stable, two parent household have worse outcomes along many dimensions (Brown, 2010; Watts-English et al., 2016; etc.). As with Table 4, Figure 6 Panel B shows that neither shock

14. This index is calculated by Rupasingha et al. (2000), and includes information on voter turnout rates, the fraction of people who return census forms, and the various measures of participation in community organizations.

explains almost any of the national variation in income persistence (i.e. relative income). Commute time is also very important, and likely proxies for spatial mismatch.

Unlike the variation in fracking reserves/import competition, baseline CZ characteristics are not exogenous with respect to the mobility measures. Parents concerned with the opportunities available to their children would likely choose to locate in CZs with characteristics conducive to upward mobility. This sorting would likely lead to overestimating the importance of baseline covariates, and so would attenuate the amount of variance in mobility explained by the two labor demand shocks. This is because the location of parents is "locked in" by 2000, a year before any substantial evidence about the location or size of fracking reserves becomes common knowledge. The same argument holds for why parents or children moving away from either the Rust Belt or the South would attenuate the relevant effect sizes.

Since shale CZs only account for one quarter of all CZs in the US, this cross-country analysis limits the explanatory power of fracking intensity. The results for the U.S. compare (conditional on covariates) shale CZs to the entire rest of the country. While this comparison is informative, it does not tell us about the explanatory power of the intensity of the fracking boom *within* areas directly able to benefit from production. To address this, I restrict my attention to shale CZs only in Figure 7. Panel A shows that simulated fracking production is the single largest explanatory factor of the variation of absolute mobility within shale CZs, aside from marriage rates. Even within shale CZs, however, Panel B shows that fracking intensity did not meaningfully affect the degree of income persistence between parents and their children.

The largest explanatory factor of income persistence is exposure to Chinese import competition, although the magnitude is indistinguishable from the proportion of variance explained by the percentage of single mothers. Conversely, fracking variation explains almost nothing of income persistence. We can also see that the R-Squared is much smaller for income persistence, with only a little over half of the variance being explained by the included covariates.

V.B Heterogeneity by Gender and Parental Income

To further investigate the effects of the boom and bust on children from different parental backgrounds, I also consider the "causal effects of place" calculated by Chetty and Hendren (2018). Using similar individual-level tax data as in the mobility measures, Chetty and Hendren (2018) estimates the percent change in income that can be causally linked to where children grew up. Briefly, these causal effects are estimated by leveraging variation in the timing of moves across CZs, and by comparing outcomes for children *within* families based on the age of the child at the time of the move. For now, I take as given that these measures represent a reasonable approximation of the causal effects of place. I focus on the percent change in income associated with 20 years of exposure to a particular CZ, which approximates the effect of spending one's entire childhood in the same place. All results are relative to the population-weighted average CZ in the country.

I report estimates from Equation (5) for boys and girls born to low income parents and high income parents in Table 5 and Table 6, respectively. Unsurprisingly, the income effects of the fracking boom are entirely concentrated among boys. Boys from low-income backgrounds experience huge increases in income relative to the average CZ, while boys from high-income backgrounds also receive substantial income benefit, consistent with the fracking boom not affecting income persistence.

The declines in earnings potential among children born to poorer households driven by Chinese import competition are also very large, but not robust to the inclusion of state fixed effects. For both shocks, the effects on female children are inconsistent, and flip sign and significance with the inclusion of state fixed effects. These results both confirm that we are seeing the result for exactly the group we should expect, and highlight the magnitude of the mobility results. Despite the fact that the effect of these shocks is highly concentrated among one gender, we still see large subsequent changes in intergenerational mobility.

Chetty and Hendren (2018) show that the "causal effects of place" decline linearly with the age of exposure, but are still relevant for influencing earnings later in life up until age 23. To the extent that some commuting zones experience immediate effects from both shocks in the early 2000's, my results are unable to disentangle the direct effect on children's mobility through local labor market conditions in adulthood and the residual childhood exposure effects of place. The youngest children in the 1980-1982 cohort are 19 in 2001, and so children experience at most 4 years of childhood exposure effects given that the first treatment year for both shocks is 2001.

V.C Mechanisms and Robustness: QCEW Results

The most obvious channel through which the two labor demand shocks influence upward mobility is clearly increased wage earnings and employment opportunities. To get a sense for how quickly local labor market conditions reacted, I use yearly earnings and employment data from the QCEW to trace the dynamic effects of boom/bust exposure on wages and employment using the following event-study style specification:

$$
\begin{aligned}
y_{gt} = & \sum_{t=1996}^{2012} \beta_t * \mathbb{1}\{year = t\} * (\sum_{2000}^{2012} sim.new\ value_g) \\
& + \sum_{t=1996}^{2012} \rho_t * \mathbb{1}\{year = t\} * WTO\ Gap_g \\
& + \sum_{t=1996}^{2012} \Omega_t * \mathbb{1}\{year = t\} * \mathbf{X}_{g,1990} + \gamma_g + \lambda_t + \epsilon_{gt}
\end{aligned} \tag{6}
$$

where β_t captures the effect of an additional \$1000 of simulated production exposure in year t, relative to 2000, the last year before fracking initial adoption and the omitted year in all following event studies. $\sum_{2000}^{2012} sim.new\ value_g$ proxies for the recoverable reserves based only on the geological characteristics of CZ g. ρ_t is the analogous term for a unit increase in $WTO\ Gap_g$.

For all the event studies, I also include baseline CZ characteristics from the 1990 census ($\mathbf{X}_{g,1990}$), interacted with a full set of time dummies Ω_g. Including these interactions allows the relationship between initial characteristics and the outcome of interest to vary from year to year, and improves precision. I also control for time-invariant CZ characteristics (γ_g) and year-specific shocks (λ_t).

Figure 8 reports the results from Equation (6). Despite an initial lag, which is unsurprising given the gradual adoption of fracking technology, boom CZs experience a sustained rise in both employment and earnings. Specifically, and standard deviation shift in simulated reserves leads to a roughly 3 percent increase in employment and earnings, with no sign of abatement by the end of the sample. These more muted results in the period directly after 2000, which can also be seen in the raw production data, provide supporting evidence that the majority of the causal effect of the fracking boom on mobility is driven by changes children face when they enter the labor market.

A standard deviation shift in the $WTO\ Gap_g$ led to more immediate and dramatic changes, with close to a 10 percent reduction in both earnings and employment up to a decade after the initial shock. Figure 9 shows that both of these changes are robust to accounting for the other, suggesting that I am not conflating, for example, some pre-existing likelihood of being insulated from the China trade shock with the likelihood of discovering oil and natural gas. Given the sizable, relative changes in earnings, it is not surprising that both shocks altered absolute mobility, which measures relative differences in household income for children born to parents across CZs.

Chetty et al. 2014 emphasizes the strong correlation of non-labor market factors like commute times and single motherhood with absolute mobility, but the primarily labor demand shocks focused on here can have downstream consequences on these characteristics. Broad measures of social well-being generally changed for the worse due to the manufacturing decline, as several papers have shown negative downstream effects on marriage (Autor et al., 2019), subsequent job churn (Autor et al,, 2016) and even mortality (Pierce and Schott, 2020). To the extent that the loss of work eroded the social factors that contribute to mobility, negative labor demand shocks have an exacerbated impact on overall regional inequality.

In terms of the response of these non-labor market factors to the fracking boom, Kearney and Wilson (2018) find that marriage rates do not change in response to fracking production, so household income is not mechanically increasing as more joint-income households form. Additionally, the human capital responses to the fracking boom were actually negative, as high school dropout rates increased in boom counties (Cascio and Narayan, 2015). While other research has shown that some areas, especially the Bakken shale in North Dakota, experienced substantial in-migration (Wilson, 2020), this mechanism actually biases the results away from finding that the fracking boom increased intergenerational mobility. The income measures for both parents and children used to calculate the mobility measures in Chetty et al. 2014 are based on the filing location of the parents prior to the fracking boom. This means that a child who moves to work for a fracking job in say, 2005, is still counted as resident of the origin CZ, and so some of the beneficiaries of fracking jobs are actually contributing to income growth in non-fracking CZs. Additionally, true residents of fracking CZs would experience reduced wage growth as the supply of low-skill workers increases due to the migratory responses to the boom.

V.D Cross-country Mobility Absent the Boom/Bust

As a final test of the impact of both local labor demand shocks on absolute mobility, I compare the counterfactual distributions of what cross-country mobility would have looked like absent both the fracking boom and the manufacturing bust. Specifically, we want some idea of what the geographic variation of mobility within the US would look like if, for example, the fracking boom never took place. As a simple exercise, I take the estimated coefficients from Table 3 and multiply these by the actual values of simulated fracking production and the WTO tariff gap, respectively. Then, I adjust the actual values of absolute mobility to create a rough estimate of the counterfactual distributions.

The results of this exercise are shown in Figure 10, where Panel A shows results for the lower 48 states, and Panel B restricts attention to CZs over shale plays. For the counterfactual distribution absent the fracking boom, we can see a slight leftward shift in the distribution of absolute mobility, which is much more pronounced when we restrict our focus to shale CZs exclusively. We can see that in Panel B, the right tail of the distribution is an important margin of change, consistent with the concentration of immense amounts of production in certain CZs shown in the Figure A.2. In both figures, we can see a sizeable leftward shift of the entire distribution of absolute mobility measures compared to the counterfactual scenario where China did not enter the WTO.

VI Discussion and Conclusion

In this paper, I show that absolute mobility for the 1980-1982 birth cohort, or the expected outcomes of children born to low-income parents, was substantively altered by the fracking boom and increased Chinese import competition. I show these effects were sizeable, and not driven by pre-existing differences in characteristics predictive of mobility. The positive effects from the fracking boom are likely also not driven by any "virtuous cycle", where social factors positively related to mobility were impacted by the fracking boom, as other research finds no change in marriage rates and education *declines* in boom counties. Overall, fracking intensity and exposure to Chinese import competition explain close to 15% of the national variation in absolute upward mobility.

My results indicate that local labor market conditions in the U.S. matter substantially for absolute upward mobility. However, I find less evidence that the fracking boom or the manufacturing bust altered the relationship between parental income and children's outcome. This result is very similar to Bütikofer et al. (2018), who found that the the oil boom in Norway broke the link between fathers and *grandsons* in terms of income persistence, but that income still persisted between fathers and sons, and between sons and grandsons.

While local labor market conditions clearly matter for mobility, it also remains to be seen whether sizeable positive shocks translate into sustained regional development. Black et al. (2005) found positive employment and earnings spillovers into other industries as a result of the coal boom, but even larger *negative* spillovers as a result of the subsequent bust. Precipitated in part by the COVID-19 pandemic, the fracking boom appears to be slowing, if not reversing.[15] The evidence from this paper suggests that the South Atlantic region, where manufacturing employment was growing prior to China's entry into the WTO, suffered persistent losses which it had yet to recover from a decade out. Future research should seek to analyze the long-term consequences of temporary low-skill job booms on mobility in general, and how communities heavily invested in a certain form of employment can rebuild and re-skill in order to recover. Finally, continuing the work of understanding how social factors are shaped by labor demand shocks as in Kearney and Wilson (2018) and Autor et al. (2019) (especially when these shocks are skewed heavily in favor of one gender) and how these two forces interact seems crucial to understanding upward mobility more broadly.

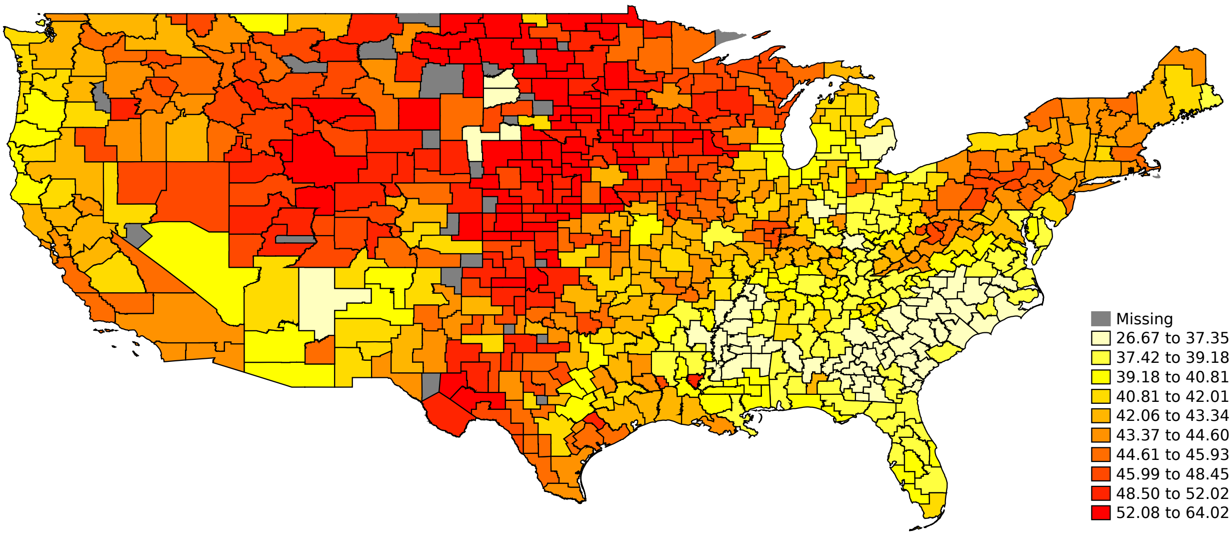
15. Source: https://www.wsj.com/articles/this-is-what-it-looks-like-when-a-texas-oil-boom-busts-11594440031

VII Figures

Figure 1: Geographic Variation in Mobility and Fracking/Chinese Competition Exposure

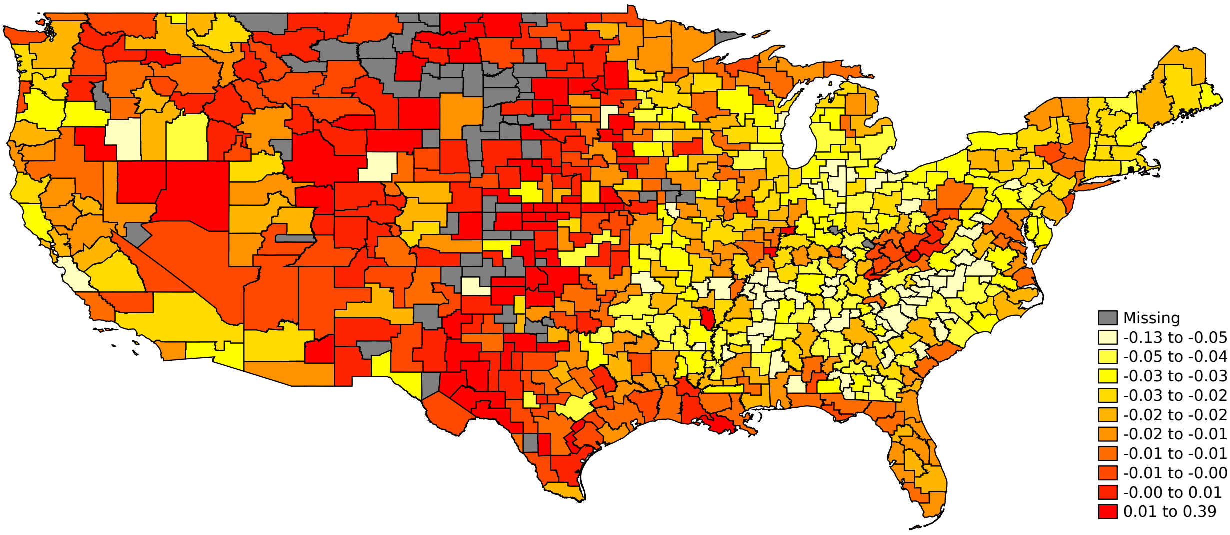
Panel A. Absolute Upward Mobility

Mean: 43.94 / Median: 43.34 / SD: 5.68



Panel B. 2000 to 2012 Δ in Mining/Manufacturing Employment

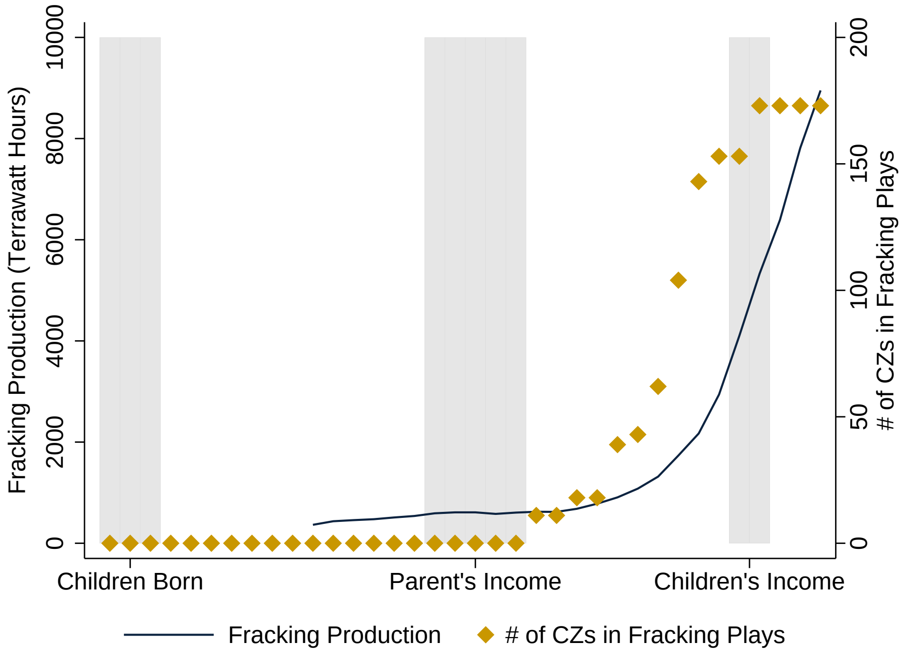
Mean: -0.02 / Median: -0.02 / SD: 0.03



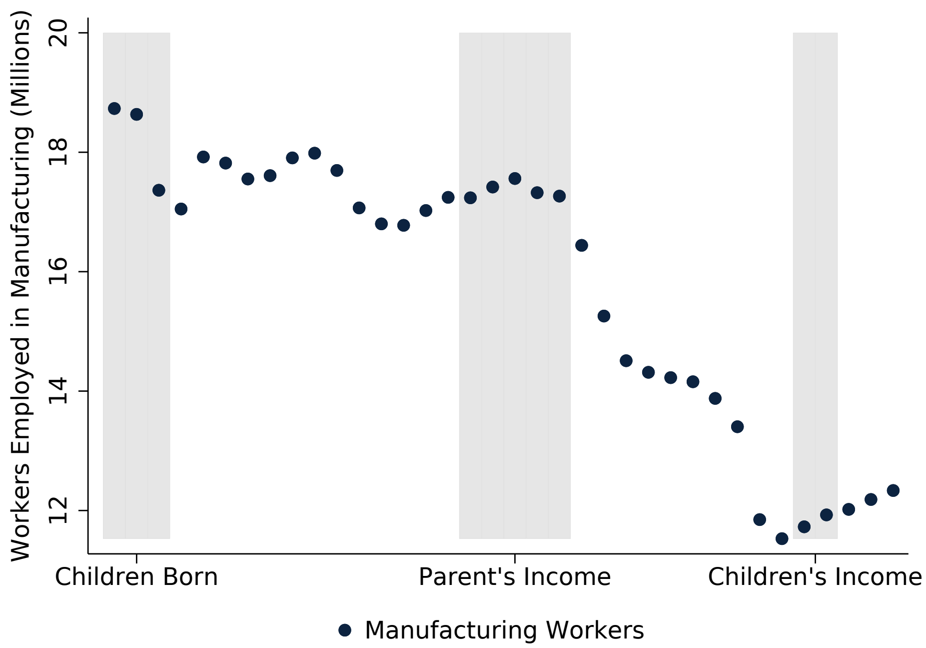
Notes: Panel A plots the deciles of "Absolute Upward Mobility" taken from Chetty et al. (2014) at the commuting zone level. Absolute Upward Mobility measures the expected rank in the national income distribution of a child (from the 1980-1982 birth cohort) born to parents at the 25^{th} percentile of the national parental income distribution. Darker values indicate that, on average, children born to low-income parents achieved higher positions in the national distribution of children's income than their peers born to low-income parents elsewhere. Panel B maps the deciles of differences between the 2000 and 2012 employment to population ratio, where employment is limited to only natural resource extraction and manufacturing. The employment data come from the QCEW, while the contemporaneous population measures come from SEER.

Figure 2: Opportunity Atlas Cohort Exposure to the Fracking Boom and Manufacturing Bust

Panel A. Fracking Production and Adoption

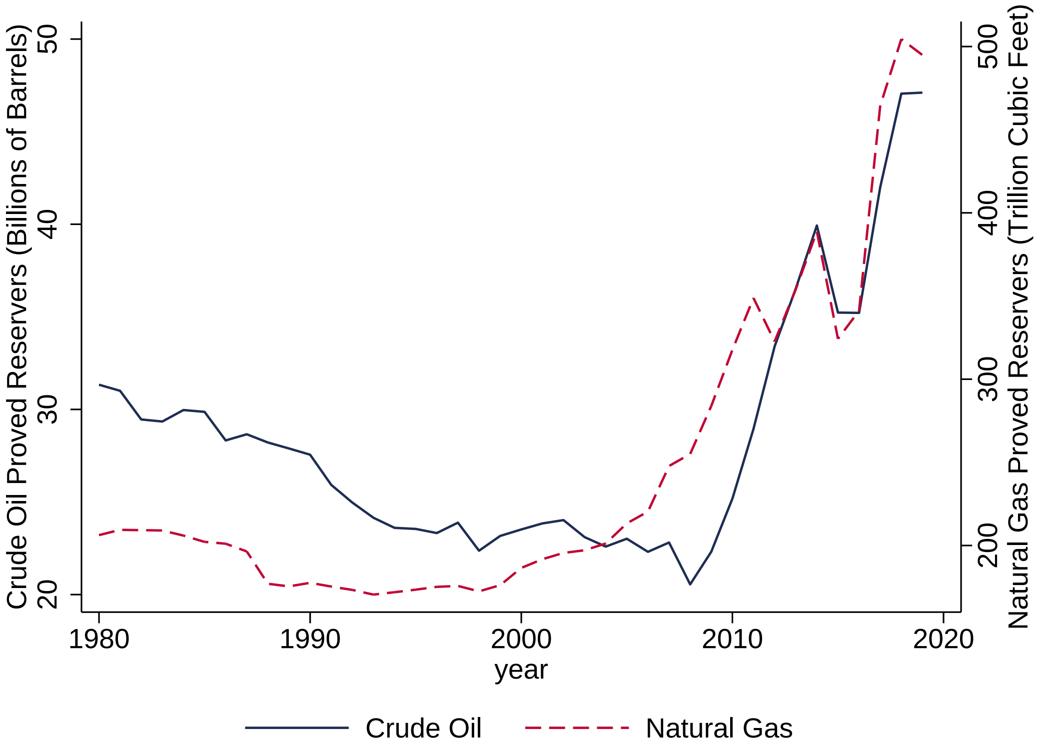


Panel B. Manufacturing Employment



Notes: Panel A plots the national sum of production from fracking wells, which is calculated from monthly, well-level production data provided by Enverus. Fracking wells are defined by the orientation of the wellbore, and I include both horizontal and directional wells. The diamonds indicate the number of commuting zones which had begun fracking by that year, and the fracking start dates come from Bartik et al. (2019). Panel B plots the number of U.S. workers employed in manufacturing, which was obtained from the Federal Reserve Economic Database (FRED). The shaded bars indicate times important for the creation of the mobility measures for the 1980-82 birth cohort from the Opportunity Atlas. Parental income is measured from 1996-2000, while children's income is measured from 2011-2012.

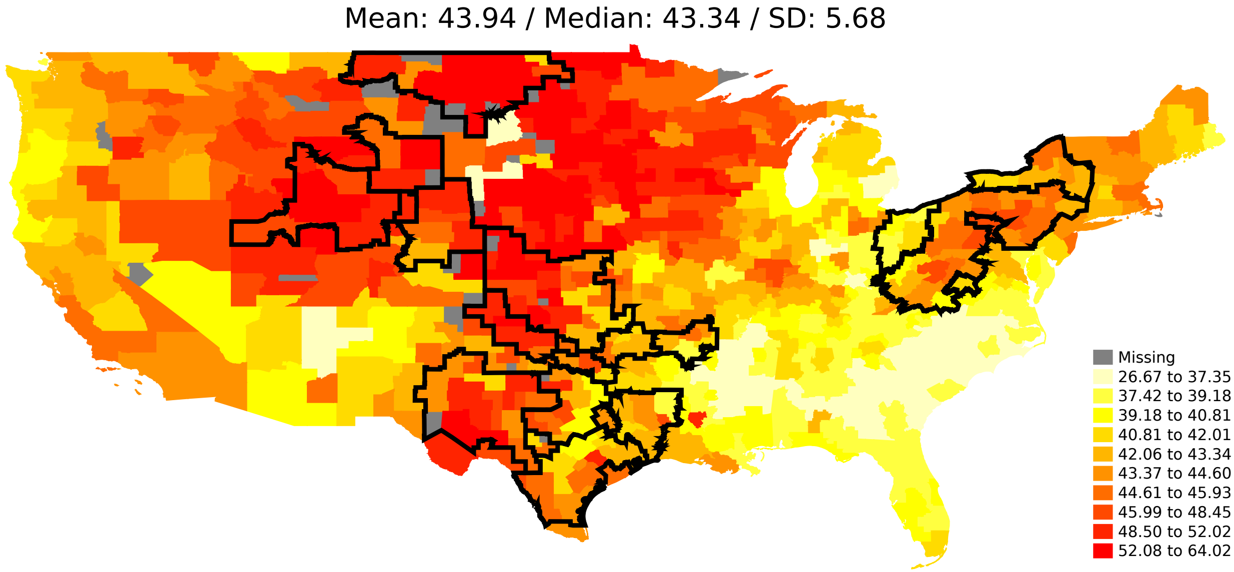
Figure 3: Proved Reserves



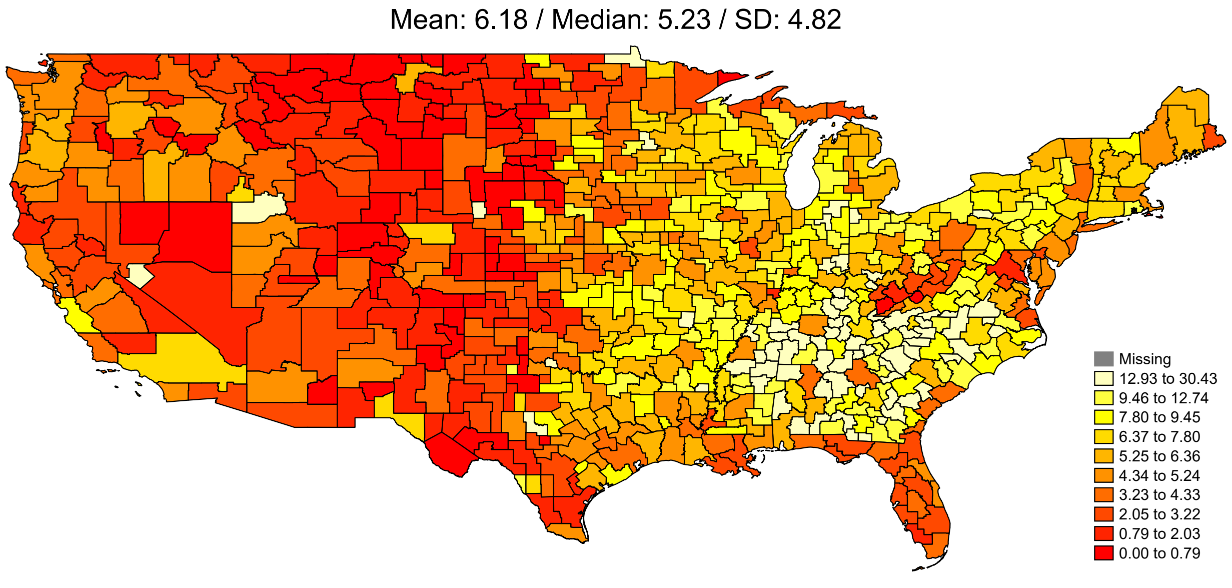
Notes: This figure plots the amount of proved reserves of oil and natural gas. Proved reserves are "estimated volumes of hydrocarbon resources that analysis of geologic and engineering data demonstrates with reasonable certainty are recoverable under existing economic and operating conditions". These are estimates from the EIA, which are updated yearly to reflect changes in previous production, technological advancements, updated survey information, and other factors which impact production. The large growth in proved reserves is directly attributed by the EIA to advancements in directional drilling and hydraulic fracturing.

Figure 4: Geographic Variation in Mobility and Fracking/Chinese Competition Exposure

Panel A. Mobility and Fracking Potential

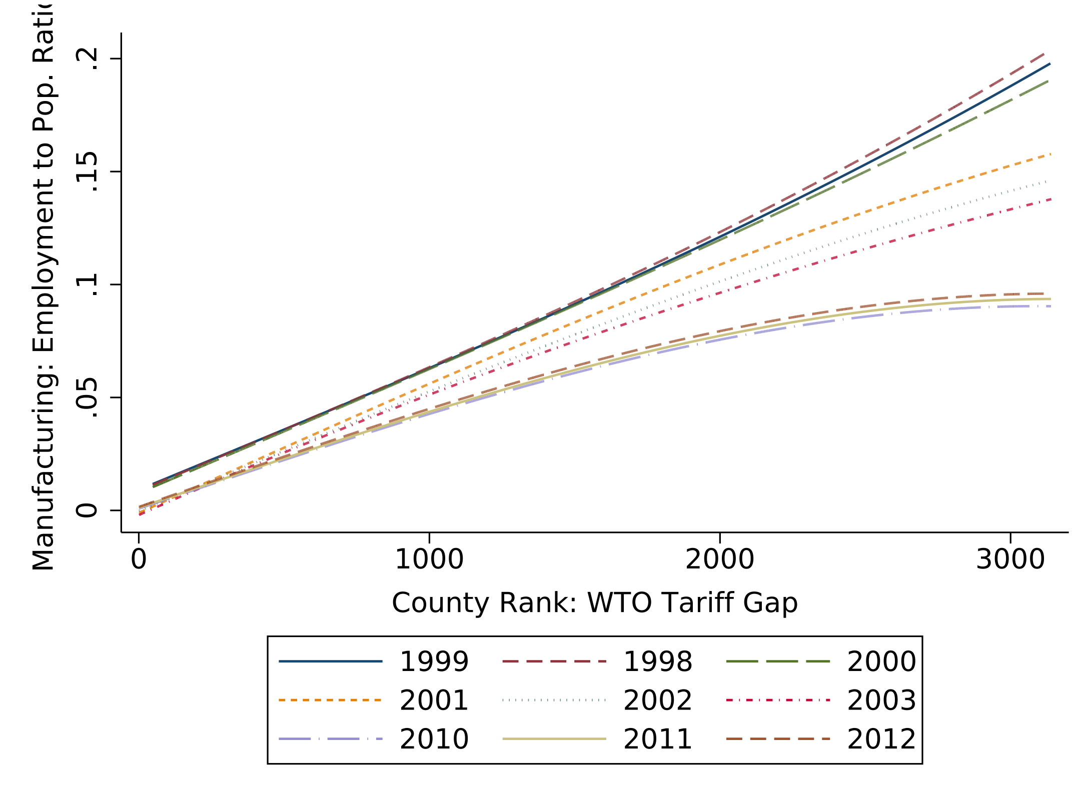


Panel B. WTO Tariff Gap



Notes: The thick, dark borders In Panel A outline shale plays assigned fracking start dates by 2012 in Bartik et al. (2019), while the underlying measure of mobility is unchanged from Figure 1 Panel A. Panel B plots deciles of the employment weighted tariff reduction measure, WTO Gap$_g$ *discussed in Section II. In Panel B, lighter areas correspond to areas most impacted by import competition with China.*

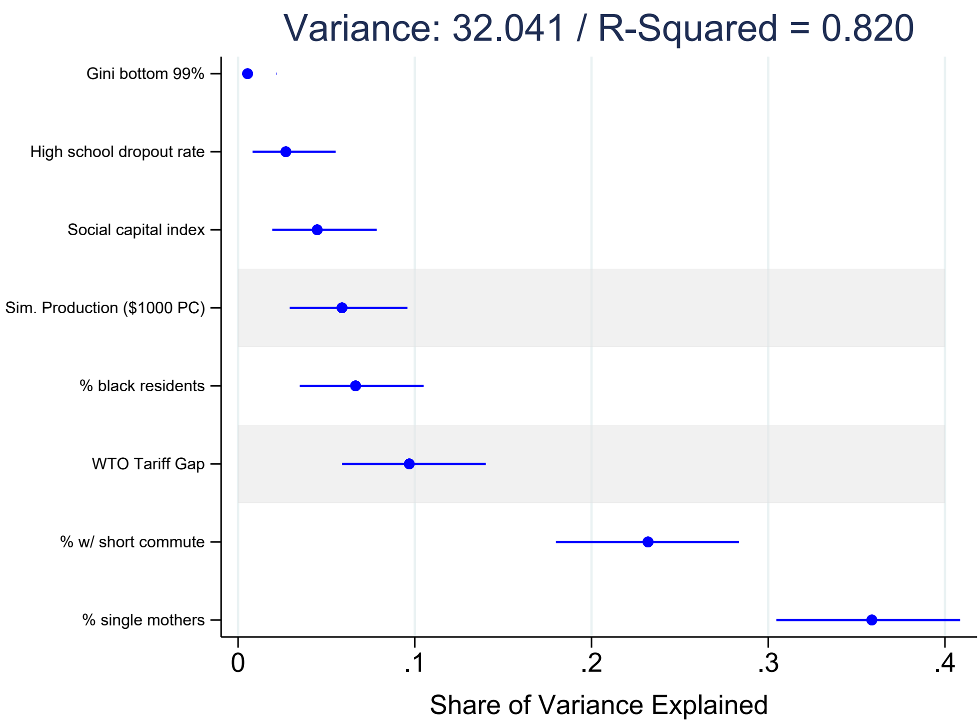
Figure 5: WTO Tariff Gap and Employment - Treatment Dosage



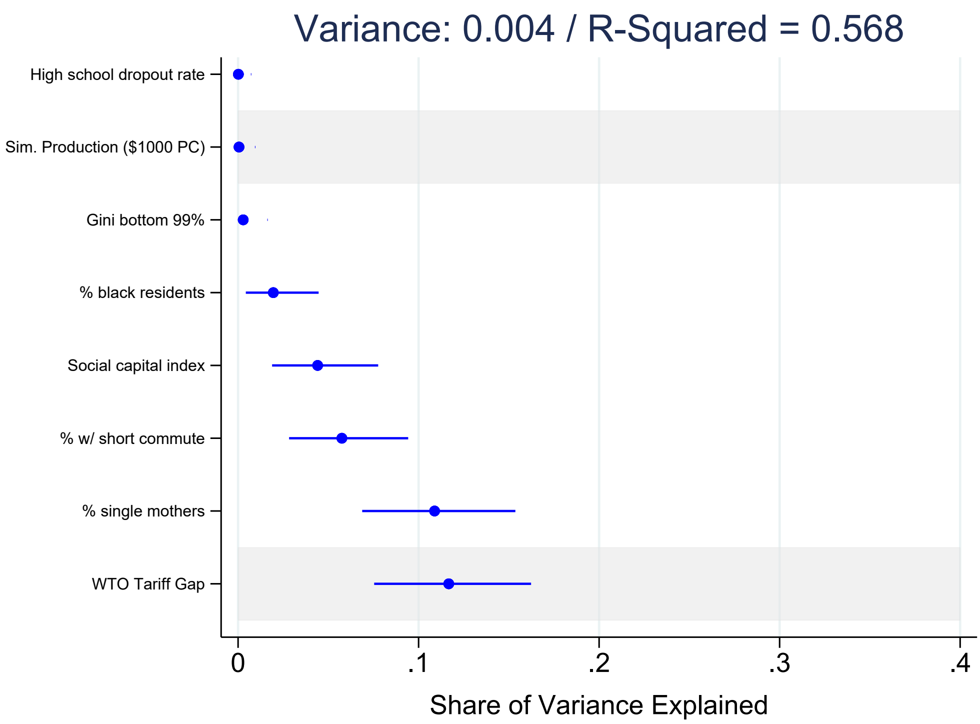
Notes: This figure plots the ratio of manufacturing employment to contemporaneous population for most US counties. I omit Hawaii, Alaska, and Virginia due to missing QCEW or SEER data. The number of workers in manufacturing is taken from the QCEW data, and the contemporaneous population is taken from the SEER data. For ease of interpretation, I fit a non-linear polynomial through the data for each year, instead of plotting the ratio of interest for each county in each year. Each county is ranked based on the associated, time-invariant WTO Tariff Gap discussed in Section II, and measures how exposed a counties industries were to Chinese import competition. In the case of a tie, county rank is assigned randomly.

Figure 6: ANCOVA Results - Lower 48 States

Panel A. Absolute Mobility



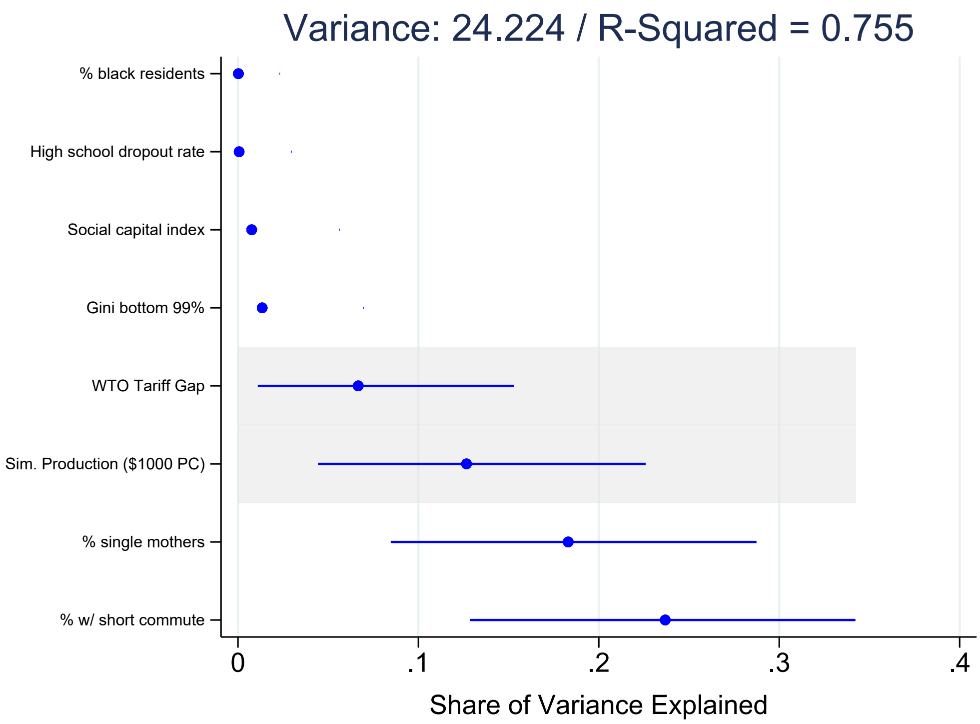
Panel B. Income Persistence



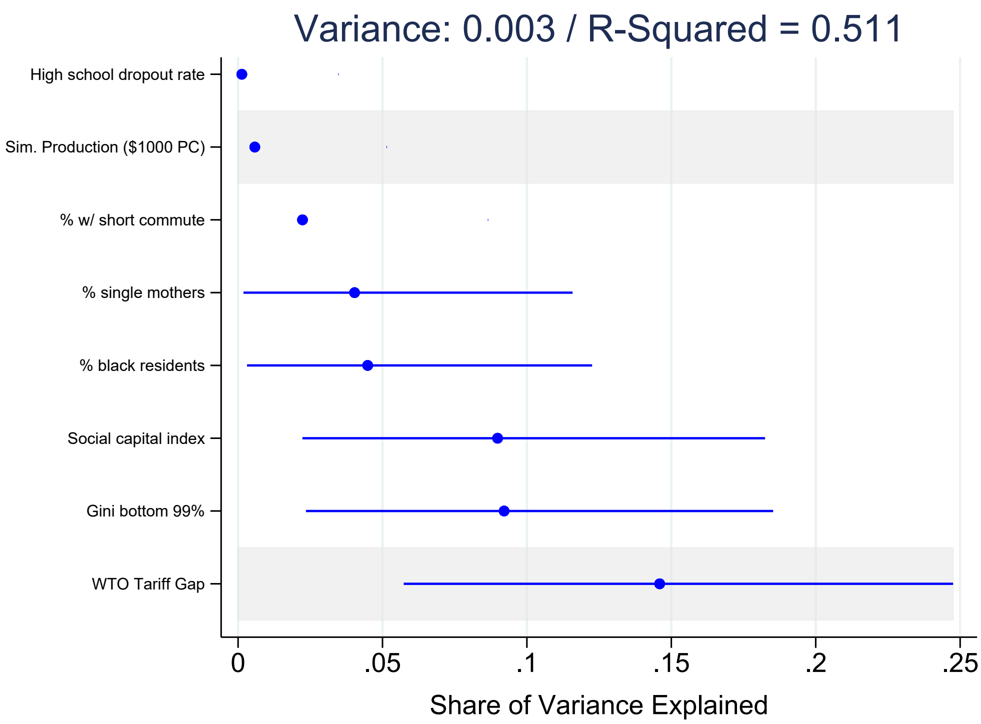
Notes: These figures show the results of an ANCOVA analysis, where each symbol corresponds to η^2, or the amount of the variation in the outcome of interest explained by a specific covariate. The bands represent 95 percent confidence intervals. The included covariates are the same included as controls in Table 1, and the R-Squared measures correspond to in Panel A and Panel B are identical to those reported in column 2 and column 4, respectively.

Figure 7: ANCOVA Results - Shale CZs Only

Panel A. Absolute Mobility



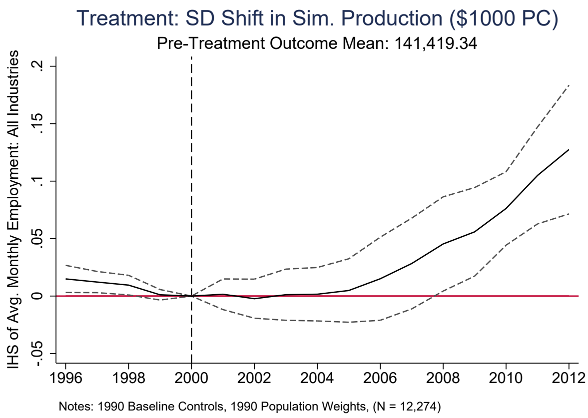
Panel B. Income Persistence



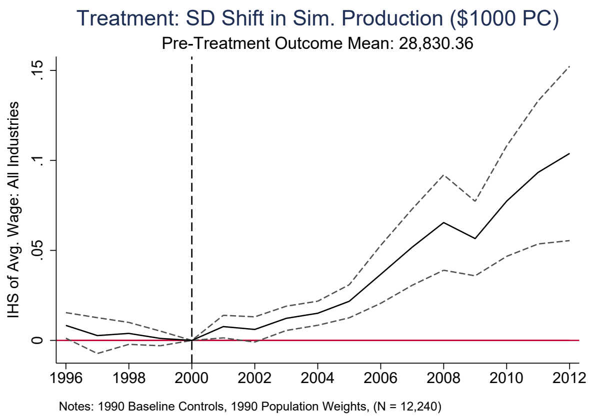
Notes: These figures show the results of an ANCOVA analysis, where each symbol corresponds to η^2, or the amount of the variation in the outcome of interest explained by a specific covariate. The bands represent 95 percent confidence intervals. The included covariates are the same included as controls in Table 1. These figures restrict attention to only those commuting zones which intersect, in whole or in part, with a shale play, as shown in Figure 1.

Figure 8: Event Studies - QCEW Outcomes

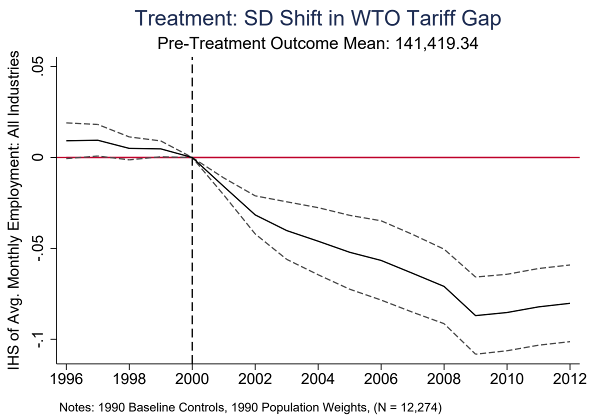
Panel A. Fracking and Employment



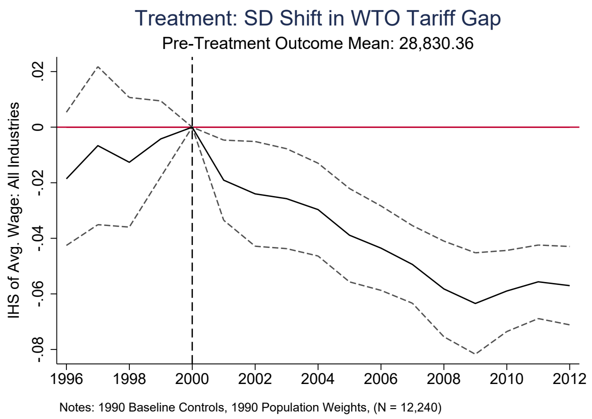
Panel B. Fracking and Earnings



Panel C. WTO Gap and Employment



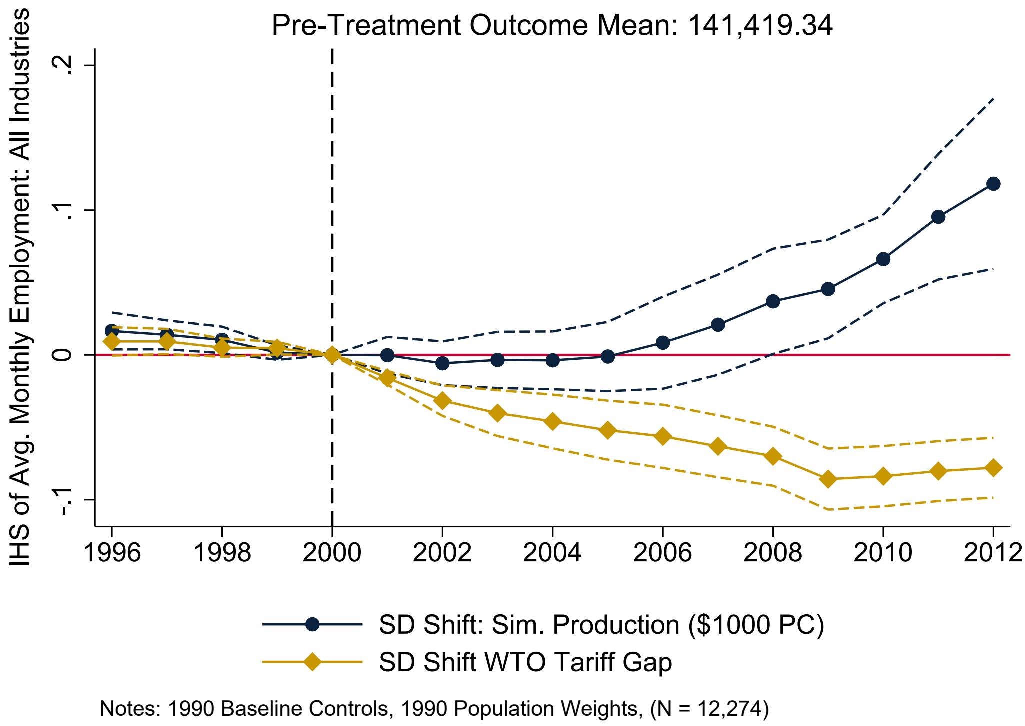
Panel D. WTO Gap and Earnings



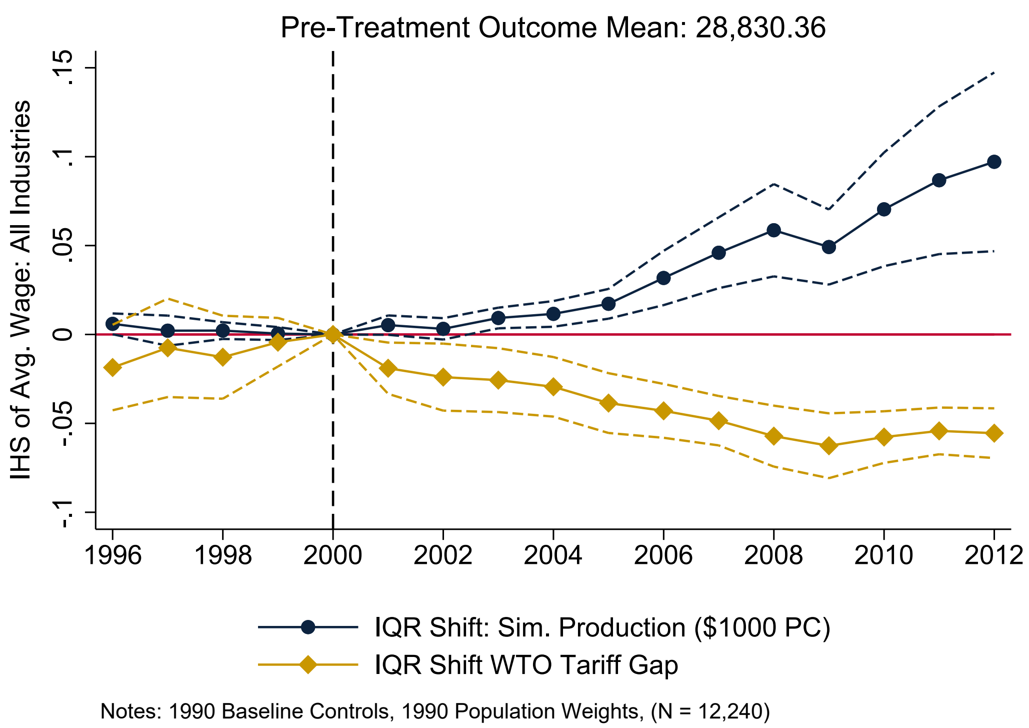
Notes: This figure plots the results from 4 separate regressions. Panels A and B report the $beta_t$ coefficients from a version of Equation (6) that excludes the ρ_t terms. Panels C and D report the rho_t coefficients from a version of Equation (6) that excludes the β_t terms. The sold black line connects the point estimates and the dashed line represent 95 percent confidence intervals. For Panels A and C, the outcome of interest is the inverse hyperbolic sine of the average monthly number of workers in all industries. For Panels B and D, the outcome of interest is the (inverse hyperbolic sine of) the average weekly wage multiplied by 52, which approximates the average annual wage. All regressions include the controls listed in Table 1, and are weighted by the 1990 population. The unweighted, 1996-2000 average of each outcome is reported as the Pre-Treatment Outcome Mean. The IQR shifts for each coefficient are calculated as linear combinations of the regression estimates.

Figure 9: Fracking vs. Chinese Import Competition - Employment and Earnings

Panel A. Employment



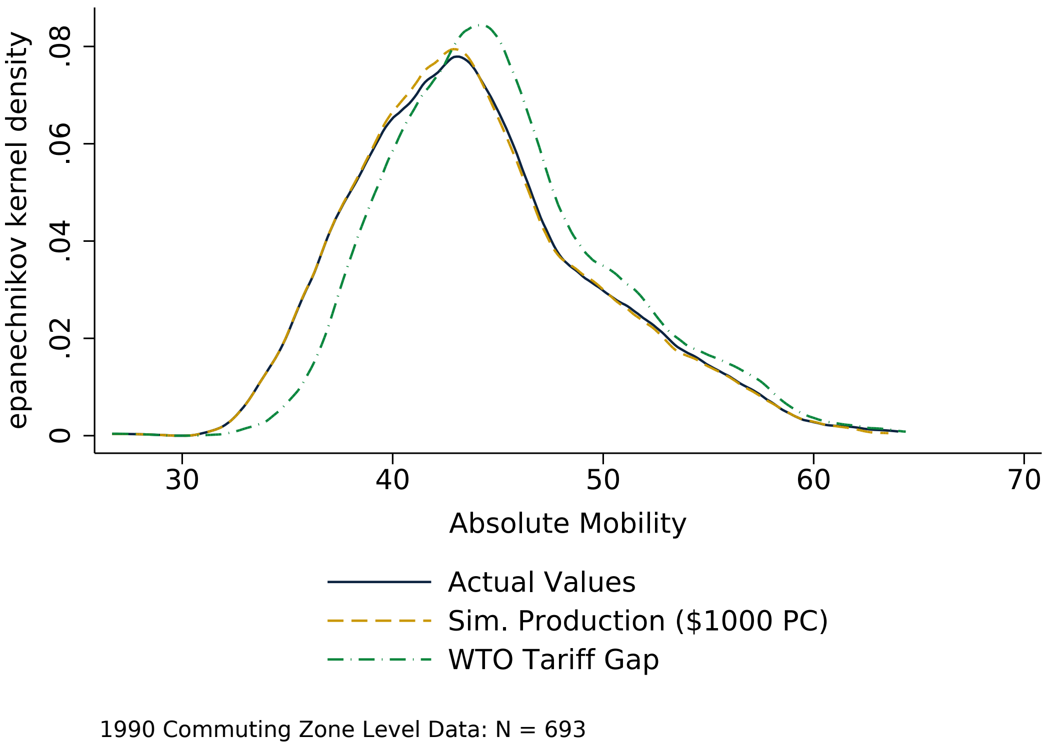
Panel B. Earnings



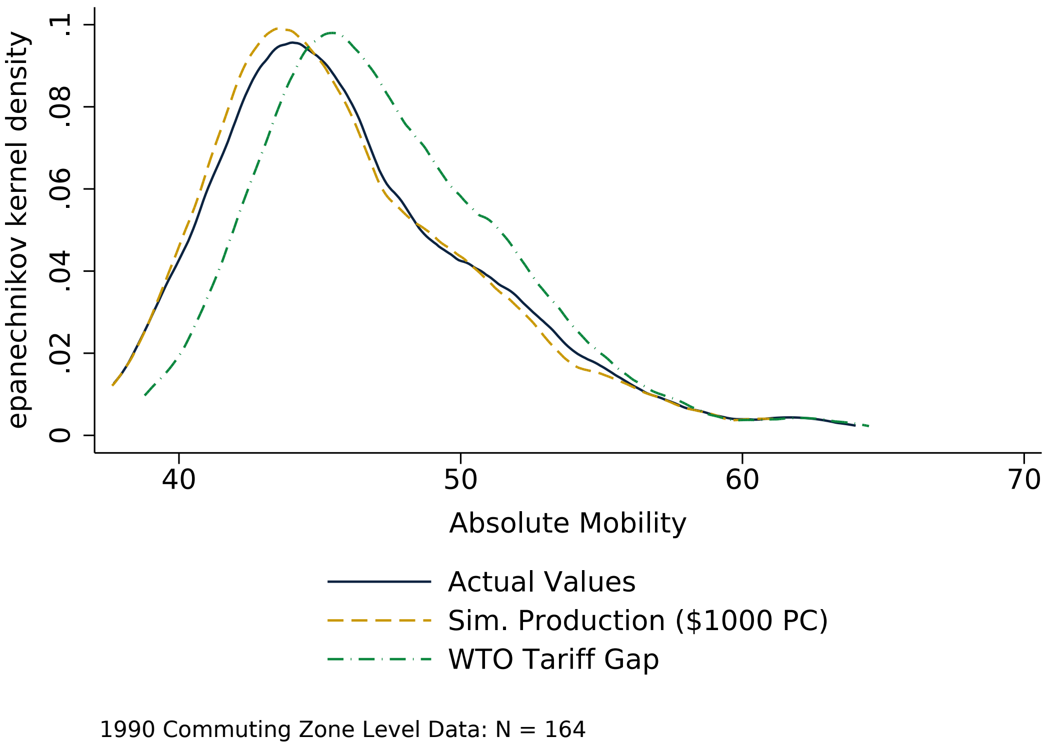
Notes: Panel A and Panel B report the event-study coefficients from Equation (6), where the β_t coefficients for simulated fracking are represented by dark blue circles and the ρ_t coefficients for WTO Tariff Gap are represented by gold diamonds. Each circle/diamond corresponds to a scaled point estimate, while the dotted lines represent 95 percent confidence intervals. The IQR shifts for each coefficient of interest are calculated as linear combinations of the regression estimates. For Panel A, the outcome of interest is the inverse hyperbolic sine of the average monthly number of workers employed in all industries. For Panel B, the outcome of interest is the average weekly wage multiplied by 52, which approximates the average annual wage. All regressions include the controls shown in Table 1. The 1996-2000 average of each outcome of interest is reported as the Pre-Treatment Outcome Mean.

Figure 10: Counterfactual Distributions - Absolute Mobility Distributions

Panel A. Lower 48 States



Panel B. Shale CZs Only



Notes: These panels report the Epanechnikov kernel density of absolute mobility from the exercise described in Section V.D. *Panel A reports results for every commuting zone in the lower 48 states, while Panel B reports results for those commuting zones which intersect, in whole or in part, with any shale play.*

VIII Tables

Table 1: Summary Statistics - Differences by Shale Presence

	Any Fracking	No Fracking	Diff.
Absolute Upward Mobility (+)	46.24	43.34	2.90***
	(4.92)	(5.70)	[0.46]
Income Persistence (-)	0.32	0.33	-0.01
	(0.05)	(0.07)	[0.01]
% w/ short commute (+)	47.97	44.32	3.65**
	(14.25)	(13.26)	[1.22]
Gini bottom 99% (-)	0.30	0.30	-0.00
	(0.05)	(0.06)	[0.00]
High school dropout rate (-)	-0.01	0.00	-0.01***
	(0.02)	(0.02)	[0.00]
Social capital index (+)	0.18	0.17	0.01
	(1.12)	(1.35)	[0.10]
% single mothers (-)	18.81	20.62	-1.82***
	(3.80)	(5.66)	[0.38]
% black residents (-)	4.32	9.10	-4.78***
	(5.51)	(13.60)	[0.72]
Observations	173	549	722

Notes: This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones which intersect in whole or in part with a shale play (Any Fracking) and those commuting zones which do not (No Fracking). The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.
($p < .05$, ** $p < .01$, *** $p < .001$)*

Table 2: Summary Statistics - Differences by Chinese Competition Exposure

	Above Med. *WTO Gap*	Below Med. *WTO Gap*	Diff.
Absolute Upward Mobility (+)	42.44	45.72	-3.28***
	(5.05)	(5.79)	[0.41]
Income Persistence (-)	0.35	0.30	0.05***
	(0.05)	(0.06)	[0.00]
% w/ short commute (+)	40.59	49.80	-9.21***
	(9.61)	(15.32)	[0.95]
Gini bottom 99% (-)	0.31	0.30	0.01
	(0.06)	(0.06)	[0.00]
High school dropout rate (-)	0.00	-0.00	0.01**
	(0.02)	(0.02)	[0.00]
Social capital index (+)	-0.02	0.37	-0.39***
	(1.13)	(1.41)	[0.10]
% single mothers (-)	21.22	19.16	2.07***
	(5.59)	(4.84)	[0.39]
% black residents (-)	11.12	4.80	6.32***
	(14.63)	(8.40)	[0.89]
Observations	361	361	722

Notes: This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones which are above or below the national median of Chinese import competition exposure (WTO Gap$_g$ from Equation (4)). The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.
($p < .05$, ** $p < .01$, *** $p < .001$)*

Table 3: The Fracking Boom and Manufacturing Bust - Absolute Mobility

	Absolute Upward Mobility					
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shale Play	2.455*	1.208*	0.771*			
	[0.922]	[0.499]	[0.357]			
> Median Manu. Share 2000	-2.365*	-1.239**	-0.213			
	[0.950]	[0.355]	[0.258]			
SD Shift: Sim. Production				0.807***	0.597***	0.335**
				[0.099]	[0.110]	[0.098]
SD Shift: WTO Tariff Gap				-2.201***	-0.900***	-0.306*
				[0.399]	[0.152]	[0.134]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	44.03	44.03	44.03	44.03	44.03	44.03
R-Squared	0.0873	0.8070	0.8788	0.1766	0.8202	0.8818
Observations	693	693	690	693	693	690

Notes: This table reports results from a modified version of Equation (1) with controls and the inclusion of an indicator for commuting zones with above median manufacturing employment in the first two columns and from a modified version of Equation (5) with a measure of the WTO Tariff Gap in Columns (3) and (4). Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.
($p < .05$, ** $p < .01$, *** $p < .001$)*

Table 4: The Fracking Boom and Manufacturing Bust - Income Persistence

	Income Persistence					
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shale Play	-0.001	0.014**	0.005			
	[0.008]	[0.005]	[0.003]			
> Median Manu. Share 2000	0.044***	0.028***	0.010*			
	[0.010]	[0.006]	[0.004]			
SD Shift: Sim. Production				-0.003*	-0.001	-0.000
				[0.001]	[0.001]	[0.001]
SD Shift: WTO Tariff Gap				0.029***	0.018***	0.010***
				[0.004]	[0.002]	[0.002]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	0.33	0.33	0.33	0.33	0.33	0.33
R-Squared	0.1137	0.5522	0.6685	0.1999	0.5678	0.6756
Observations	693	693	690	693	693	690

Notes: This table reports results from a modified version of Equation (1) with controls and the inclusion of an indicator for commuting zones with above median manufacturing employment in the first two columns and from a modified version of Equation (5) with a measure of the WTO Tariff Gap in Columns (3) and (4). Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.
($p < .05$, ** $p < .01$, *** $p < .001$)*

Table 5: % Income Δ from 20 Years of Exposure - Children Born to Low Income Parents

	Income Persistence					
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shale Play	-0.002	0.012*	-0.001			
	[0.008]	[0.006]	[0.005]			
> Median Manu. Share 2000	0.036***	0.033***	0.016***			
	[0.008]	[0.005]	[0.004]			
SD Shift: Sim. Production				-0.002	0.001	-0.002
				[0.008]	[0.006]	[0.008]
SD Shift: WTO Tariff Gap				0.026***	0.019***	0.011***
				[0.003]	[0.002]	[0.002]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	0.33	0.33	0.33	0.33	0.33	0.33
R-Squared	0.0634	0.3752	0.4873	0.1256	0.3827	0.4932
Observations	2,748	2,748	2,747	2,748	2,748	2,747

Notes: This table reports results from a modified version of Equation (5) with controls in odd columns and from Equation (5) in even columns. Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. The outcomes of interest are described in detail in the Appendix. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.
($p < .05$, ** $p < .01$, *** $p < .001$)*

Table 6: % Income Δ from 20 Years of Exposure - Children Born to High Income Parents

	All Kids		Girls		Boys	
	(1)	(2)	(3)	(4)	(5)	(6)
SD Shift: Sim. Production	0.609**	0.345**	0.043	-0.310*	0.942**	0.792**
	[0.226]	[0.099]	[0.180]	[0.150]	[0.313]	[0.229]
SD Shift: WTO Tariff Gap	-0.122	0.299	0.424	0.627	-0.512	-0.037
	[0.288]	[0.218]	[0.373]	[0.340]	[0.297]	[0.282]
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects?	No	Yes	No	Yes	No	Yes
Outcome Mean	-1.08	-1.12	-3.87	-3.93	1.30	1.29
R-Squared	0.4762	0.7082	0.3626	0.6422	0.4849	0.6290
Observations	672	669	673	670	676	673

Notes: This table reports results from a modified version of Equation (5) with controls in odd columns and from Equation (5) in even columns. Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. The outcomes of interest are described in detail in the Appendix. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.
($p < .05$, ** $p < .01$, *** $p < .001$)*

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36

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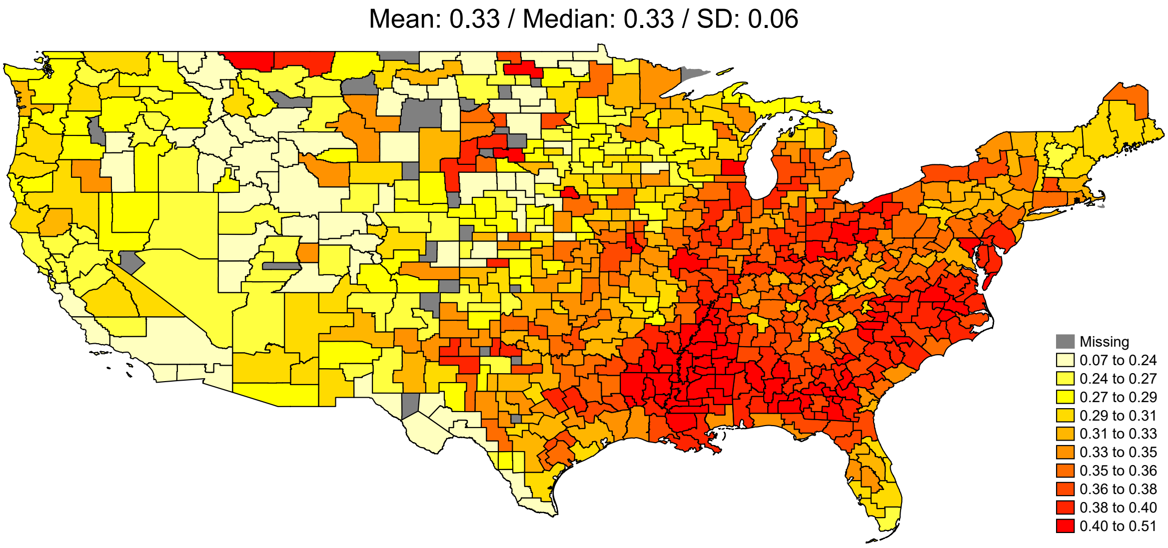
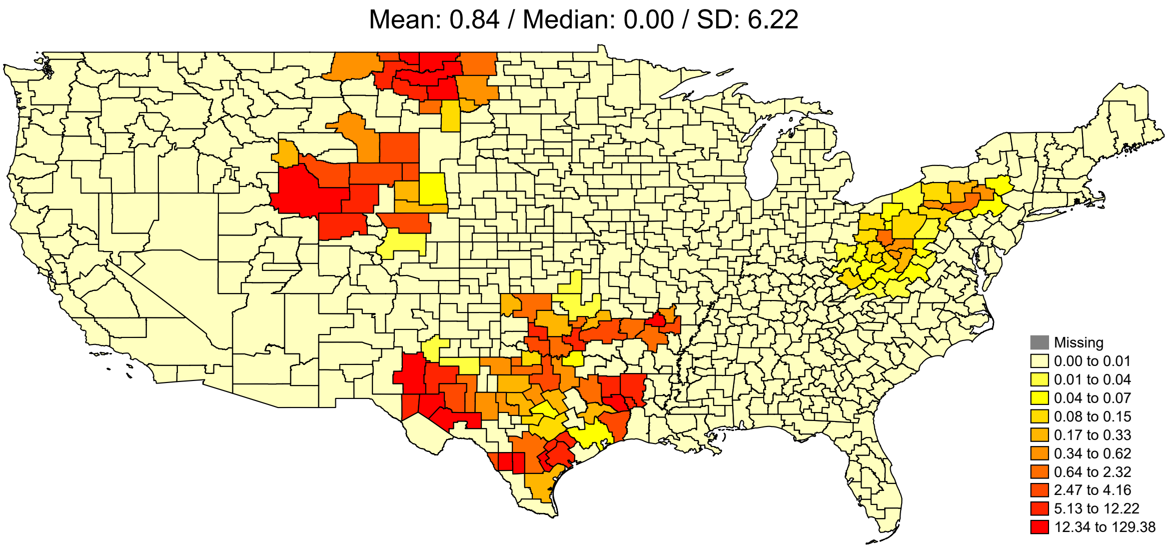
A Appendix Figures and Tables

Figure A.1: Deciles of Income Persistence)



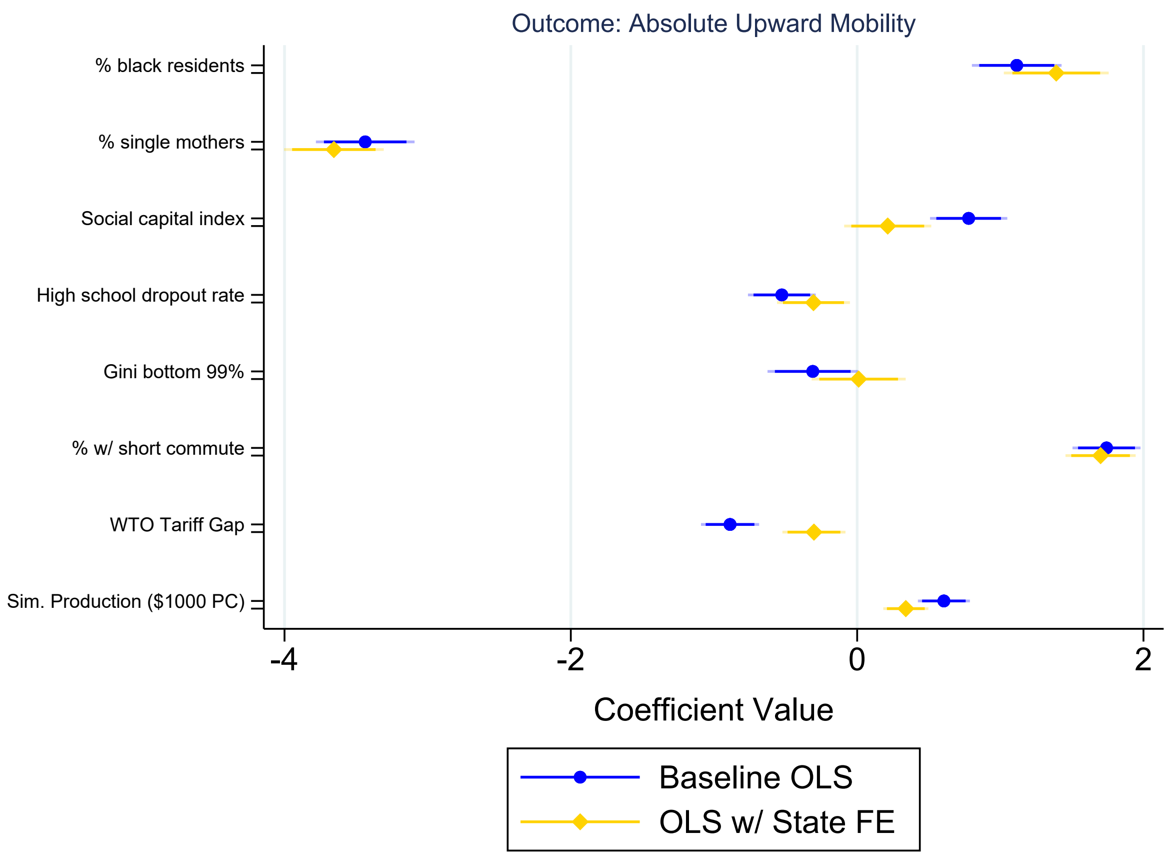
Notes: This figure maps the measure of income persistence from Chetty et al. (2014), split into deciles. See section Section III.B *for details on how this variable is constructed.*

Figure A.2: Deciles of Simulated Production ($1000 PC)



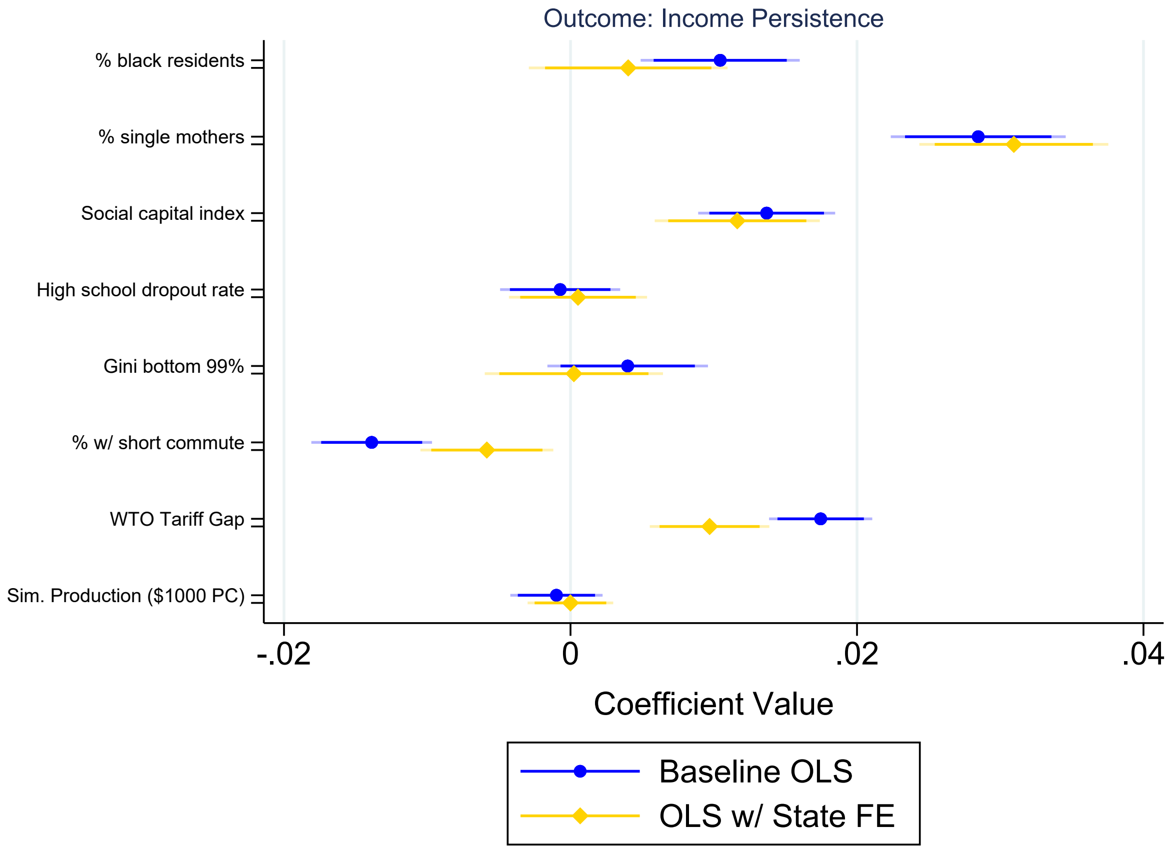
Notes: This figure maps the total value of simulated fracking production from 2001 to 2012 in terms of thousands of dollars per capita, split into deciles. See section Section IV.A *for details on how this variable is constructed*

Figure A.3: Coefficient Values - Absolute Upward Mobility Regression



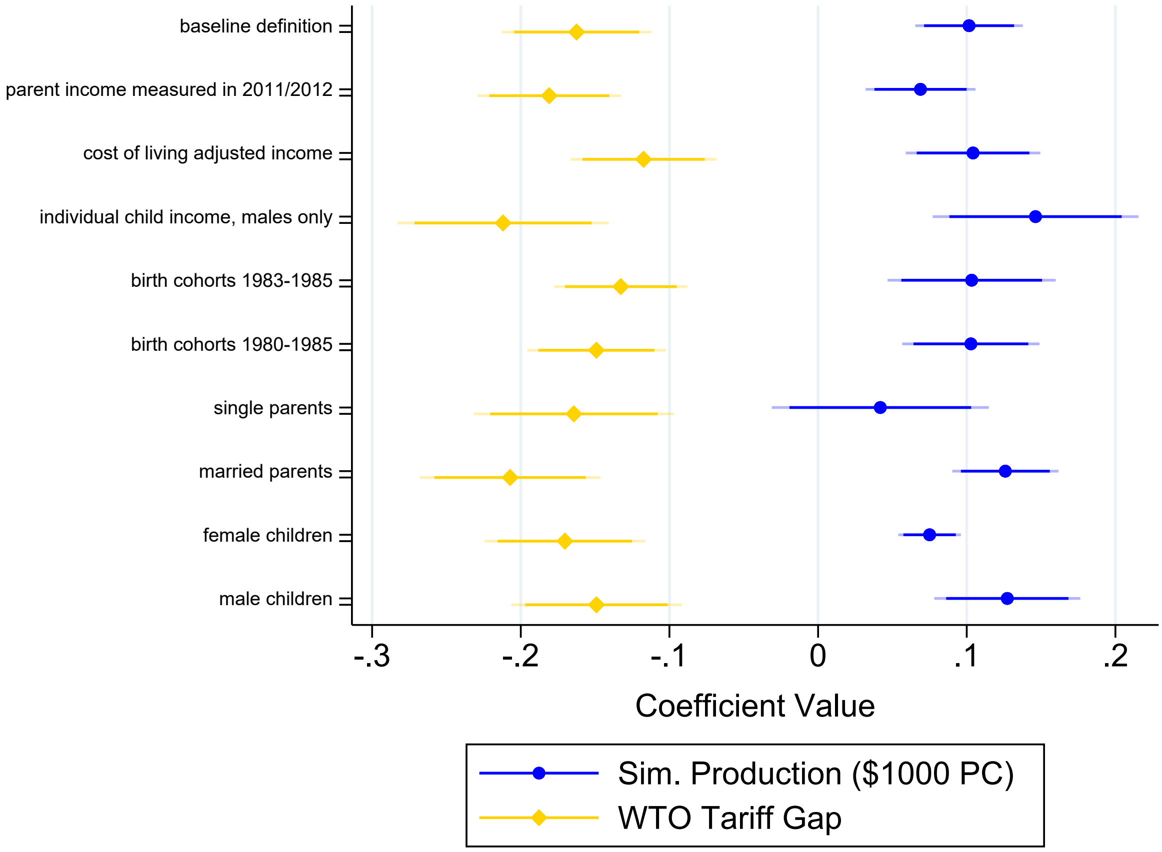
Notes: This figure plots the point estimate, 90% and 95 percent confidence intervals for each independent variable included in Table 3. All variables are normalized by subtracting their mean value and dividing by the standard deviation.

Figure A.4: Coefficient Values - Income Persistence Regression



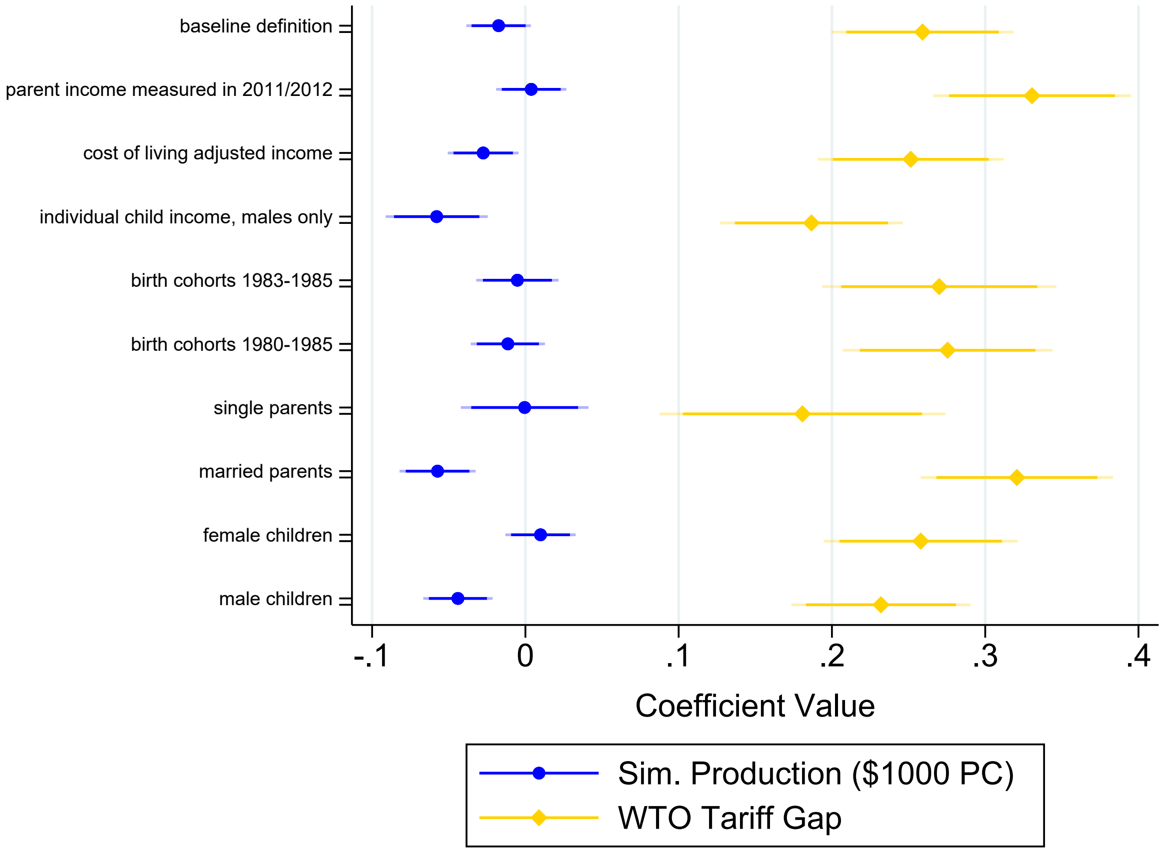
Notes: This figure plots the point estimate, 90% and 95 percent confidence intervals for each independent variable included in Table 4. All variables are normalized by subtracting their mean value and dividing by the standard deviation.

Figure A.5: Robustness to Definitions - Absolute Upward Mobility



Notes: This figure plots the point estimate, 90% and 95 percent confidence intervals for each independent variable included in Table 3. The specification corresponds to Column 5 from that table. The outcome variables are variable definitions of absolute upward mobility taken from Chetty et al. (2014).

Figure A.6: Robustness to Definitions - Income Persistence



Notes: This figure plots the point estimate, 90% and 95 percent confidence intervals for each independent variable included in Table 4. The specification corresponds to Column 5 from that table. The outcome variables are variable definitions of income persistence taken from Chetty et al. (2014).

Table A.1: Summary Statistics - Differences Within Shale CZs

	Above Med. Fracking	Below Med. Fracking	Diff.
Absolute Upward Mobility (+)	46.62	45.87	0.74
	(4.96)	(4.89)	[0.77]
Income Persistence (-)	0.31	0.33	-0.01
	(0.06)	(0.05)	[0.01]
% w/ short commute (+)	48.28	47.67	0.61
	(13.88)	(14.70)	[2.17]
Gini bottom 99% (-)	0.31	0.29	0.02*
	(0.05)	(0.04)	[0.01]
High school dropout rate (-)	-0.00	-0.01	0.01**
	(0.02)	(0.01)	[0.00]
Social capital index (+)	-0.10	0.46	-0.55**
	(1.05)	(1.13)	[0.17]
% single mothers (-)	19.20	18.41	0.79
	(3.71)	(3.86)	[0.58]
% black residents (-)	4.79	3.84	0.95
	(6.62)	(4.07)	[0.83]
Observations	87	86	173

Notes: This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones that intersect with a shale play by the instensity of fracking production. The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.
(p < .05, ** p < .01, *** p < .001)*

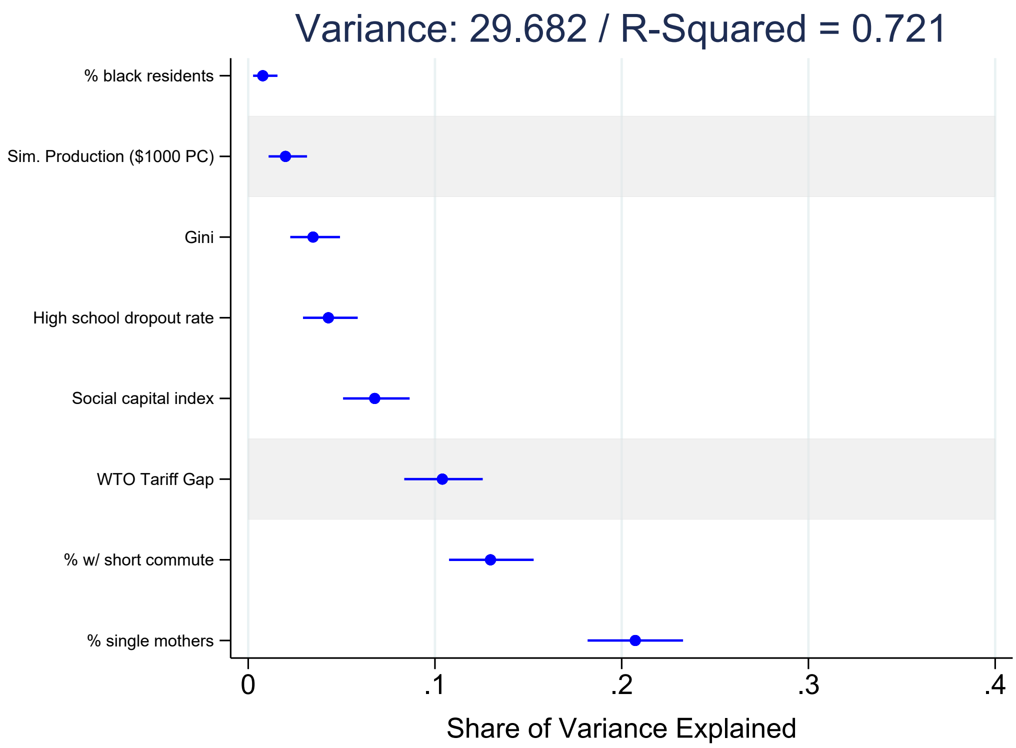
Table A.2: Summary Statistics - Differences by Shale Presence

	Any Fracking	No Fracking	Diff.
Absolute Upward Mobility (+)	45.82	43.02	2.80***
	(4.47)	(5.50)	[0.24]
Income Persistence (-)	0.33	0.33	-0.01*
	(0.07)	(0.07)	[0.00]
% w/ short commute (+)	0.44	0.40	0.04***
	(0.14)	(0.14)	[0.01]
Gini (-)	0.38	0.38	-0.00
	(0.07)	(0.09)	[0.00]
High school dropout rate (-)	0.03	0.04	-0.01***
	(0.02)	(0.03)	[0.00]
Social capital index (+)	0.15	-0.03	0.18**
	(1.19)	(1.38)	[0.06]
% single mothers (-)	0.18	0.20	-0.02***
	(0.05)	(0.07)	[0.00]
% black residents (-)	0.04	0.10	-0.06***
	(0.07)	(0.15)	[0.00]
Observations	521	2,588	3,109

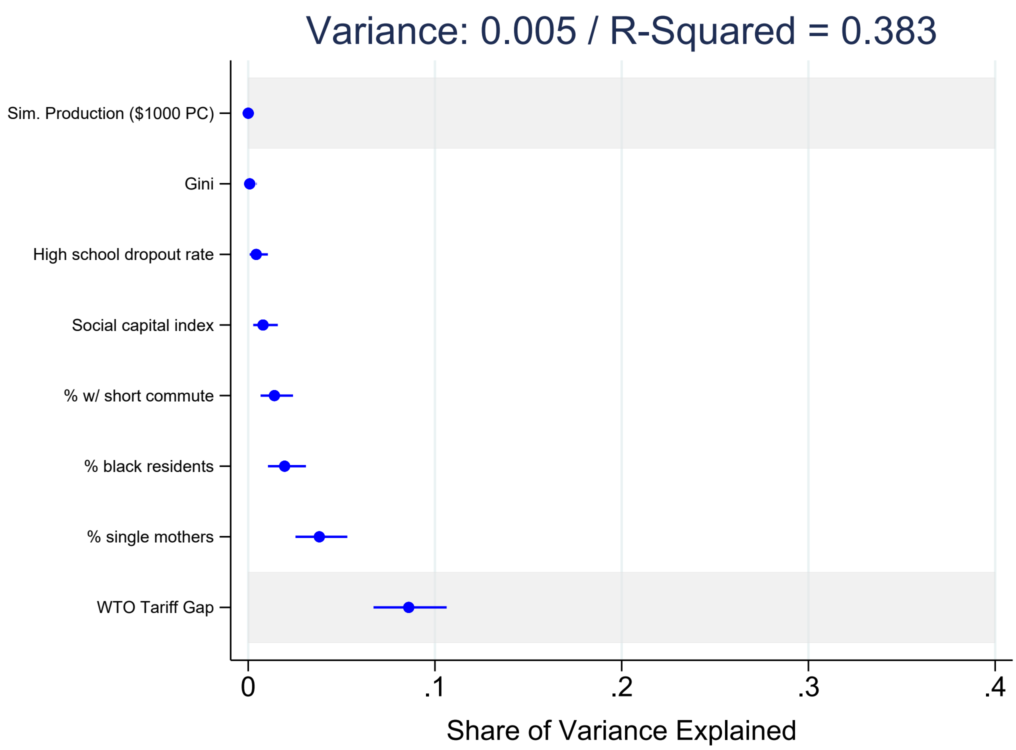
Notes: This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones which intersect in whole or in part with a shale play (Any Fracking) and those commuting zones which do not (No Fracking). The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.
(p < .05, ** p < .01, *** p < .001)*

Figure A.7: ANCOVA Results - Lower 48 States

Panel A. Absolute Mobility



Panel B. Income Persistence



Notes: These figures show the results of an ANCOVA analysis, where each symbol corresponds to η^2, or the amount of the variation in the outcome of interest explained by a specific covariate. The bands represent 95 percent confidence intervals. The included covariates are the same included as controls in Table 1, and the R-Squared measures correspond to in Panel A and Panel B are identical to those reported in column 2 and column 4, respectively.

Table A.3: Summary Statistics - Differences by Chinese Competition Exposure

	Above Med. *WTO Gap*	Below Med. *WTO Gap*	Diff.
Absolute Upward Mobility (+)	42.24	44.91	-2.67***
	(5.01)	(5.60)	[0.20]
Income Persistence (-)	0.35	0.31	0.04***
	(0.07)	(0.07)	[0.00]
% w/ short commute (+)	0.37	0.44	-0.07***
	(0.11)	(0.15)	[0.00]
Gini (-)	0.38	0.39	-0.01**
	(0.08)	(0.10)	[0.00]
High school dropout rate (-)	0.04	0.04	0.01***
	(0.03)	(0.03)	[0.00]
Social capital index (+)	-0.21	0.21	-0.42***
	(1.19)	(1.46)	[0.05]
% single mothers (-)	0.20	0.19	0.02***
	(0.07)	(0.06)	[0.00]
% black residents (-)	0.11	0.06	0.05***
	(0.16)	(0.12)	[0.01]
Observations	1,555	1,554	3,109

Notes: This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones which are above or below the national median of Chinese import competition exposure (WTO Gap_g from Equation (4)). The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.
(p < .05, ** p < .01, *** p < .001)*

Table A.4: The Fracking Boom and Manufacturing Bust - Absolute Mobility

	Absolute Upward Mobility					
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shale Play	2.590**	1.467***	0.927***			
	[0.887]	[0.405]	[0.249]			
> Median Manu. Share 2000	-1.410*	-1.570***	-0.585**			
	[0.692]	[0.261]	[0.185]			
SD Shift: Sim. Production				2.733***	2.292***	1.572***
				[0.521]	[0.371]	[0.426]
SD Shift: WTO Tariff Gap				-1.928***	-1.065***	-0.455***
				[0.286]	[0.111]	[0.106]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	43.46	43.46	43.46	43.46	43.46	43.46
R-Squared	0.0504	0.7114	0.7958	0.1312	0.7212	0.7987
Observations	2,748	2,748	2,747	2,748	2,748	2,747

Notes: This table reports results from a modified version of Equation (1) with controls and the inclusion of an indicator for commuting zones with above median manufacturing employment in the first two columns and from a modified version of Equation (5) with a measure of the WTO Tariff Gap in Columns (3) and (4). Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.
(p < .05, ** p < .01, *** p < .001)*

Table A.5: The Fracking Boom and Manufacturing Bust - Income Persistence

	Income Persistence					
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shale Play	-0.002	0.012*	-0.001			
	[0.008]	[0.006]	[0.005]			
> Median Manu. Share 2000	0.036***	0.033***	0.016***			
	[0.008]	[0.005]	[0.004]			
SD Shift: Sim. Production				-0.002	0.001	-0.002
				[0.008]	[0.006]	[0.008]
SD Shift: WTO Tariff Gap				0.026***	0.019***	0.011***
				[0.003]	[0.002]	[0.002]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	0.33	0.33	0.33	0.33	0.33	0.33
R-Squared	0.0634	0.3752	0.4873	0.1256	0.3827	0.4932
Observations	2,748	2,748	2,747	2,748	2,748	2,747

Notes: This table reports results from a modified version of Equation (1) with controls and the inclusion of an indicator for commuting zones with above median manufacturing employment in the first two columns and from a modified version of Equation (5) with a measure of the WTO Tariff Gap in Columns (3) and (4). Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate.
($p < .05$, ** $p < .01$, *** $p < .001$)*