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Abstract

This thesis is focused on the responses of workers through labor supply adjustment, transfer program participation and human capital investment to a changing labor market. Specifically, the papers that comprise this dissertation use state and metropolitan area-level variation to analyze the effects of changes in employment growth, income growth and income dispersion on participation in disability insurance, first time enrollments in community college and four-year universities, and residential sorting.

The first paper employs a shift-share design to establish a causal link between declining labor demand in low wage, highly automated ("routine") occupations and rising disability participation. From 2000 to 2011, moving from the 10th to the 90th percentile of the predicted decline in routine employment corresponded to a 0.82 percentage point increase in disability. The model explains 78.6% of the increase in disability for all prime-age workers from 2000 to 2011. This accounts for 10.3% of the employment decline over the 2000s. Notably, this paper presents the first causal evidence that the effects are stronger for those with harder-to-verify diagnostic claims.

The second paper, coauthored with Lancelot Henry de Frahan, fills the gap in the existing literature on the causal effects of rising inequality on human capital investment. First, we propose an instrumentation strategy that yields a vector of instruments from a predicted local wage distribution by interacting initial industry employment shares at the metropolitan level with changes to the within-industry distribution of wages at the national level. With this instrumentation strategy, we are able to separately analyze the causal impact of changing inequality from changes in mean income on postsecondary enrollments. This paper establishes an empirical fact: predicted increases in local wage inequality depress rates of enrollment in postsecondary schooling. In our main analysis on community college enrollments, we find that moving from the 10th to the 90th percentile of changes in wage

inequality corresponds to a 2.05 percentage point decrease in first-year, full-time aggregate community college enrollments. Further, we find evidence of a causal relationship between rising local inequality and residential sorting on an income basis which sheds light on a possible mechanism driving our main result. The instrumentation strategy introduced in this paper could allow researchers to assess the causal relationship between inequality and other economic phenomena.

Chapter 1

Where Are the Workers? Technological Change, Rising Disability and the Employment Puzzle of the 2000s: A Regional Approach

1.1 Introduction:

This paper addresses a central question of the US labor market in the 2000s: where are the workers? The ensuing work argues that weakening demand for labor in highly automated ("routine") occupations disproportionately pushed US factory and service sector workers out of the employment ranks and onto the disability rolls over the 2000s. The motivation arises from a few important facts: (1) employment broadly has been declining in the 2000s; (2) disability participation has been increasing over this period; (3) there is evidence of a relationship between declining local employment and rising disability; (4) employment for workers employed in routine occupations has been persistently declining in the 2000s.

By focusing on the employment shock to those who stand to gain the most from participation in DI, workers displaced from low-paying, high DI replacement rate jobs on the factory line or in the back office, this paper connects the broad employment declines of the 2000s to the concurrent rise in disability. The analysis employs a shift-share design to answer the question: did cities with employment losses in routine occupations experience resulting increases in local disability participation? I instrument for changes to local routine employment by using a measure of the importance of routine employment in the locality in year 2000 interacted with national changes to routine employment. Importantly, this paper answers the questions: How much of the rise in disability during the 2000s can be attributed to declining labor market opportunities associated with technological change? In turn, how much of the broad decline in employment in the 2000s can be attributed to disability take-up resulting from the secular decline in routine employment? In doing so, I find that the decline in labor demand for routine occupations contributed to the rise in disability and to the decline in employment rates during the 2000s. These effects were found to be largest for non-college middle age and pre-retirement workers.

My approach in this paper follows in the tradition of Black, Daniel and Sanders (2002) and Autor and Duggan (2003) by using local and regional variation to explore the relationship between disability and weak labor markets. Specifically, I construct a panel of Metropolitan Statistical Areas (MSAs) from the Census and American Community Survey (ACS) from which I use variation in the local impact of national changes to routine employment to obtain estimates of the effect of employment and wage changes on disability participation.[1] This analysis exploits two main specifications: the change in local disability participation rates on the predicted change in routine employment, and the change in local disability participation on the change in local wages resulting from predicted changes in routine employment.[2]

As a preview of the results, this paper provides clear evidence that as local employment opportunities decline, disability participation increases. Over the entire decade (2000 to 2011), moving from the 10th to the 90th percentile of the predicted decline in local routine employment corresponded to a 0.82 percentage point increase in disability for prime-age men and women. Results are much stronger for pre-retirement workers. Moving from the 10th to the 90th percentile of the predicted decline in local routine employment corresponded to a 2.08 percentage point increase in

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[1] Data for the analysis in the paper compiled through IPUMS from 2000 Census and pooled 2009, 2010, and 2011 American Community Survey (ACS) with sample restricted to non-institutionalized population age 21-64 with an assigned MSA.

[2] Migration could be important to the question of disability with respect to selection bias. If during the period of interest (2000 to 2011) the most employable workers migrated out of areas which received negative routine employment shocks, estimates would be biased upward. Section 1.6.4 and the analysis in Tables A1.3 –A1.4 of the Appendix address the question of selection bias by separately estimating effects of declining routine employment or declining wages on disability participation for migrants and non-migrants. The analysis in Tables A1.3-A1.4 suggests that migrants do not have stronger attachments to the labor force than non-migrants.

disability for non-college men and women age 55 to 64 compared to an increase of 0.79 percentage points for non-college men and women age 45 to 54. Further, disability participation is highly elastic to wage shocks. From 2000 to 2011, the elasticity of disability participation with respect to wages is estimated as -2.49 for prime-age men and women.

The above results give rise to a natural question, how do the marginally disabled access DI benefits? Many diagnostic claims such as diabetes or heart conditions are easily verifiable and difficult to manipulate; however, two classes of claims, mental and musculoskeletal (such as back pain) disease, are more difficult to verify and are susceptible to manipulation. To gain insight into the mechanism, I utilized state-level administrative data of DI claims by diagnostic claim type and employed a shift-share analysis of routine employment changes. States with weakening labor markets, as predicted by declining demand for routine occupations, saw larger effects to mental and musculoskeletal claims relative to all other claim types. From 2000 to 2011, mental and musculoskeletal diagnostic claims rose by 1.4 percentage points. In contrast, claims for all other diagnostic categories increased by 0.5 percentage points. From 2000 to 2011, moving from the 10th to the 90th percentile of the predicted decline in local routine employment corresponded to a 0.44 percentage point increase in the local disability rate for mental and musculoskeletal claims in comparison to a 0.15 percentage point increase in all other claims. These results are suggestive of moral hazard in that states with weak labor markets due to declining routine sector employment saw much greater increases in harder-to-verify disabilities.

In summary, this paper establishes a causal link between declining labor demand in highly automated sectors and increased disability participation and shows that much of the increase in disability participation and decline in broad employment over the 2000s can be explained by weakening labor demand in routine occupations. My model explains 78.6% of the increase in disability for all prime-age men and women from 2000 to 2011. This accounts for 10.3% of the employment decline for all prime-age men and women over the 2000s. This suggests that the transition to disability can explain some of the decline in employment over the 2000s; further, this suggests the employment decline may be persistent. Remarkably, this paper presents the first such causal evidence that disability participation among those with harder-to-verify claims such as mental illness or back pain is more responsive to weakening labor demand than disability participation among those with easier-to-verify claims.

The work in this paper is particularly related to a few strands of literature on disability and weak labor markets. Black, Daniel and Sanders (2002) exploit variation in local earnings growth within states to answer what happens to DI participation as local wages change. Using the coal and steel booms and busts of the 1970s and 1980s and the initial local presence of these industries as a source of identification, they estimate disability elasticities with respect to wage changes between -0.3 and -1.05, depending on the specification and labor market slackness. Autor and Duggan (2003) disentangle the effects of an expanded supply of federal disability benefits following a liberalization of DI eligibility in 1984 from the effects of expanded demand for transfer income due to a softening labor market. Their design exploits cross-state variation in replacement rates to instrument for benefits supplied and uses a weighted sum of national industry employment changes to instrument for changes in demand for transfer income. They find that DI application rates became 2 to 3 times more responsive to labor demand shocks following the 1984 liberalization.

Autor, Dorn and Hanson (2013) examine the effects of supply-driven import shocks, from China, on trade-exposed US manufacturing employment. While the primary focus is labor market outcomes, they also analyze take-up of transfer programs including DI and Trade Adjustment Assistance (TAA). The analysis focuses on the period 1990 to 2007, uses aggregate DI payments data from the SSA, and finds that disability payments are elastic to the import shock from China. Further, the dollar increase in per capita DI payments is over thirty times as large as the dollar increase in TAA payments. Autor, Dorn and Hanson (2013) is relevant to this paper and important to the disability literature in its steps to further connect disability participation and weak labor markets; however, as it focuses on the period 1990 to 2007, it does not address the severity or persistence of the employment declines, particularly for the low-skilled, of the 2000s. The analysis in this paper is distinct in that it focuses on the large, persistent employment declines of the 2000s to answer how much of the decline in employment can be attributed to increased disability resulting from weakening labor demand. Specifically, this paper incorporates a larger labor demand shock, encompassing dislocations resulting from both trade and automation, and disaggregates effects by gender, age and educational attainment. Importantly, this paper provides insights into the potential mechanisms.

In its efforts to explore the contribution of increasing disability to declining labor force participation, this project also has ties to seminal work on disability by Parsons (1980, 1991) and Bound (1989, 1991). Using variation in replacement rates in the cross-section, Parsons (1980) attributes the entire postwar (1948-1976) decline in employment for prime-age males to the establishment of DI and the growth of general welfare. Using rejected DI applicants as a control group, Bound (1989) attributes less than half of the postwar decline in the labor force participation of older men to DI. The cornerstone of the debate between Parsons (1991) and Bound (1991) has centered around potential endogeneity concerns regarding variation in replacement rates and potential internal validity concerns regarding use of rejected applicants as a control group. This paper sidesteps the debate by using as a source of identification a structural shift away from routine employment to show that in weak labor markets disability is a first-order margin of adjustment for employment and earnings loss.[3]

[3] Finally, this paper connects important recent work on declining labor force participation in the 2000s by Moffitt (2012), Charles, Hurst, and Notowidigdo (2013), and Autor and Dorn (2013) to increasing disability participation.

1.2 Motivating Trends

Figure 1.1 documents the decline in employment broadly over the 2000s among prime-age men and women by skill attainment.[4] From 2000 to 2007, the employment-to-population ratio for prime-age men and women fell by 1.7 percentage points.[5] From 2007 to 2010, the years associated with the Great Recession, the employment-to-population ratio for prime-age men and women fell by 5 percentage points. Remarkably, employment did not rebound after the end of the recession. These losses were acute among those without four-year college attainment: employment for non-college men and women fell by 7.6 percentage points from 2000 to 2013.

While it is clear that increasingly some workers are exiting and choosing not to re-enter the labor force, it is less clear where they are headed. A potential explanation may be increased participation in the federal disability insurance program for workers (DI). Figure 1.2 documents the rise in disability for prime-age men and women by skill attainment over the last decade.[6] Prior to the recession (2000 to 2007), the disability rate for prime-age men and women increased by 0.31 percentage points. During the recession (2007 to 2010), the disability rate for prime-age men and women increased by 0.24 percentage points. Over the entire 2000s (2000 to 2013), the disability rate for prime-age men and women increased by 0.76 percentage points.

Moving beyond national trends in falling employment and rising disability, Figures 1.3 and 1.4 build a potential explanation to the employment puzzle of the 2000s. These figures document the strong correlational relationship between rising DI participation and declining employment-to-

[4] Prime-age refers to ages 21-64. Figures are computed from the historical March CPS with sample restricted to non-institutional adults with an assigned Metropolitan Statistical Area (MSA).
[5] Moffitt (2012) documents pre-recession employment trends and finds that the employment-to-population ratio for men and women age 16-64 fell from 74.1 percent in 2000 to 71.8 percent in 2007, a reversal of 30 years of increasing employment in the US.
[6] Details about the identification of the disabled in the CPS, Census/ACS and SSA data are discussed in detail in Section 1.5. Figures are calculated from the historical March CPS.

population ratios.[7] Figure 1.3 shows that metropolitan areas that experienced declines in the employment-to-population ratio for all prime-age men and women also experienced increases in the disability-to-population ratio over the 2000s. From 2000 to 2011, moving from the 10th percentile to the 90th percentile of the decline in the employment-to-population ratio was associated with a 0.23 percentage point increase in the disability rate. This relationship is particularly pronounced among those without four-year college attainment who are nearing the age of retirement. In 2011, DI participation amongst non-college men and women age 55 to 64 was as high as 25 percent or more in some metropolitan areas.[8] Figure 1.4 documents the correlation between declining employment-to-population ratios and increasing disability-to-population ratios among non-college men and women age 55 to 64 from 2000 to 2011. Moving from the 10th percentile to the 90th percentile of the decline in the employment-to-population ratio is associated with a 0.59 percentage point increase in disability.

The backdrop for the broad employment declines in Figure 1.1 is a narrower employment decline which was set in motion in the 1980s and has come to characterize the labor market of the 2000s—the decline in employment in highly automated sectors such as the manufacturing and service sectors.[9] A well-established literature refers to this process as skill-biased technological change.[10] In a simple framework, we can think of the labor market as divided into thirds: thought-intensive ("abstract") jobs, highly automated ("routine") jobs, and jobs that require dexterity or personal interaction

[7] Figures 1.3, 1.4 use data from the 2000 Census and the American Community Survey where the years 2009, 2010 and 2011 are pooled to represent the year 2011. Figure 1.3 includes non-institutionalized men and women age 21-64 who self-identify as living in a MSA. Figure 1.4 includes non-institutionalized men and women age 55-64 without four-year college attainment who self-identify as living in a MSA. Both figures use the MSA as the unit of observation and each dot is weighting by the prime-age population of the MSA in 2000. There are 283 MSAs.

[8] MSAs with more than 25% of non-college men and women 55-64 on DI include Alexandria, LA, Rocky Mount, NC, Pueblo, CO, Houma-Thibodoux, LA, Jackson, MI, Tuscaloosa, LA, Hattiesburg, MS, Ocala, FL, Anniston, AL, Johnson City, TN, Flint, MI, and Gadsden, AL.

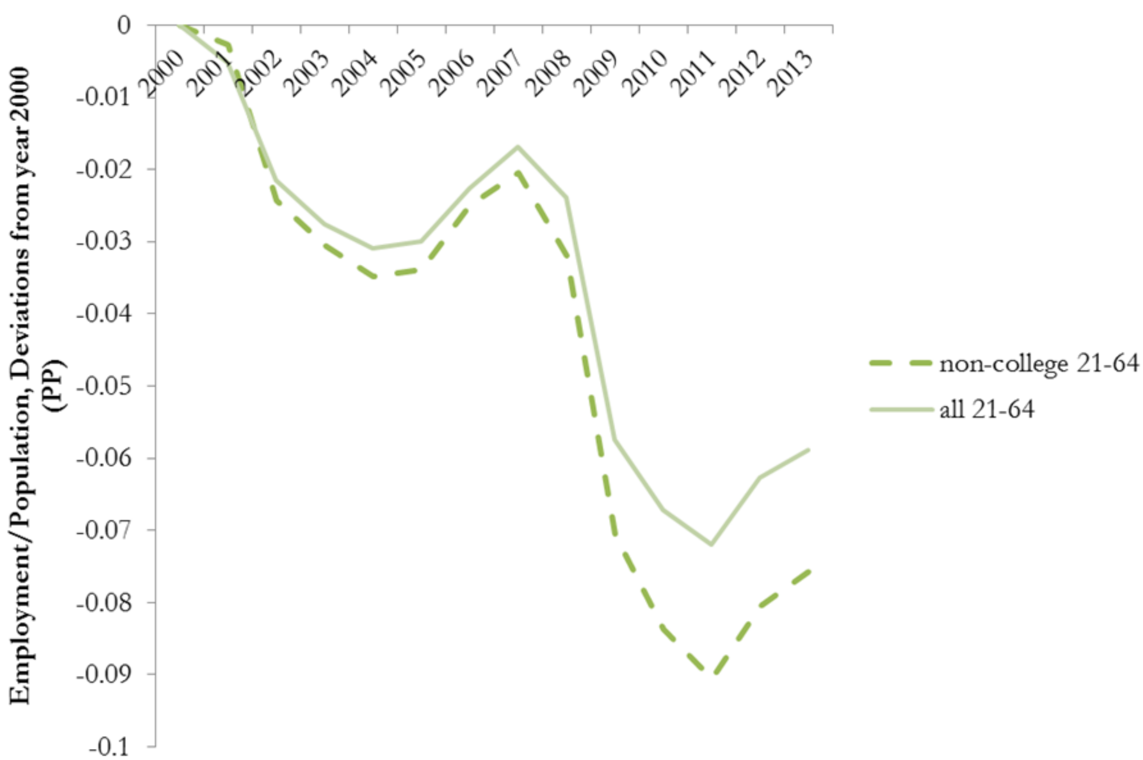
[9] Declining employment in highly automated occupations, in the 2000s, has been documented in a recent literature by Charles, Hurst, and Notowidigdo (2013) and Autor and Dorn (2013).

[10] Declining employment in highly automated occupations, since the 1980s, has been documented by Acemoglu (1999), Autor, Levy and Murnane (2003), and Autor et al (2006). See also Goos and Manning (2007), Goos et. al (2009), and Jaimovich and Siu (2012).

("manual"). Routine jobs are displaced by automation or computerization. Specifically, I identify routine occupations as the three-digit occupations codes that correspond to the manufacturing and administrative services sectors. In 1980, 21.5% of prime-age men and women were employed in routine occupations. This fell to 15.6% in 2000 and further eroded to 12.4% by 2013. These effects were most acute for those without four-year college attainment ("non-college"). Routine employment for college men increased by 1.15 percentage points while routine employment for non-college men fell by 2.75 percentage points from 2000 to 2013. Routine employment for college women increased by 1.07 percentage points while routine employment for non-college women declined by 5.83 percentage points over the 2000s. Figure 1.5 documents the erosion of employment in routine occupations over the last decade by skill attainment.

Figure 1.1

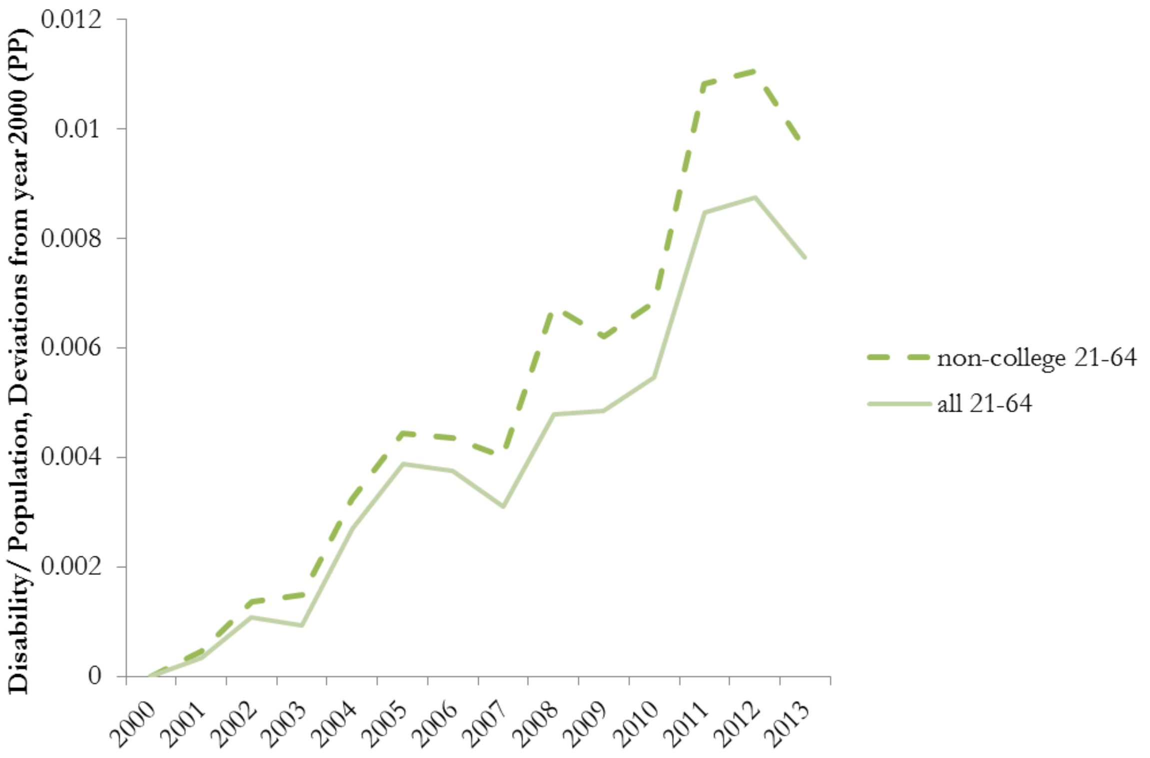
Trends in Employment, 2000-2013



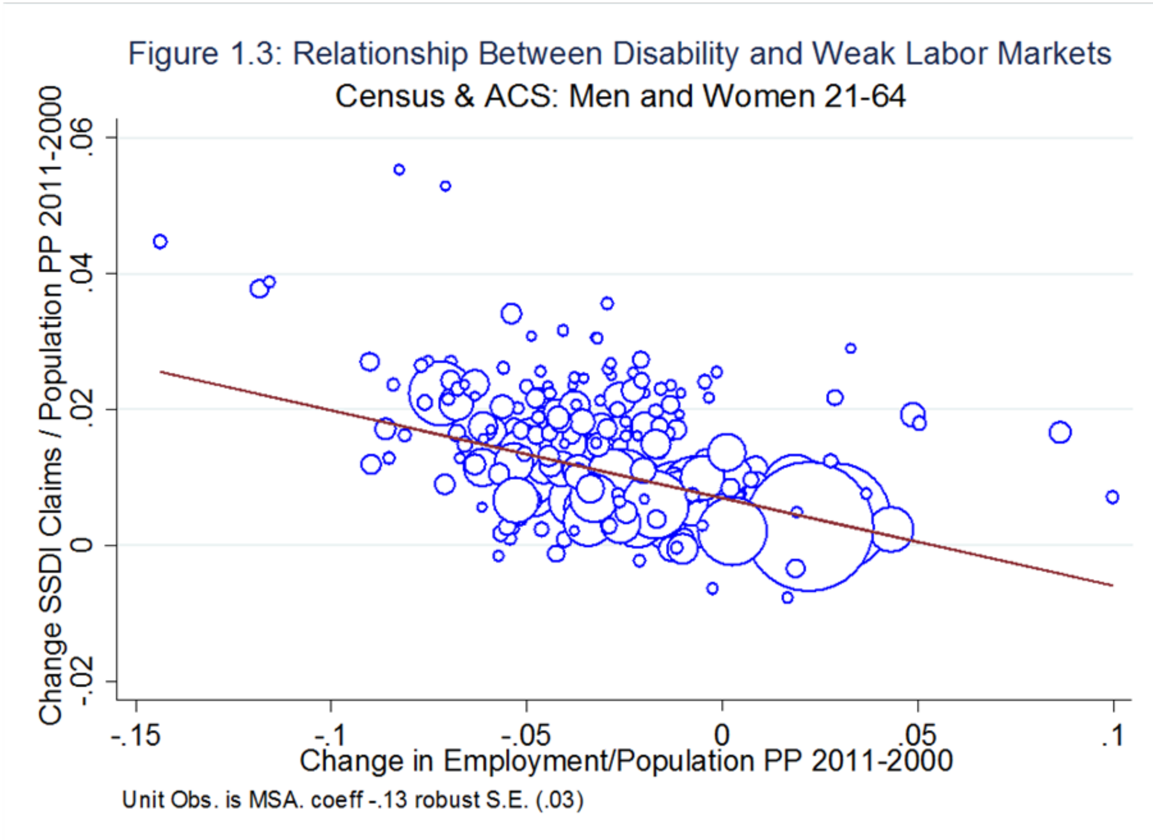
Note: Data is from March CPS 2000-2013. Civilian, non-institutional, ages 21-64.

Figure 1.2

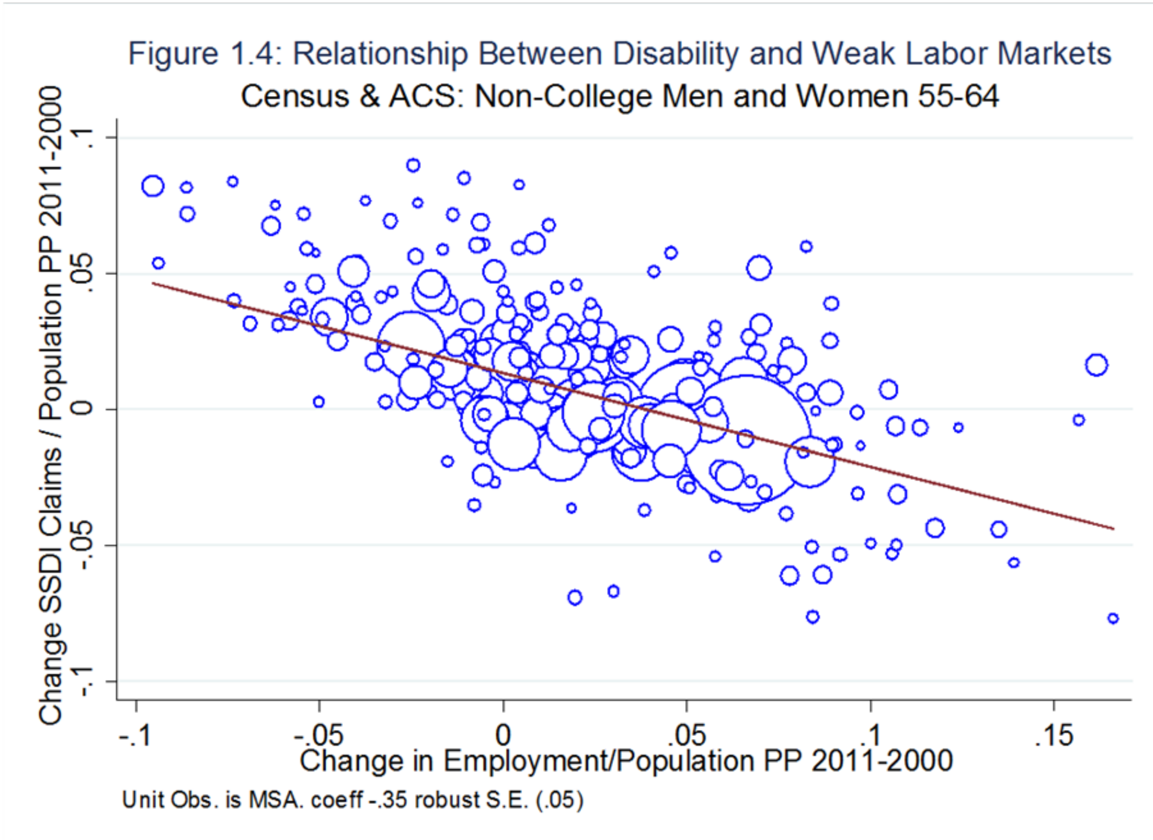
Trends in Disability, 2000-2013



Note: Data from March CPS 2000-2013. Civilian, non-institutional, ages 21-64.



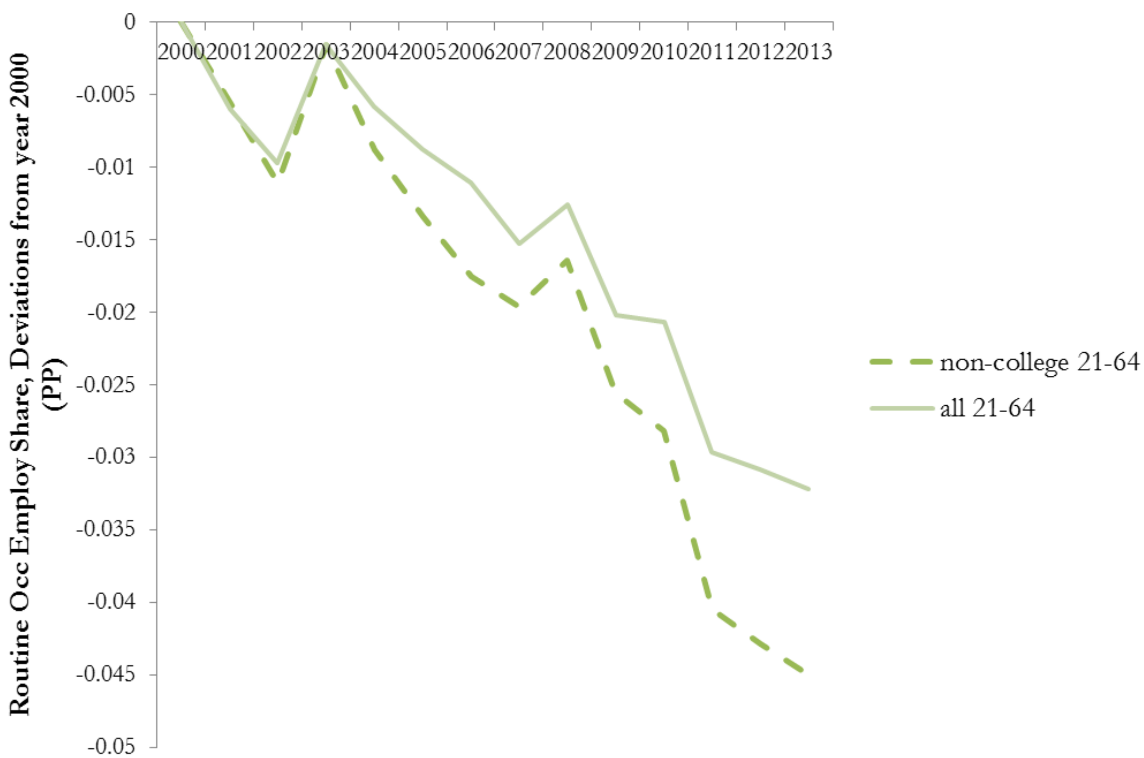
Note: Data is from the 2000 Census and the American Community Survey where the years 2009, 2010 and 2011 represent the year 2011. DI receipt for population age 21-64 identified as those with non-zero Social Security income and employment status as "not in labor force". Each cell is a MSA with N = 283. Each cell weighted by age 21-64 population in MSA in year 2000.



Note: Data is from the 2000 Census and the American Community Survey where the years 2009, 2010 and 2011 represent the year 2011. DI receipt for population age 55-64 identified as those with non-zero Social Security income and employment status as "not in labor force". Each cell is a MSA with N= 283. Each cell weighted by age 55-64 population in MSA in year 2000.

Figure 1.5

Trends in Routine Occupation Employment, 2000-2013



Note: Data is from March CPS 2000-2013. Civilian, non-institutional, ages 21-64. Routine occupations represents manufacturing and administrative services occupations.

1.3 About Social Security Disability Insurance

In its original conception in the Social Security Act Amendments of 1954, DI allowed disabled workers to carve out periods of non-employment tied to disability from counting against work history requirements for future Social Security retirement income receipts. (SSA 2000). Through Congressional action in the 1960s and 1970s, the DI program was expanded to resemble the modern DI program. Over the 1970s and early 1980s, Congress seesawed between tightening and loosening access to benefits. The 1970s saw large growth in the DI program following the Social Security Act

Amendments of 1972.[11] In response to program growth in the 1970s, a resulting contraction of benefits by Congress was enacted in 1980. In 1984, Congress loosened restrictions on the program. The Social Security Disability Benefits Reform Act of 1984 expanded the generosity of the DI program by: establishing guidelines for program exit based on medical improvement which made the SSA responsible for proving that a substantial medical improvement had taken place, making the initial screening for benefits qualification more subjective, and allowing assessment by the applicant's own physician in lieu of assessment by the SSA (SSA 2000).

In its modern form, the DI program provides income replacement and health insurance through Medicare to nonelderly adults with disabilities that prevent participation in the labor force. The program also provides benefits to eligible non-disabled spouses and children of disabled workers. DI is the largest income replacement program for nonelderly adults in the US with benefits totaling $136.9B in government expenditures in 2012, a 6.2% increase in payments from 2011. In 2012, the federal government dedicated $2.9B to administrative expenses alone (SSA 2013). In contrast, $46.6B in benefits were disbursed through all state and federal Unemployment Insurance programs in 2011—representing about 34% of federal expenditures on DI in the same period. In December 2012, 8,826,591 people received benefits through the DI worker program with 48% of recipients between the ages of 55 and 64 (SSA 2012).

For many, the application process is long, on average over 15 months, and involves an appeals process. Eligibility requires an established work history, an age requirement, an application for benefits, and a Social Security-defined disability (SSA 2000). The process begins with the applicant submitting paperwork to a local SSA field office. The field office randomly assigns cases to a Disability Determination Service (DDS) examiner who can approve or deny the application. If denied, the

[11] Bound (1989) estimates the after-tax replacement rate of the DI program reached 60% in the 1970s. Parsons (1980) documents that 8.9% of males age 45-64 received federal disability benefits in 1975.

applicant can appeal for reconsideration by DDS. If denied at the reconsideration level, the applicant can appeal to an Administrative Law Judge (ALJ). If denied at the ALJ level, the applicant can appeal further in federal court. During the application process, applicants can hire legal representation without out-of-pocket expenditure. If successful, disability lawyers can be granted fees up to 25% of past due benefits. From 2000 to 2010, SSA received 21,879,872 applications for DI worker benefits. As of June 2012, 43% of those applications were approved for benefits with 59% of awards arising from cases where the claimant's impairment did not match the official SSA impairment list but was approved on the basis of reasonable inability to pursue gainful employment.[12]

DI benefit calculation is progressive and beneficiaries with families stand to receive additional compensation beyond individual worker benefits. The monthly DI benefit, the primary insurance amount (PIA), is based on earnings from age 21 to the year of first eligibility for DI, the recipient's average indexed monthly earnings (AIME).[13] The PIA is calculated as the sum of: 90% of the first $816 of the AIME, 32% of amount of AIME between $816 and $4917, and 15% of amount of AIME over $4917 (Primary Insurance Amount 2014). Recipients through the DI worker program receive a monthly benefit equal to 100% of the PIA. Eligible households can receive transfers up to 188% of the PIA. In 2012, the average monthly benefit was $1,130 and the average monthly family benefit for a disabled worker, wife and children was $1,945 (SSA 2012).[14] These benefits are comparable to those received by individuals and families with Social Security retirement benefits.[15]

Unlike other displaced worker programs, such as UI, the disability program is absorbing. Once on DI, beneficiaries exit upon death, retirement, medical recovery, or voluntary return to work.

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[12] Figures computed from Table 59 of SSA's "Annual statistical report on the social security disability insurance program 2012."

[13] To calculate the AIME, the SSA takes the full calendar years of earnings from age 21 to the year of first eligibility for DI dropping the 5 lowest years of earnings. $AIME = \sum(highest\ annual\ earnings)/(months\ in\ computation)$

[14] Monthly benefits are received after a 5-month waiting period.

[15] In 2012 the average monthly benefit for retired workers was $1,262 and the average monthly family benefit for a retired worker, wife and children was $2,603. In 2011, the average weekly benefit for UI was $295.79 (SSA 2012).

Despite some Congressional and agency intervention, voluntary exit has been low.[16] In 2012, 38,228 workers terminated DI benefits to return to work, representing 0.43% of all DI worker benefit recipients in that year (SSA 2012).

1.4 Empirical Model:

This paper explores the response of participation in a transfer program which prohibits employment, the DI program, to a shock in routine occupation labor demand. Although the following model is focused on disability, it borrows from a similar empirical model established in Charles, Hurst, and Notowidigdo (2013). The analysis exploits variation across MSAs, denoted *k*, over time, denoted *t*. In this model, each MSA is an island, allowing for the possibility of migration. Assuming that the labor demand and labor supply curves can be approximated by log linear functions, the local labor market can be characterized:

$$L_{k,t}^{D} = \alpha_{k,t}^{D} - \varepsilon_{l}^{D} lnw_{k,t} \tag{1.1}$$

$$L_{k,t}^{S} = \alpha_{k,t}^{S} + \varepsilon_{l}^{S} lnw_{k,t} \tag{1.2}$$

where $L_{k,t}^{D}$ is the labor demand function and L_{kt}^{S} is the labor supply function with real log wages, $lnw_{k,t}$, and semi-elasticity of labor demand with respect to wages, ε_{l}^{D}, and semi-elasticity of labor supply with respect to wages, ε_{l}^{S}. The terms $\Delta\alpha_{k}^{D}$ and $\Delta\alpha_{k}^{S}$ represent shifters of the labor demand and labor supply curves. The equilibrium is characterized:

$$\Delta lnw_{k} = lnw_{k,t+1} - lnw_{k,t} = \Delta\alpha_{k}^{D} \frac{1}{\varepsilon_{l}^{S}+\varepsilon_{l}^{D}} - \Delta\alpha_{k}^{S} \frac{1}{\varepsilon_{l}^{S}+\varepsilon_{l}^{D}} \tag{1.3}$$

$$\Delta L_{k} = L_{k,t+1} - L_{k,t} = \Delta\alpha_{k}^{S} \frac{\varepsilon_{l}^{D}}{\varepsilon_{l}^{D}+\varepsilon_{l}^{S}} + \Delta\alpha_{k}^{D} \frac{\varepsilon_{l}^{S}}{\varepsilon_{l}^{D}+\varepsilon_{l}^{S}} \qquad (1.4).$$

[16] In 1999, under the Ticket to Work (TTW) and Work Incentives Improvement Act, Congress created a voucher program for DI recipients to receive vocational rehabilitation services and job search assistance. Additionally, the SSA developed a work incentive program which allows recipients to work on a part-time basis and receive benefits. As of 2011, recipients who earn over $720/month can work and retain benefits until they have worked for 9 months over a 60 month interval at which time they would exit DI. Stapleton, Schimmel (2010) found that less than 0.05% of all DI and SSI recipients participated in TTW in 2006.

The central goal of this paper is to identify local labor demand changes in order to understand how employment changes affect disability participation.[17] Local labor demand changes, $\Delta\alpha_k^D$, can be expressed as a linear function of changes in demand for labor in routine occupations, Δx_k^R, changes in demand for labor in all other industries, Δx_k^O, local demographic controls, $Q_{k,t}$, and any unobservable factors or noise, ϵ_k:

$$\Delta\alpha_k^D = \delta^R \Delta x_k^R + \delta^O \Delta x_k^O + \delta^Q Q_{k,t} + \epsilon_k \qquad (1.5).$$

Plugging equation (1.5) into equation (1.3) yields the parameterized wage function:

$$\Delta lnw_k = \alpha_1^w \Delta x_k^R + \gamma^w Q_k + \varphi_k^w \qquad (1.6)$$

with parameters:

$$\alpha_1^w = \delta^R \frac{1}{\varepsilon_l^S + \varepsilon_l^D} \qquad (1.7)$$

$$\gamma_w = \delta^Q \frac{1}{\varepsilon_l^S + \varepsilon_l^D} \qquad (1.8)$$

$$\varphi_k^w = (\delta^0 \Delta x_k^O + \epsilon - \Delta\alpha_k^S) \frac{1}{\varepsilon_l^S + \varepsilon_l^D} \qquad (1.9).$$

In order to answer the central question of this paper, how much of the rise in disability during the 2000s can be attributed to declining labor market opportunities, I estimate $\partial\Delta D_k/\partial\Delta x_k^R$ and $\partial\Delta D_k/\partial\Delta lnw_k$. To do so, I begin by characterizing the change in share of the local population who receives DI benefits, ΔD_k, as a function of real wage growth, Δlnw_k, and noise and unobservable factors, μ_k:

[17] In the analysis, I control for initial characteristics, Q_k, of the area that may affect the presence of disabled people in the area (large urban areas may have more public goods that make those areas palatable to the disabled such as accessible public transportation) or affect local preference for/stigma against government assistance. Any time-invariant attributes of the area drop out in differencing. Instrument is constructed using the employment counts for all civilian, non-institutional workers age 21-64. By constructing the instrument for all local prime-age workers, the analysis allows employment, wage and disability responses for specific groups (i.e. college women) to be affected by shocks to local labor demand aggregately allowing for group-specific spillovers. For example, dentists may experience wage declines if a large labor demand shock to routine workers reduces the customer base.

$$\Delta D_k = \theta \Delta lnw_k + \mu_k \qquad (1.10).$$

Substituting equations (1.3) and (1.5) into equation (1.10) and parameterizing yields a convenient linear expression for estimating the effect of a shock to routine occupation labor demand on local disability participation:

$$\Delta D_k = \beta_1^D \Delta x_k^R + \gamma^D Q_k + \varphi_k^D \qquad (1.11)$$

with parameters:

$$\beta_1^D = \delta^R \frac{\theta}{\varepsilon_l^S + \varepsilon_l^D} \qquad (1.12)$$

$$\gamma^D = \delta^Q \frac{\theta}{\varepsilon_l^S + \varepsilon_l^D} \qquad (1.13)$$

$$\varphi_k^D = (\delta^0 x_k^O + \epsilon - \Delta\alpha_k^S) \frac{\theta}{\varepsilon_l^S + \varepsilon_l^D} \qquad (1.14).$$

In this paper, I estimate $\partial\Delta D_k / \partial\Delta x_k^R$ and $\partial\Delta D_k / \partial\Delta lnw_k$ for the entire population of men and women age 21-64 and for finer groups based on skill, gender and age over the period 2000 to 2011. The OLS estimations run equation (1.11) on actual local routine occupation employment changes or equation (1.10) on actual changes in local wages. However, there are two main concerns in using the OLS estimation: endogeneity and measurement error. With respect to endogeneity, factors that affect local routine occupation employment and wages such as local labor supply shares or public health shocks may vary with time and across locations and also affect disability participation. With respect to measurement error, as discussed in Griliches and Hausman (1985), when using a differencing strategy in panel data estimations, it is desirable to use an external instrument beyond lagged values of relevant variables. To address both of these issues, I utilize an instrument to shock local routine occupation employment used in Autor and Dorn (2013). Specifically, I construct a shift-share instrument for routine employment following the construction and utilization of this type of instrument from Bartik (1991) and Blanchard and Katz (1992). The instrument, $\Delta\widehat{x_k}$, is expressed as:

$$\Delta\widehat{x_k} = \sum_{j=1}^{J} \vartheta_{k,j,t}(\rho_{.k,j,t+1} - \rho_{.k,j,t}) \quad (1.15)$$

where k indexes the MSA, *j* indexes three-digit routine occupations and *t* indexes time, $\vartheta_{k,j,t}$ is the initial endowment within an MSA of employment in occupation *j*, and $(\rho_{.k,j,t+1} - \rho_{.k,j,t})$ represents changes in national employment within an occupation with MSA *k* excluded.[18] The identifying assumption is that confounding changes in local routine employment such as a change in local taste for leisure or a local public health shock are exogenous to national changes in demand for labor in routine occupations. Furthermore, MSAs have distinct pre-existing mixes and levels of routine employment which allows national shocks to affect MSAs differentially.

The model employed in the main analysis obtains estimates for $\partial\Delta D_k/\partial\Delta\hat{x}_k^R$, the change in disability on the predicted change in routine occupation employment, from Two Stage Least Squares (2SLS). The first stage of the 2SLS model is characterized:

$$\Delta x_k^R = \beta_1^R \widehat{\Delta x}_k + \gamma^R Q_k + \varphi_k^R + \epsilon_k \quad (1.16).$$

The second stage, and the main equation used in estimation, is characterized as:

$$\Delta D_k = \beta_1^R \Delta\hat{x}_k^R + \gamma^R Q_k + \varphi_k^R + \epsilon_k \quad (1.17)$$

where $\Delta\hat{x}_k^R$ represents the predicted values from the regression of actual changes in routine occupation employment on the shift-share instrument, Q_k is a vector of controls, φ_k^R is unobservable and ϵ_k is a mean-zero regression error. The coefficient of interest, β_1^R, measures $\partial\Delta D_k/\partial\Delta\hat{x}_k^R$ the effect of a predicted change in local routine employment on changes in local disability rates defined as the number of people with non-zero DI payments/ population.

To estimate $\partial\Delta D_k/\partial\Delta lnw_k$, I utilize a Two-Stage Least Squares model (2SLS) with the first stage and second stage respectively:

[18] All estimations in this analysis are in first differences. Thus, any time-invariant differences --demographic, policy, or other-- across MSAs are differenced out. Over the main time period of interest, the 2000s, *t* is 2000 and *t+1* is 2011.

$$\Delta ln w_k = \alpha_1^w \Delta\widehat{x_k} + \gamma^w Q_k + \varphi_k^w + \epsilon_k \quad (1.18)$$

$$\Delta D_k = \beta_{1IV}^W \Delta\widehat{ln w_k} + \gamma^W Q_k + \varphi_k^W + \epsilon_k \quad (1.19)$$

The coefficient of interest, β_{1IV}^W, measures $\partial\Delta D_k/\partial\Delta ln\widehat{w}_k$ – the effect of the portion of local wages that is moved by the exogenous shock to routine employment on changes in local disability rates.[19] Equation (1.19) is the main estimating equation used in the analysis of the effect of predicted changes in wages on disability participation.

1.5 Data

The main analysis in this paper utilizes a panel of MSAs in the Census and the American Community Survey (ACS) over the entire 2000s. The panel is constructed from individual level extracts from the 2000 Census 5% file and the 2009-2011 ACS files from the Integrated Public Use Microsamples (IPUMS) database (Ruggles et. al., 2010). In order to improve precision of estimates, ACS sample years are pooled such that the years 2009, 2010 and 2011 represent the year 2011. The combined Census and ACS sample is restricted to the non-institutionalized population age 21-64 who self-identify as living in a MSA. There are 283 MSAs in the combined sample. The sample was collapsed at the MSA level and employment-to-population ratios, disability-to-population ratios, employment shares, and mean regression-adjusted log wages were computed for each MSA. MSA-level regressions have standard errors clustered at the state-level to account for potential correlation in error terms related to state-level policy which may be time-varying and thus not differenced out in estimation. All estimates are weighted by the population in a MSA in year 2000 in order to assign greater weight to cells with less noise. Table 1.1 displays summary statistics of interest from the Census and the ACS at the MSA level.

[19] ΔD_k in these estimations is defined as the log difference in local disability rates over time in order to yield an elasticity.

This paper utilizes the historical March Current Population Survey (CPS) for the years 2000 to 2013 to establish national trends in routine employment shares, disability-to-population ratios, and employment-to-population ratios. Further, I use a state-level panel from the CPS from 1998-2000 and 2009-2011 to perform a robustness check on the main results in this paper at the state level. In order to improve precision of estimates, CPS sample years are pooled such that the years 1998, 1999 and 2000 represent the year 2000 and 2009, 2010 and 2011 represent the year 2011. The sample is constructed from individual level extracts from the IPUMS CPS database (King et. al., 2010). As with the Census and the ACS, the sample is restricted to the non-institutionalized population age 21-64.

In addition to public use microdata, this paper also utilizes aggregate administrative data from the SSA, *The Annual Statistical Report on the Social Security Disability Insurance Program*, for the years 2000-2013. This data is released in both brochure and extractable table form on the SSA public website. It provides national and state level data on DI and SSI program participation including aggregate statistics on payments, participation counts, and exit and participation counts disaggregated by diagnostic group. This paper uses the participation counts disaggregated by diagnostic group by state and merges that data to Census/ACS state-level population counts for people age 21-64 to estimate participation rates per diagnostic group. Table A1.1 of the Appendix displays summary statistics of interest from the SSA claims data, the Census and the ACS, and the Historical March CPS at the state level.

Variable Definitions:

In a simple framework, routine occupations are displaced by skill-biased technological change. Specifically, routine occupations involve tasks that can be performed by a mechanized process or a computer whereas computers are complements to abstract occupations and cannot replace manual occupations. In Autor, Levy, and Murnane (2003), Dorn (2009) and Autor and Dorn (2013), routine occupations are classified utilizing task descriptions from the fourth edition of the U.S. Department of Labor's Dictionary of Occupational Titles (DOT).[20] The task-based classification system is broad. Replicating the classification system employed in Dorn (2009) and Autor and Dorn (2013) yielded 117 routine three-digit occupations including occupations that typically cannot be replaced by computerization or automation, such as veterinarians, painters and sculptors, and lawyers and judges. The bulk of the occupation codes that are identified by the Autor/Dorn measure are in the manufacturing or administrative service sectors and are reasonably displaced by automation or computerization. Thus, this paper employs a sector-based definition of routine employment. Routine occupations are defined as three-digit occupations codes that correspond to employment in the manufacturing or administrative services sectors. The sector-based definition of routine occupations, employed in this paper, identifies 94 three-digit occupations. Across data sets, routine employment is decreasing over the 2000s. In 2000, routine employment for all men and women age 21-64 in the Census was 16.1% compared to 15.6% in the historical March Current Population Survey (CPS). This fell to 13.6% and 12.6% in 2011 in the ACS and CPS respectively. Notably, routine occupations as identified by the task-based system did not experience as dramatic declines over the entire 2000s as those identified by the sector-based system: in the CPS from 2000 to 2013 task-based and sector-based routine employment fell by 2.2 percentage points and 3.2 percentage points respectively.[21]

[20] Abstract tasks score high in managerial and interpersonal tasks and quantitative reasoning requirements. Routine tasks which are cognitive in nature involve setting limits, tolerances or standards and routine tasks which are manual in nature involve high values for finger dexterity. Manual tasks involve high values for eye-hand-foot coordination. In order to classify an occupation *j* as routine, a routine index is calculated

$$R_j = \ln(r_{j,1980}) - \ln(a_{j,1980}) - \ln(m_{j,1980})$$

where r_j represents a 0 to 10 intensity score for routine tasks, a_j represents a 0 to 10 intensity score for abstract tasks and m_j represents a 0 to 10 intensity score for manual tasks. Dorn (2009) ranks three-digit occupation codes by R_j and classifies the top 1/3 as routine occupations.

[21] For robustness, the complete list of routine occupations used in this paper is also available in Table A1.9 of the Appendix. Additionally, the routine occupations used in a task-based approach are provided in Table A1.10 of the Appendix.

A key independent variable is mean wage growth in a MSA. Wages are computed for individuals with strong labor force attachment—workers with full-time employment and few prior non-employment spells. Full-time employment is characterized as working 30 hours a week with minimum income in the prior year of $5,000. Few previous non-employment spells are characterized by working a minimum of 48 weeks in the prior year. Wages are regression-adjusted by age (flexible), weekly hours worked, highest grade of schooling completion and race (where race other than Caucasian or African American is the excluded group). Mean regression-adjusted wage growth from 2000 to 2011 for all prime-age men and women was -8.7%. In comparison, without adjusting wages, mean wage growth from 2000 to 2011 for all prime-age men and women was -2.3%.

The Census and ACS do not track disability per se. In order to measure disability in these data sets, I use a proxy measure. The disability rate, D_k, is constructed from the Social Security Income variable (INCSS) which includes survivor's benefits, U.S. Government railroad retirement pension benefits, DI income, and retirement income. A person with a non-zero value for INCSS who is not in the labor force and under the age of 65 is classified as disabled. This variable is a proxy for the true DI rate and may include participants in the survivor benefits and railroad pensions programs or early recipients of Social Security retirement income. In the main sample, the disabled were more likely to be older, female, and less educated than the non-disabled. In the sample year 2011 among the disabled, 54% were female; the median age was 59 and 96% of the disabled lacked four-year college attainment. In contrast, in the 2011 sample among the non-disabled, 51% were female; the median age was 40 and 73% of the sample lacked four-year college attainment. Table A1.2 of the Appendix compares changes in disability rates at the state level across the Census/ACS, SSA Administrative data and the Historical March CPS. Across data sets, the disability rate is increasing over the 2000s. In 2000, the Census proxy DI measure is smaller than the administrative measure from the SSA while the CPS measure is larger. In 2011, both the ACS and CPS proxy DI measures are smaller than the SSA administrative measure.

Thus, it appears that the main proxy measure used in this analysis, the Census/ACS DI rate, is not over-counting the disabled.

In the SSA data, disability rates are calculated for each state for easily verifiable disabilities and harder-to-verify disabilities. Easily verifiable disabilities include all claim types that are not mental or musculoskeletal claims including congenital anomalies, endocrine, nutritional, and metabolic diseases, infectious and parasitic diseases, injuries, neoplasms, and diseases of the: blood and blood-forming organs, circulatory system, digestive system, genitourinary system, nervous system and organs, respiratory system, skin and subcutaneous tissue. Harder-to-verify disabilities include mental and musculoskeletal diseases. Disability rates for these claims are defined as the count of persons with these claims per state divided by the state population of men and women age 21-64. In 2011, 62.6% of disabilities with claim information were classified as mental and musculoskeletal claims, 34.5% with claim information of disabilities were classified as all other claims, and the remaining 2.9% had undisclosed claim information.

Table 1.1 Descriptive Statistics: MSA-level Census & ACS

				Percentiles				
	N	Mean	St. Dev.	Min	25	50	75	Max
Labor market variables 2000-2011								
Non-college men and women 21-64								
Δ employment rate (pp)	283	-0.025	0.037	-0.152	-0.050	-0.029	0.000	0.113
Δ disability rate (pp)	283	0.012	0.008	-0.011	0.006	0.010	0.015	0.059
Δ ln(residualized wages)	283	-0.087	0.048	-0.238	-0.120	-0.092	-0.057	0.109
Δ Share of Pop Employed in Routine Occ (pp)	283	-0.030	0.013	-0.101	-0.038	-0.028	-0.022	0.014
All men and women 21-64								
Δ employment rate (pp)	283	-0.019	0.030	-0.144	-0.038	-0.021	0.001	0.100
Δ disability rate (pp)	283	0.009	0.007	-0.008	0.004	0.008	0.012	0.055
Δ ln(residualized wages)	283	-0.078	0.042	-0.237	-0.103	-0.084	-0.051	0.075
Δ Share of Pop Employed in Routine Occ (pp)	283	-0.025	0.010	-0.091	-0.030	-0.023	-0.018	0.013

Table 1.1 Cont'd Descriptive Statistics MSA-level Census & ACS

	N	Mean	St. Dev.	Percentiles				
				Min	25	50	75	Max
2000 baseline controls MSAs								
population	283	734522	3143055	74106	117043	209261	476333	4.97E+07
share of population African American	283	10.1%	10.0%	0.2%	2.3%	6.9%	14.2%	46.1%
share of employed with college attainment	283	25.7%	7.1%	12.6%	20.4%	24.7%	29.6%	53.2%
share of population age 21-25	283	11.8%	3.4%	5.4%	10.0%	11.1%	12.6%	29.9%
share of population age 26-30	283	11.8%	1.4%	7.3%	10.8%	11.7%	12.7%	15.7%
share of population age 31-35	283	12.2%	1.04%	8.9%	11.5%	12.3%	12.9%	14.9%
share of population age 36-40	283	14.0%	1.02%	10.4%	13.4%	14.0%	14.6%	17.1%
share of population age 41-45	283	13.6%	0.96%	9.7%	13.1%	13.7%	14.2%	16.8%
share of population age 46-50	283	12.1%	0.96%	8.0%	11.6%	12.1%	12.6%	14.8%
share of population age 51-55	283	10.1%	1.04%	6.4%	9.5%	10.2%	10.8%	14.1%
share of population age 56-60	283	7.9%	1.2%	5.0%	7.1%	7.8%	8.5%	13.4%

Note: Data is from the 2000 Census and the American Community Survey 2009-2011. 2011 is pooled years 2009, 2010, 2011. Unit of Observation is the Metropolitan Statistical Area (MSA). Sample includes all people 21-64 who do not live in institutions and have an assigned MSA. Weights = cell size in 2000. Routine occupations represent manufacturing and administrative services occupations.

1.6 Results

The analysis begins with estimations of equation (1.17), the effect of a predicted change in routine employment on change in local disability rates:

$$\Delta D_k = \beta_1^R \Delta\hat{x}_k^R + \gamma^R Q_k + \varphi_k^R + \epsilon_k \, .$$

In these estimations, the change in the disability rate is a response to a shock to local routine labor demand. In the analysis, I control for initial characteristics, Q_k, of the area that may affect the presence of disabled people in the area (large urban areas may have more public goods that make those areas palatable to the disabled such as accessible public transportation) or affect local preference for/stigma against government assistance. Formally, Q_k controls for total prime-age population, share of the labor force with college attainment, share of the population that is African American, and age demographics.[22] As the model is difference-in-differences, any time-invariant characteristics of the MSA which may affect disability fall out in estimation. Across specifications, the following results provide clear evidence of a causal relationship between weakening labor markets and rising disability participation.

Likewise, predicted declines in wages cause increases in local disability rates. The wage regressions estimate equation (1.19) and yields estimates for $\partial\Delta D_k / \partial\Delta\widehat{lnw_k}$:

$$\Delta D_k = \beta_{1IV}^W \Delta\widehat{lnw_k} + \gamma^W Q_k + \varphi_k^W + \epsilon_k$$

In these estimations, the change in the disability rate is a response to a shock to local wages. As in the employment regressions, I control for initial characteristics, Q_k, of the area that may affect the

[22] The specification without Q_k yields slightly larger results. For all prime-age men and women the regression coefficient for equation (1.17) estimated with Q_k is -0.30 with standardized coefficient -0.0032. For all prime-age men and women the regression coefficient for equation (1.17) in reduced form is -0.49 with standardized coefficient -0.0043. Both models are strongly statistically significant.

presence of disabled people in the area or affect local preference for/stigma against government assistance.

1.6.1 First Stage Results:

The central goal of this paper is to test a causal link between declining employment associated with technological change and increased disability participation. As detailed in Section 1.4, the main analysis in this paper involves shocking local routine employment through the use of a shift-share instrument. The first stage is characterized as:

$$\Delta x_k^R = \beta_1^R \widehat{\Delta x_k} + \gamma^R Q_k + \varphi_k^R + \epsilon_k$$

where Δx_k^R represents the actual change in routine employment in MSA *k*, $\Delta\widehat{x_k}$ represents the national change in routine employment, excluding MSA *k*, interacted with the initial endowment of routine employment in MSA *k* at time *t*, Q_k represents a vector of local demographic controls in time *t*, φ_k^R represents unobservable factors, and ϵ_k represents mean-zero regression error.

Figure A1.1 of the Appendix provides graphical evidence of the strength of the first stage over the entire 2000s. The slope coefficient from the regression of actual changes in routine employment on predicted changes in routine employment from 2000 to 2011 is 1.25 with standard error 0.19. The final row of Table 1.2 and the final row of the top panel of Table 1.5 display the first stage F statistics from the change in routine employment shares on the shift-share routine instrument by gender and educational attainment and by age and educational attainment. With first stage F statistics ranging from 62.9 to 90.2, the instrument strongly predicts actual changes in routine employment.

This paper also explores the effect of changes in wages resulting from technological change on disability participation. In doing so, I predict wage changes using the shift-share routine instrument. The first stage for the wage regression is characterized as:

$$\Delta lnw_k = \alpha_1^w \Delta\widehat{x_k} + \gamma^w Q_k + \varphi_k^w + \epsilon_k$$

where Δlnw_k is the actual change in the log of mean regression-adjusted wages in MSA *k*, $\Delta\widehat{x_k}$ represents the predicted change in routine employment in MSA *k*, Q_k represents a vector of local demographic controls in time *t*, φ_k^w represents unobservable factors, and ϵ_k represents mean-zero regression error.

Table 1.3 estimates the first stage for the 2SLS wage model and obtains estimates for $\partial\Delta lnw_k/\partial\Delta\widehat{x_k}$. The first stage F statistics for the 2SLS wage model are displayed in the final row of Table 1.4. For non-college prime-age men and women, the first stage F statistics are 11.3 and 12.2 respectively indicating the first stage for the ensuing 2SLS model is strong. The first stage is not strongly predictive for college women with a first stage F statistic of 4.2.

1.6.2 Results by Gender and Skill Attainment

Table 1.2 estimates equation (1.17) for gender, skill attainment groups from 2000 to 2011 in order to obtain estimates for $\partial\Delta D_k/\partial\Delta\hat{x}_k^R$. In all tables estimating equation (1.17), each column represents a gender and educational attainment (age and educational attainment) group. The top row represents the regression coefficient with the row below the standard errors presenting standardized coefficients, the regression coefficient scaled by a 1 cross-MSA standard deviation change in predicted routine employment, for ease in comparison of results across specifications. The rows below the standardized coefficients represent the mean change in disability for the group of interest (for example, men without four-year college attainment) weighted by the group population in MSA *k* in year 2000, the mean actual change in routine occupation employment for all prime-age men and women weighted by the group population in MSA *k* in year 2000, and the mean value of the shift-share routine instrument for all prime-age men and women weighted by the group population in MSA *k* in year 2000.

The fifth column represents results for all prime-age men and women. Moving from the 10th to the 90th percentile of the predicted decline in local routine employment corresponded to a 0.82

percentage point increase in disability. The first and second columns present results for groups of particular interest, men and women without four-year college attainment. Due to the progressive nature of the DI income replacement formula, a reasonable prediction would be for stronger effects among the non-college population in comparison to groups with four-year college attainment. Indeed, the largest effects are for non-college men and non-college women. Moving from the 10th to the 90th percentile of the predicted decline in local routine employment corresponded to 1.02 and 1.13 percentage point increase in the local disability rate for these groups respectively. The mean cross-MSA increases in disability for these groups over 2000 to 2011 were 1.10 and 1.3 percentage points respectively. In contrast, the effects for college men and women over this period were in fact smaller. Moving from the 10th to the 90th percentile of the predicted decline in local routine employment corresponded to 0.02 and 0.15 percentage point increase in the local disability rate for these groups respectively. The mean cross-MSA increases in disability for these groups over 2000 to 2011 were 0.6 and 0.7 percentage points respectively.

Estimating this model by OLS yields smaller coefficients; this is consistent with attenuation bias arising from measurement error in the time series. Table A1.7 of the Appendix presents results from the OLS model (changes in disability on actual changes in routine occupation employment shares to results). For all prime-age women, the coefficient for the effect of changes in actual routine employment on changes in disability is -0.18 compared with -0.30 from the 2SLS estimates with a standardized coefficient of -0.0025 compared with a standardized coefficient from the 2SLS model of -0.0032.

Moving on to the analysis of the effect of wage changes on disability participation, Table 1.4 estimates equation (1.19) and yields estimates for $\partial \Delta D_k / \partial \Delta ln\widehat{w}_k$. The top panel of Table 1.4 provides OLS results with the bottom panel presenting results from the 2SLS regression. As with the tables estimating equation (1.17), the columns in these tables represent gender by educational attainment (age by educational attainment) groups with the fifth column providing results for all prime-age men and women. For all prime-age men and women, the disability participation elasticity with respect to predicted wages recovered from the 2SLS model is -2.49 in comparison to OLS estimates for the disability participation elasticity with respect to actual wages of -0.79 Again, due to the progressive nature of the DI benefits replacement formula, results for men and women without four-year college attainment are of particular interest. For non-college men, the disability participation elasticity with respect to wages from the 2SLS model is -2.39 in comparison to OLS estimates of -0.59.

It should be noted that the estimated elasticities for women are larger than those estimated for men. For non-college women, the disability participation elasticity with respect to wages from the 2SLS model is -3.83 compared to -2.39 for non-college men. However, the effects for men and women are much closer in the employment counts model. Comparing the regression coefficients presented in Column 1 and 2 of Table 1.2, the effects of predicted changes in routine occupation employment on DI participation were -0.381 and -0.409 for non-college men and women respectively.

Table 1.2 Change in Disability in Response to Predicted Change in Routine Occupation Employment Age 21-64, By Skill Attainment: 2000-2011

	Non-college Men	Non-college Women	College Men	College Women	All
$\beta_{\Delta \text{ predicted routine share all}}$	-0.381	-0.409	-0.009	-0.058	-0.301
robust standard error	0.081	0.082	0.087	0.077	0.065
1σ standardized effect	-0.0040	-0.0044	0.000	-0.0006	-0.0032
mean Δ disability rate	0.011	0.013	0.006	0.007	0.009
mean actual Δ routine share all	-0.025	-0.024	-0.025	-0.025	-0.025
mean Δ predicted routine share all	-0.025	-0.025	-0.025	-0.025	-0.025
First Stage F Statistic	85.2	79.0	62.9	65.9	77.6

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects for IV re-scaled by 1 standard deviation in predicted change in routine employment shares. First stage for 2SLS: change in routine employment on routine shift-share instrument. Data: 2000 Census and American Community Survey. 2011 is pooled 2009, 2010, 2011. Routine occupations represent manufacturing and administrative service occupations.

Table 1.3 Change in Wage in Response to Change in Routine Occupation Employment Age 21-64, By Skill Attainment 2000-2011

	Non-college Men	Non-college Women	College Men	College Women	All
$\beta_{\Delta \text{ routine shift-share instrument}}$	4.054	2.258	3.170	1.891	3.200
robust standard error	1.207	0.646	1.042	0.922	0.908
1σ standardized effect	0.0282	0.0157	0.0220	0.0131	0.0222
mean Δ ln(residualized wages)	-0.087	-0.037	0.016	0.065	-0.078
mean actual Δ routine share all	-0.025	-0.024	-0.025	-0.025	-0.025
mean Δ routine shift-share instrument all	-0.009	-0.009	-0.008	-0.008	-0.009
Adjusted R^2	0.27	0.34	0.19	0.16	0.29

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects re-scaled by 1 standard deviation in residualized wage growth. Data: 2000 Census and American Community Survey. 2011 is pooled 2009, 2010, 2011. Routine occupations represent manufacturing and administrative services occupations.

Table 1.4 Change in Disability in Response to Change in Wages: Actual and Predicted by Change in Routine Occupation Employment Age 21-64, By Skill Attainment 2000-2011

	Non-college Men	Non-college Women	College Men	College Women	All
OLS					
estimated DI participation elasticity	-0.590	-0.448	-0.714	-0.616	-0.792
robust standard error	0.238	0.306	0.510	0.587	0.286
1σ standardized effect	-0.040	-0.022	-0.057	-0.038	-0.037
mean Δ ln(disability rate)	0.262	0.286	0.388	0.409	0.263
mean Δ ln(residualized wages)	-0.087	-0.037	0.016	0.065	-0.078
2SLS					
estimated DI participation elasticity	-2.394	-3.826	-1.928	-3.724	-2.485
robust standard error	0.831	1.115	1.531	2.213	0.773
1σ standardized effect	-0.082	-0.101	-0.069	-0.088	-0.072
mean Δ ln(disability rate)	0.262	0.286	0.388	0.409	0.263
mean Δ ln(residualized wages)	-0.087	-0.037	0.016	0.065	-0.078
mean predicted Δ ln(residualized wages)	-0.072	-0.021	0.013	0.069	-0.069
First Stage F Statistic	11.3	12.2	9.2	4.2	12.4

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects for OLS re-scaled by 1 standard deviation in growth in residualized wages. Standardized effects for IV re-scaled by 1 standard deviation in predicted growth in residualized wages. First stage for 2SLS: residualized wages on routine shift-share. Wages: full-time, regression-adjusted. Data: 2000 Census and American Community Survey. 2011 is pooled 2009, 2010 2011. Routine occupations represent manufacturing and administrative services occupations.

1.6.3 Results by Age and Educational Attainment

As documented in Parsons (1980) and Bound (1989), effects may be expected to differ by age and skill attainment. Specifically, one may predict larger effects among low-skill, older men and women, those with the poorest reemployment prospects following separation. This sub-section disaggregates results by age and skill attainment groups with the young population represented as ages 25-44, the middle-age population represented as ages 45-54 and the pre-retirement population represented as ages 55-64. I find larger effects of predicted changes in routine employment on disability for the pre-retirement group, but smaller effects of predicted changes in wages on disability for the pre-retirement group.

The first panel of Table 1.5 estimates equation (1.17) for each group over 2000 to 2011. The fifth column presents results for all men and women age 55-64 without four-year college attainment. For non-college pre-retirement men and women, moving from the 10th to the 90th percentile of the predicted change in local routine employment corresponds to a 2.07 percentage point increase in the local disability rate. In comparison, for men and women age 25-44 without four-year college attainment, moving from the 10th to the 90th percentile of the predicted change in local routine employment corresponds to a 0.67 percentage point increase in the local disability rate.

The second panel of Table 1.5 estimates first stage wage equation results for each age, skill group. The final row of Table 1.5 presents F statistics from the first stage. The first stage is most predictive for those aged 25 to 44 with first stage F statistics of 14.9 and 14.4 for non-college and all men and women respectively. The first stage is less predictive for those age 45 to 54 and 55 to 64 with first stage F statistics ranging from 6.3 to 9.3. The third panel of Table 1.5 estimates equation (1.19) to obtain estimates for $\partial \Delta D_k / \partial \Delta \widehat{\ln w_k}$ for each age, skill group. Standardized effects of predicted changes in wages on disability participation are larger for the young and middle-age groups than for the pre-retirement groups. For non-college and all men and women age 25-44, standardized effects are -0.15 and -0.14 respectively. For non-college and all men and women age 45-54, standardized effects are -0.11 and -0.098 respectively. In comparison, for non-college and all men and women age 55-64, standardized effects are -0.057 and -0.037 respectively.

Table 1.5 Change in Disability in Response to Predicted Change in Routine Occupation Employment, Wages By Age*Skill Attainment: 2000-2011

	Non-college 25-44	All 25-44	Non-college 45-54	All 45-54	Non-college 55-64	All 55-64
Δ Disability x Δ in Routine Employment						
$\beta_{\Delta \text{ predicted routine share all}}$	-0.242	-0.179	-0.287	-0.216	-0.761	-0.542
robust standard error	0.067	0.050	0.084	0.068	0.185	0.176
1σ standardized effect	-0.0026	-0.0019	-0.0031	-0.0023	-0.0081	-0.0057
mean Δ disability rate	0.003	0.001	0.009	0.007	0.003	-0.002
mean actual Δ routine share all	-0.024	-0.025	-0.025	-0.025	-0.025	-0.025
mean Δ predicted routine share all	-0.025	-0.025	-0.025	-0.025	-0.025	-0.025
First Stage F Statistic	78.5	74.2	87.8	82.6	90.2	83.9
Δ Wages x Δ Routine Employment						
$\beta_{\Delta \text{ routine shift-share instrument}}$	3.569	3.430	2.754	2.705	2.569	2.892
robust standard error	0.939	0.886	1.104	1.030	0.978	0.949
1σ standardized effect	0.025	0.024	0.019	0.019	0.018	0.020
mean Δ ln(residualized wages)	-0.096	-0.087	-0.067	-0.067	-0.108	-0.106
mean actual Δ routine share all	-0.024	-0.025	-0.025	-0.025	-0.025	-0.025
mean Δ routine shift-share instrument all	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009
Adjusted R^2	0.37	0.30	0.21	0.22	0.10	0.11

Table 1.5 Cont'd Change in Disability in Response to Predicted Change in Routine Occupation Employment, Wages By Age*Skill Attainment: 2000-2011

	Non-college 25-44	All 25-44	Non-college 45-54	All 45-54	Non-college 55-64	All 55-64
Δ Disability x Δ Wages						
estimated disability participation elasticity	-4.677	-4.661	-3.253	-3.003	-2.100	-1.346
robust standard error	1.605	1.659	1.500	1.339	0.990	0.704
1σ standardized effect	-0.153	-0.140	-0.108	-0.098	-0.057	-0.037
mean Δ ln(disability rate)	0.163	0.080	0.275	0.267	0.019	-0.015
mean Δ ln(residualized wages)	-0.096	-0.087	-0.067	-0.067	-0.108	-0.106
mean predicted Δ ln(residualized wages)	-0.073	-0.072	-0.059	-0.063	-0.105	-0.107
First Stage F Statistic	14.4	14.9	6.3	6.9	6.9	9.3

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects for IV in top panel re-scaled by 1 standard deviation in predicted change in routine employment shares. First stage for 2SLS top panel: change in routine employment on routine shift-share. Standardized effects for residualized wages on routine shift-share regression re-scaled by 1 standard deviation in growth in residualized wages. Standardized effects for IV in bottom panel re-scaled by 1 standard deviation in predicted growth in residualized wages. First stage for 2SLS bottom panel: residualized wages on routine shift-share. Wages: full-time, regression-adjusted. Data: 2000 Census and American Community Survey. 2011 is pooled 2009, 2010, 2011 Routine occupations represent manufacturing and administrative services occupations.

1.6.4 Migration

Blanchard and Katz (1992) famously highlighted the importance of regional migration in response to unemployment shocks. Glaeser and Gyourko (2005) document that college workers out-migrate when a city receives a negative labor demand shock. Topel (1986), and Bound and Holzer (2000) establish that non-college workers are less mobile than college workers. Notowidigdo (2011) attributes the immobility of non-college workers to lower incidence for non-college workers of adverse demand shocks due to the progressive nature of transfer program eligibility formulas.

The IPUMS data allows identification of migration over 5 years in the 2000 Census and over one year in the ACS. In 2000, migrants are identified as those who have moved into the MSA in the last 5 years. In 2011, migrants are identified as those who have moved into the MSA in the last year. Local populations of prime-age adults are overwhelmingly composed of people who have not moved into the MSA in the last year. In 2011, the cross-MSA mean ratio of migrants to local population was 6.8%. However, the issue of migration could be important to the question of disability with respect to selection bias. If during the period of interest, the most employable workers migrated out of areas which received negative routine employment shocks, the effects estimated for $\partial \Delta D_k / \partial \Delta x_k$ and $\partial \Delta D_k / \partial \Delta lnw_k$ would be biased upward.

The analysis in Tables A1.3 and A1.4 of the Appendix address the question of selection bias by estimating equation (1.17) for migrants and non-migrants. The analysis in Tables A1.3 and A1.4 suggests that migrants do not have stronger attachments to the labor force than non-migrants. Over the 2000s (2000 to 2011), the disability rate among all prime-age non-migrants increased, on average, by 0.6 percentage points. The disability rate among all prime-age migrants also increased, on average, by 0.6 percentage points.[23] Table A1.3 estimates equation (1.17) for non-college men and women and all prime-age men and women by migration status with the top panel estimating effects for non-migrants, the bottom panel estimating effects for migrants. For all prime-age men and women, moving from the 10th to the 90th percentile of the predicted decline in local routine employment corresponded to a 0.72 percentage point increase in disability for non-migrants and a 0.77 percentage point increase for migrants. For non-college men and all prime-age men and women, the effects are larger for migrants than non-migrants. For non-college women the effects are smaller for migrants, however they are not significant.

Table A1.4 estimates equation (1.17) over the 2000s (2000 to 2011) for migrants and non-migrants by age, educational attainment with the top panel estimating effects for non-migrants, the bottom panel estimating effects for migrants. For non-college men and women age 55-64, moving from the 10th to the 90th percentile of the predicted routine occupation employment corresponds to a 1.51 percentage point increase in disability for non-migrants and a 2.69 percentage point increase for migrants. For non-college men and women age 25-44, moving from the 10th to the 90th percentile of the predicted routine occupation employment corresponds to a 0.59 percentage point increase in disability for non-migrants and a 1.05 percentage point increase for migrants. For non-college men and women age 45-54, standardized effects were larger for non-migrants, however they were not significant.

Ex ante, a specific form of selection bias that could not be eliminated by the shift-share instrument or through the differencing strategy was of potential concern—out-migration of those

[23] From 2000 to 2011, it would appear that the employment rate for prime-age migrants decreased by 7.56 percentage points while the employment rate for non-migrants decreased by 1.80 percentage points. However, these figures may be misleading because migrants in the 2000 Census have 5 years to assimilate to a MSA and locate employment while migrants in the ACS (2011) have 1 year to locate employment. In comparing disability rates among migrants in the Census and migrants in the ACS, the same measurement issue may not be as concerning as DI is a federal program.

with the strongest attachment to the labor market. Ex post, the analysis in this section suggests that this form of selection bias was not at play as migrants composed a small portion of local populations in the periods of interest and the analysis in Tables A1.3 and A1.4 shows that disability effects among migrants were of larger magnitude than those for non-migrants. Combined, these results suggest that effects estimated in Sections 1.6.2 and 1.6.3 and counterfactual estimates obtained in Section 1.7 may be conservative.

1.6.5 Results by Diagnostic Claim Type

Naturally, previous economic work on disability and weakening labor markets has attempted to address the mechanism. Mueller, Rothstein and von Wachter (2013) provide a helpful framework for considering the cases for counter-cyclicality in disability. One case is that employers may be less-inclined to hire workers who are limited by a disability in tight labor markets. This is the "true" disability case. The moral hazard case follows Black, Daniel and Sanders (2002) and Autor and Duggan (2003)—a worker with a disability that does not inhibit work applies for benefits when his reservation wage, the DI transfer, exceeds his market wage. The final case, another moral hazard case, is that workers use DI to insure against employment, not wage, losses. Autor and Duggan provide some descriptive evidence that is suggestive of moral hazard. They show that relative to cohorts who entered disability rolls prior to the 1984 liberalization, post-1984 cohorts tended to be younger and have higher distributions of diagnostic claims in low mortality diseases such as mental and musculoskeletal claims.

My ideal exercise to shed light on the mechanism at play would be to separately estimate equation (1.17) by diagnostic claims that may be more difficult to independently verify, mental and musculoskeletal claims, and diagnostic claims that are more easily independently verified, all other claims. Through the *Annual Statistical Report on the Social Security Disability Insurance Program*, the SSA provides information on DI claims by diagnostic type annually. The finest level of disaggregation provided is the state. Thus, I modified the strategy used elsewhere in this paper and exploit cross-state labor market variation. I use participation counts disaggregated by diagnostic claim type by state and Census/ACS state-level population counts for people age 21-64 to estimate participation rates per diagnostic group.

Descriptively, I observe larger increases in harder-to-verify claims than easily verified claims over both time periods. Over the entire 2000s (2000 to 2011), mental and musculoskeletal (such as back pain) claims rates increased by 1.4 percentage points where the disability rate for all other claims combined increased by 0.5 percentage points.

Table 1.6 estimates equation (1.17) for mental and musculoskeletal claims and all other claims for 2000 to 2011. Moving from the 10th to the 90th percentile of the predicted decline in routine employment corresponded to a 0.44 percentage point increase in mental and musculoskeletal claims compared to a 0.15 percentage point increase for all other claim types. These results are suggestive of moral hazard in that states with weak labor markets saw much greater increases in harder-to-verify disabilities.

Table 1.6 Change in Disability in Response to Predicted Change in Routine Occupation Employment Age 21-64, By Claim Type: 2000-2011

2000-2011	Mental and Musculoskeletal	All Other
$\beta_{\Delta \text{ predicted routine share all}}$	-0.196	-0.075
robust standard error	0.079	0.026
1σ standardized effect	-0.0017	-0.0006
mean Δ disability type rate	0.014	0.005
mean actual Δ routine share all	-0.025	-0.025
mean Δ predicted routine share all	-0.024	-0.024
First Stage F Statistic	77.7	77.7

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 50 states. Weights = state population age 21-64 in year t. Standardized effects for IV re-scaled by 1 standard deviation in predicted change in routine employment shares. First stage for 2SLS: change in routine employment on routine shift-share. Data: 2000 Census, American Community Survey, Annual Statistical Report on SSDI 2000 and 2011. In ACS: 2011 is pooled 2009, 2010, 2011. Routine occupations represent manufacturing and administrative services occupations.

1.6.6 Robustness

There are two ancillary concerns with regard to the main results of this paper. These concerns, discussed briefly here, are addressed in detail in A1.1 Robustness Appendix. The first is whether the effects of routine employment losses on disability over the decade reflect contamination from the recession. I explore this issue by conducting the main analysis in the period pre-dating the great recession, 2000 to 2007. For all prime-age men and women, the coefficient for the effect of predicted employment losses on disability, which is presented in Table A1.5 of the Appendix, is similar to that obtained for the period 2000 to 2011 with coefficients -0.34 and -0.30 respectively and smaller magnitude standardized effects over the pre-recessionary period, -0.0024 compared with -0.0032 over the entire 2000s. The analysis shows that the main results, while smaller in magnitude, are present even before the Great Recession. Consistent with the main results, effects are larger for those without college attainment.

The second concern is whether the main results are unique to Census/ACS data or can be replicated in another large public data set, the Historical March CPS. I replicate the main analysis at the state-level in the Census/ACS and the Historical March CPS. Estimates for the effect of declining routine labor demand on disability participation yield similar results with regression coefficients -0.204 and -0.199 in the Census/ACS and CPS respectively. Further, as in the previous results in this paper, disability participation is highly elastic to predicted wage changes associated with technological change. However, the first stage is not strongly predictive in the state-level panels in either data set and the elasticity from the CPS is almost twice as large as that estimated from the Census/ACS with respective elasticities of -3.08 and -1.67 respectively.

1.7 Counterfactual Estimates

The results presented in Section 1.6 establish a strong causal relationship between weakening labor demand in routine occupations and increasing DI participation and offer a potential mechanism, moral hazard. However, some questions remain: How much of the increase in DI over the last decade can be attributed to weakening labor demand? Finally, how much do movements into DI contribute to the current decline in employment?

Table 1.7 addresses these questions by applying the model to national values for changes in the disability-to-population and routine occupation employment shares from the ACS. Formally, Table 1.7 obtains estimates for the share of the actual change in disability that can be explained by the shift-share routine instrument. Each column represents a gender, educational attainment group. The first row presents regression coefficients obtained from estimates of equation (1.17) in Table 1.2. The second row presents actual cross-MSA mean changes in routine employment shares for all prime-age men and women weighted by the MSA population of the gender, skill group of interest in the year 2000. The third row presents actual cross-MSA mean changes in disability. The fourth row presents predicted cross-MSA mean changes in disability (multiplying row 1 by row 2). The final row presents the main value of interest: the share of the actual change in disability predicted by the model (row 4 divided by row 3).

Over the 2000s, the model predicts an increase in disability of 0.7 percentage points for all prime-age men and women. The actual change in disability for all prime-age men and women over this period was 0.9 percentage points. Thus, the model accounts for 79% of the increase in disability over this period. Dividing the predicted change in disability, 0.7 percentage points, by the change in employment for all prime-age men and women from 2000 to 2011, 7.2 percentage points, the share of the decrease in employment explained by increases in disability due to softening labor markets is 10.3%.

The model is also strongly predictive for those without four-year college attainment. Column 1 of Table 1.7 presents results for non-college men. The actual change in disability for non-college men over this period was 1.1 percentage points. The model predicts an increase in disability of 0.9 percentage points. Thus, the model accounts for 87% of the increase in disability for prime-age men without college attainment over the 2000s. The share of the change in employment for non-college men explained by increases in disability due to softening labor markets is 8.2%. Column 2 of Table 1.7 presents results for non-college women. The actual change in disability was 1.3 percentage points whereas the model predicted an increase of 1.0 percentage points. The model explains 76% of the increase in disability for prime-age non-college women over the 2000s. This accounts for 13.8% of the change in employment for non-college women from 2000 to 2011.[24]

Together, the counterfactual results in this section suggest that the increases in disability over the entire 2000s (2000 to 2011) are largely attributed to the decline in routine occupation labor demand over this period with 87% of the increase for prime-age non-college men attributed to predicted declines in routine labor demand. Over the entire 2000s, a considerable portion of the decline in employment is explained by increases in disability resulting from technological change. About 8.2% of the decline in employment for non-college men, 13.8% of the decline in employment for non-college women and approximately 10.3% of the decline in employment for all men and women over the 2000s can be attributed to increases in disability resulting from softening routine occupation labor demand.

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[24] A similar exercise is replicated using the results from the state-level analysis in the Historical March CPS and shows that the model is strongly predictive in the CPS. The top panel of Table A1.6 of the Appendix provides the regression coefficient, cross-state mean actual change in the disability rate, and cross-state mean actual change in routine employment shares. From 2000 to 2011, the actual disability rate increased by 0.68 percentage points. The model predicts that disability would increase by 0.68 percentage points. This accounts for 9.48% of the decline in employment for prime-age men and women over the 2000s.

Table 1.7 National Model Predictions

	Non-college Men	Non-college Women	All
2000-2011			
$\beta_{\Delta \text{ predicted routine share all}}$	-0.381	-0.409	-0.301
mean actual Δ routine occupation share all	-0.025	-0.024	-0.025
actual Δ disability rate	0.011	0.013	0.009
predicted Δ disability rate	0.009	0.010	0.007
share Δ disability explained by routine shift-share instrument	0.866	0.760	0.786

Note: Coefficients, actual changes in routine occupation shares, and actual changes in disability from Table 2. Predicted change = coeff * actual change in routine occupation shares. Share of actual change explained by routine shift-share = predicted/actual. Data: 2000 Census and American Community Survey. 2011 is pooled 2009, 2010, 2011. Routine occupations represent manufacturing and administrative services occupations.

1.8 Conclusion

The 2000s presented a puzzle to those who have looked to the labor market with interest: the phenomenon of declining employment pre-dating the Great Recession, accelerating during the recession and persisting beyond the recovery. The combined results of this paper address this puzzle by examining the interplay between declining labor demand in highly automated occupations and rising disability. The facts are staggering: (1) across specifications, declining employment associated with technological change causes increased DI participation; (2) most of the increase in disability over the 2000s is explained by weakening labor demand for routine occupations; (3) about 10% of the decline in employment for all prime-age men and women over the 2000s is explained by increases in disability caused by weakening routine labor demand; (4) effects are more concentrated among those with harder-to-verify diagnostic claims. These results may raise policy concerns about the existing structure of the DI program and about the nature of programs which address unemployment broadly and long-term unemployment specifically, especially for workers without four-year college attainment. Unlike UI, DI requires recipients to sever ties with the formal labor market and is an absorbing state. Once a worker enters DI, he is unlikely to return to work, is permanently eligible for Medicare health benefits, and his family is potentially eligible for permanent benefits. This suggests that the increase in non-employment documented over the last decade may persist over the long run.

Chapter 2

Rising Wage Inequality and Human Capital Investment with Lancelot Henry de Frahan

2.1 Introduction

This paper analyzes the real effects of rising local wage inequality on human capital investment and establishes an empirical fact: predicted increases in local wage inequality cause declines in enrollment rates in both community colleges and four-year institutions. The context of our research question is a labor market in which returns to workers have become increasingly unequal over the last 30 years. Figure 2.1 documents trends in wage inequality in the March Current Population Survey (CPS) from 1980 to 2008.[1] Across any measure of dispersion, inequality has been on the rise since 1980. The Gini coefficient in wages, a measure of overall inequality, increased from 0.34 in 1980 to 0.43 in 2008. At the upper tail, the difference in log wages between workers at the 90th and 50th percentiles of the wage distribution, widened from 0.72 in 1980 to 0.84 in 2008. From 1980 to 2008, the difference in log wages between those with and without four-year college attainment more than doubled from 0.30 in 1980 to 0.68 in 2008.[2]

The phenomenon of rising wage inequality occupies considerable space in the public forum. In the policy realm, the declining relative position of the American middle class was a recurrent theme in every State of the Union address during the Obama presidency, and income inequality has featured as

[1] Time series constructed from authors' calculations from the March CPS 1980-2008 of non-institutional individuals age 21 to 64 with strong attachment to the labor force (work at least 30 hours a week, 48 weeks a year and earn at least $5,000/ year in 2000$). The "90-50" refers to the log difference in wages of workers at the 90th and 50th percentiles of the wage distribution. The "skill premium" refers to the log difference in wages of workers with and without four-year college attainment.

[2] Authors' calculations from the March CPS 1980-2008 in wages of those who are strongly attached to the labor market in real 2000$.

a topic of debate in the 2016 Presidential primary season. In bestsellers, newspaper columns and blog posts, economists have directed public attention to the rise in inequality.[3] The academic literature has focused almost exclusively on chronicling the upward trend in wage inequality. Juhn, Murphy, and Pierce (1993) documents the rise in wage inequality for men in the March CPS. From 1963 to 1989, real wages for men at the 10th percentile declined by 5 percent whereas real wages for men at the 90th percentile rose by about 40 percent.[4] Autor, Katz, and Kearney (2008) highlights the slowdown in lower tail inequality growth relative to increases at the upper tail from 1987 to 2005.[5] Using administrative tax data to follow income growth at the top of the income distribution, Piketty and Saez (2003) establishes a Kuznets U-shaped pattern in the top decile's income share from 1917 to 1998.[6] With respect to well-being, studies such as Aguiar and Bils (2015) have tracked the simultaneous rise of income and consumption inequality over this period.[7]

Concurrent to the rise in wage inequality, a compositional change was underway in the US labor market. A hallmark of the post-War labor market was a rapid accumulation of schooling by workers. For every birth cohort from 1875 to 1950, college completion increased. However, for birth cohorts from 1950 to 1965 college completion flattened. This first college attainment slowdown is documented in Goldin and Katz (2008). Using the March CPS from 1994 to 2014, we show evidence for a *second* schooling slowdown. Figure 2.2 presents trends in predicted postsecondary schooling for birth cohorts from 1960 to 1990.[8] Among men, postsecondary schooling slows for the 1970 to 1981

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[3] See Cochrane (2014), Krugman (2015), Piketty (2014), Stiglitz (2012), and Putnam (2015).
[4] See also Katz and Murphy (1992); Murphy and Welch (1992).
[5] Using the March CPS the authors show that from 1979 to 1987, the difference in log wages between those at the 90th percentile and those at the 50th percentile (90-50) and those at the 50th percentile and the 10th percentile (50-10) increased. From 1987 there were steep increases in 90-50 persist from 1987 to present, but that growth in lower tail inequality dampens.
[6] Kuznets (1955) posited that trends in income inequality over time would take on a U-shape as a country grows.
[7] See also Fisher, Johnson, Smeeding (2012) and Attanasio, Hurst and Pistaferri (2012).
[8] Time series constructed from authors' calculations from the March CPS 1994-2014 of non-institutional individuals age 25-54. We predict any postsecondary schooling separately for men and women by using a linear probability model of any schooling beyond grade 12 on birth year, an age quartic, and normalized year fixed effects where the first and last year

birth cohorts before increasing again for later cohorts perhaps in response to the Great Recession. For women, whose schooling rates are higher, the slowdown is less pronounced and shorter in duration.

The timing of the increasing national trends in wage inequality and the slowdown in college attainment is suggestive, but not informative, about the potential relationship between inequality and human capital investment. A natural question arises: what are the causal effects, if any, of rising wage inequality on human capital investment? Economic theory offers three primary channels through which we may expect human capital and wage dispersion to be related: (1) by altering an individual's incentives to invest in human capital, (2) by affecting local policy responses such as the level of expenditures on local public goods tied to schooling, and (3) through inequality's impact on neighborhoods through the channel of residential sorting. Each channel offers a unique prediction for the sign of the gradient of changes in schooling on changes in wage inequality.

We begin by considering the impact of a changing wage distribution on incentives to invest in human capital. Monetary returns to education depend on the individual's wage once skill has been acquired and the individual's wage in the absence of additional skill.[9] In the labor market, a premium may be offered for worker skill whether that be formal training or experience. As the relative premium paid to skilled labor increases, the incentives to acquire skill intensify and postsecondary schooling enrollments increase (Katz and Murphy 1992).[10] Theories that tie rising inequality with policy responses are ambiguous with respect to enrollment effects. If voters demand more public goods in

effects = 0 following Hall (1968). A distinction from Goldin and Katz (2008) is that our measure of attainment is any postsecondary schooling beyond grade 12 whereas Goldin and Katz track college completion.

[9] As noted in Roy (1951), this mark-up is based on a counterfactual and not directly observable. Even so, the current wage distribution likely contains considerable information about the monetary gains from college.

[10] While standard theories of the skill premium suggest that increasing inequality may increase schooling propensities, there are other stories that suggest a negative relationship between inequality and schooling. For example, if inequality results in more binding liquidity constraints, this may prevent potential students from accumulating human capital (Carneiro and Heckman 2002). If the poor are more likely to be on the margin of the enrollment decision, an increase in wage dispersion in the presence of credit constraints may result in aggregate declines in enrollment.

the face of rising inequality, and human capital production is increasing in the quantity and quality of public goods, enrollments may increase (Meltzer and Richard 1981). On the other hand, if increasing inequality provokes political friction this may adversely affect the quality and quantity of public goods thereby negatively impacting human capital investment (Benabou 1996, 2000). Finally, inequality may negatively impact human capital accumulation by affecting neighborhood composition. An increase in inequality may cause changes in residential sorting patterns based on income which may cause children from lower income households to attend lower quality schools leaving them ill-prepared for further education (Durlauf 1996). Theoretically the causal impact of rising local wage inequality on aggregate postsecondary enrollments is uncertain.

To date, there has been little empirical work exploring the causal relationship between recent rising wage inequality and postsecondary schooling enrollments.[11] In this paper, we fill the gap in the existing literature on the consequences of rising inequality by proposing an instrumentation strategy that yields a vector of instruments for the local wage distribution. Our instrumentation strategy is nested in the universe of papers that achieve identification by exploiting regional variation in industrial mix. Early examples of this strategy include Murphy and Topel (1987) and Bartik (1991).[12] Most of this literature has used these shift-share instruments to predict changes to mean wages. By interacting initial industry employment shares at the metropolitan level with changes to the within-industry *distribution* of labor earnings at the national level, we are able to exogenously shock the local *distribution* of income.

To test the effects of rising wage inequality on human capital investments, we estimate a Two Stage Least Squares (2SLS) model in differences with first-time, full-year enrollments as the main outcome of interest. We use income data from the 2000 Census and the 2006 to 2008 American

[11] In Section 2.2, we discuss the effects of the changing skill premium on human capital investment in more detail.
[12] See also Neumann and Topel (1991) and Blanchard and Katz (1992). Recent examples include Aizer (2010); Autor, Dorn and Hanson (2013); Notowidigdo (2011); Sloane (2015).

Community Survey and educational data from the Integrated Postsecondary Education Data System (IPEDS) survey and the October Education Supplement to the Current Population Survey (CPS) in our estimations. As a preview of our results, we find consistent evidence that increasing predicted wage inequality causes declines in local community college and four-year institution enrollments. In our main analysis in the IPEDS data on community college enrollments, we find that moving from the 10th to the 90th percentile of predicted changes in the 90-50 difference corresponds to a 2.05 percentage point decrease in first-year, full-time aggregate community college enrollments. Further, predicted increases in mean wages are also associated with declines in community college enrollments though the evidence is slightly less robust to the choice of specification. We verify the robustness of these findings in the CPS October Education Supplement. A 1 standard deviation increase in the 90-50 difference caused a 0.5 percentage point decline in community college enrollments from 2000 to 2008. Moving from the 10th to the 90th percentile of the predicted change in the 90-50 difference caused a 1.28 percentage point decrease in aggregate enrollments. From 1994 to 2000, the cross-MSA average community college enrollment rate was 7.2%. As in the IPEDS results, increased growth also depressed community college enrollments.[13]

With respect to four-year enrollments, we may be concerned that declines in community college enrollments resulting from predicted increases in inequality may reflect substitution to four-year institutions. However, in the analysis of first-time enrollments in four-year institutions, we find that predicted increases in inequality also depress four-year enrollments. In the four-year institution enrollment results, using the IPEDS data on first-time, full-year enrollments in bachelor-degree-granting institutions, a 1 standard deviation predicted increase in the 90-50 is associated with a 0.1

[13] As with any paper using regional variation, we may be concerned about selective migration. Specifically, we may be concerned about selected migration. In Section 2.6, we provide evidence that suggests that while migrants are different than non-migrants on some observable characteristics such as gender, age, race and skill attainment, across MSAs that received large and small predicted changes in inequality, migrants are highly similar.

percentage point decrease in aggregate enrollments and gender-specific enrollments. Once we instrument for changes to the 90-50, the standardized coefficients from growth attenuate.

The main empirical fact established in this paper, that rising predicted wage inequality causes decreasing community college and four-year enrollments above and beyond changes in mean income, may potentially be explained by theories tied to income sorting. In order to test this mechanism, we directly test the causal impact of rising wage inequality on income segregation. We would think of a segregated city as one in which richer individuals tend to live in the same neighborhoods while poor families would live close to each other. Formally, we use Census-tract level data from the National Historical Geographic Information System (NHGIS) to construct a Herfindahl-style index of income segregation, the Rank Order Theory Index, following the construction of such measures in a well-developed literature on income segregation.[14] We estimate a Two Stage Least Squares (2SLS) model in differences with changes in the Rank Order Theory Index as the main outcome of interest. We find evidence that predicted increases in local wage inequality causes increasing segregation. A 1 standard deviation increase in the predicted 90-50 in wages causes a 0.26 of a 1 standard deviation increase in our measure of segregation in the main sample.

Beyond exploring the causal impacts of rising wage inequality on human capital investment, our paper develops a strategy to examine causal effects of rising wage inequality on a variety of outcomes. There is a growing amount of empirical work in sociology, public health, and economics documenting *associations* between rising income inequality and other questions of interest-- mortality, crime, happiness, residential sorting, local government revenues, and local government expenditures on public goods.[15] This literature is largely descriptive; thus, information about the real effects of

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[14] The Rank Order Theory index is developed in Reardon and Firebaugh (2002) and Reardon (2011). It is also used in Reardon and Bischoff (2011, 2013) and in Chetty et al. (2014).

[15] See, respectively, Kaplan, et al (1996), Kennedy, et al (1996), Fajnzlber, et al (2002), Wilkinson and Pickett (2009), Dynan and Ravina (2007), Alesina et al (2000), Reardon and Bischoff (2011a,b; 2013), Watson(2009), Boustan, et al (2012)

increasing wage inequality is missing from both the academic and public debates. With our instrumentation strategy, that uses regional variation in industrial mix to achieve identification, we gain insight into more than simply correlations in the data and start to assess the causal impact of rising inequality on policy relevant outcomes.

There is an existing literature that has endeavored to predict moments of the income distribution aside from the mean. Using a manufacturing employment shift-share instrument to predict changes to the 80-20 family income ratio, Watson (2009) examines the impacts of increasing income inequality on residential segregation. In order to assess the effects of local inequality on tax revenues and public expenditures, Boustan, Ferreira, Winkler and Zolt (2013) predicts changes to the Gini coefficient at the county level by fixing the initial county income distribution using counts in income rank bins interacted with growth in these national income bins. Bertrand, Kamenica and Pan (2014) predict changes to the mean and specific percentiles of the income distribution by gender for each marriage market.[16] Our instrument is different from these existing strategies in the following important ways: (1) we are able to predict changes to the entire distribution of income; (2) we are able to pick up national trends in between-industry dispersion in addition to shocks that tend to increase within-industry dispersion of wages; and (3) we do not rely as much on the initial local income structure as methods that fix the initial distribution by income bin concentrations.[17]

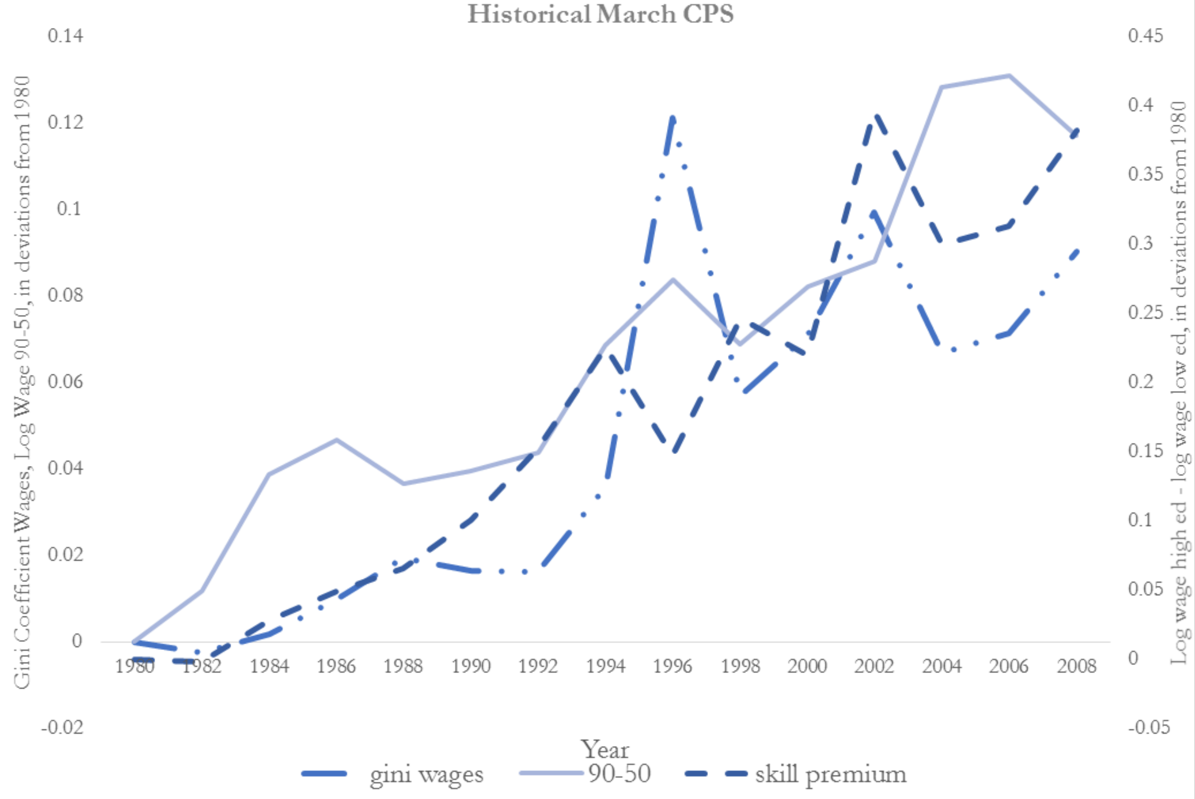
In summary, this paper introduces a novel instrumentation strategy to predict changes in the wage distribution in order to test the causal link between rising inequality and human capital investment. We find that predicted increases in the 90-50 and the Gini coefficient, holding the mean constant, are

[16] Specifically, they predict yearly gender-specific income percentiles for each marriage market by weighting national within-industry race- and gender-specific income percentiles by base-year state-level, within-industry, race- and gender-specific employment shares.

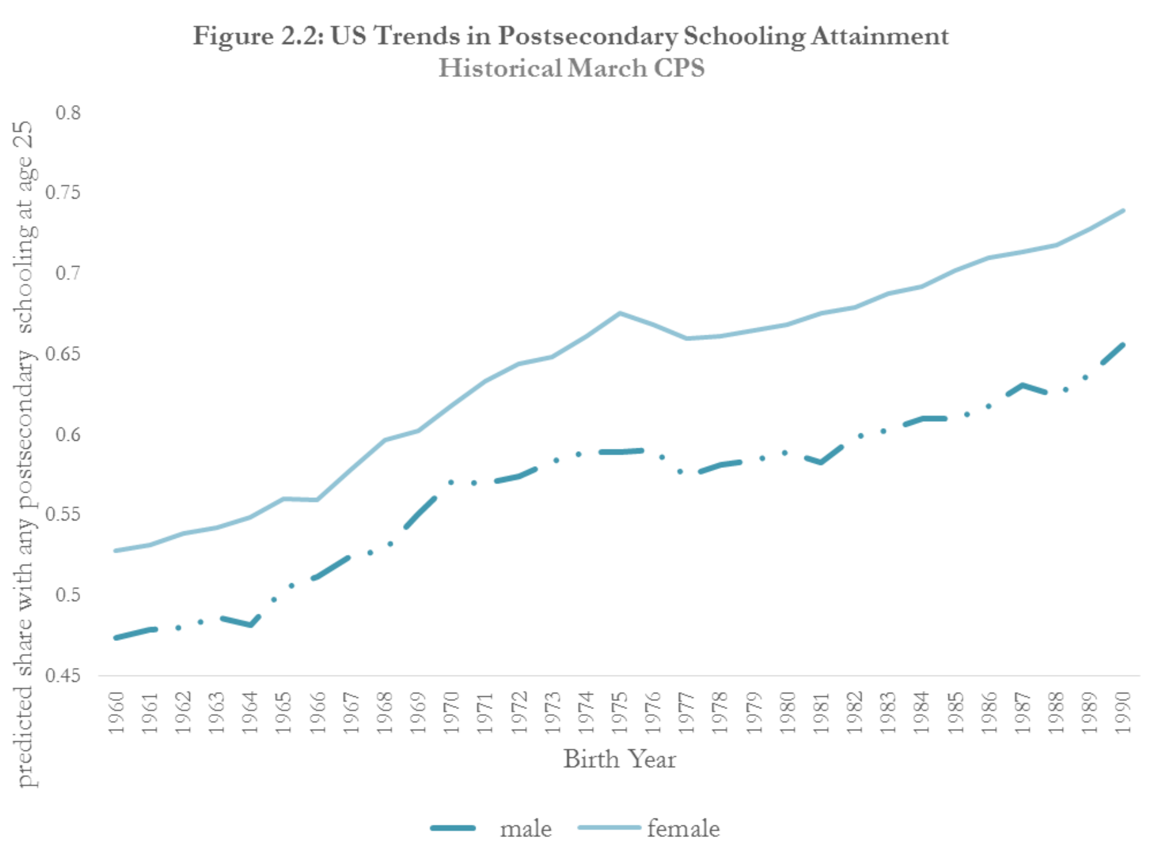
[17] In Table A2.1 of the Appendix, we decompose the between and within components of the variance of log wages to better understand the predictive power of each component. This sheds light on the empirical contribution of our instrumentation strategy which utilizes both the between- and within-industry variation in wages.

causally related to decreasing enrollment rates in community college. Further, we propose and provide evidence of increased income segregation as a mechanism. Finally, our instrumentation strategy may be employed to test the causal impact of increasing inequality on other outcomes of interest. We proceed in Section 2.2 by detailing the main theoretical arguments that link changes to the wage distribution with schooling decisions.

Figure 2.1: US Trends in Wage Inequality
Historical March CPS



Note: Historical March CPS. Sample restricted to ages 21-64, non-institutional, who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$ and have a MSA identifier.



Note: March Historical CPS. Sample restricted to non-institutional native population. Postsecondary schooling includes any schooling beyond grade 12. Fraction is measured on population between 25 and 54 in the survey year and is adjusted for age effects. We report predicted share in the birth cohort with some college at 25.

2.2 Literature on the Mechanisms Linking Wage Inequality and Schooling

As discussed briefly in Section 2.1, theory is ambiguous with respect to the relationship between changes in the wage distribution and human capital investment. Although the ensuing analysis estimates a gross effect of changes in the wage distribution on human capital investment, the sign on the slope coefficient is suggestive of dominant mechanisms. There are three main avenues through which human capital and wage dispersion could be related: (1) by altering an individual's incentives to invest in human capital, (2) by affecting local policy responses such as the level of expenditures on local public goods tied to schooling, and (3) through inequality's impact on neighborhoods through the channel of residential sorting. In this section we describe the existing literature supporting each mechanism and delineate the accompanying predictions.

Arguably the most familiar theoretical link between human capital investment and inequality rests in how changing the distribution of income can change incentives. A large literature focused on the skill premium posits a positive relationship between increases in a specific variety of wage inequality-- the premium offered in the market to skilled workers over those with less skill—and investment in human capital. Katz and Murphy (1992) argue that the large increase in inequality observed over the last decades in the US has been driven by an increase in the demand for skilled workers relative to unskilled workers which in turn has raised the skill premium. They show that individuals have responded by investing in education. According to basic economic theory, increases in wage inequality driven by increases in the skill premium would incentivize college enrollment. Curiously, if we return to Figures 2.1 and 2.2, the national trend in rising wage inequality and the concurrent slowdown in postsecondary schooling provide little initial evidence of this hypothesis at work over the 2000s. Further, Figure A2.1 of the Appendix shows no relationship in the cross-section between the rising relative return to skill of those with four-year college attainment and first-time, full-year enrollments in four-year institutions over the 2000s.

Moving on, we consider the shape of the relationship between income and human capital. Although the theoretical shape of the relationship between income and likelihood of college enrollment is uncertain, most credible theories would posit that income has either a zero or a positive effect on investments in human capital. The literature on the causal impact of income on human capital investment has focused on credit constraints. Under a specific set of assumptions, in models without credit constraints, family or personal income has no effect on human capital investment. In a world with credit constraints, the relationship between human capital and income may be non-linear (and positive); thus, changes to the distribution of income within the population may induce changes in aggregate enrollment. For this reason, credit constraints have occupied a central space in the human capital literature. While there is a well-documented correlation between family income and educational attainment, the existence of a causal impact of income on college attendance and the presence of credit constraints are still subject to debate in the literature.[18] Using data from the CNLSY, Caucutt, Lochner and Park (2015) finds richer parents spend more time and money investing in their children's human capital. This is particularly relevant to the college attendance decision because of the recursive nature of human capital: human capital is an important input in the production of future human capital.[19] As a result, individuals with a higher level of skills tend to have higher returns from college. If poorer parents tend to invest less in the human capital of their children, they may be less likely to enroll in college. If poorer students are more likely to be on the margin of postsecondary schooling, an increase in wage inequality may induce aggregate reductions in enrollments.

Now, consider that human capital and wage inequality could be linked through an effect of inequality on some other aggregate variables – aggregate public good provision or residential sorting, for example. Meltzer and Richard (1981), and other papers with a pivotal median voter, predict increased redistribution in locations with increasing inequality.[20] It follows as tax revenues increase local officials may increase public goods such as increasing the number of local community colleges or improve the quality of existing public goods. Other models such as Benabou (1996, 2000) predict falling public good provision in the face of increasing inequality as a more fractured electorate cannot settle on a consensus provision. To the extent that public goods enter into the production function of

[18] Cameron and Heckman (1998, 2001), Keane and Wolpin (2001) and Cameron and Taber (2004) find little role for credit constraints on college enrollment using the NLSY79 data. Lochner and Monge-Naranjo (2012) survey studies of the impact of credit constraints on human capital and conclude that "credit constraints have recently become important for schooling and other aspects of households' behavior". Dahl and Lochner (2012) also find a positive, moderate effect of parental income on children's test scores using quasi-experimental variations induced by changes in the EITC.

[19] See Cunha and Heckman (2007); Heckman and Mosso (2014).

[20] See also Alesina and Rodrik (1994), Persson and Tabellini (1994).

human capital, they may be positively related. If human capital production is positively related to the level and quality of public goods, enrollments may increase in a world with more public goods, all else equal, and may decline in a world with declining levels and quality of public goods.

There are several models that link changes in the income distribution with increased residential sorting on the basis of income. Tiebout (1956) develops a model in which municipalities offer different levels of public goods associated with different tax rates. With no preference heterogeneity, income is perfectly correlated with willingness to pay for public goods and rich and poor perfectly segregate. Epple and Platt (1998) introduce heterogeneity in preferences. As a result, willingness to pay for public goods is not perfectly correlated with income resulting in partial segregation in equilibrium. When income inequality increases, income becomes a stronger predictor of willingness to pay for public goods relative to preference heterogeneity. As a result, it becomes less likely that a poor family will outbid a rich family to be in the neighborhood with better composition and higher level of public goods and segregation increases in equilibrium. Durlauf (1996) develops a model of persistent poverty in which income inequality generates incentives for rich families to segregate from poorer families. In the model, the productivity of human capital investments depends on neighborhood income composition. As a result of segregation, segregated poor individuals decrease human capital investments. If individuals at the margin of the college-going decision are concentrated in the lower end of the income distribution, increases in income inequality would reduce aggregate enrollment through increases in segregation.

Many studies have examined the impact of neighborhood effects on returns to education.[21] There are two main channels through which neighborhood effects can potentially operate: fiscal externalities and sociological or psychological effects. In a world where individuals are segregated, increases in

[21] Durlauf (2004) surveys theoretical and empirical work on neighborhood effects and finds many studies with evidence of neighborhood effects.

income inequality mechanically cause fiscal externalities. Fiscal externalities occur because of the local financing of certain public goods. As an individual's neighbors get richer, tax revenue, and the quality of public goods, increases. This problem has been known by policy-makers who have moved to more centralized models of school funding to avoid funding inequities. To the extent that the quality of public goods is an input into human capital and to the extent that financing is local, fiscal externalities may matter to individual's college enrollment decision. The second channel through which neighborhood effects operate are sociological and psychological effects. An individual living in a neighborhood with few college graduates may have uncertainty about, or a lack of awareness of, the returns to college. If networks have high salience in job search, returns to investing in human capital may be lower in segregated poor neighborhoods. Empirically, a recent literature on the equality of opportunity by Chetty and Hendren (2015) and Chetty, Hendren and Katz (2015) argues the importance of childhood location to later life outcomes.[22] With this organizing framework in mind, we proceed to the empirical analysis.

2.3 Describing Metropolitan-level Wage Inequality

2.3.1 Wage Data

This paper primarily uses a sample of 192 MSAs in the Census and the American Community Survey (ACS) from 2000 to 2008.[23] As our educational data has the most complete coverage for the 2000s, we focus on the period from 2000 to 2008. The panel is constructed from individual level and household level extracts from the 2000 Census 5% file and the 2006 to 2008 ACS files from the Integrated Public Use Microsamples (IPUMS) database (Ruggles et al., 2010). We pool the years 2006, 2007 and 2008 to represent the year 2008 in order to improve precision of estimates. In order to avoid

[22] See also Putnam (2015).
[23] These 192 MSAs in the main sample do not change over time and match to MSAs in the IPEDS survey.

contamination from the Great Recession, we end in the year 2008. The sample is restricted to the non-institutionalized population age 21 to 64 who live in a MSA and do not have business or farm income. The sample was collapsed at the MSA level to compute MSA-specific variables. MSA-level regressions have standard errors clustered at the state-level to account for potential correlation in error terms related to state-level policy which may be time-varying and thus not differenced out in estimation. All estimates are weighted by the population in a MSA in year 2000 in order to assign greater weight to cells with less noise.

Table 2.1 displays summary statistics of interest from the Census and the ACS at the MSA level. With respect to the legacy of postsecondary schooling in a MSA, there is quite a bit of variation in our sample. We use the share of the prime age population with four years of college attainment in 1980 as a measure of historical human capital for a MSA. Across the 192 MSAs in our sample, the mean historical college share was 17.8%. The MSA with the smallest college share in 1980 was Danville, VA at 8.6%. The most educated MSA in 1980 was Ann Arbor, MI at 36.6%.

The distribution of hourly wages is estimated over a sample including individuals age 21 to 64 who report currently working at least 30 hours a week and who report having worked at least 48 weeks during the prior year. We also restrict the sample to those who earned at least $5,000 in the prior year. We compute the wage by dividing annual earnings during the prior year by an estimate of the number of hours worked in the prior year. We estimate hours worked during the prior year by multiplying reported current usual hours worked per week by the number of actual weeks worked in the previous year. These restrictions reduce measurement error since wages are better measured for workers with strong attachment to the labor force. All earnings measures are converted to real 2000$ using the Consumer Price Index (CPI).[24]

We compute distributional measures, such as the Gini coefficient, percentiles, the skill premium, the 90-50 and the 50-10, in wages by MSA, year. The cross-MSA mean Gini coefficient in wages in the year 2000 was 0.34 with a standard deviation of 0.02. The MSA with the lowest overall inequality, as measured by the Gini coefficient, in the year 2000 was St. Cloud, MN, and the MSA with the highest overall inequality in the year 2000 was Los Angeles-Long Beach, CA. With respect to upper tail inequality, the cross-MSA mean 90-50 difference in 2000 was 0.71. The MSA with the lowest upper tail inequality, as measured by the 90-50, was Appleton-Oshkosh-Neenhah, WI, and the MSA with the highest upper tail inequality in 2000 was McAllen-Edinburg-Pharr-Mission, TX. At the lower tail, the cross-MSA mean 50-10 difference in 2000 was 0.69. The MSA with the lowest lower tail inequality in 2000 was Wausau, WI. The MSA with the highest lower tail inequality in 2000 was Los Angeles-Long Beach, CA.

[24] An important caveat about using income and wage data from the Census and ACS is that the data is top coded. A literature using tax data such as Piketty and Saez (2001, 2006) emphasize the dramatic increase in incomes of the top 1%. We will be able to capture inequality driven by other parts of the wage distribution. From 2000 to 2008, if we look at the growth in real wages among those strongly attached to the workforce, wages at the 90th percentile grew by 4.74%. Wages at the 50th percentile grew by 0.25%. Wages at the 10th percentile declined by 4.08%.

Table 2.1 Summary Statistics Baseline Characteristics

Baseline Characteristics	N	Mean	St. Dev	Min	25	50	75	Max
Wage	192	17.769	2.392	12.132	16.327	17.310	18.816	27.826
Gini Coefficient	192	0.335	0.023	0.281	0.319	0.333	0.350	0.396
90-50 Difference	192	0.711	0.058	0.575	0.673	0.705	0.751	0.868
Log Population	192	12.882	1.071	11.278	12.039	12.661	13.633	16.329
Black Share	192	10.68%	9.84%	0.22%	2.68%	7.32%	16.63%	43.76%
Female Employment Share	192	67.11%	5.46%	46.08%	64.20%	67.59%	70.26%	80.67%
Low Immigrant Share	192	2.50%	2.54%	0.07%	0.72%	1.43%	3.44%	13.01%
Population Share with College Attainment in 1980	192	17.84%	4.83%	8.58%	14.52%	17.03%	20.47%	36.64%
IPEDS Average Community College Enrollment 1994 to 2000	192	5.20%	3.33%	0.36%	3.02%	4.67%	6.53%	19.32%
IPEDS Average Community College Male Enrollment 1994 to 2001	192	4.79%	3.24%	0.04%	2.83%	4.33%	5.99%	17.91%
IPEDS Average Community College Female Enrollment 1994 to 2001	192	5.61%	3.50%	0.71%	3.30%	4.93%	6.82%	20.87%
CPS Average Community College Enrollment 1994 to 2000	135	3.56%	2.19%	0.47%	2.04%	3.14%	4.71%	11.19%
CPS Average Community College Male Enrollment 1994 to 2001	101	4.27%	3.53%	0.44%	2.17%	3.47%	5.12%	26.55%

Table 2.1 Cont'd Summary Statistics Baseline Characteristics

Baseline Characteristics	N	Mean	St. Dev	Min	25	50	75	Max
IPEDS Average Four-Year Female Enrollment 1994 to 2000	187	6.92%	5.39%	0.01%	3.07%	5.45%	9.67%	30.87%
CPS Average Four-Year Enrollment 1994 to 2000	156	7.22%	4.58%	0.98%	4.35%	6.55%	9.26%	30.73%
CPS Average Four-Year Male Enrollment 1994 to 2000	130	7.54%	5.50%	0.73%	3.91%	6.31%	9.78%	33.33%
CPS Average Four-Year FemaleEnrollment 1994 to 2000	137	7.93%	5.25%	1.26%	4.61%	7.05%	10.01%	32.96%
Residential Segregation 2000	212	0.097	0.033	0.025	0.073	0.098	0.120	0.178
Residential Segregation 90th Percentile 2000	212	0.124	0.044	0.033	0.087	0.126	0.156	0.224
Residential Segregation 10th Percentile 2000	212	0.099	0.027	0.074	0.097	0.122	0.122	0.196

Note: Data for mean wages, 90-50 difference, Gini coefficient, log population, black share, female employed share, low immigrant share and 1980 college education share is from the 1980, 2000 U.S. Census. Individual wages computed for those age 21-64 who work 30 hours per week, a minimum of 48 weeks/year with minimum annual salary $5,000. Education data is from the Integrated Postsecondary Education Data System (IPEDS) and the October Supplement of the Current Population Survey (CPS). In the IPEDS data, enrollment rate is averaged over years 1994 to 2000. Enrollment rates are calculated by scaling enrollment counts from IPEDS by interpolated population counts for non-institutional people age 18 to 25 from the Census and ACS. In the CPS, enrollment rates are calculated by combining information from questions asked about full-time enrollment status, current year in school, and type of institution. We construct first-time, full-year enrollment counts by counting people age 18 to 25 in first-year of school by level on a full-time basis and scaling by population of non-institutional people age 18 to 25 from the CPS. Data used to compute segregation measures is from the National Historical Geographic Information System (NHGIS). Neighborhoods correspond to Census tracts and are aggregated to the MSA-level. Following Reardon, Bischoff (2011,

2.3.2 Trends in Metropolitan-level Wage Inequality

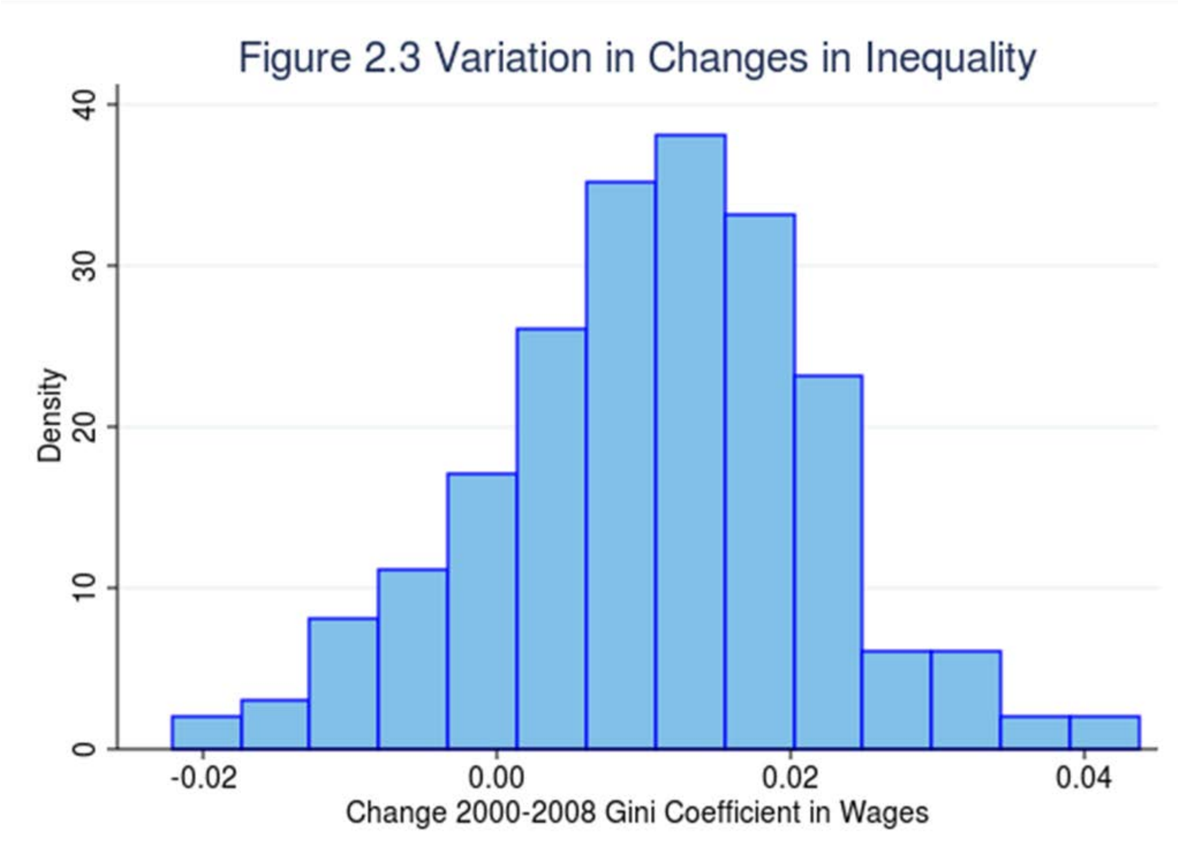
In Section 2.1, we described a national wage distribution that was becoming increasingly unequal over time. If we look at four measures of wage inequality from the March CPS, the Gini coefficient, variance of log wages, the 90-50, and the 50-10, from 2000 to 2008 each measure increased by 4.7%, 5.5%, 4.4%, and 2.5% respectively. However, across MSAs, the experience with respect to changes in the wage distribution are quite different. Figure 2.3 presents a histogram of the changes in Gini coefficient in wages for the 192 MSAs in our main sample. The cross-MSA mean change in the Gini coefficient over the 2000s is 0.01 with a standard deviation of 0.01.

At the upper tail of the wage distribution, the cross-MSA mean change in the 90-50 over the 2000s is 0.04 with a standard deviation of 0.04. The MSA with the largest reduction in upper tail inequality, as defined by the change in the 90-50 difference, over the 2000s is Terre Haute, IN. The MSA with the largest increase in upper tail inequality over the 2000s is Joplin, MO followed by Visalia-Tulare-Porterville, CA and Bakersfield, CA. If we focus on changes in inequality at the lower end of the wage distribution, the cross-MSA mean change in the 50-10 over the 2000s was 0.04 with a standard deviation of 0.04. The MSA with the largest reduction in inequality at the lower end of the wage distribution, defined as the change in the 50-10 difference, was Muncie, IN. The MSA with the largest increase in lower tail inequality over the 2000s was Trenton, NJ followed by Greeley, CO.

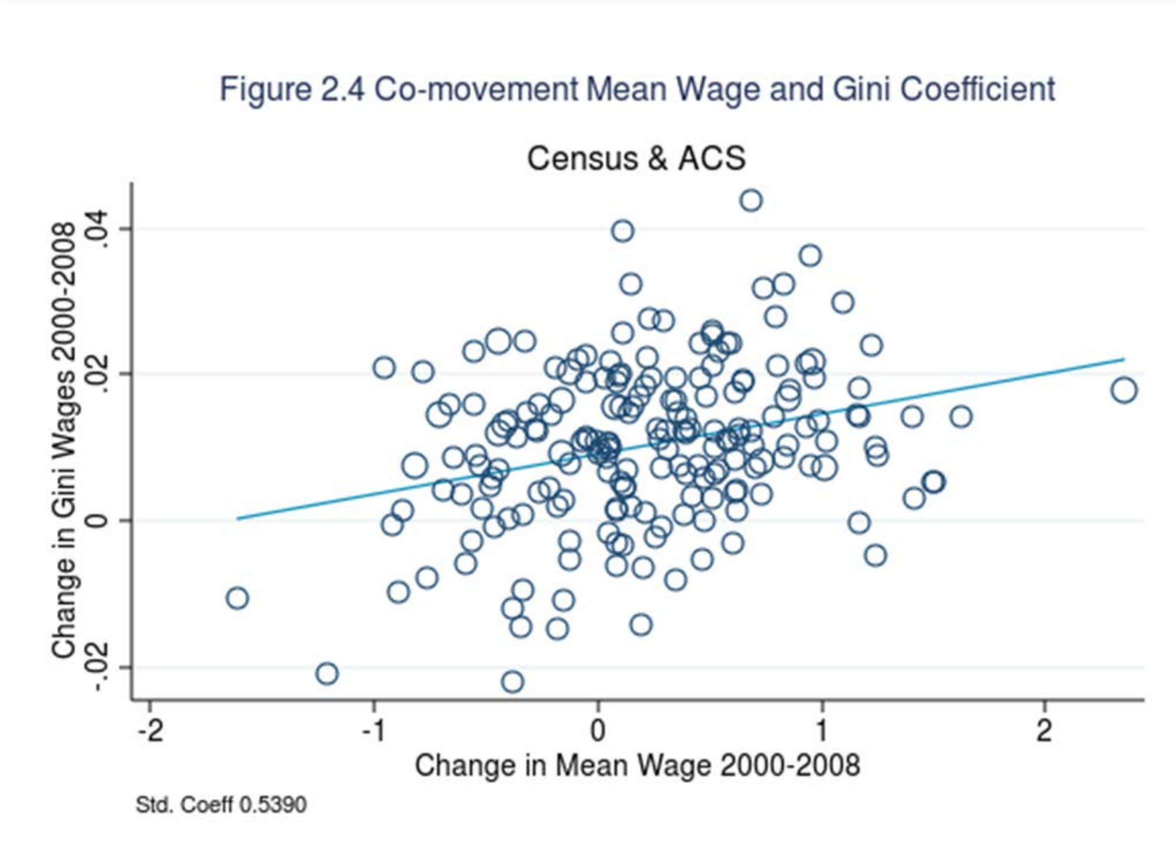
With respect to changes to the mean of the wage distribution, wages grew modestly across the MSAs in our sample over the 2000s. The cross-MSA mean change in wages in 2000$ was $0.23 with a standard deviation of $0.59. As with changes in the dispersion of wages over the 2000s, there is a great deal of variation in changes in wage levels across MSAs over the 2000s. The MSA with the largest decline in mean wages over the 2000s was Flint, MI which experienced a real wage decline of $1.61 over the 2000s followed by Waco, TX and Salem, OR. The MSA with the largest increase in mean wages over the 2000s was Washington, DC/MD/VA which experienced real wage growth of $2.36 over the 2000s followed by Baltimore, MD and Norfolk-VA Beach-Newport News, VA.

In this section, we established an important fact about changes in inequality over the 2000s: there is heterogeneity in the sign and magnitude of changes in measures of wage dispersion across the 192 MSAs in our main sample. A second important fact about changes to the wage distribution over the 2000s is the co-movement between changes in the mean wage and changes in the Gini coefficient in wages over the 2000s. Figure 2.4 plots the correlation between the change in the mean wage from 2000 to 2008 and the change in the Gini coefficient in wages over the same period. There is a positive slope coefficient— MSAs that experienced increases in mean wages over the 2000s also experienced increases in overall inequality—with a 1 standard deviation change in mean wages corresponding to a 0.54 of a 1 standard deviation movement in the Gini coefficient. With respect to the variance of wages and the mean wage, there is a considerable amount of co-movement. From 2000 to 2008, the correlation between changes in the variance of log wages and the mean was 0.60. However, with respect to changes in both upper tail and lower tail inequality, co-movement seems to be less of a concern. The correlation between changes in the 50-10 difference and the change in mean wages over the 2000s was 0.05. Similarly, the correlation between changes in the 90-50 difference and the change in the mean wage over the 2000s was 0.02.

The co-movement between measures of overall inequality such as the Gini coefficient and the mean wage raises an empirical concern with respect to identifying the causal effects of changes in inequality on human capital. In order to isolate the effects of inequality, it will be necessary to separately control for, and ideally instrument for, changes in the mean of the wage distribution. We discuss this in more detail in Section 2.4.



Note: Data is from the 2000 Census and American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Cross-MSA density of change in Gini coefficient in wages. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$.



Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$.

2.4 Predicting Changes in Inequality and Growth

2.4.1 Instrumentation Strategy

In Section 2.3, we documented the changes in both the mean and the dispersion of the wage distribution over the 2000s across the 192 MSAs in our main estimations. Our analysis aims to exploit the considerable variation in changes in wage inequality across municipalities to draw inference about the relationship between rising inequality and human capital investment. A proposed estimation strategy is to regress the changes in enrollment rates on changes in a measure of inequality, such as the local Gini coefficient in wages, controlling for baseline demographic characteristics:

$$\Delta Enrollments_k = \beta_0 + \beta_1 \Delta Gini_k + \gamma\, Q_k + \varphi_k + \epsilon_k \tag{2.1}$$

where $\Delta Enrollments_k$ represents the change in the enrollment rate in MSA *k* from *t* to *t+1*, $\Delta Gini_k$ represents the change in the Gini coefficient of wages in MSA *k* from *t* to *t+1*, Q_k is a vector of baseline controls, φ_k is unobservable and potentially correlated with the change in the Gini coefficient and ϵ_k is a mean-zero regression error. The coefficient of interest, β_1, aims to measure $\frac{\partial \Delta Enrollments_k}{\partial \Delta Gini\ wages_k}$, the effect of a change in local inequality on local enrollment rates. While this strategy has the appealing feature of removing any time-invariant MSA unobservable confounders, this difference-in-differences model introduces several identification threats which preclude causal inference about the relationship between inequality and schooling.

There are four main concerns with the OLS results. The first is regarding permanent versus transitory shocks. An estimation strategy that relies on differencing may absorb transitory shocks. Our coefficients may suffer from attenuation bias. Decisions about schooling have potentially long-term impacts; ideally, we would like to identify the responses to permanent changes in the wage distribution. For that reason, we would like to use plausibly exogenous national, instead of local, changes in the wage distribution. The second is measurement error.[25] Specifically, the earnings and employment data we use to compute wages is from survey data. Noise in this data may lead to attenuation bias in our estimates. Third, the OLS estimation cannot rule out reverse causation. A well-defined literature on skill-biased technological change, such as Autor, Katz and Kearney (2006), raises the possibility that

[25] Griliches and Hausman (1985) establishes that panel data estimations that utilize differencing strategies should ideally use an external instrument beyond lagged values of relevant variables.

changes in the skill profile may impact the local wage distribution. In order to isolate the causal chain that rising wage inequality impacts schooling investments, we wish to instrument for inequality. Lastly, time-varying local factors such as local labor supply elasticity or local policy may be correlated with changes to both the wage distribution and educational investments.

We borrow insights from labor, public, and macroeconomics to propose an instrumentation strategy for predicting changes in local inequality. Our instrumentation approach begins with the assumption that MSA-level earnings distributions are weighted sums of the earnings distribution of each industry within the MSA:

$$F^k(y) = \sum_{j=1}^{n} \vartheta_j^k F_j^k(y) \tag{2.2}$$

where $F^k(y)$ is the CDF of earnings of MSA *k*, ϑ_j^k is the share of workers in MSA *k* employed in three-digit industry *j*, and $F_j^k(y)$ is the CDF of earnings in industry *j* within MSA *k*. We can predict changes to the CDF of earnings in MSA *k* between time *t* and *t*+1 by interacting the industry weights at time *t* and national estimates of the within-industry distribution of income in time *t* and *t+1*:

$$\Delta\hat{F}^k(y) = \sum_{j=1}^{n} \vartheta_{j,t}^k \left[F_{j,t+1}^{Nat}(y) - F_{j,t}^{Nat}(y)\right] \tag{2.3}$$

$$= \sum_{j=1}^{n} \vartheta_{j,t}^k F_{j,t+1}^{Nat}(y) - \sum_{j=1}^{n} \vartheta_{j,t}^k F_{j,t}^{Nat}(y) \tag{2.4}$$

$$= \hat{F}_{t+1}^k - \hat{F}_t^k \tag{2.5}.$$

Once we have obtained the plausibly exogenous CDFs of earnings at the MSA level, we can take the derivative to obtain the PDFs in *t* and *t+1:*

$$\Delta\hat{f}^k = \hat{f}_{t+1}^k - \hat{f}_t^k \tag{2.6}$$

and calculate any moment of interest such as the mean, variance, specific percentile, or the Gini coefficient in t and *t+1*. For example, our instrument for the Gini coefficient could be expressed:

$$\Delta G_k = Gini(\hat{f}^k_{t+1}) - Gini(\hat{f}^k_t) \qquad (2.7).$$ [26]

Similarly, our instrument for the mean wage could be expressed:

$$\Delta w_k = mean(\hat{f}^k_{t+1}) - mean(\hat{f}^k_t) \qquad (2.8).$$

We argue that the initial industry mix in an MSA is likely to be uncorrelated with the trend in college enrollment apart from its effect through the wage distribution. If this is true, our instrument is valid. Intuitively, there are two types of shocks driving changes in predicted inequality. First, an increase in the dispersion of wages within an industry will lead to predicted inequality increases in the MSAs where this industry is a large share of employment. In other words, our instrument picks up national trends in within-industry dispersion.[27] Second, the instrument also reflects shocks that tend to increase between-industry dispersion of wages. For instance, if an already high-paying industry experiences a large growth in mean wage, this would tend to increase inequality in MSAs where this industry is a large share of employment. Similarly, if a low-paying industry experiences a large decline, the instrument would predict an increase in inequality in MSAs where this industry is important.[28]

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[26] Specifically, we begin construction of our instrument by counting the number of employed, prime age, non-institutional people in each three-digit industry in the year 2000 and dividing by the total MSA-level employment count in order to obtain employment shares by industry, $\vartheta^k_{j,t}$.[26] We proceed by estimating the empirical CDF of wages within each three-digit industry nationally at 127 different wage levels in 2000 and 153 wages levels in 2008. The maximum wage in the national distribution is \$254 in 2000 and \$306 in 2008. These different wage levels at which we estimate the empirical CDF are not equally spaced between zero and the maximum; instead we evaluate the CDF on a finer grid a lower wage levels because there is more data in that region. Then, we weight each industry earnings distribution by $\vartheta^k_{j,t}$ and fit a spline to obtain an empirical CDF for each MSA. We then take the derivative in order to obtain a MSA-specific PDF from which we can calculate moments of interest in years *t* and *t+1*. In Figure A2.4 of the Appendix, we provide a simplified example of construction of the instrument.

[27] The variance of wages within an industry may change due to technological changes such as computerization, automation, or superstar effects.

[28] Fluctuations in world prices, trade, and changing in tastes of consumers are examples of shocks that would shift the overall level of wages in specific industries.

As outlined in Section 2.1, we can identify a few important advantages of our instrumentation strategy: (1) by using initial industry shares we soak up less initial inequality than methods that fix the initial distribution by income bin concentrations; (2) we avoid the restrictive assumption that income mobility does not occur within locations over long differences; (3) our instrument will pick up shocks to inequality that result from both within- and across-industry variation; (4) we are able to predict changes to the entire distribution of income

In order to identify the causal impact of changes in wage inequality on human capital attainment, it is both necessary and desirable to separate growth effects. In Section 2.3, we provided an empirically-motivated reason we may want to separately control for changes to the mean of the wage distribution. Over the 2000s, many MSAs that experienced growth in mean wages also experienced increases in the Gini coefficient in wages. Further, there is a theoretically-motivated reason we may wish to separate growth effects—specifically, there may be differing theoretical predictions for the relationship between inequality and schooling and growth and schooling. Rational agents compare the costs and benefits of postsecondary education. An important component of educational costs is foregone earnings.[29] An empirical literature finds that increasing wages of low-skill workers, disincentivizes postsecondary schooling.[30]

[29] This is a common feature of human capital models such as Mincer (1958) and Becker (1964).

[30] Charles, Hurst and Notowidigdo (2015) show strong evidence that individuals respond to increases in the opportunity cost of going to college: in the 2000s MSAs experiencing rapid growth in housing-related employment had lower enrollment in postsecondary institutions. Black, McKinnish and Sanders (2005) use coal-related booms and busts in the Appalachian States to show that an increase in the wage of low-skilled workers reduces incentives to enroll in high school. They estimate that a 10% increase in the low-skilled workers' wage lead to a 5 to 7% decrease in high school enrollment rates. Atkin (2012) shows that growth in export manufacturing in Mexico decreased human capital investment by increasing the low-skilled wage therefore raising the opportunity cost of schooling for students at the margin.

For these reasons, we modify our strategy by separately analyzing the effects of changes in mean wages on enrollment rates.[31] We could modify equation (2.1) to include predicted changes to the Gini coefficient and a control for the change in mean wages:

$$\Delta Enrollments_k = \beta_0 + \beta_1 \Delta\widehat{Gini}_k + \beta_2 \Delta wage_k + \gamma\, Q_k + \varphi_k + \epsilon_k \qquad (2.9).$$

Including actual changes in mean wages would subject our conclusions about β_2, the effect of wage growth on enrollment rates, to the same identification concerns as using actual changes in inequality: measurement error, contamination from time-varying local unobservables such as policy, and reverse causation. Thus, we utilize our instrumentation strategy to separately shock mean wages.

2.4.2 Identification

The main specification that we will use in testing the causal relationships between changes in inequality and schooling and changes in growth and schooling is a Two Stage Least Squares (2SLS) model with simultaneous first stages. We characterize the first stage for predicting changes in mean wages:

$$\Delta wage_k = \propto_0 + \propto_1 \Delta w_k + \propto_2 \Delta G_k + \gamma\, Q_k + \epsilon_k \qquad (2.10)$$

where Δw_k is the distributional instrument to predict changes to mean wages, ΔG_k is the distributional instrument to predict changes in the Gini coefficient, Q_k is a vector of baseline controls, and $\epsilon_k$is a mean-zero noise term.

We characterize the first stage for predicting changes in the Gini coefficient in wages:

[31] This estimation strategy identifies the effect of rising local wage inequality holding the mean constant. We would like to unpack the industries that are important in MSAs where increases in inequality of this nature are occurring. In Table A2.2. of the Appendix, we provide information on the larger industry categories that are important to identification.

$$\Delta Gini_k = \mu_0 + \mu_1 \Delta w_k + \mu_2 \Delta G_k + \gamma\, Q_k + \epsilon_k \tag{2.11}$$

where Δw_k is the distributional instrument to predict changes to mean wages, ΔG_k is the distributional instrument to predict changes in the Gini coefficient, Q_k is a vector of baseline controls, and $\epsilon_k$is a mean-zero noise term.

Thus, the second stage which is our main estimating equation is expressed:

$$\Delta Enrollments_k = \beta_0 + \beta_1 \Delta \widehat{Gini}_k + \beta_2 \Delta \widehat{wage}_k + \gamma\, Q_k + \epsilon_k \qquad (2.12).$$

where $\Delta \widehat{wage}_k$ is the predicted mean wage for MSA *k* from the equation (2.10) and $\Delta \widehat{Gini}_k$ is the predicted Gini coefficient in wages for MSA *k* from equation (2.11). The coefficient β_1 is the effect of changes in local inequality on enrollment rates and β_2 is the effect of changes in growth on enrollment rates.

Table 2.2 presents the first stage results. The top two panels present first stage results for a model which predicts changes to the Gini coefficient in wages and mean wages. The final two panels present first stage results for a model which predicts changes to the 90-50 difference in log wages and mean wages. The first panel presents the point estimates for $\propto_1$. Column 1 presents results for a reduced model. The slope coefficient from the regression of actual changes in mean wages on predicted changes in the mean instrument from 2000 to 2008 is 1.24 with standard error 0.25. The first stage F statistic from the reduced model of the change in mean wages on the mean instrument is 24.12. Column 2 presents results for a controlled model with baseline controls for log population, black share of the population, share of the population that is non-native and does not have four-year college attainment, and share of the population that had four-year college attainment in 1980. The slope coefficient from the controlled regression of actual changes in mean wages on the mean instrument from 2000 to 2008 is 1.64 with standard error 0.31. The first stage F statistic from the controlled model of the change in mean wages on the shift-share mean instrument is 28.72. Across specifications, the mean instrument positively predicts changes in mean wages with first stage F statistics well over the rule of thumb of 10.

The second panel presents the point estimates for μ_1. Column 1 presents results for a reduced model. The slope coefficient from the regression of actual changes in the Gini coefficient in wages on the distributional instrument for the Gini coefficient from 2000 to 2008 is 1.00 with standard error 0.26. The first stage F statistic from the reduced model is 14.85. Column 2 presents results for a controlled model with baseline controls for log population, black share of the population, share of the population that is non-native and does not have four-year college attainment, and share of the population that had four-year college attainment in 1980. The slope coefficient from the controlled regression is 0.96 with standard error 0.29. The first stage F statistic from the controlled is 11.25. As with the first stage for changes in mean wages, the instrument positively predicts changes in the Gini coefficient in wages with first stage F statistics well over the rule of thumb of 10. We expect the coefficient to be positive and close to 1.[32]

The third and fourth panels of Table 2.2 present first stage results for predicting changes in the 90-50 difference in log wages and the mean wage. As with the Gini coefficient, we predict changes to the upper tail well with the slope coefficient for the actual change in the 90-50 difference on the instrument for the 90-50 ranging from 1.29 to 1.42 depending on specification with first stage F statistics ranging from 14.72 to 19.70. Figure 2.5 visually represents the reduced form first stage for

[32] Column 3 of Table 2.2 shows first stage results on the sample of 135 MSAs that are used in our analysis of community college enrollments in the CPS. Consistent with the first stage results on the entire sample, coefficients for $\propto_1$, $\frac{\partial\, mean\ wage}{mean\ wage\ instrument}$, are positive and significant with point estimates of 1.97 and 1.92 for the models including the Gini coefficient and 90-50 instruments respectively. The first stage F statistics are over the rule of thumb of 10 with values 18.53 and 18.62 for the models including the instruments for the Gini coefficient and 90-50 respectively. The coefficient for $\frac{\partial\, Gini\ coefficient\ wages}{Gini\ instrument}$ is positive and significant with point estimate 1.83 with first stage F statistic of 15.35. The coefficient for $\frac{\partial\, 90-50\ wages}{90-50\ instrument}$ is positive and significant with point estimate 1.42 with first stage F statistic of 19.70.

predicting changes in the 90-50 difference—it plots the correlation between the 90-50 instrument and changes in the 90-50 difference. The slope coefficient from this reduced form regression is 1.39 with a standard error of 0.34 and a first stage F statistic of 16.32.[33]

As a final check on the first stages of our analysis, it is necessary to check the correlation between the instrument that predicts changes in the wage distribution, the instrument for the inequality measure of choice, and the instrument that predicts changes in the mean of the wage distribution. If there was a high degree of collinearity between these instruments, and almost no residual variation in the instrument for inequality after controlling for our growth instrument, our identification strategy would fail. Figure 2.7 plots the correlation between the mean shift share instrument and the distributional 90-50 difference instrument after we have residualized by log population in the base year. Figure A2.10 in the Appendix plots the correlation between the mean shift share instrument and the distributional Gini coefficient instrument after we have residualized by log population in the base year. If all of the MSAs were lined up on the fit line, we would conclude that our dual instrumentation strategy relies on few locations to provide identification. In contrast, we see in both Figures 2.7 and A2.10 that many locations lie off of the regression line. There is a negative gradient between both changes in the mean instrument and changes in the Gini coefficient instrument and changes in the mean instrument and changes in the 90-50 instrument. The adjusted R square for the regression of the Gini coefficient instrument on the mean instrument is 0.03 which suggests that there is considerable variation in the predicted Gini coefficient once we control for growth. With respect to the relationship between the instruments for the 90-50 and the mean, we can see that they are more (inversely) related than the Gini coefficient instrument and the mean instrument. However, the R square for the regression of the 90-50 instrument on the mean instrument is 0.07.

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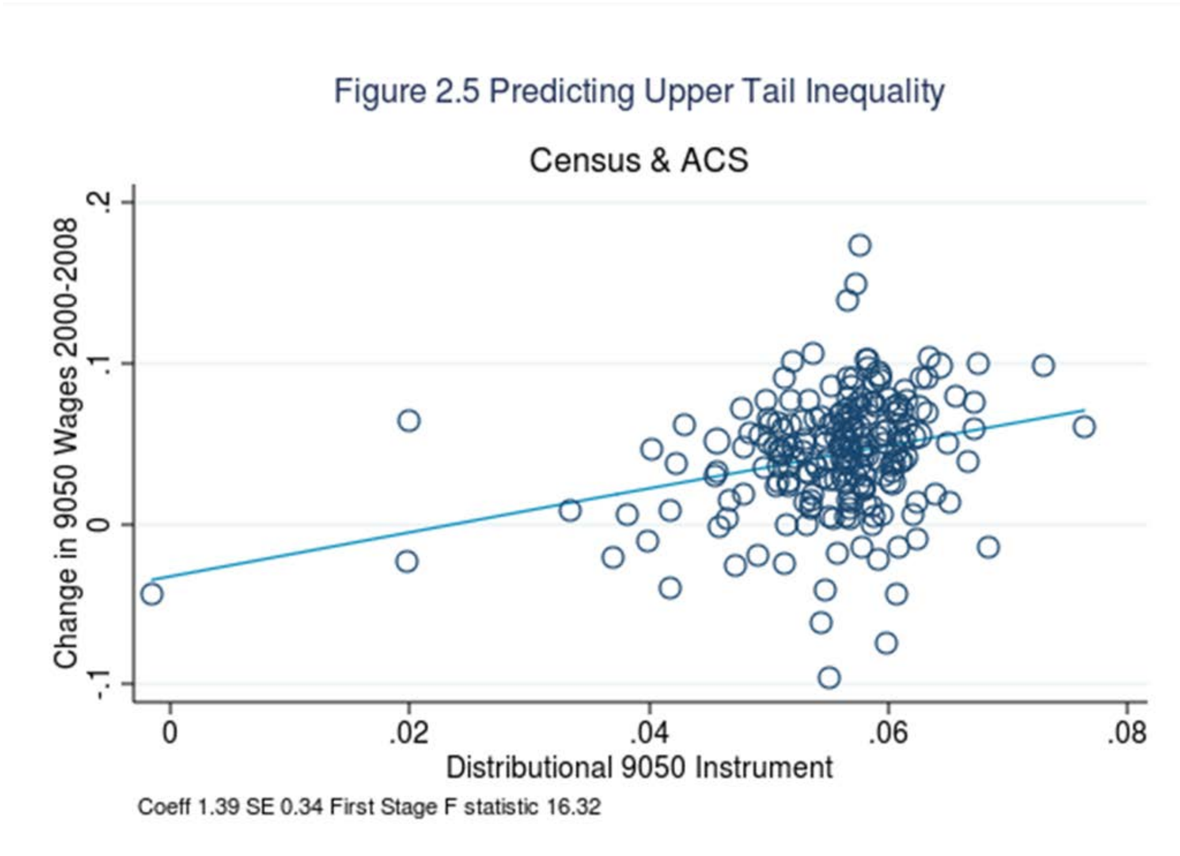
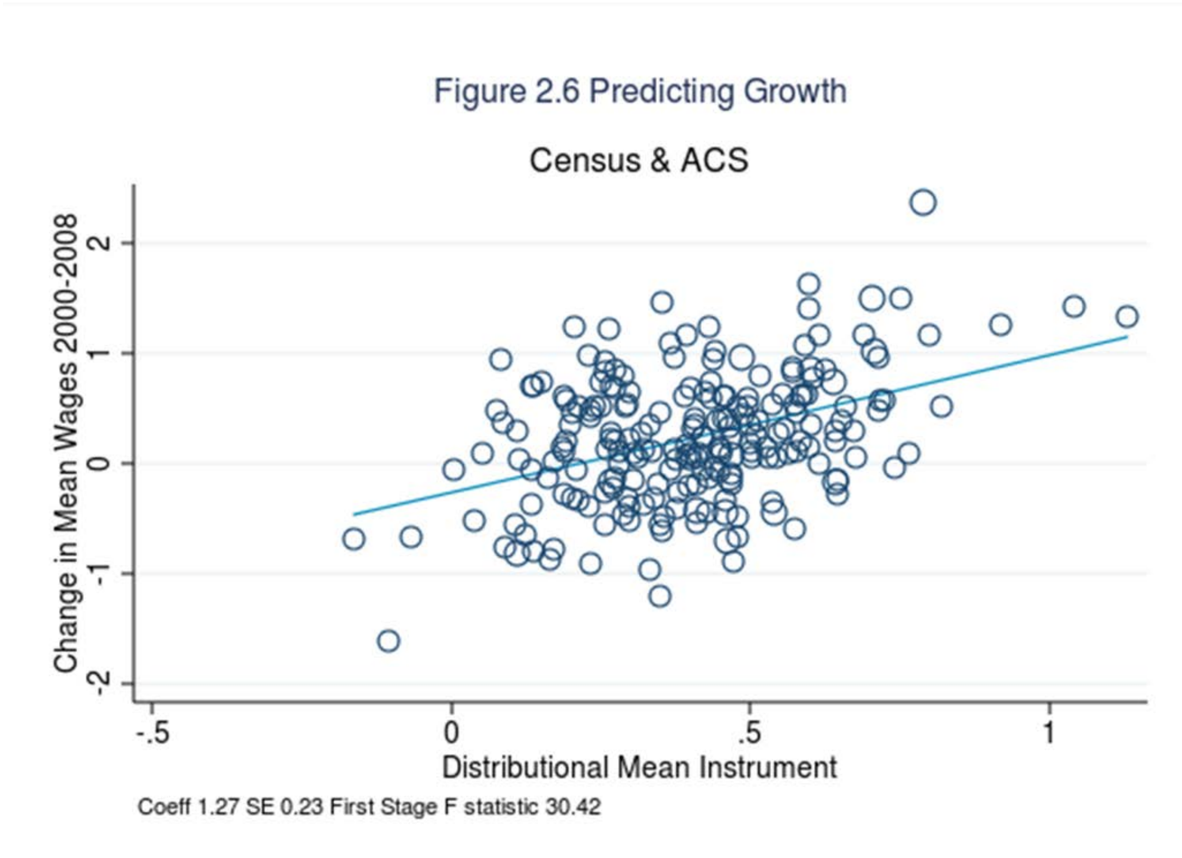
[33] Figures A2.5 to A2.9 of the Appendix show first stages for other statistics of interest. It is important to note that this strategy is less predictive at the bottom of the distribution as evident in Figures 2.8 and 2.9.



Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. This figure represents the following regression: change in the 90-50 in wages on a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions to predict changes to the 90-50. Standard errors are clustered at the state level.



Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. This figure represents the following regression: change in the mean wage on a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions to predict changes to the mean. Standard errors are clustered at the state level.

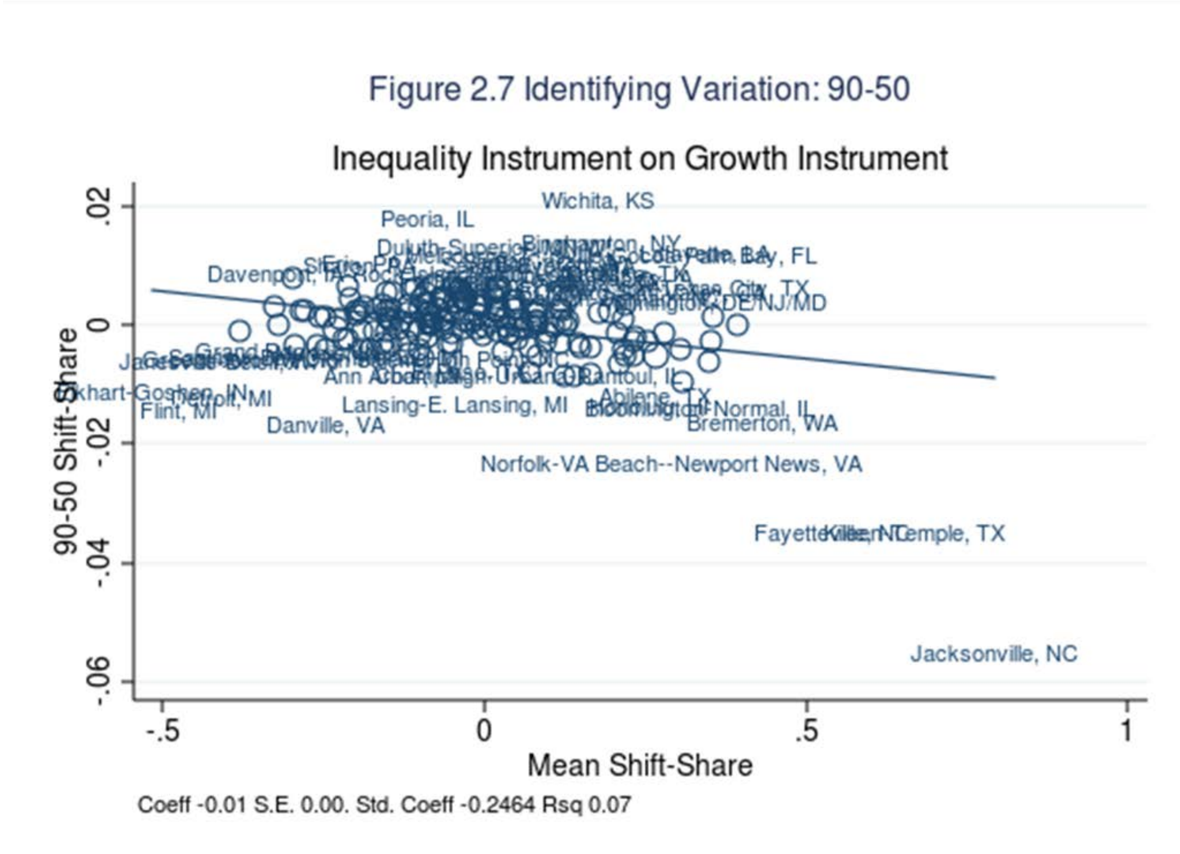
Table 2.2 First Stage Results, Predicting Wage Growth and Wage Inequality: 2000-2008

Gini Coefficient	**Reduced**	**Controlled**	**Selected Sample Controlled**
Individual Wages: Predicting Growth			
β instrument mean wages	1.236***	1.637***	1.965***
robust standard error	0.252	0.306	0.457
First Stage F Statistic instrument mean wages	24.12	28.72	18.53
Individual Wages: Predicting Inequality			
β instrument Gini coefficient	1.000***	0.956***	1.831***
robust standard error	0.260	0.285	0.467
First Stage F Statistic instrument Gini coefficient	14.85	11.25	15.35
90-50 Difference			
Individual Wages: Predicting Growth			
β instrument mean wages	1.262***	1.687***	1.917***
robust standard error	0.251	0.297	0.444
First Stage F Statistic instrument mean wages	25.230	32.33	18.62
Individual Wages: Predicting Inequality			
β instrument 90-50	1.409***	1.288***	1.420***
robust standard error	0.345	0.336	0.320
First Stage F Statistic instrument 90-50	16.690	14.72	19.70
N	212	212	135

Note: Data is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week, a minimum of 48 weeks/year with minimum annual salary $5,000. In the controlled models (Columns 2,3), we include the following controls: year 2000 log MSA population, year 2000 female employment

Table 2.2 Cont'd First Stage Results, Predicting Wage Growth and Wage Inequality: 2000-2008

share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. In Column 3, we restrict to the 135 MSAs used in the aggregate analysis of community college enrollments in the CPS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the Gini coefficient, and the 90-50 difference. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable/ standard deviation of the y variable.



Note: Data is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. We include the 192 MSAs from our main analysis. The 90-50 is the difference in log wage at the 90th and 50th percentiles of the MSA. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to the mean wage and the 90-50 difference.

2.5 Effects of Inequality and Growth on Postsecondary Schooling

Our analysis of the causal impacts of rising wage inequality on human capital investments focuses on first-time, full-year enrollments as the main outcome of interest. We use both administrative and survey data in our estimations.[34] Through the National Center for Education Statistics (NCES), the

[34] We focus on enrollment instead of attainment outcomes because we cannot observe degree completion in the administrative data. We are particularly interested in effects of inequality and growth on the population on the margin of community college attendance. In the survey data, it is difficult to truly measure Associate and other two-year degree

US Department of Education collects enrollment information for all degree-granting, postsecondary institutions that participate in federal financial aid programs authorized under Title IV of the Higher Education Act of 1965. The NCES releases fall enrollment counts to the public through the IPEDS survey. In order to construct aggregate and gender-specific enrollment counts per MSA, we use a version of the IPEDS data set in which the MSA has been hand-coded.[35] Enrollment counts are aggregated to the MSA level. We match 192 MSAs to the sample of MSAs for which we computed mean wage and Gini coefficients in the Census/ACS data. As the IPEDS survey is administrative data and less prone to measurement error, our main findings focus on this data set. It should be noted that the IPEDS survey presents aggregate enrollment counts with information tied to the institution and not the student. This introduces a limitation in terms of controlling for relevant student characteristics such as age, race, family structure and parental income. Importantly, the MSA identifier is tied to the address of the institution and not the address of the student. To the extent to which students exit the MSA that they grew up in, this could be problematic. Lau (2014) provides evidence from the Beginning Postsecondary Survey (BPS) that this may be of less concern for community college enrollments as the median distance from family home of a community college student is about 10 miles. In contrast, this may be more problematic for four-year institution students as the median distance from family home to college is about 50 miles.

In addition to the administrative data from IPEDS, we also use survey data, the Historical October Education Supplement to the Current Population Survey (CPS), to provide robustness checks to the main results. Our CPS sample is constructed from individual-level extracts from the IPUMS CPS database (King et al., 2010). It is worth noting the disadvantages of the CPS; namely, we are restricted

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completion without scooping up students in early years of bachelor-degree programs. The educational attainment outcomes constructed from survey data such as the CPS or Census and ACS would also more likely introduce contamination effects of endogenous migration. Therefore, we focus on enrollments.

[35] We thank Kerwin Charles, Erik Hurst and Matthew Notowidigdo for sharing the hand-matched IPEDS data.

to a smaller set of MSAs and responses may be prone to recall or other reporting error. An advantage of the CPS lies in the ability to extract information at the student level such as age and broad residence location.

In both the IPEDS and CPS, we evaluate effects on community college and four-year enrollments. Community college enrollments include counts for community and technical colleges. Four-year university enrollments include counts for public and private universities that grant bachelor degrees. Institutions that do not receive federal financial aid through Title IV are not included in our IPEDS data set.[36] For the IPEDS analysis, we construct enrollment rates by scaling enrollment counts by the non-institutional population age 18 to 25. In order to obtain yearly population counts, we use data from the 1990 and 2000 Census and the 2005 to 2011 ACS. We interpolate populations for the years 1994 to 1999 and 2001 to 2004 by using a linear approximation. For the CPS analysis, enrollment rates are calculated by combining information from questions asked about full-time enrollment status, current year in school, and type of institution. We construct first-time, full-year enrollment counts by counting people age 18 to 25 in first-year of community college or a four-year institution on a full-time basis and scale by the population of non-institutional people age 18 to 25 from the CPS. For the CPS, we only include MSAs with sufficient observations of non-institutional people age 18 to 25 with non-missing educational information.

Our analysis focuses on two long differences: a difference concurrent with the shock to inequality and a delayed long difference. For the concurrent long difference, our dependent variable is the mean

[36] Because some for-profit schools do not receive Title IV funds, these institutions are underrepresented in IPEDS. This sector has been growing fast in recent decades. As documented in Ruch (2001), the number of for-profit postsecondary institutions grew by 112% from 1990 to 2001. To the extent to which students who attend in for-profit institutions are observably different than those who attend traditional two-year and four-year institutions, this exclusion may be important. Lau (2014) presents evidence from the Beginning Postsecondary Survey (BPS) that students who attend for-profit institutions are older, score lower on the SAT, have lower high school GPAs, are more likely to hold a GED, are less likely to receive financial support from family, and are more likely to have come from single parent, low-income homes. We should observe these students in the CPS data, however.

enrollment rate for years 2001 to 2008 minus the mean enrollment rate for years 1994 to 2000. We view the years 1994 to 2000 as untreated period as they pre-date the inequality shock that we constructed. We assume that any inequality shocks that occurred in the pre-period are orthogonal to the constructed shock. For the delayed difference, in IPEDS, our dependent variable is the mean enrollment rate for years 2005 to 2011 minus the mean enrollment rate for years 1994 to 2000. In the CPS, the dependent variable for the delayed difference is the mean enrollment rate for years 2004 to 2010 minus the mean enrollment rate for years 1994 to 2000. In an alternate specification using the IPEDS data, we difference enrollments for the year 2000 from average enrollments for the pooled years 2006 to 2008. This strategy matches the pooling and differencing strategy used in construction of the right hand side variables but may introduce more noise in terms of measurement of enrollment rates.

In all of the human capital estimations, we include baseline controls for log population, black share of the population, female employment share, share of the population that is non-native and does not have four-year college attainment, and share of the population that had four-year college attainment in 1980. We control for base year population, black share, female labor force participation, and low immigrant share due to accessibility concerns. Large urban areas may have an infrastructure in place, such as public transportation, which improves access to local campuses or may simply have more institutions to choose from. The black share of a population may be correlated to accessibility issues related to discrimination. The female employment share may also be related to discrimination and also to affordable local childcare resources. Areas with large low immigrant shares may see lower enrollments due to language-related accessibility issues. Finally, as noted in Glaeser, Resseger and Tobio (2009), some cities have a legacy of postsecondary education which is highly correlated with current human capital outcomes such as high school drop-out rates. Therefore, we control for historical levels of human capital. All regressions are weighted by log population in the year 2000.

Standard errors are clustered at the state level to account for potential correlation arising from state-level policy interventions.

Although enrollment rates in the IPEDS survey and CPS should be similar, they differ with the CPS four-year enrollment counts outpacing those from IPEDS over the 2000s and the CPS two-year enrollment counts falling below those from IPEDS for much of the 2000s.[37] Figure A2.3 of the Appendix presents trends in enrollment counts for community college and four-year institutions over the 2000s. For the 192 MSAs included in our analysis from IPEDS, the cross-MSA mean total enrollment rate in community college for the years 1994 to 2000 was 5.20%. There is considerable variation across MSAs in baseline enrollments. The lowest enrollment MSA for community college had an enrollment rate of 0.36% compared to the highest enrollment MSA which had an enrollment rate of 19.32%. The cross-MSA mean enrollment rate in four-year institutions for the years 1994 to 2000 was 6.33%. The lowest enrollment MSA had an enrollment rate of 0.01% compared to the highest enrollment MSA which had an enrollment rate of 26.21%. For the 135 MSAs included in our analysis from the CPS, the cross-MSA mean total enrollment rate in community college for the years 1994 to 2000 was 3.56%. The cross-MSA mean total enrollment rate in community college for the years 1994 to 2000 was 7.22%. Female enrollments in four-year institutions outpaced those of men in both IPEDS and the CPS. In the CPS, male enrollments in community colleges was higher than that of women, however, in IPEDS women had higher enrollment rates in community colleges.[38]

In the following sub-sections, we discuss results of the effects of rising wage inequality and wage growth on community college and four-year institution enrollments. Across specifications, we find that predicted increases in the 90-50 difference and the Gini coefficient are associated with declining

[37] This is also noted in Barrow and Davis (2012) which documents community college and four-year university enrollments in both the IPEDS survey and October CPS in the wake of the Great Recession.
[38] Further summary statistics for baseline enrollment information are presented in Table 2.1.

enrollments. With regard to wage growth, we find that predicted increases in mean wages are associated with declining community college enrollments. However, changes in predicted wage growth have no effect on four-year institution enrollments. Results are robust to including controls for baseline characteristics of the MSA.

2.5.1 Community College Estimates

We begin our analysis of the causal impacts of rising wage inequality on postsecondary schooling investments by focusing on first-time, full-year enrollments in two-year programs such as community college and technical schools. Table 2.3 presents results in IPEDS for the difference concurrent with the shocks to wage inequality and wage growth. We present three estimation strategies in this table: (1) Ordinary Least Squares (OLS); (2) an Instrumental Variables (IV) strategy in which we regress the change in average enrollments directly on the instruments; (3) an Instrumental Variables strategy that uses Two Stage Least Squares (2SLS). The top panel of the table presents results from the OLS estimation. Columns 1 through 3 present results for changes to the upper tail of the wage distribution, the 90-50 difference in log wages, which approximates relative skill premium. Columns 4 through 6 present results for changes to overall inequality, the Gini coefficient in wages. In the OLS model, actual changes in upper tail inequality, the 90-50 difference, have no effect on community college enrollments, and all effects load on growth. A 1 standard deviation increase in the mean wage is associated with a 0.3 percentage point decrease in aggregate enrollments. With respect to overall inequality, a 1 standard deviation increase in the Gini coefficient is associated with a 0.2 percentage point decrease in aggregate enrollments and gender-specific enrollments. As in the OLS model with the 90-50, a 1 standard deviation increase in the mean wage is associated with a 0.3 percentage point decrease in aggregate enrollments.

As discussed in Section 2.4, there are concerns regarding the OLS results: confounding responses to transitory shocks, measurement error, local time-varying confounders, and reverse causation. For these reasons, we would like to instrument.[39] The bottom panel of Table 2.3 presents 2SLS results where changes to mean wages, the 90-50 difference, and the Gini coefficient are predicted using a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions. A 1 standard deviation predicted increase in the 90-50 difference caused a 0.8 percentage point decline in community college enrollments from 2000 to 2008. Moving from the 10th to the 90th percentile of changes in wage inequality corresponds to a 2.05 percentage point decrease in first-year, full-time aggregate community college enrollments. In 2000, the cross-MSA average enrollment rate was 5.20%. If we think of changes in the 90-50 difference as approximating changes to the skill premium, the negative coefficient provides evidence against the skill premium hypothesis.[40] Considering predicted changes in overall inequality, a 1 standard deviation predicted increase in the Gini coefficient caused a 0.6 percentage point decline in community college enrollments from 2000 to 2008. Moving from the 10th to the 90th percentile of changes in wage inequality corresponds to a 1.54 percentage point decrease in first-year, full-time aggregate community college enrollments. A 1 standard deviation predicted increase in mean wages caused a 0.4 percentage point decline in community college enrollments from 2000 to 2008 although growth effects are not significant once we instrument for either the 90-50 or the Gini coefficient.

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[39] To the extent that local policy affected the initial industry mix and the initial industry mix is correlated with long-term trends in enrollment, our instrumentation strategy would be subject to critique.

[40] The correlation between changes in the difference in log wages of those at the 90th and the 50th percentiles of the wage difference and changes in the difference in log wages of those with and without four-year college attainment is 0.39 over the 2000s. Alternatively, we estimate a 2SLS model where we predict changes in the skill premium with an instrument for the 90th percentile in log wages. The slope coefficient on the predicted change in the skill premium is -0.51 with standard error 0.29. A 1 standard deviation predicted increase in the skill premium corresponds to a 1.03 percentage point decline in community college enrollments. This seems to provide evidence against the skill premium hypothesis, locally, with respect to community college enrollments. It should be noted that the first stage is not as strong as our other models with a first stage F statistic of 5.06.

The second panel of Table 2.3 presents the results for regressing directly on the instruments for inequality and growth. A 1 standard deviation increase in the instrument for the 90-50 caused a 0.5 percentage point decline in community college enrollments. A 1 standard deviation increase in the instrument for the Gini coefficient caused a 0.3 percentage point decline in community college enrollments. The standardized coefficients for changes in the instruments for the 90-50 and the Gini coefficient are smaller than the standardized coefficients from the 2SLS results.

In considering the impacts of changes to the wage distribution on human capital investment, we may wish to consider longer term impacts. Table 2.4 presents results in IPEDS for the delayed enrollment response. The dependent variable is the mean community college enrollment rate for years 2005 to 2011 minus the mean community college enrollment rate for years 1994 to 2000. Again, in the OLS estimations, growth seems to have the strongest effects. A 1 standard deviation increase in mean wages is associated with 0.5 and 0.4 percentage point declines in community college enrollments in the models where we control for changes in the 90-50 and the Gini coefficient respectively. The 2SLS results for inequality are larger than the standardized effects on inequality from the shorter term effects. A 1 standard deviation predicted increase in the 90-50 caused a 1.0 percentage point decline in community college enrollments from 2005 to 2011. A 1 standard deviation predicted increase in the Gini coefficient caused a 0.7 percentage point decline in community college enrollments from 2005 to 2011.

We verify the robustness of the causal impact of rising inequality on community college enrollments established in Table 2.3 in the administrative data by turning to survey data. The bottom panel of Table A2.3 of the Appendix presents 2SLS results for the effects of rising wage inequality and wage growth on community enrollment rates as calculated in the CPS October Education Supplement. A 1 standard deviation increase in the 90-50 caused a 0.5 percentage point decline in community college enrollments from 2000 to 2008. A 1 standard deviation increase in the Gini coefficient caused a 0.6 percentage point decline in community college enrollments from 2000 to 2008. Moving from the 10th to the 90th percentile of the change in the Gini coefficient caused a 1.54 percentage point decrease in aggregate enrollments. From 1994 to 2000, the cross-MSA average community college enrollment rate was 7.22%. Increased growth depressed community college enrollments. A 1 standard deviation increase in predicted mean wages decreased community college enrollments by 0.5 and 0.3 percentage points in models that control for predicted changes to the 90-50 and the Gini coefficient respectively.

As a falsification test on our main findings in the IPEDS data, we regress changes in first-time, full-year enrollments from the period from 1990 to 2000 on the predicted changes in the 90-50 difference and mean wage, and the Gini coefficient and mean wage, using our shift-share instrumentation strategy. These results are presented in Table A2.5 of the Appendix. If the changes in inequality predicted by our instruments is predictive of changes to enrollments in the period pre-dating the shock, we may be worried that MSAs that are moved by the instrument are serially different than those who do not receive large shocks in predicted inequality. In the 2SLS model in which we regress changes in first-time, full-year community college enrollments on predicted changes in the Gini coefficient, the slope coefficient is highly insignificant: -0.23 with standard error of 2.17. The coefficient on growth is positive and also highly insignificant: 0.002 with standard error of 0.020. In the 2SLS model in which we regress changes in first-time, full-year community college enrollments on predicted changes in the 90-50, the slope coefficient is negative and insignificant: -0.37 with standard error of 0.38. The coefficient on growth is negative and also highly insignificant: 0.002 with standard error of 0.018.

Table 2.3 Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

	90-50			Gini Coefficient		
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
OLS						
β Δ inequality	-0.009	-0.027	0.008	-0.198	-0.184	-0.214
robust standard error	0.039	0.036	0.044	0.143	0.123	0.169
standardized coefficient	0.000	-0.001	0.000	-0.002	-0.002	-0.002
β Δ mean wage	-0.006*	-0.005	-0.007*	-0.005*	-0.004	-0.006*
robust standard error	0.003	0.003	0.004	0.003	0.003	0.003
standardized coefficient	-0.003	-0.003	-0.004	-0.003	-0.002	-0.003

Table 2.3 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

		90-50			Gini Coefficient	
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
Instrumental Variables						
β instrument inequality	-0.704***	-0.691***	-0.717**	-1.815**	-1.902***	-1.753*
robust standard error	0.269	0.230	0.318	0.826	0.708	0.979
standardized coefficient	-0.005	-0.005	-0.005	-0.003	-0.003	-0.003
β instrument mean wage	-0.019	-0.015	-0.022	-0.016	-0.013	-0.019
robust standard error	0.016	0.014	0.017	0.015	0.014	0.017
standardized coefficient	-0.004	-0.003	-0.004	-0.003	-0.002	-0.004

Table 2.3 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

	90-50			Gini Coefficient		
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
2SLS						
β Δ predicted inequality	-0.563**	-0.553***	-0.574**	-1.990*	-2.021**	-1.977
robust standard error	0.257	0.221	0.296	1.141	0.957	1.342
standardized coefficient	-0.008	-0.008	-0.009	-0.006	-0.006	-0.006
β Δ predicted mean wage	-0.014	-0.012	-0.016	-0.013	-0.011	-0.015
robust standard error	0.010	0.008	0.011	0.011	0.010	0.013
standardized coefficient	-0.004	-0.003	-0.005	-0.004	-0.003	-0.004
N	192	192	192	192	192	192

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Education data is from the Integrated Postsecondary Education Data System (IPEDS).

Table 2.3 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

The dependent variable is mean enrollment rate for years 2001 to 2008 minus mean enrollment rate for years 1994 to 2000. Enrollment rates are calculated by scaling first-time, full-year enrollment counts for junior colleges and technical institutions from IPEDS by interpolated population counts for non-institutional people age 18 to 25 from the Census and ACS. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3) 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the 90-50 difference, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

Table 2.4 Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25
Aggregate and By Gender: 2000-2011

		90-50			Gini Coefficient	
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
OLS						
β Δ inequality	0.001	-0.010	0.013	-0.133	-0.134	-0.131
robust standard error	0.026	0.025	0.029	0.182	0.164	0.208
standardized coefficient	0.000	-0.001	0.001	-0.001	-0.001	-0.001
β Δ mean wage	-0.008*	-0.006*	-0.009*	-0.007*	-0.006*	-0.008*
robust standard error	0.004	0.004	0.005	0.004	0.003	0.004
standardized coefficient	-0.005	-0.004	-0.005	-0.004	-0.003	-0.005

Table 2.4 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2011

	90-50			Gini Coefficient		
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
Instrumental Variables						
β instrument inequality	-0.823**	-0.779**	-0.870*	-2.408*	-2.415**	-2.419*
robust standard error	0.376	0.309	0.449	1.219	1.012	1.440
standardized coefficient	-0.006	-0.005	-0.006	-0.004	-0.004	-0.004
β instrument mean wage	-0.027	-0.025	-0.029	-0.024	-0.022	-0.025
robust standard error	0.021	0.018	0.024	0.020	0.017	0.023
standardized coefficient	-0.005	-0.005	-0.006	-0.005	-0.004	-0.005

Table 2.4 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2011

	90-50			Gini Coefficient		
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
2SLS						
β Δ predicted inequality	-0.291**	-0.275**	-0.307*	-2.608*	-2.587**	-2.642
robust standard error	0.141	0.118	0.166	1.502	1.285	1.734
standardized coefficient	-0.010	-0.009	-0.010	-0.007	-0.007	-0.007
β Δ predicted mean wage	-0.018	-0.017*	-0.020	-0.018	-0.017	-0.019
robust standard error	0.012	0.010	0.014	0.014	0.012	0.016
standardized coefficient	-0.005	-0.005	-0.006	-0.005	-0.005	-0.006
N	192	192	192	192	192	192

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2009, 2010, and 2011 represent the year 2011. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Education data is from the Integrated Postsecondary Education Data System (IPEDS).

Table 2.4 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments, Ages 18-25
Aggregate and By Gender: 2000-2011

The dependent variable is mean enrollment rate for years 2005 to 2011 minus mean enrollment rate for years 1994 to 2000. Enrollment rates are calculated by scaling first-time, full-year enrollment counts for junior colleges and technical institutions from IPEDS by interpolated population counts for non-institutional people age 18 to 25 from the Census and ACS. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3) 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the 90-50, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

2.5.2 Four-Year Institution Estimates

Our analysis separately analyzes the effects of rising wage growth and inequality by postsecondary schooling type for two important reasons. First, the tuition and time costs, entry requirements, and benefits to a bachelor's degree exceed those of an associate's degree. Second, there may be a degree of substitution across classes of degrees. As a preview of the results, we find that rising predicted wage inequality causes modest declines in four-year enrollments. This result suggests that the decline in community college enrollments is not resulting from substitution from community college to four-year institutions.

Using the IPEDS data on first-time, full-year enrollments in bachelor-degree-granting institutions, Table 2.5 presents results for the effects of changes in wage inequality and growth on university enrollments. The top panel of Table 2.5 presents results from the OLS estimation. With respect to upper tail inequality, a 1 standard deviation increase in the 90-50 corresponds to a 0.1 percentage point decline in four-year college enrollments.[41] A 1 standard deviation increase in the Gini coefficient is associated with a 0.2 percentage point decrease in aggregate enrollments and gender-specific enrollments. This result is significant and consistent with the standardized effects from the OLS estimations on community college enrollments in Table 2.3. The OLS results for growth point to a positive association between rising mean wages and four-year enrollments.

In the bottom panel of Table 2.5, the 2SLS model, we instrument for changes to the 90-50, Gini coefficient, and mean wage using our shift-share instrumentation strategy. Although the slope coefficients are insignificant, the sign is suggestive that potential students in MSAs that received predicted inequality shocks did not substitute from community college enrollment to four-year

[41] Alternatively, we estimate a 2SLS model where we predict changes in the skill premium with an instrument for the 90th percentile in log wages. The slope coefficient on the predicted change in the skill premium, which is insignificant, is 0.05 with standard error 0.14. A 1 standard deviation predicted increase in the skill premium corresponds to a 0.09 percentage point increase in first-time, full-year four-year college enrollments.

enrollment. Once we instrument for changes to the Gini coefficient, a 1 standard deviation change in inequality corresponds to a 0.3 percentage point decline in four-year enrollments. A 1 standard deviation predicted increase in the 90-50 corresponds to a 0.1 percentage point decline in four-year enrollments. Once we instrument for changes to mean wages, the standardized coefficients from growth attenuate.

Table 2.6 presents the delayed results in IPEDS for four-year institution enrollments. The dependent variable is mean four-year enrollment rate for years 2005 to 2011 minus mean four-year enrollment rate for years 1994 to 2000. As with the earlier period regression, the OLS effects for predicted changes in the 90-50 are small and insignificant. With respect to overall inequality, a 1 standard deviation increase in the Gini coefficient is associated with a 0.3 percentage point decrease in aggregate enrollments. A 1 standard deviation increase in mean wages increases four-year institution enrollments by 0.4 percentage points. As with the IPEDS results in Table 2.5, once we instrument, the point estimates for inequality and growth are not statistically significant and growth effects in the lagged difference attenuate once we instrument. In the 2SLS model in the bottom panel of Table 2.6, results for the 90-50 are highly insignificant. A 1 standard deviation predicted increase in the Gini coefficient causes a 0.3 percentage point decrease in four-year institution enrollments.

Table 2.4 of the Appendix extends the analysis on four-year institution enrollments to the CPS data. While the results from the CPS are largely insignificant, we do see negative effects of increases in actual and predicted wage inequality on four-year enrollments. It is interesting to note that in the CPS, the point estimates on actual and predicted increases in wage growth are positive.

We would like to more directly address the incentive question: does a rising skill premium to college graduates bid people into four-year institution enrollment? In order to do this, we instrument for the skill premium by using a standard wage shift-share instrument to predict mean wages for those with four-year college attainment and those with a high school diploma and below. Surprisingly even when we instrument directly for the skill premium, MSAs with predicted increases in the skill premium did not experience increases in first-time, four-year institution enrollments. Table 2.7 presents the skill premium results. The OLS effects are insignificant. In the instrumented specification in the second panel of Table 2.7, the point estimates are negative. In the IPEDS data, the aggregate effects and effects for men are negative and significant. In the 2SLS model in the bottom panel of Table 2.7, results are insignificant.

In conclusion, we find that predicted increases in the 90-50 and Gini coefficient are associated with large declines in community college enrollments. Further, when we directly instrument for the skill premium, MSAs with predicted increases in the skill premium did not experience increases in four-year institution enrollments. In our main analysis in the IPEDS data on community college enrollments, we find that moving from the 10th to the 90th percentile of changes in the 90-50 difference corresponds to a 2.05 percentage point decrease in first-year, full-time aggregate community college enrollments. Predicted increases in mean wages are also associated with declines in community college enrollments. This is true in the case of aggregate enrollments, for both male and female enrollments, in the CPS data, in the later period and is robust to the inclusion of baseline controls and to a falsification test. In the four-year institution enrollment results, we also find evidence that predicted increases in inequality are associated with declines in first-time, full-year enrollments in both the IPEDS survey and CPS. However, in the IPEDS survey, we find no impacts of changes in growth on enrollments once we instrument. In the CPS, we do find some evidence that predicted increases in mean wages are associated with increases in four-year institution enrollments however these results are mostly not statistically significant.

The robust findings of the negative impact of increasing local wage inequality on community college and four-year institution enrollments may suggest that a mechanism outside of the rising skill premium may be at play.

Table 2.5 Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25
Aggregate and By Gender: 2000-2008

	90-50			Gini Coefficient		
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
OLS						
β Δ inequality	-0.019	-0.026	-0.010	-0.211**	-0.145	-0.276**
robust standard error	0.049	0.036	0.066	0.101	0.100	0.119
standardized coefficient	-0.001	-0.001	0.000	-0.002	-0.002	-0.003
β Δ mean wage	0.056*	0.038*	0.075*	0.004***	0.003***	0.006***
robust standard error	0.029	0.023	0.040	0.001	0.001	0.002
standardized coefficient	0.002	0.001	0.003	0.003	0.002	0.003

Table 2.5 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

		90-50			Gini Coefficient	
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
Instrumental Variables						
β instrument inequality	-0.046	-0.157	0.087	-1.097	-1.320**	-0.832
robust standard error	0.156	0.149	0.195	0.675	0.626	0.790
standardized coefficient	0.000	-0.001	0.001	-0.002	-0.002	-0.002
β instrument mean wages	-0.001	-0.005	0.003	-0.001	-0.005	0.002
robust standard error	0.005	0.005	0.006	0.005	0.005	0.006
standardized coefficient	0.000	-0.001	0.001	0.000	-0.001	0.000

Table 2.5 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25
Aggregate and By Gender: 2000-2008

	90-50			Gini Coefficient		
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
2SLS						
β Δ predicted inequality	-0.037	-0.125	0.069	-0.876	-1.084*	-0.632
robust standard error	0.128	0.137	0.149	0.568	0.615	0.609
standardized coefficient	-0.001	-0.002	0.001	-0.003	-0.003	-0.002
β Δ predicted mean wage	-0.001	-0.004	0.002	-0.001	-0.004	0.001
robust standard error	0.003	0.004	0.003	0.004	0.005	0.004
standardized coefficient	0.000	-0.001	0.001	0.000	-0.001	0.000
N	187	187	187	187	187	187

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Education data is from the Integrated Postsecondary Education Data System (IPEDS). The dependent variable is mean enrollment rate for years 2001 to 2008 minus mean enrollment rate for years 1994 to 2000. Enrollment rates are calculated by scaling first-time, full-year enrollment counts for institutions awarding bachelor degrees from IPEDS by interpolated population

Table 2.5 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

counts for non-institutional people age 18 to 25 from the Census and ACS. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the 90-50, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

Table 2.6 Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25
Aggregate and By Gender: 2000-2011

		90-50			Gini Coefficient	
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
OLS						
β Δ inequality	-0.005	-0.017	0.008	-0.282*	-0.180	-0.384**
robust standard error	0.030	0.020	0.043	0.141	0.122	0.178
standardized coefficient	0.000	-0.001	0.001	-0.003	-0.002	-0.004
β Δ mean wage	0.005**	0.004**	0.006**	0.007***	0.005**	0.008**
robust standard error	0.002	0.002	0.003	0.002	0.002	0.003
standardized coefficient	0.003	0.003	0.004	0.004	0.003	0.005

Table 2.6 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2011

		90-50			Gini Coefficient	
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
Instrumental Variables						
β instrument inequality	-0.026	-0.177	0.147	-1.298	-1.541*	-1.023
robust standard error	0.206	0.163	0.282	0.949	0.786	1.173
standardized coefficient	0.000	-0.001	0.001	-0.002	-0.003	-0.002
β instrument mean wage	-0.002	-0.008	0.003	-0.003	-0.007	0.002
robust standard error	0.007	0.007	0.009	0.008	0.007	0.009
standardized coefficient	0.000	-0.001	0.001	-0.001	-0.001	0.000

Table 2.6 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2011

		90-50			Gini Coefficient	
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
2SLS						
β Δ predicted inequality	-0.009	-0.063	0.053	-1.045	-1.276*	-0.785
robust standard error	0.075	0.067	0.097	0.765	0.733	0.883
standardized coefficient	0.000	-0.002	0.002	-0.003	-0.004	-0.002
β Δ predicted mean wage	-0.001	-0.005	0.002	-0.002	-0.005	0.001
robust standard error	0.004	0.005	0.005	0.005	0.006	0.005
standardized coefficient	0.000	-0.001	0.001	-0.001	-0.001	0.000
N	187	187	187	187	187	187

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2009, 2010, and 2011 represent the year 2011. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Education data is from the Integrated Postsecondary Education Data System (IPEDS). The dependent variable is mean enrollment rate for years 2005 to 2011 minus mean enrollment rate for years 1994 to 2000. Enrollment rates are calculated by scaling first-time, full-year enrollment counts for institutions awarding bachelor degrees from IPEDS by interpolated population counts for non-institutional people age 18 to 25 from the Census and ACS. We present 3 estimation strategies in this table: (1) OLS; (2) a

Table 2.6 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments, Ages 18-25
Aggregate and By Gender: 2000-2011

specification where we regress change in enrollments directly on our instruments; and (3 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the 90-50, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

Table 2.7 Effects of Changing Skill Premium, Growth on Four-Year Institution Enrollments, Ages 18-25
Aggregate and By Gender: 2000-2008

		IPEDS			CPS	
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
OLS						
β Δ inequality	-0.008	0.009	-0.028	0.003	-0.205	0.033
robust standard error	0.040	0.043	0.046	0.090	0.142	0.146
standardized coefficient	0.000	0.000	-0.001	0.000	-0.007	0.001
β Δ mean wage	0.003**	0.002*	0 .004**	-0.001	0.002	0.006
robust standard error	0.002	0.001	0.002	0.006	0.008	0.006
standardized coefficient	0.002	0.001	0.003	-0.001	0.001	0.004
Instrumental Variables						
β instrument inequality	-0.489*	-0.332	-0.675**	-0.456	-0.174	-1.254
robust standard error	0.264	0.261	0.308	1.108	1.983	1.673
standardized coefficient	-0.002	-0.002	-0.003	-0.002	-0.001	-0.006
β instrument mean wages	-0.002	-0.006	0.001	0.026	0.011	0.071**
robust standard error	0.005	0.005	0.006	0.037	0.047	0.033
standardized coefficient	0.000	-0.001	0.000	0.005	0.002	0.012

Table 2.7 Cont'd Effects of Changing Skill Premium, Growth on Four-Year Institution Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

		IPEDS			CPS	
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
2SLS						
β Δ predicted inequality	-0.276	-0.226	-0.345	-0.012	0.036	0.020
robust standard error	0.185	0.168	0.223	0.527	1.472	0.760
standardized coefficient	-0.005	-0.004	-0.007	0.000	0.001	0.000
β Δ predicted mean wage	-0.009	-0.009	-0.009	0.014	0.006	0.038
robust standard error	0.008	0.008	0.010	0.027	0.030	0.025
standardized coefficient	-0.003	-0.003	-0.003	0.004	0.002	0.012
First Stage F Statistic Skill Premium	14.5	14.5	14.5	20.540	3.030	16.090
First Stage F Statistic Mean	33.2	33.2	33.2	27.610	21.740	26.720
N	189	189	189	157	130	138

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Education data is from the Integrated Postsecondary Education Data System (IPEDS) and from the October Supplement of the Current Population Survey. In the CPS, enrollment rates are calculated by combining information from questions asked about full-time enrollment status, current year in school, and type of institution. We construct first-time, full-year enrollment counts by counting people age 18 to 25 in first-year of school by level on a full-time basis and scaling by population of non-institutional

Table 2.7 Cont'd Effects of Changing Skill Premium, Growth on Four-Year Institution Enrollments, Ages 18-25 Aggregate and By Gender: 2000-2008

people age 18 to 25 from the CPS. The dependent variable is mean enrollment rate for years 2001 to 2008 minus mean enrollment rate for years 1994 to 2000. In IPEDS, enrollment rates are calculated by scaling first-time, full-year enrollment counts for institutions awarding bachelor degrees from IPEDS by interpolated population counts for non-institutional people age 18 to 25 from the Census and ACS. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3) 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages. A standard shift-share wage instrument is used to predict the premium to workers with 4 years of college attainment over workers with a high school diploma or less. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

2.6 Migration

Papers utilizing regional variation are subject to concerns about selected migration. An established literature on regional labor markets has highlighted that regional migration is a response to employment shocks and these responses may differ by skill level.[42] In this section, we address the issue of migration by: (1) establishing that MSAs that receive large predicted inequality shocks experience population increases among those ages 18 to 25; (2) discuss and sign the nature of the potential bias from selected migration; and (3) show evidence that suggests our findings are not quantitatively altered by the migration responses in the sample.

To begin, we are interested in migration of young, potential students in response to changes in inequality and growth. Table 2.8 regresses changes in population of non-institutional people age 18 to 25 on changes in the 90-50, the Gini coefficient and mean wages. Columns 1 and 2 examine these effects in a model where we shock upper tail inequality, the 90-50 difference in wages, controlling for changes to mean wages. Column 1 examines effects for the whole age 18 to 25 population which would include migration from abroad, other states, and other locations within the state. Column 2 examines changes in the population of people age 18 to 25 who reside in their state of birth; changes in this variable would represent intrastate migration. In the OLS results, there are no significant effects of changes in inequality on population. In the instrumented model in the center panel of Table 2.8, we find predicted increases in inequality cause increases in population. A 1 standard deviation increase in the instrument for the 90-50 increases the population of those age 18 to 25 by 0.31 of 1 standard deviation. A 1 standard deviation increase in the distributional instrument for the 90-50 increases the native-state population of those age 18 to 25 by 0.23 of 1 standard deviation. We find that wage growth

[42] Blanchard and Katz (1992) document regional migration responses to rising unemployment. In Glaeser and Gyourko (2005), college workers exit cities with negative labor demand shocks. In Topel (1986), and Bound and Holzer (2000), non-college workers are less mobile than college workers. In Notowidigdo (2011), the progressive nature of transfer program eligibility formulas induces low skill workers to remain in areas with negative demand shocks.

also has a positive effect, yet insignificant, on population growth. A 1 standard deviation increase in the mean wage instrument increases the population of those age 18 to 25 by 0.04 of 1 standard deviation. A 1 standard deviation increase in the mean wage instrument increases the native-state population of those age 18 to 25 by 0.10 of 1 standard deviation. In the bottom panel, we present the 2SLS estimates. A 1 standard deviation predicted increase in the 90-50 corresponds to 0.47 of a 1 standard deviation increase in the total population age 18 to 25 and a 0.34 of a 1 standard deviation increase in the native population age 18 to 25. With respect to mean growth, a 1 standard deviation predicted increase in mean wages causes a 0.09 and 0.13 of a 1 standard deviation increase in the total and native populations respectively. The growth effects on the native population are significant.

Columns 3 and 4 examine these effects in a model where we shock overall inequality, the Gini coefficient in wages, controlling for changes to mean wages. Column 3 examines effects for the whole population age 18 to 25, and Column 4 examines changes in the population of people age 18 to 25 who currently reside in their state of birth. Consistent with the 90-50 results, the OLS results are not significant for inequality. The 2SLS results for the Gini coefficient, presented in the bottom panel of Table 2 of the Appendix, also yield large population increases. A 1 standard deviation predicted increase in the Gini coefficient corresponds to 0.47 of a 1 standard deviation increase in the total population age 18 to 25 and a 0.33 of a 1 standard deviation increase in the native population age 18 to 25. With respect to growth, a 1 standard deviation predicted increase in mean wages causes a 0.08 and 0.12 of a 1 standard deviation increase in the total and native populations respectively; however, growth effects are not significant.

We have established that MSAs that experienced large predicted increases in both upper tail and overall inequality experienced population booms both in the form of overall migration and intrastate migration. As we are focused on human capital outcomes, migration may be particularly concerning if migrants look different than non-migrants on the basis of human capital attainment. Our outcome variable is first-time, full-year enrollees at community colleges and four-year institutions. If young migrants have already attained postsecondary education, they will be less likely to be first-time enrollees. An increase in this type of migration would cause enrollment rates to decline as the denominator increases. If high income parents migrate into MSAs with predicted increases in wage inequality and their children are more likely to enroll in postsecondary schooling, we may see an *increase* in enrollments due to the change in composition. Likewise, if young migrants have a latent taste for human capital, even if they migrate without higher levels of human capital attainment, they may be more likely to seek postsecondary schooling. This would result in *increases* in enrollment rates in the presence of this form of selected migration. In our main analyses, we estimated *negative* effects of predicted changes in inequality on community college and four-year enrollments. Thus, if these mechanisms were at work, our main results would be even more negative in the absence of migration.

In the presence of selected migration, enrollment *rates* may decline even in the presence of increasing enrollment *counts* if increasing inequality bids migrants into a MSA. If we only focused on changing enrollment rates, this type of migration may lead us to falsely reject the skill premium hypothesis due to population effects churning through the denominator. For this reason, it is imperative to consider separately the numerator: enrollment counts. We estimate a 2SLS model using the difference in enrollment *counts* instead of enrollment *rates*. For community college enrollments, the slope coefficient on the predicted change in the 90-50 is -45858.56 with standard error 15470.56. The slope coefficient on the predicted change in the Gini coefficient is also negative: -219205.8 with standard error 105738.3. With respect to four year enrollment counts, the slope estimates in counts are not significant. The slope coefficient on the predicted change in the 90-50 is 433.13 with standard error 12891.54. The slope coefficient on the predicted change in the Gini coefficient is negative which is consistent with the results in rates, but is not significant: -32053.33 with standard error 40461.24. We find that absolute enrollment levels are declining even as the population of those age 18 to 25 is increasing. Thus, our main findings are truly the result of declining enrollment activity not due to local population changes.

Although overall migration of people age 18 to 25 is increasing in MSAs with large predicted shocks in inequality, the causal effect of changes in inequality on community college enrollments is still present absent population changes. Now, we take a deeper look into the type of people who are migrating. As discussed in the previous section, the IPEDS survey does not provide information about the characteristics of students. Thus, we cannot separate migrants from non-migrants in the IPEDS data. However, the March Historical CPS does provide information on the migration status of individuals.[43] Using information from a question of recent migration status, we are able to identify migrants in the sample.[44] Following the pooling strategy we used in construction of the CPS education variables, we compute several summary statistics of interest for the 135 MSAs used in the CPS aggregate analyses over the periods 1994 to 2000 and 2001 to 2008. Figure A2.11 of the Appendix compares demographic characteristics of young migrant and non-migrant populations in MSAs within and across periods depending on whether the MSA has an above- or below-median predicted change in the Gini coefficient. In Figure A2.11, we see that migrants are different than non-migrants on at least two dimensions: they are more likely to be white and more likely to have four-year college attainment. However, across MSAs that receive large predicted increases in inequality and those that do not, these patterns are stable.

In conclusion, we find that MSAs that receive large predicted increases in inequality have population increases. However, once we remove population effects by using enrollment counts instead of enrollment rates as our outcome variable, our main results are still present. In the CPS, we

[43] In our analysis on enrollments, we use the October CPS which does not have migration variables. Thus, in this exercise we use the March CPS which does have migration variables and restrict to the same MSAs used in the October CPS to gain insight into the characteristics of migrants and non-migrants in the MSAs used in our analysis.
[44] We use the variable migrate1 in IPUMS CPS and identify migrants as people who did not live in the same house or the same county the year before.

find migrants are slightly more likely to be white and more educated than young non-migrants. However, the differences between migrant and non-migrant populations are similar across large predicted inequality and small predicted inequality MSAs and are stable over time. Thus, we do not think that education results from the CPS are a product of selected migration.

Table 2.8 Effects of Changing Inequality, Growth on Population, Ages 18-25
Entire Population and Native-to-State Population: 2000-2008

	90- 50		Gini Coefficient	
	Population Age 18-25	Native Population Age 18-25	Population Age 18-25	Native Population Age 18-25
OLS				
β Δ inequality	0.502	0.304	0.386	-0.872
robust standard error	0.402	0.469	1.285	1.437
standardized coefficient	0.159	0.072	0.037	-0.062
β Δ mean wage	0.024	0.040*	0.023	0.043*
robust standard error	0.018	0.022	0.022	0.026
standardized coefficient	0.122	0.147	0.114	0.161
Instrumental Variables				
β instrument inequality	4.588***	4.612**	17.820***	16.344**
robust standard error	1.414	1.965	4.226	6.396
standardized coefficient	0.308	0.229	0.314	0.213
β instrument mean wage	0.023	0.078	0.009	0.060
robust standard error	0.057	0.069	0.057	0.071
standardized coefficient	0.039	0.098	0.015	0.076

Table 2.8 Cont'd Effects of Changing Inequality, Growth on Population, Ages 18-25
Entire Population and Native-to-State Population: 2000-2008

	90- 50		Gini Coefficient	
	Population Age 18-25	**Native Population Age 18-25**	**Population Age 18-25**	**Native Population Age 18-25**
2SLS				
β Δ predicted inequality	3.527***	3.514**	19.269***	18.284**
robust standard error	1.378	1.835	7.037	9.023
standardized coefficient	0.465	0.343	0.469	0.330
β Δ predicted mean wage	0.036	0.069**	0.032	0.062
robust standard error	0.033	0.034	0.055	0.054
standardized coefficient	0.092	0.129	0.082	0.117
N	212	212	212	212

Note: Data is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008 and years 2009, 2010 and 2011 represent the year 2011. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. The dependent variables are (1) non-institutional population age 18-25; (2) non-institutional population age 18-25 who were born in state of current residence. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3) 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the 90-50, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable/ standard deviation of the y variable.

2.7 Effects of Inequality and Growth on Residential Segregation

This section explores the impact of rising local wage inequality on an important feature of local community—the income composition of neighborhoods. Income segregation refers to the spatial distribution of income across neighborhoods. Income segregation is therefore a different concept than wage inequality though the latter is a necessary condition: In MSAs in which most of the community's income is held by a small group, the rich can select to disperse throughout the MSA's neighborhoods or reside in a selected few neighborhoods. A segregated MSA would be one in which richer individuals tend to live in the same neighborhoods while poor families would live close to each other.

There are two channels through which income segregation potentially matters to skill acquisition and human capital investment: (1) fiscal externalities; and (2) "sociological or psychological effects"[45]. To the extent that individuals with different income sort across governments such as school districts and municipalities, tax revenue and therefore the amount of public goods consumed by individuals will differ and be correlated with individual income. Generally, close proximity to rich neighbors improves local amenities such as more and better quality parks, libraries and even schools.[46] In addition to these fiscal externalities, neighborhoods matter as networks. Neighborhoods are the first level of community outside the boundaries of family life. As such, they serve as classrooms for one's earliest knowledge of the labor market and serves as an entry point into civic, political and educational networks. Therefore, these small communities may play an important role in the formation and accumulation of both social and human capital.

A large literature on human capital acquisition has shown the recursive nature of human capital: current level of human capital is an important input in the production of future human capital.[47] As a

[45] For a survey of the literature on neighborhood effects see Durlauf (2004).
[46] Though school funding is increasingly centralized at the state-level to limit differences in school expenditures per capita across school districts.
[47] Cunha and Heckman (2007); Heckman and Mosso (2014).

result, the returns to secondary education depend heavily on the quality of an individual's past education which in turn may have been affected by the composition of her neighborhood. Also, returns might be lower for individuals in poorer neighborhoods if networks and personal connections are important in order to find a job and realize the monetary gains from higher education. Finally, perceived returns may also be lower (or uncertain) to an individual who is not surrounded by many educated neighbors. For these reasons, income segregation may decrease enrollment in postsecondary education in homogenously poor neighborhoods. If individuals at the margin of college enrollment decision are concentrated in the lower end of the income distribution, income segregation would decrease aggregate enrollment. Durlauf (1996) and Benabou (1996) develop theoretical models in which the productivity of investment in human capital depends on neighborhood composition. In both models, segregation causes lower social mobility and potentially inefficient aggregate output.

Between 1980 and 2008, the cross-MSA mean difference between the 10th and the 90th percentile of mean Census tract[48] income has nearly doubled from $34,592 to $68,237 (expressed in the real value of a dollar in 2000). Of that increase, 13% can be attributed to a change in the sorting of households[49]. The change in sorting appears to have the largest incidence in poorer neighborhoods. Around 27% of the $11,012 increase in the average difference between the 10th and the 50th percentile of mean Census tract income can be attributed to the change in sorting of households. These large changes in relative mean neighborhood income suggest that fiscal externalities are potentially important.

[48] In our empirical analysis and following much of the literature on segregation, we use Census tracts as our definition of neighborhoods.

[49] Mean income in each Census tract is estimated using NHGIS' household income data at the tract level. These data only indicates the number of households in different relatively narrow "income bins". We assume that the tract-distribution of income within each bin perfectly mirrors the MSA distribution within that bin. The fraction of the change attributable to sorting is calculated in the following way. First, we estimate a counterfactual mean income for each tract in 2008 by holding the 1980 income percentile composition of each tract constant but imputing the 2008 income corresponding to each percentile in the MSA. Second, we compute the counterfactual 90-10 difference in mean neighborhood income. Third, the fraction of the change attributable to sorting is 1-(counterfactual 90-10 difference)/(actual 90-10 difference).

How we define income segregation is of critical importance when discussing the relationship between segregation and inequality. For example, if income segregation is defined as the variance of mean neighborhood income, it is mechanically related to income inequality. Consider a city with some positive degree of sorting across neighborhoods. If income inequality increases in that city, even holding everyone's location and rank in the income distribution constant, mean income in the richer neighborhoods will increase relative to mean income in the poorer neighborhoods. In a world with non-zero degree of income segregation, increases in income inequality have direct consequences in terms of fiscal externalities. There is another mechanism through which increases in income inequality translate into increased differences in mean income between poor and rich neighborhoods: sorting. To conceptualize this mechanism, let us consider a measure of income segregation that is not mechanically related to inequality: the Rank Order Theory Index (henceforth denoted by H).[50] H is a measure of evenness of the spatial distribution of individuals with respect to income. We could conceptualize this measure as a variant of a Herfindahl index.[51] It ranks all households in the MSA according to their income. It then compares the distribution of "ranks" in the MSA income distribution within each neighborhood.

Specifically, we construct this measure by following Reardon and Firebaugh (2002) and Reardon (2011). First, we estimate H(p) at every percentile p corresponding to the endpoints of the available income bins in each MSA. H(p) is a Theil index measuring to what extent the proportion of individuals below percentile p in each neighborhood differs from p:

$$H(p) = 1 - \sum_j \frac{pop_j * E_j(p)}{pop_{msa} * E(p)} \tag{I}$$

[50] The Rank Order Theory index is developed in Reardon and Firebaugh (2002) and Reardon (2011). It is also used in Reardon and Bischoff (2011, 2013) and in Chetty et al. (2014).
[51] Herfindahl (1950)

where j indexes Census tracts and

$$E(p) = p * log_2\left(\frac{1}{p}\right) + (1-p) * log_2\left(\frac{1}{1-p}\right) \tag{II}$$

Both in 2000 and 2008, 16 income bins are reported. In each MSA, H(p) is evaluated at 16 different percentiles corresponding to the endpoints of each bin.[52] In theory, the Rank Theory Index is computed as follows:

$$H = 2log_2(2)\int_p E(p)H(p)dp \tag{III}$$

As H(p) can only be measured at 16 different percentiles, we interpolate. We fit a 4th order polynomial using OLS to approximate H(p). Reardon (2011) shows that the Rank Theory Index is approximately equal to a weighted sum of the coefficients of this regression.

If the distribution within each neighborhood perfectly mirrors the overall distribution in the MSA (which is a uniform distribution), H takes value zero denoting perfect integration. If all of the variation in ranks is across neighborhoods, H takes value one, denoting perfect segregation. Because this measure relies only on individuals' rank in the income distribution it is insensitive to changes that leave everyone's rank and neighborhood constant. Increased dispersion in the distribution of household income will leave H unchanged as long as households' location and rank does not change.

Data to measure segregation come from the US Census 2000 summary tape files 3A and ACS pooled sample 2005-2009.[53] For simplicity, we will refer to the 2005-2009 pooled data as the 2008 data. The summary tape files report the number of households in different income bins within each Census tract. Income segregation is regressed on the Gini coefficient and the log difference between the 90th and 50th percentile of the pre-tax wage distribution.

[52] The endpoints correspond to different percentiles in different MSAs.
[53] Data are obtained through the National Historical Geographic Information System (NHGIS).

The correlation between income inequality and segregation is documented in a small literature on income segregation and inequality.[54] While we use the same measure of segregation as Reardon and Bischoff (2011) and exploit regional variation as in Watson (2009), we improve on the existing literature by instrumenting for income inequality. Further, we are able to disentangle growth effects through the simultaneous use of an instrument for growth and inequality.[55]

The results that follow indicate that the sociological environment in which poor children grow up may change as a result of wage inequality. Specifically, we show that increases in the Gini coefficient lead to relatively large increases in H. Figure 2.8 presents a visual representation of the reduced form model of changes in segregation on predicted changes in the Gini coefficient. A 1 standard deviation predicted increase in the Gini coefficient corresponds to 0.69 of a 1 standard deviation increase in our segregation measure. Wage inequality increases sorting of households along income rank.

This result raises the question of the theoretical underpinnings for a causal empirical link between inequality and segregation. The model in Durlauf (1996) exhibits theoretical support for this feature. Because the productivity of human capital investment depends on the income distribution in the neighborhood, the incentives to segregate increase with differences in income between rich and poor. In the model, the mechanism through which rich segregate from the poor is the imposition of zoning restrictions. It provides a comprehensive model tying together the location decision of families and the consequences of neighborhood composition on families' outcomes as well as a theoretical motivation of why increases in income inequality might lead to increases in income segregation. In Tiebout (1956), rich and poor individuals have different preferences over public goods; they perfectly segregate in equilibrium because they choose to locate in neighborhoods with a different level of

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[54] Mayer (2001); Watson (2009); Reardon and Bischoff (2011)

[55] Watson (2009) uses a manufacturing Bartik instrument to exogenously shock income inequality. Her specification does not allow her to separate the effects of inequality from growth because the manufacturing Bartik is positively correlated with inequality but also negatively correlated with growth. She finds standardized effects as high as 0.9.

public goods. Epple and Platt (1998) introduce random noise in individuals' preferences so that willingness to pay for public good is not perfectly correlated with income: their equilibrium exhibits partial segregation. With an increase in income inequality, income becomes a more important predictor of preferences over public goods relative to the random noise component of preferences. As a result, willingness to pay for public good correlates more strongly with income and it becomes less likely that a poor family be willing to overbid a rich family to locate in the neighborhood with better composition: income segregation increases with inequality. In Tiebout (1956) and Epple and Platt (1998), individuals care about the amount of public good provided in the neighborhood. More generally, individuals may have preferences directly over their neighbors' income or over characteristics correlated with income as in Guerrieri, Hartley and Hurst (2013). As long as neighbors' income is a normal good, segregation will occur.

Our estimation strategy closely matches the pooling and differencing strategy used in construction of the right hand side variables. We difference segregation (H) in 2000 from segregation for the pooled years 2005 to 2009. In all of the segregation estimations, we include baseline controls for log population, black share of the population, share of the population that is non-native and does not have four-year college attainment, and share of the population that had four-year college attainment in 1980. All regressions are weighted by log population in the year 2000. Standard errors are clustered at the state level to account for potential correlation arising from state-level policy interventions.

Table 2.9 shows the effects of changes in inequality and growth on residential segregation. The top panel presents the OLS results. The OLS results reveal a strong and statistically significant association between the Gini coefficient and income segregation. The log difference between the 90th and 50th percentile of the wage distribution is also positively correlated with residential segregation though this relationship is not statistically significant.

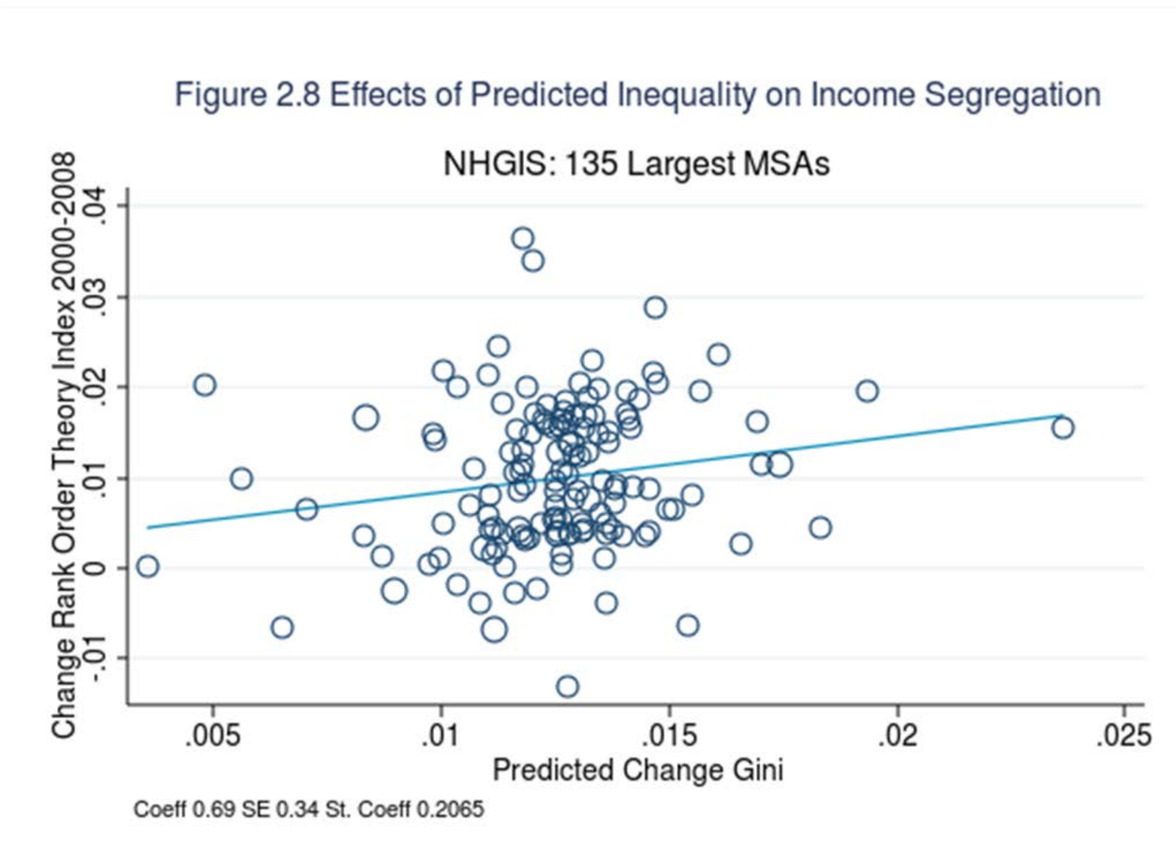
As with the human capital models, we may be concerned about drawing causal inference from the OLS results. Neighborhood selection has potentially long-term impacts and residential ownership is sticky. We want to assess the impact of structural changes; thus, we would like to instrument and avoid idiosyncratic local shocks that may be picked up with our differencing strategy. As with the human capital estimations, the OLS strategy cannot rule out reverse causation. In order to isolate the causal chain that rising wage inequality impacts residential sorting, we wish to instrument for inequality. Thirdly, time-varying local factors such as local labor supply elasticity or local policy may be correlated with changes to both the wage distribution and income segregation. For these three reasons, we would also like to instrument.

The middle panel of Table 2.9 shows income segregation regressed directly on the instruments. The standardized effect on the instrument for the Gini coefficient is large, positive and statistically significant. A 1 standard deviation increase in the instrument for the Gini coefficient in wages is associated with 0.16 of a 1 standard deviation increase in H. A 1 standard deviation increase in the instrument for the 90-50 log difference causes 0.16 of a standard deviation increase in the Rank Order Theory Index.

The coefficient on growth is negative but not statistically significant in all specifications. Places with increasing wages seem to have experienced a decrease in income segregation. A potential explanation is that individuals care about some of their neighbors' characteristics that are correlated with income but these preferences may exhibit strong concavity. As a result, as all boats are lifted up, the income-rank composition of one's neighbor may matter less and less and decrease incentives to segregate.

The bottom panel of Table 2.9 reports coefficients of a 2SLS regression of changes in income segregation on inequality and growth using the instruments described above. Coefficients on inequality are positive and statistically significant. A 1 standard deviation increase in the Gini coefficient causes 0.19 of a 1 standard deviation increase in segregation. The standardized coefficient on the 90-50 log difference is larger in magnitude and equal to 0.26. Coefficients on growth are negative but not statistically significant.

Table 2.9 also reports the results from regressing income segregation on inequality and growth in a smaller sample of MSAs: those for which we have enough observations to get reliable measures of enrollment in the CPS. Our results are robust to applying this sample restriction.



Note: Figure includes the largest population MSAs (the 135 used in CPS community college results). Data for the x axis is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week, a minimum of 48 weeks/year with minimum annual salary $5,000. Data used to compute the segregation measure is from the National Historical Geographic Information System (NHGIS). Neighborhoods correspond to Census tracts and are aggregated to the MSA-level. Following Reardon, Bischoff (2011, 2013), segregation is measured as the Rank Order Theory Index which is a measure of evenness of the spatial distribution of individuals with respect to income. A measure of 0 reflects perfect integration, a measure of 1 reflects perfect segregation. Figure represents a 2SLS regression. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to the mean wage and Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the ratio of the cross-MSA standard deviation of the predicted Gini coefficient to the cross-MSA standard deviation of the change in the segregation measure.

Table 2.9 Effects of Changing Inequality, Growth on Residential Segregation by Income: 2000-2008

	Gini Coefficient		90/50	
	Overall Segregation	Overall Segregation Selected Sample	Overall Segregation	Overall Segregation Selected Sample
OLS				
β Δ inequality	0.134**	0.093	0.012	0.007
robust standard error	0.058	0.091	0.010	0.014
standardized coefficient	0.168	0.113	0.103	0.058
β Δ mean wage	-0.002*	-0.002*	-0.002	-0.002
robust standard error	0.001	0.001	0.001	0.001
standardized coefficient	-0.144	-0.127	-0.105	-0.106
Instrumental Variables				
β instrument inequality	0.695***	0.941*	0.181***	0.200*
robust standard error	0.250	0.479	0.055	0.110
standardized coefficient	0.160	0.165	0.159	0.139
β instrument mean wage	-0.008*	-0.005	-0.007	-0.004
robust standard error	0.004	0.005	0.004	0.005
standardized coefficient	-0.173	-0.105	-0.160	-0.075

Table 2.9 Cont'd Effects of Changing Inequality, Growth on Residential Segregation by Income: 2000-2008

	Gini Coefficient		90/50	
	Overall Segregation	Overall Segregation Selected Sample	Overall Segregation	Overall Segregation Selected Sample
2SLS				
β Δ predicted inequality	0.690*	0.492*	0.067**	0.067*
robust standard error	0.413	0.298	0.030	0.039
standardized coefficient	0.199	0.163	0.263	0.263
β Δ predicted mean wage	-0.004	-0.002	-0.004	0.000
standard error	0.003	0.002	0.003	0.003
standardized coefficient	-0.119	-0.063	-0.118	-0.014
N	212	135	212	135

Note: Data for the right-hand side is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Individual wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Data used to compute the segregation measures is from the National Historical Geographic Information System (NHGIS). Neighborhoods correspond to Census tracts and are aggregated to the MSA-level. Following Reardon, Bischoff (2011, 2013), segregation is measured as the Rank Order Theory Index which is a measure of evenness of the spatial distribution of individuals with respect to income. A measure of 0 reflects perfect integration, a measure of 1 reflects perfect segregation. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3) 2SLS. A shift-share instrument

2.8 Conclusion

In this paper, we introduce a novel instrument for MSA-level changes in wage inequality. This allows us to uncover an important and surprising fact: rising local wage inequality depresses aggregate first-year enrollment rates in postsecondary education. In addition, we provide evidence that rising wage inequality causes increased residential sorting on an income basis. Our model predicts first-year community college enrollments will decline by 2.6 and 2.1 percentage points over the 2000s in response to changes in the 90-50 and Gini coefficient respectively.[56] Our model predicts first-year four-year institution enrollments will decline by 0.17 and 0.93 percentage points over the 2000s in response to changes in the 90-50 and Gini coefficient respectively.[57]

We do not find significant evidence for a strong effect of growth on postsecondary schooling. Simple correlations show that growth is positively correlated with enrollment in four year universities. After instrumenting, we find that the effect of overall wage growth is close to zero. If anything, places with rising overall wages seem to have experienced a decrease in community college enrollment.

The coefficient on the enrollment results suggest that the skill premium hypothesis is not at work in response to increases in *local* wage inequality. One theory that suggests a negative relationship between inequality and investment in human capital is related to neighborhood effects. Specifically, increasing inequality may cause families to increasingly sort on an income basis. That is, rich families outbid poor families for rich neighbors. As entire MSAs become more unequal, the residents also become more segregated from each other. To the extent to which neighborhood composition is influential to human capital accumulation, this may have effects on postsecondary enrollments. Through our analysis in Section 2.7, we established that there is, in fact, a causal relationship between

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[56] We calculate the model prediction by multiplying the regression coefficient from the bottom panel of Column (1) of Table 2.3 by the cross-MSA actual change in the Gini coefficient in wages over the 2000s.
[57] We calculate the model prediction by multiplying the regression coefficient from the bottom panel of Column (1) of Table 2.5 by the cross-MSA actual change in the Gini coefficient in wages over the 2000s.

rising inequality and increasing income segregation. We find that increasing inequality both at the upper tail, the 90-50 difference, and over the entire wage distribution, the Gini coefficient, cause increased residential sorting on an income basis. A 1 standard deviation predicted increase in the Gini coefficient causes 0.20 of a 1 standard deviation increase in segregation. Similarly, at the upper tail a 1 standard deviation increase in the 90-50 difference causes 0.26 of a 1 standard deviation increase in segregation.

This mechanism is consistent with two concerns in the public discussion: (1) inequality has an adverse effect on growth; and (2) inequality reduces intergenerational mobility. Though this paper did not attempt to provide direct evidence of the effect of inequality on growth and intergenerational mobility, our findings provide indirect support for these concerns. To the extent that these effects are mediated through neighborhood externalities, there is no guarantee that the overall amount and distribution of human capital investment within the population is efficient. As noted in work such as *Fault Lines* by Raghuram Rajan (2010), the growth in educational attainment has stalled, at least in the 1980s and 1990s, despite the presumed constant increase in relative demand for skills. Our results speak to this apparent puzzle: as the relative demand for skilled-workers increases, the skill premium rises and translates into higher local inequality. Individuals at the margin should respond to the increasing skill premium by investing more in their human capital. However, this effect may be muted if marginal individuals simultaneously became less prepared to attend college due to spillovers from local inequality.

The efficiency of human capital investments as well as intergenerational mobility are first-order issues; this is reflected by the space these topics currently occupy in the public forum. Our future research agenda includes securing individual finely geocoded panel data, such as the NLSY, in order to separately analyze the direct effect of individual and parental income from the direct and indirect effects of a changing wage distribution on an individual's probability of postsecondary schooling. In addition, directly observing the response at the individual level of pre-college inputs into the production of human capital to shocks to local inequality would help separate the mechanisms. Another interesting direction of research could be to relate our results to measures of educational attainment as opposed to enrollment. In order to address real effects of inequality on attainment, we would like to have data with more detailed migration information such as IRS tax data in order to satisfactorily confront issues related to selective migration. As a final word, although the results for income segregation are suggestive of a mechanism for our main result, we plan to explore other potential mechanisms, particularly those related to political economy responses to wage inequality. We hope that our findings will stimulate more research into the causal effects of rising inequality on human capital investments.

Appendix 1: Where Are the Workers?

A1.1 Robustness Discussion

There are two ancillary concerns with regard to the main results of this paper. The first is whether the effects of routine employment losses on disability over the decade reflect contamination from the recession. I explore this issue by conducting the main analysis in the period pre-dating the great recession, 2000 to 2007. The second concern is whether the main results are unique to Census/ACS data or can be replicated in another large public data set, the Historical March CPS.

Pre-recessionary Effects of Routine Occupation Employment Losses on DI Participation:

The main analysis in this paper covers the period 2000 to 2011 and, as such, includes a time when the labor market was not functioning well, the Great Recession. Over this period, non-employment for all prime-age men and women increased by 7.12 percentage points compared to 1.64 before the Great Recession (2000 to 2007).[1] Thus, the results may be potentially contaminated by the recession. Table A1.5 of the Appendix estimates equations (1.17), (1.18) and (1.19) for non-college and all prime-age men and women from 2000 to 2007. The top panel of Table A1.5 estimates the effect of predicted declines in routine occupation employment on DI participation. For all prime-age men and women, the coefficient for the effect of predicted routine employment losses on disability is similar to that obtained in Table 1.2 for the period 2000 to 2011 with coefficients -0.34 and -0.30 respectively and smaller magnitude standardized effects over the pre-recessionary period, -0.0024 compared with -0.0032 over the entire 2000s. Consistent with the main results, effects are larger for those without college attainment. Moving from the 10th to the 90th percentile of the predicted decline in routine occupation employment corresponded to an increase in disability of 0.72 percentage points for non-

[1] Figures are computed from the historical March CPS with sample restricted to non-institutional adults with an assigned MSA.

college prime-age men and women. The bottom panel of Table A1.5 estimates the effect of a predicted change in wages on disability from 2000 to 2007. For non-college and all prime-age men and women, the estimated elasticities are -2.48 and -2.66 respectively. The standardized effect for all prime-age men and women from 2000 to 2007 is smaller than that estimated in Table 1.2 from 2000 to 2011 with respective estimates of -0.062 and -0.070. The results in Table A1.5 are consistent with the main results of this paper: predicted declines in routine employment cause increased disability participation. Further, disability participation is highly responsive to predicted wage changes. It is notable that these results are present even before the Great Recession. Thus, the main results are not an artifact of employment losses simply resulting from the recession.

Regarding the magnitudes of the estimates, an existing current literature supports the result that standardized effects estimated from 2000 to 2011 are larger in magnitude than those estimated from 2000 to 2007. As documented in Glaeser, Gyourko and Saiz (2008), the 2000 to 2007 period was characterized by large increases in price-to-cost ratios in housing resulting in both positive housing wealth shocks and employment growth in the construction sector. In fact, construction sector employment for prime-age men grew by 2.6 percentage points from 2000 to 2007.[2] Further, Charles, Hurst, and Notowidigdo (2013) find masking of the labor force participation effects of changing labor demand in the manufacturing sector in this period. From 2000 to 2007, a 1 standard deviation increase in home values was enough to offset the non-employment effects of a 1 standard deviation decrease in predicted manufacturing employment for non-college men. With respect to disability, it is sensible to expect that home price appreciation may have resulted in smaller standardized effects from 2000 to 2007 than from 2000 to 2011.

[2] Figure from Charles, Hurst and Notowidigdo (2013) computed from 2000 Census and pooled 2007 ACS for non-institutional, non-college men age 21-55 with assigned MSA.

Replication of the Main Results in the Current Population Survey (CPS):

As a final robustness check, I replicate the main analysis at the state-level in the Census/ACS and the Historical March CPS. Using individual level extracts from the 2000 Census 5% file and the 2009-2011 ACS files from the Integrated Public Use Microsamples (IPUMS) database (Ruggles et. al., 2010), I construct a panel of US states. In order to improve precision of estimates, ACS sample years are pooled such that the years 2009, 2010 and 2011 represent the year 2011. The combined Census and ACS sample is restricted to the non-institutionalized population age 21-64 that self-identify as living in a state and do not reside in the District of Columbia. There are 50 states in the combined sample. The sample was collapsed at the state level and employment-to-population ratios, disability-to-population ratios, employment shares, and mean regression-adjusted log wages were computed for each state. Similarly, using individual level extracts from the IPUMS CPS database (King et. al., 2010), I construct a panel of states in the March CPS. In order to improve precision of estimates, CPS sample years are pooled such that the years 1998, 1999 and 2000 represent the year 2000 and the years 2009, 2010 and 2011 represent the year 2011. Table A1.1 of the Appendix displays summary statistics of interest from the Census, the ACS and the CPS at the state-level. Notably, the cross-state mean decline in employment from 2000 to 2011 is considerably larger in the CPS, 6.1 percentage points, than in the Census/ACS, 1.8 percentage points.[3]

Table A1.6 of the Appendix replicates the main analysis at the state-level in the Census/ACS and CPS. The top panel of Table A1.6 estimates equation (1.17) to obtain estimates for $\partial \Delta D_k / \partial \Delta \hat{x}_k^R$ for

[3] As documented in Charles, Hurst and Notowidigdo (2013) and Clark et al. (2003), employment (unemployment) in the 2000 Census is markedly smaller (larger) than 2000 employment counts in the March CPS and from BLS statistics. As noted in Census Summary File 3 Data Note 4 (2002), unemployment counts were particularly high for areas with large non-institutional group quarters such as college towns. However, the employment (unemployment) measurement error in the 2000 Census may be more pervasive than labor market variables measured in college towns. Upon restricting the sample to households, employment in the 2000 Census varies from the March CPS 2000 by about 4%. Consistent with recent empirical work on labor market outcomes, particularly exploiting regional variation such as Charles, Hurst and Notowidigdo (2013) and Autor and Dorn (2013), the analysis in this paper uses the Census and ACS data.

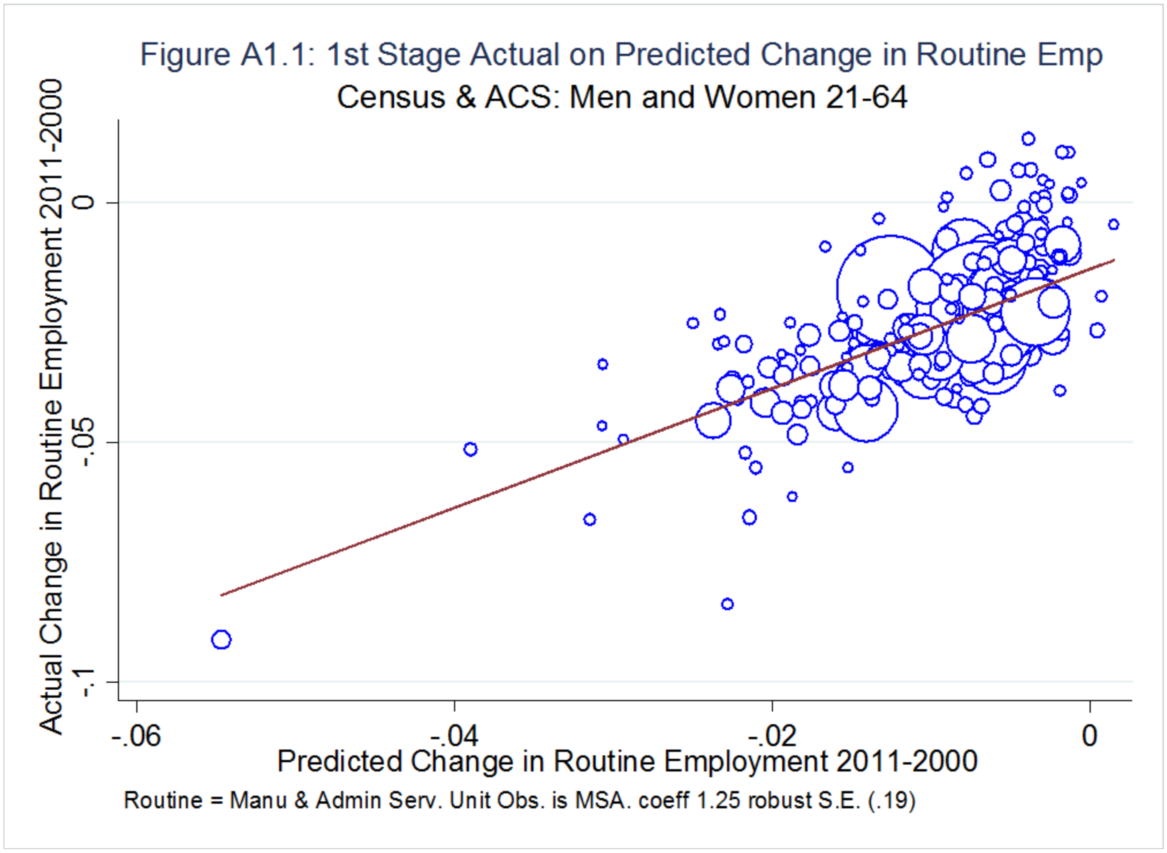
all prime-age men and women from 2000 to 2011. The first column presents estimates from the Census/ACS and the second column presents estimates from the CPS. Effects are similar across data sets with regression coefficients of -0.204 and -0.199 in the Census/ACS and CPS respectively. Moving from the 10th to the 90th percentile of the predicted change in routine occupation employment in the Census/ACS corresponded to an increase in disability of 0.44 percentage points. Moving from the 10th to the 90th percentile of the predicted change in routine occupation employment in the CPS corresponded to an increase in disability of 0.49 percentage points.

The bottom panel of Table A1.6 estimates equation (1.19) to obtain estimates for the effect of a predicted change in wages on disability participation. The elasticity estimated from the CPS is almost twice as large as that estimated from the Census/ACS with respective elasticities of -3.08 and -1.67. It should be noted that the first stage of the 2SLS wage model is not strongly predictive in either data set and is notably smaller in the CPS. The first stage F statistics from the Census/ACS and the CPS are 6.8 and 1.8 respectively.

In summary, the main results-- predicted declines in routine employment cause increases in disability participation-- are confirmed in the CPS. The magnitude of the effects across surveys is similar. Further, as in the previous results in this paper, disability participation is highly elastic to predicted wage changes associated with technological change. However, the first stage is not strongly predictive in the state-level panels in either data set.

Appendix 1: Where Are the Workers?

A1.2 Additional Figures and Tables



Note: Data is from the 2000 Census and the American Community Survey where the years 2009, 2010 and 2011 represent the year 2011. Routine Occupations represent manufacturing and service sector occupations. Each cell is a MSA. Each cell weighted by age 21-64 population in MSA in year 2000.

Table A1.1 Descriptive Statistics: State-level Census, ACS, Annual Statistical Report on SSDI & Historical March CPS

	N	Mean	St. Dev.	Percentiles Min	25	50	75	Max
Labor market variables 2000-2011 (Census, ACS)								
All men and women 18-64								
Δ employment rate (pp)	50	-0.018	0.022	-0.070	-0.031	-0.018	0.0003	0.027
Δ ACS disability rate (pp)	50	0.010	0.005	0.001	0.006	0.009	0.013	0.023
Δ SSA disability rate (pp)	50	0.018	0.006	0.010	0.014	0.016	0.022	0.037
Δ mental and musculoskeletal disability rate (pp)	50	0.014	0.005	0.007	0.010	0.013	0.017	0.027
Δ other disability rate (pp)	50	0.005	0.002	0.002	0.003	0.005	0.007	0.012
Δ ln(residualized wages)	50	-0.071	0.034	-0.170	-0.084	-0.074	-0.054	0.077
Δ Share of Pop Employed in Routine Occ (pp)	50	-0.027	0.008	-0.049	-0.032	-0.027	-0.023	0.0004
2000 baseline controls States (Census, ACS)								
population	50	9038728	7166256	367302	3788267	6322217	14200000	24700000
share of population African American	50	8.8%	8.8%	0.2%	1.7%	6.0%	13.5%	33.2%
share of employed with college attainment	50	26.3%	4.5%	19.0%	22.7%	25.5%	29.5%	37.9%
share of population age 21-25	50	10.9%	1.4%	8.3%	10.4%	10.8%	11.4%	18.3%
share of population age 26-30	50	11.6%	0.9%	9.5%	11.0%	11.6%	11.9%	14.1%
share of population age 31-35	50	12.2%	0.7%	10.4%	11.7%	12.1%	12.8%	13.6%
share of population age 36-40	50	14.1%	0.6%	12.7%	13.7%	14.1%	14.5%	15.3%
share of population age 41-45	50	13.9%	0.7%	12.3%	13.5%	13.8%	14.2%	15.9%
share of population age 46-50	50	12.4%	0.7%	10.6%	11.9%	12.3%	12.7%	13.8%
share of population age 51-55	50	10.4%	0.6%	8.1%	10.1%	10.4%	10.6%	11.9%
share of population age 56-60	50	8.1%	0.6%	6.4%	7.8%	8.1%	8.5%	9.2%

Table A1.1 Cont'd Descriptive Statistics: State-level Census, ACS, Annual Statistical Report on SSDI & Historical March CPS

Note: Data is from the 2000 Census, the American Community Survey 2009-2011 and the Annual Statistical Report on SSDI from SSA for 2000, and 2011. In the ACS: 2011 is pooled years 2009, 2010, 2011. Unit of Observation is the state. Sample includes all people 21-64 who do not live in institutions and have an assigned state identifier and do not reside in the District of Columbia. Weights = cell size in 2000. Routine occupations represent manufacturing and administrative services occupations.

Table A1.1 Cont'd Descriptive Statistics: State-level Census, ACS, Annual Statistical Report on SSDI & Historical March CPS

				Percentiles				
	N	Mean	St. Dev.	Min	25	50	75	Max
Labor market variables 2000-2011 (Historical March CPS)								
All men and women 18-64								
Δ employment rate (pp)	50	-0.061	0.020	-0.106	-0.072	-0.055	-0.0509	0.007
Δ CPS disability rate (pp)	50	0.007	0.007	-0.012	0.003	0.004	0.010	0.031
Δ ln(residualized wages)	50	-0.012	0.036	-0.081	-0.029	-0.009	0.006	0.114
Δ Share of Pop Employed in Routine Occ (pp)	50	-0.034	0.011	-0.063	-0.041	-0.033	-0.029	-0.0006
2000 baseline controls States (Historical March CPS)								
population	50	9033333	7266667	368953	3600000	6300000	14100000	25033333
share of population African American	50	11.9%	7.9%	0.2%	6.4%	11.8%	15.7%	34.2%
share of employed with college attainment	50	27.0%	4.2%	19.1%	23.8%	26.7%	28.9%	35.8%
share of population age 21-25	50	11.2%	1.2%	7.9%	10.4%	11.2%	12.2%	16.1%
share of population age 26-30	50	12.1%	1.1%	9.4%	11.3%	12.2%	13.1%	14.5%
share of population age 31-35	50	13.0%	0.8%	10.4%	12.5%	13.2%	13.6%	14.5%
share of population age 36-40	50	14.3%	0.8%	11.2%	14.0%	14.4%	14.7%	16.5%
share of population age 41-45	50	13.8%	0.7%	11.3%	13.2%	13.9%	14.3%	16.0%
share of population age 46-50	50	11.9%	0.7%	9.6%	11.3%	11.9%	12.3%	14.4%
share of population age 51-55	50	9.7%	0.8%	8.1%	9.0%	9.7%	10.3%	11.9%
share of population age 56-60	50	7.5%	0.8%	5.0%	7.0%	7.4%	8.1%	10.0%

Table A1.1 Cont'd Descriptive Statistics: State-level Census, ACS, Annual Statistical Report on SSDI & Historical March CPS

Note: Data is from the Historical March CPS 2009-2011. In the CPS: 2011 is pooled years 2009, 2010, 2011. Unit of Observation is the state. Sample includes all people 21-64 who do not live in institutions and have an assigned state identifier and do not reside in the District of Columbia. Weights = cell size in 2000. Routine occupations represent manufacturing and administrative services occupations.

Table A1.2 Measuring DI Receipt Across Data Sets: Census, ACS, Annual Statistical Report on SSDI & Historical March CPS

				Percentiles				
	N	Mean	St. Dev.	Min	25	50	75	Max
Disability Counts 2000								
2000 Census disability count	50	212945	141031	6887	100449	180940	320069	474347
2000 SSA disability count	50	227383	147128	8058	103579	214878	307654	505244
2000 March CPS disability count	50	255291	165804	7285	117691	229396	445465	525055
Disability Counts 2011								
2011 ACS disability count	50	304288	194773	12009	139662	259183	453543	643638
2011 SSA disability count	50	372690	234286	13949	177847	332261	589893	789472
2011 March CPS disability count	50	334246	214502	10226	165608	311262	509851	687606

Note: The Census/ACS and March CPS do not measure DI per se. These surveys ask about income from Social Security which includes survivor's benefits, U.S. Government railroad retirement pension benefits, DI income, and retirement income. In order to measure DI in these data sets, I proxy for DI receipt as those with non-zero Social Security income who are not in the labor force and under the age of 65. As this variable proxies the true DI rate, this table compares the proxied counts with administrative data from the Social Security Administration that has been released to the public at the state level. Data is from the 2000 Census, the 2009-2011 ACS, the Annual Statistical Report on SSDI from SSA for 2000 and 2011, and the Historical March CPS 1998-2000 and 2009-2011. Unit of Observation is the state. Sample includes all people 21-64 who do not live in institutions, have an assigned state identifier and do not reside in the District of Columbia. Weights = cell size in 2000. The 2011 ACS, 2000 CPS, and 2011 CPS samples are pooled over 3 years; counts for pooled samples have been divided by 3 for comparability.

Table A1.3 Change in Disability in Response to Predicted Change in Routine Occupation Employment Ages 21-64, By Migration Status 2000-2011

	Non-college Men	Non-college Women	All
Non-migrant			
$\beta_{\Delta \text{ predicted routine share all}}$	-0.334	-0.367	-0.262
robust standard error	0.081	0.077	0.062
1σ standardized effect	-0.0036	-0.0039	-0.0028
mean Δ disability rate	0.007	0.010	0.006
First Stage F Statistic	85.2	79.0	77.6
Migrant			
$\beta_{\Delta \text{ predicted routine share all}}$	-0.718	-0.071	-0.284
robust standard error	0.136	0.162	0.068
1σ standardized effect	-0.0076	-0.0008	-0.0030
mean Δ disability rate	0.007	0.012	0.006
First Stage F Statistic	85.2	79.0	77.6

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects for IV re-scaled by a standard deviation cross-MSA standard deviation in predicted change in routine employment shares. First stage for 2SLS: change in routine employment on routine shift-share. In 2000, migrants are identified as those who have moved into the MSA in the last 5 years. In 2011, migrants are identified as those who have moved into the MSA in the last year. Data is from the 2000 Census and American Community Survey where the years 2009, 2010 2011 represent 2011. Routine occupation represents manufacturing and administrative services occupations.

Table A1.4 Change in Disability in Response to Change in Routine Occupation Employment By Migration Status, Age*Skill Attainment

	Non-college 25-44	All 25-44	Non-college 45-54	All 45-54	Non-college 55-64	All 55-64
Non-migrant						
$\beta_{\Delta \text{ predicted routine share all}}$	-0.214	-0.166	-0.296	-0.221	-0.557	-0.363
robust standard error	0.061	0.046	0.074	0.059	0.175	0.162
1σ standardized effect	-0.0023	-0.0018	-0.0032	-0.0024	-0.0059	-0.0038
mean Δ disability rate	0.002	0.000	0.009	0.007	0.003	-0.002
First Stage F Statistic	78.5	74.2	87.8	82.6	90.2	83.9
Migrant						
$\beta_{\Delta \text{ predicted routine share all}}$	-0.388	-0.241	-0.162	-0.048	-0.986	-1.248
robust standard error	0.164	0.107	0.305	0.249	0.578	0.385
1σ standardized effect	-0.0041	-0.0026	-0.0017	-0.0005	-0.0105	-0.0132
mean Δ disability rate	0.013	0.001	0.016	0.012	0.015	0.012
First Stage F Statistic	78.5	74.2	87.8	82.6	90.2	83.9

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects for IV re-scaled by 1 standard deviation in predicted change in routine employment shares. First stage for 2SLS: change in routine employment on routine shift-share. In 2000, migrants are identified as those who have moved into the MSA in the last 5 years. In 2011, migrants are identified as those who have moved into the MSA in the last year. Data is from the

Table A1.4 Cont'd Change in Disability in Response to Change in Routine Occupation Employment By Migration Status, Age*Skill Attainment

2000 Census and American Community Survey where the years 2009, 2010, 2011 represent the year 2011. Routine occupations represent manufacturing and administrative services occupations.

Table A1.5 Change in Disability in Response to Predicted Change in Routine Occupation Employment, Wages
By Age*Skill Attainment: 2000-2007

	Non-college	All
Δ Disability x Δ Routine Employment		
$\beta_{\Delta \text{ predicted routine share all}}$	-0.399	-0.347
robust standard error	0.125	0.111
1σ standardized effect	-0.0028	-0.0024
mean Δ disability rate	0.008	0.006
mean actual Δ routine share all	-0.015	-0.016
mean Δ predicted routine share all	-0.016	-0.016
First Stage F Statistic	25.1	22.7
Δ Wages x ΔRoutine Employment		
$\beta_{\Delta \text{ routine shift-share instrument}}$	4.614	4.219
robust standard error	0.795	0.851
1σ standardized effect	0.056	0.017
mean Δ ln(residualized wages)	-0.032	-0.023
mean actual Δ routine share all	-0.015	-0.016
mean Δ routine shift-share instrument	-0.003	-0.003
Adjusted R^2	0.40	0.35

Table A1.5 Cont'd Change in Disability in Response to Predicted Change in Routine Occupation Employment, Wages By Age*Skill Attainment: 2000-2007

	Non-college	All
Δ Disability x Δ Wages		
estimated disability participation elasticity	-2.477	-2.658
robust standard error	0.628	0.612
1σ standardized effect	-0.062	-0.059
mean Δ ln(disability rate)	0.188	0.180
mean Δ ln(residualized wages)	-0.032	-0.023
mean predicted Δ ln(residualized wages)	-0.021	-0.016
First Stage F Statistic	33.7	24.6

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects for IV in top panel re-scaled by 1 standard deviation in predicted change in routine employment shares. First stage for 2SLS top panel: change in routine employment on routine shift-share. Standardized effects for residualized wages on routine shift-share regression re-scaled by 1 standard deviation in growth in residualized wages. Standardized effects for IV in bottom panel re-scaled by 1 standard deviation in predicted growth in residualized wages. First stage for 2SLS bottom panel: residualized wages on routine shift-share. Wages: full-time, regression-adjusted. Data is from the 2000 Census and American Community Survey where the years 2005, 2006, 2007 represent 2007. Routine occupations represent manufacturing and administrative services occupations.

Table A1.6 Comparing Estimates Across Data Sets: Census/ACS and Historical March CPS, State-level
All Men and Women Ages 21-64: 2000-2011

	Census/ACS	CPS
Δ Disability x Δ Routine Employment		
$\beta_{\Delta \text{ predicted routine share all}}$	-0.2049	-0.1994
robust standard error	0.0663	0.1611
1σ standardized effect	-0.0017	-0.0019
mean Δ disability rate	0.010	0.007
mean actual Δ routine share all	-0.025	-0.0342
mean Δ predicted routine share all	-0.024	-0.0328
First Stage F Statistic	77.7	15.3
Δ Wages x ΔRoutine Employment		
$\beta_{\Delta \text{ routine shift-share instrument}}$	3.359	0.878
robust standard error	1.288	0.652
1σ standardized effect	0.015	0.009
mean Δ ln(residualized wages)	-0.071	-0.012
mean actual Δ routine share all	-0.025	-0.034
mean Δ routine shift-share instrument	-0.010	-0.016
Adjusted R^2	0.31	0.41

Table A1.6 Cont'd Comparing Estimates Across Data Sets: Census/ACS and Historical March CPS, State-level
All Men and Women Ages 21-64: 2000-2011

	Census/ACS	CPS
Δ Disability x Δ Wages		
estimated disability participation elasticity	-1.673	-3.077
robust standard error	0.678	3.286
1σ standardized effect	-0.051	-0.098
mean Δ ln(disability rate)	0.258	0.145
mean Δ ln(residualized wages)	-0.071	-0.012
mean predicted Δ ln(residualized wages)	-0.056	-0.010
First Stage F Statistic	6.8	1.8

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 50 States. Weights = cell size in year t. Standardized effects for IV in top panel re-scaled by 1 standard deviation in predicted change in routine employment shares. First stage for 2SLS top panel: change in routine employment on routine shift-share. Standardized effects for residualized wages on routine shift-share regression re-scaled by 1 standard deviation in growth in residualized wages. Standardized effects for IV in bottom panel re-scaled by 1 standard deviation in predicted growth in residualized wages. First stage for 2SLS bottom panel: residualized wages on routine shift-share. Wages: full-time, regression-adjusted. Data is from the 2000 Census, American Community Survey, Historical March CPS. In the ACS, 2010 is pooled 2009, 2010, 2011. In the CPS, 2000 is pooled 1998, 1999, 2000. 2011 is pooled 2009, 2010, 2011. Routine occupations represent manufacturing and administrative services occupations.

Table A1.7 Change in Disability in Response to Change in Routine Occupation Employment: OLS Estimates By Skill Attainment, Ages 21-64: 2000-2011

	Non-college Men	Non-college Women	College Men	College Women	All
OLS					
$\beta_{\Delta \text{ actual routine share all}}$	-0.245	-0.220	-0.031	-0.096	-0.175
robust standard error	0.062	0.059	0.050	0.043	0.050
1σ standardized effect	-0.0036	-0.0032	-0.0004	-0.0014	-0.0025
mean Δ disability rate	0.011	0.013	0.006	0.007	0.009
mean actual Δ routine share all	-0.025	-0.024	-0.025	-0.025	-0.025
Adjusted R^2	0.41	0.40	0.22	0.12	0.54

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects re-scaled by 1 standard deviation change in routine employment shares. Data is from the 2000 Census and American Community Survey where the years 2009, 2010, 2011 represent 2011. Routine occupations represent manufacturing and administrative services occupations.

Table A1.8 Change in Disability in Response to Change in Routine Occupation Employment: OLS Estimates By Age*Skill Attainment: 2000-2011

	Non-college 25-44	All 25-44	Non-college 45-54	All 45-54	Non-college 55-64	All 55-64
OLS						
$\beta_{\Delta \text{ actual routine share all}}$	-0.124	-0.083	-0.191	-0.142	-0.348	-0.244
robust standard error	0.036	0.030	0.075	0.056	0.129	0.121
1σ standardized effect	-0.0018	-0.0012	-0.0028	-0.0021	-0.0051	-0.0036
mean Δ disability rate	0.003	0.001	0.010	0.008	0.004	-0.001
mean actual Δ routine share all	-0.024	-0.025	-0.025	-0.025	-0.025	-0.025
Adjusted R^2	0.25	0.28	0.20	0.24	0.30	0.26

Note: Controls (year t, de-meaned): age, population, %population black, %employed with college attainment. N= 283 MSAs. Weights = cell size in year t. S.E. clustered by state. Standardized effects re-scaled by 1 standard deviation in routine occupation shares. Data is from the 2000 Census and American Community Survey where the years 2009, 2010, 2011 represent 2011. Routine occupations represent manufacturing and administrative service occupations.

Table A1.9 Defining Routine Occupations in *Where Are the Workers?*

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Computer and peripheral equipment operators	308	308	308	308	308
Secretaries and stenographers	313	570	570	313, 314	570
Typists	315	582	582	315	582
Interviewers, enumerators, and surveyors	316	316	316	316	316
Hotel clerks	317	317	317	317	317
Transportation ticket and reservation agents	318	318	318	318	318
Receptionists and other information clerks	319	540	540	319, 323	540
Correspondence and order clerks	326	326	326	326	326
Human resources clerks (excluding payroll, timekeeping)	328	328	328	328	328
Library assistants	329	329	329	329	329
File clerks	335	335	335	335	335
Record clerks	336	520, 542	520, 542	325, 336	520, 542
Bookkeepers and accounting/auditing clerks	337	337	337	337	337
Payroll and timekeeping clerks	338	338	338	338	338
Billing clerks and related financial records processing	344	511	511	339, 343, 344	511
Mail and paper handlers	346	346	346	346	346
Office machine operators, n.e.c.	347	590	590	345, 347	590
Telephone operators	348	348	348	348	348
Other telecom operators	349	349	349	349	349
Postal clerks (excluding mail carriers)	354	354	354	354	354
Mail carriers for postal service	355	355	355	355	355
Mail clerks, outside of post office	356	356	356	356	356

Table A1.9 Cont'd Defining Routine Occupations in *Where Are the Workers?*

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Messengers	357	357	357	357	357
Dispatchers	359	359	359	359	359
Shipping and receiving clerks	364	364	364	364	364
Stock and inventory clerks	365	365	365	365	365
Meter readers	366	366	366	366	366
Weighers, measurers, and checkers	368	368	368	368	368
Material recording, sched., prod., plan., expediting cl.	373	373	373	373	373
Insurance adjusters, examiners, and investigators	375	375	375	375	375
Customer service reps, invest., adjusters (excluding insurance)	376	376	376	376	376
Eligibility clerks for government prog., social welfare	377	377	377	377	377
Bill and account collectors	378	378	378	378	378
General office clerks	379	586	586	379	586
Bank tellers	383	383	383	383	383
Proofreaders	384	384	384	384	384
Data entry keyers	385	385	385	385	385
Statistical clerks	386	386	386	386	386
Teacher's aides	387	254	254	387, 467	254
Machinists	637	637	637	637	637
Boilermakers	643	643	643	643	643
Precision grinders and fitters	644	644	644	644	644

Table A1.9 Cont'd Defining Routine Occupations in *Where Are the Workers?*

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Patternmakers and model makers	645	806	806	645, 656, 676	806
Engravers	649	649	649	649	649
Other metal and plastic workers	653	652, 816	652	646, 653, 654	652
Cabinetmakers and bench carpeters	657	657	657	657	657
Furniture/wood finishers, other precision wood workers	658	851	851	658, 659	851
Dressmakers, seamstresses, and tailors	666	835	835	666, 667	835
Upholsterers	668	668	668	668	668
Shoemakers, other precision apparel and fabric workers	669	833	833	669, 674	833
Hand molders and shapers (excluding jewelers)	675	675	675	675	675
Optical goods workers	677	677	677	677	677
Dental laboratory and medical applicance technicians	678	678	678	678	678
Other precision and craft workers	684	822	822	684	822
Butchers and meat cutters	686	686	686	686	686
Bakers	687	687	687	687	687
Batch food makers	688	688	688	688	688
Water and sewage treatment plant operators	694	694	694	694	694
Plant and system operators, stationary engineers	696	696	696	696	696
Other plant and system operators	699	699	699	699	699
Lathe, milling, and turning machine operatives	703	801	801	703, 704, 705	801
Punching and stamping press operatives	706	706	706	706	706
Rollers, roll hands, and finishers of metal	707	707	707	707	707

Table A1.9 Cont'd Defining Routine Occupations in *Where Are the Workers?*

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Drilling and boring machine operators	708	708	708	708	708
Grinding, abrading, buffing, and polishing workers	709	709	709	709	709
Forge and hammer operators	713	713	713	713	713
Molders and casting machine operators	719	719	719	719	719
Metal platers	723	723	723	723	723
Heat treating equipment operators	724	724	724	724	724
Sawing machine operators and sawyers	727	727	727	727	727
Nail, tacking, shaping and joining mach ops (wood)	729	854	854	728, 729	854
Other woodworking machine operators	733	855	855	726, 733	855
Typesetters and compositors	736	736	736	736	736
Winding and twisting textile and apparel operatives	738	738	738	738	738
Knitters, loopers, and toppers textile operatives	739	739	739	739	739
Textile cutting and dyeing machine operators	743	836, 840	840	743	840
Textile sewing machine operators	744	744	744	744	744
Shoemaking machine operators	745	745	745	745	745
Clothing pressing machine operators	747	747	747	747	747
Miscellanious textile machine operators	749	749	749	749	749
Cementing and gluing machine operators	753	753	753	753	753
Packers, fillers, and wrappers	754	754	754	754	754
Extruding and forming machine operators	755	792, 872	792, 872	755, 758	792, 872
Mixing and blending machine operators	756	756	756	756	756

Table A1.9 Cont'd Defining Routine Occupations in *Where Are the Workers?*

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Separating, filtering, and clarifying machine operators	757	757	757	757	757
Food roasting and baking machine operators	763	763	763	763	763
Washing, cleaning, and pickling machine operators	764	764	764	764	764
Paper folding machine operators	765	765	765	765	765
Furnance, kiln, and oven operators, apart from food	766	766	766	766	766
Slicing, cutting, crushing and grinding machine	769	785, 871	785, 871	768, 769	785, 871
Photographic process workers	774	774	774	774	774
Machine operators, n.e.c.	779	894, 896	894, 896	673, 693, 714, 715, 717, 725, 759, 777, 779, 798	894, 896
Welders, solderers, and metal cutters	783	771, 772, 773, 775	771, 772, 773, 775	783, 784	771, 772, 773, 775
Assemblers of electrical equipment	785	785	785	785	785

Note: *Where Are the Workers?* builds on a literature that classifies occupations into 3 broad skill groups: abstract, routine and manual notably Autor, Levy, and Murnane (2003), Dorn (2009) and Autor and Dorn (2013). Abstract tasks score high in managerial and interpersonal tasks and quantitative reasoning requirements. Routine tasks which are cognitive in nature involve setting limits, tolerances or standards and routine tasks which are manual in nature involve high values for finger dexterity. Manual tasks involve high values for eye-hand-foot coordination. That literature employs a task-based classification system. In order to classify an occupation *j* as routine, a routine index is calculated

$$R_j = \ln(r_{j,1980}) - \ln\left(a_{j,1980}\right) - \ln(m_{j,1980})$$

Table A1.9 Cont'd Defining Routine Occupations in *Where Are the Workers?*

where r_j represents a 0 to 10 intensity score for routine tasks, a_j represents a 0 to 10 intensity score for abstract tasks and m_j represents a 0 to 10 intensity score for manual tasks. Dorn (2009) ranks three-digit occupation codes by R_j and classifies the top 1/3 as routine occupations. This classification system is broad and includes some occupations which we may not think of as displaced by automation or computerization.

Where Are the Workers? also uses the Dorn (2009) cross-walked 3-digit occupation codes (Column (2)) but employs a sector-based classification system. The sector-based system identifies 3-digit occupations which correspond to the manufacturing and service sector occupations where $\ln(r_{j,1980}) - \ln(a_{j,1980}) - \ln(m_{j,1980}) > 0$. All of the routine occupations used in the paper are named above. Columns (3)-(6) lists the corresponding 3-digit occupation codes in the data sets used in the paper: 2000 Census, 2009-2011 American Community Survey, 1998-2000 Historical March CPS, 2009-2011 Historical March CPS.

Table A1.10 Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Financial managers	7	7	7	7	7
Funeral directors	19	19	19	19	19
Accountants and auditors	23	23	23	23	23
Insurance underwriters	24	24	24	24	24
Purchasing agents (agric)	28	28	28	28	28
Architects	43	43	43	43	43
Atmospheric and space scientists	74	74	74	74	74
Physical scientists, n.e.c.	76	76	76	76	76
Pharmacists	96	96	96	96	96
Dieticians and nutritionists	97	97	97	97	97
Lawyers and judges	178	210, 211	210	178, 179	210
Writers and authors	183	183	183	183	183
Painters, sculptors, craft-artists, and print-makers	188	188	188	188	188
Photographers	189	189	189	189	189
Editors and reporters	195	195	195	195	195
Announcers	198	198	198	198	198
Dental hygienists	204	204	204	204	204
Health record technologists and technicians	205	205	205	205	205
Drafters	217	217	217	217	217
Air traffic controllers	227	227	227	227	227
Legal assistants and paralegals	234	234	234	234	234

**Table A1.10 Cont'd Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)**

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Insurance sales occupations	253	253	253	253	253
Real estate sales occupations	254	254	254	254	254
Financial service sales occupations	255	255	255	255	255
Advertising and related sales jobs	256	256	256	256	256
Cashiers	276	276	276	276	276
Office supervisors	303	303	303	303	303
Secretaries and stenographers	313	570	570	313, 314	570
Typists	315	582	582	315	582
Interviewers, enumerators, and surveyors	316	316	316	316	316
Transportation ticket and reservation agents	318	318	318	318	318
Receptionists and other information clerks	319	540	540	319, 323	540
Correspondence and order clerks	326	326	326	326	326
Human resources clerks (excluding payroll, timekeeping)	328	328	328	328	328
File clerks	335	335	335	335	335
Record clerks	336	520, 542	520, 542	325, 336	520, 542
Bookkeepers and accounting/auditing clerks	337	337	337	337	337
Payroll and timekeeping clerks	338	338	338	338	338

Table A1.10 Cont'd Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Billing clerks and related financial records processing	344	511	511	339, 343, 344	511
Mail and paper handlers	346	346	346	346	346
Office machine operators, n.e.c.	347	590	590	345, 347	590
Telephone operators	348	348	348	348	348
Other telecom operators	349	349	349	349	349
Postal clerks (excluding mail carriers)	354	354	354	354	354
Mail clerks, outside of post office	356	356	356	356	356
Messengers	357	357	357	357	357
Dispatchers	359	359	359	359	359
Shipping and receiving clerks	364	364	364	364	364
Stock and inventory clerks	365	365	365	365	365
Meter readers	366	366	366	366	366
Weighers, measurers, and checkers	368	368	368	368	368
Material recording, sched., prod., plan., expediting cl.	373	373	373	373	373
Insurance adjusters, examiners, and investigators	375	375	375	375	375
Customer service reps, invest., adjusters (excluding insurance)	376	376	376	376	376
Eligibility clerks for government prog., social welfare	377	377	377	377	377

Table A1.10 Cont'd Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Bill and account collectors	378	378	378	378	378
General office clerks	379	586	586	379	586
Bank tellers	383	383	383	383	383
Proofreaders	384	384	384	384	384
Data entry keyers	385	385	385	385	385
Statistical clerks	386	386	386	386	386
Administrative support jobs, n.e.c.	389	522, 583, 593	522, 593	369, 374, 389	522, 593
Laundry and dry cleaning workers	408	830	830	403, 747, 748	830
Guards and police, except public service	426	391, 392	391, 392	426	391, 392
Bartenders	434	434	434	434	434
Cooks	436	400, 402	400, 402	404, 436, 437	400, 402
Dental Assistants	445	364	364	445	364
Barbers	457	450	450	457	450
Hairdressers and cosmetologists	458	458	458	458	458
Motion picture projectionists	467	441	441	773	441
Auto body repairers	514	514	514	514	514
Machinery maintenance occupations	519	519	519	519	519
Repairers of data processing equipment	525	525	525	525	525
Precision makers, repairers, and smiths	535	535	535	535	535

Table A1.10 Cont'd Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Tool and die makers and die setters	634	634	634	634	634
Machinists	637	637	637	637	637
Boilermakers	643	643	643	643	643
Precision grinders and fitters	644	644	644	644	644
Patternmakers and model makers	645	806	806	645, 656, 676	806
Engravers	649	649	649	649	649
Furniture/wood finishers, other precision wood workers	658	851	851	658, 659	851
Upholsterers	668	668	668	668	668
Hand molders and shapers (excluding jewelers)	675	675	675	675	675
Optical goods workers	677	677	677	677	677
Other precision and craft workers	684	822	822	684	822
Butchers and meat cutters	686	686	686	686	686
Bakers	687	687	687	687	687
Lathe, milling, and turning machine operatives	703	801	801	703, 704, 705	801
Drilling and boring machine operators	708	708	708	708	708
Grinding, abrading, buffing, and polishing workers	709	709	709	709	709

Table A1.10 Cont'd Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Molders and casting machine operators	719	719	719	719	719
Metal platers	723	723	723	723	723
Nail, tacking, shaping and joining mach ops (wood)	729	854	854	728, 729	854
Typesetters and compositors	736	736	736	736	736
Winding and twisting textile and apparel operatives	738	738	738	738	738
Knitters, loopers, and toppers textile operatives	739	739	739	739	739
Textile cutting and dyeing machine operators	743	836, 840	840	743	840
Shoemaking machine operators	745	745	745	745	745
Clothing pressing machine operators	747	747	747	747	747
Miscellanious textile machine operators	749	749	749	749	749
Packers, fillers, and wrappers	754	754	754	754	754
Extruding and forming machine operators	755	792, 872	792, 872	755, 758	792, 872
Mixing and blending machine operators	756	756	756	756	756

Table A1.10 Cont'd Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)

Occupation Name	Dorn (2009)	Census 2000	ACS 2009-2011	CPS 1998-2000	CPS 2009-2011
Food roasting and baking machine operators	763	763	763	763	763
Washing, cleaning, and pickling machine operators	764	764	764	764	764
Slicing, cutting, crushing and grinding machine	769	785, 871	785, 871	768, 769	785, 871
Photographic process workers	774	774	774	774	774
Assemblers of electrical equipment	785	785	785	785	785
Production checkers, graders, and sorters in manufacturing	799	874	874	689, 796, 797, 799	874
Parking lot attendants	813	813	813	813	813
Crane, derrick, winch, hoist, longshore operators	848	951, 956	951, 956	845, 848, 849	951, 956
Production helpers	873	895	895	873, 874	895
Garbage and recyclable material collectors	875	875	875	875	875
Machine feeders and offbearers	878	878	878	878	878
Garage and service station related occupations	885	885	885	885	885
Vehicle washers and equipment cleaners	887	887	887	887	887
Packers and packagers by hand	888	888	888	888	888

Table A1.10 Cont'd Alternate Definitions of Routine Occupations:
Using Task-Based Definitions of Routine Occupations from Dorn (2009) and Autor, Dorn (2013)

Note: *Where Are the Workers?* builds on a literature that classifies occupations into 3 broad skill groups: abstract, routine and manual notably Autor, Levy, and Murnane (2003), Dorn (2009) and Autor and Dorn (2013). Abstract tasks score high in managerial and interpersonal tasks and quantitative reasoning requirements. Routine tasks which are cognitive in nature involve setting limits, tolerances or standards and routine tasks which are manual in nature involve high values for finger dexterity. Manual tasks involve high values for eye-hand-foot coordination. That literature employs a task-based classification system. In order to classify an occupation *j* as routine, a routine index is calculated

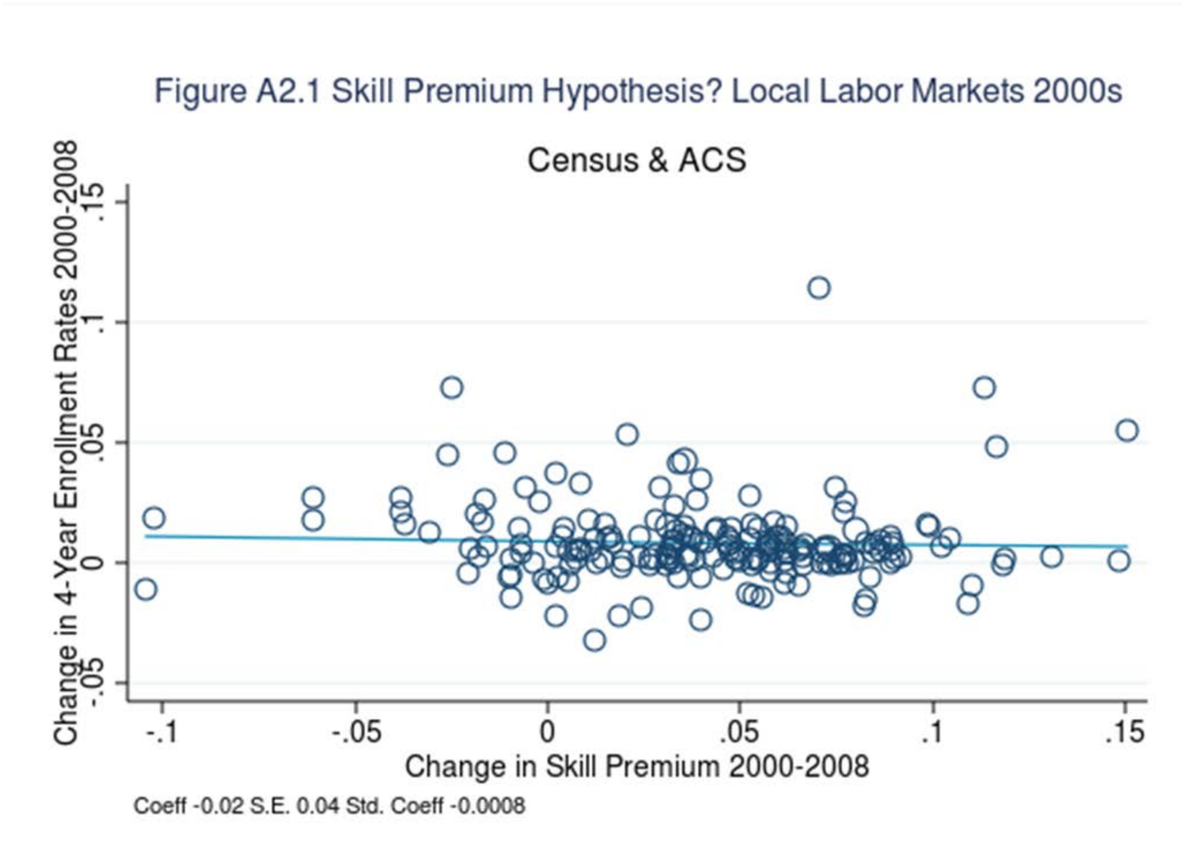
$$R_j = \ln(r_{j,1980}) - \ln\left(a_{j,1980}\right) - \ln(m_{j,1980})$$

where r_j represents a 0 to 10 intensity score for routine tasks, a_j represents a 0 to 10 intensity score for abstract tasks and m_j represents a 0 to 10 intensity score for manual tasks. Dorn (2009) ranks three-digit occupation codes by R_j and classifies the top 1/3 as routine occupations.

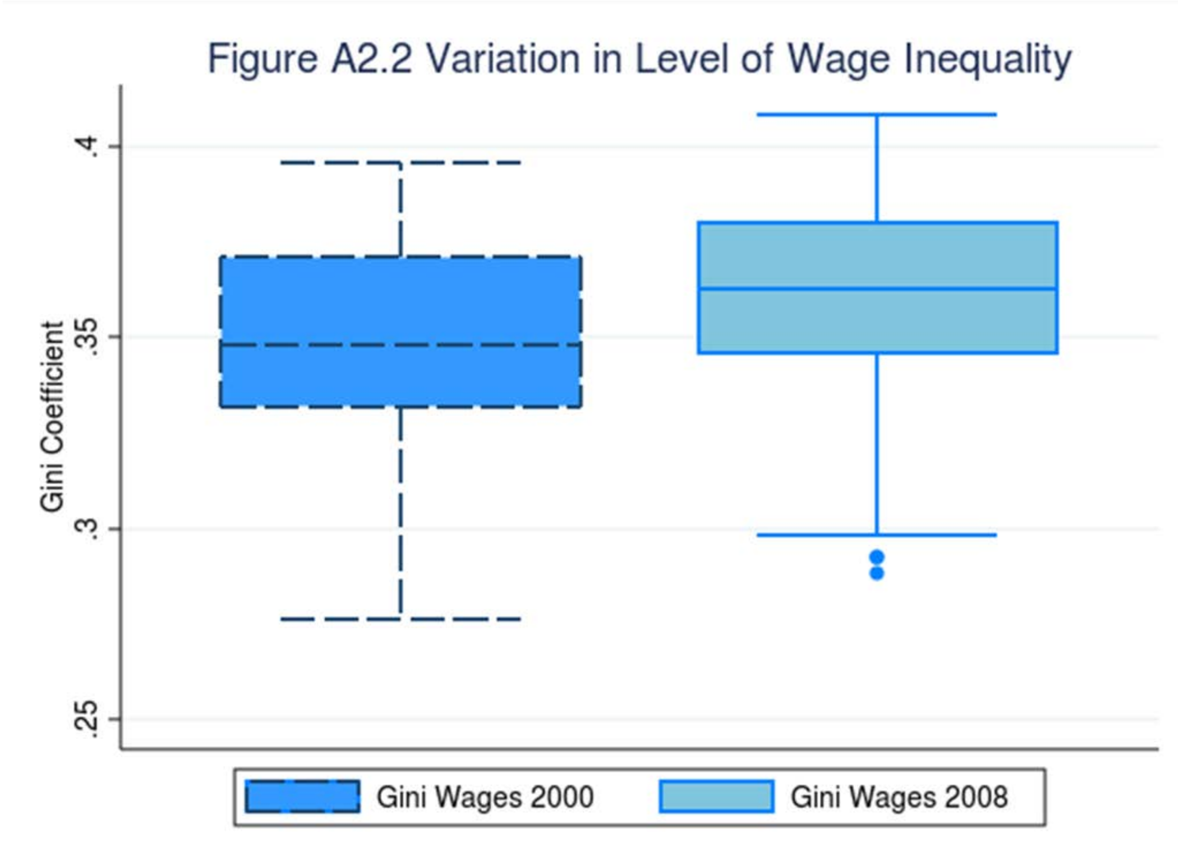
This table identifies the routine occupations as defined using the task-based classification system detailed above. Column (2) presents the Dorn (2009) cross-walked 3-digit codes. Columns (3)-(6) include the 3-digit codes occupation codes cross-walked to the data sets used in *Where Are the Workers?* : 2000 Census, 2009-2011 American Community Survey, 1998-2000 Historical March CPS, 2009-2011 Historical March CPS.

Appendix 2: Rising Wage Inequality and Human Capital Investment

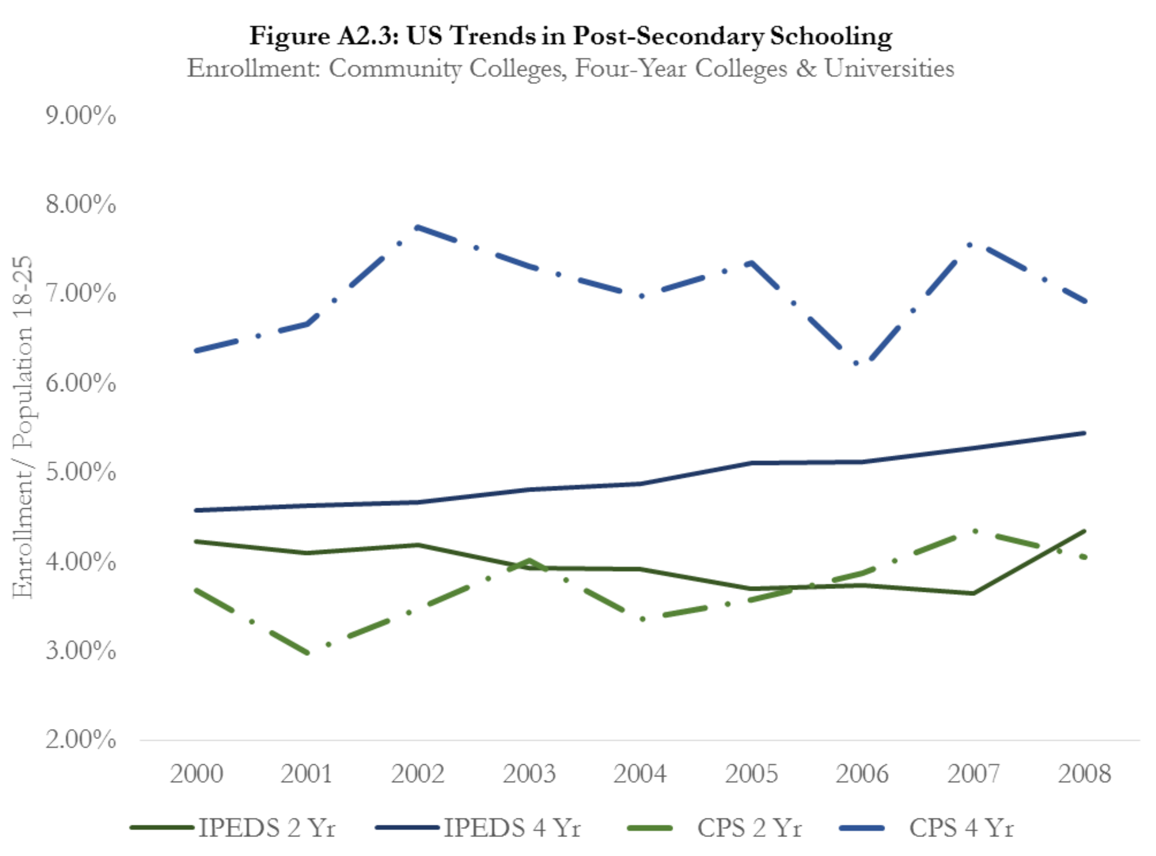
A2.1 Additional Figures and Tables



Note: Wage data (x axis) is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. Education data (y axis) is from the Integrated Postsecondary Education Data System (IPEDS) Change in the enrollment rate is the difference between enrollments average over years 2001 to 2008 minus enrollments averaged over years 1994 to 2000. Each cell is a MSA. Each cell weighted by population in MSA in year 2000.



Note: Cross-MSA distribution of level of wage inequality (Gini coefficient) in years 2000 and 2008. Data is from the 2000 Census and American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$.



Note: First-time, full year enrollment counts / non-institutional population age 18-25. Sample restricted to same 204 MSAs. Data is from IPEDS and Historical October CPS Educational Supplement.

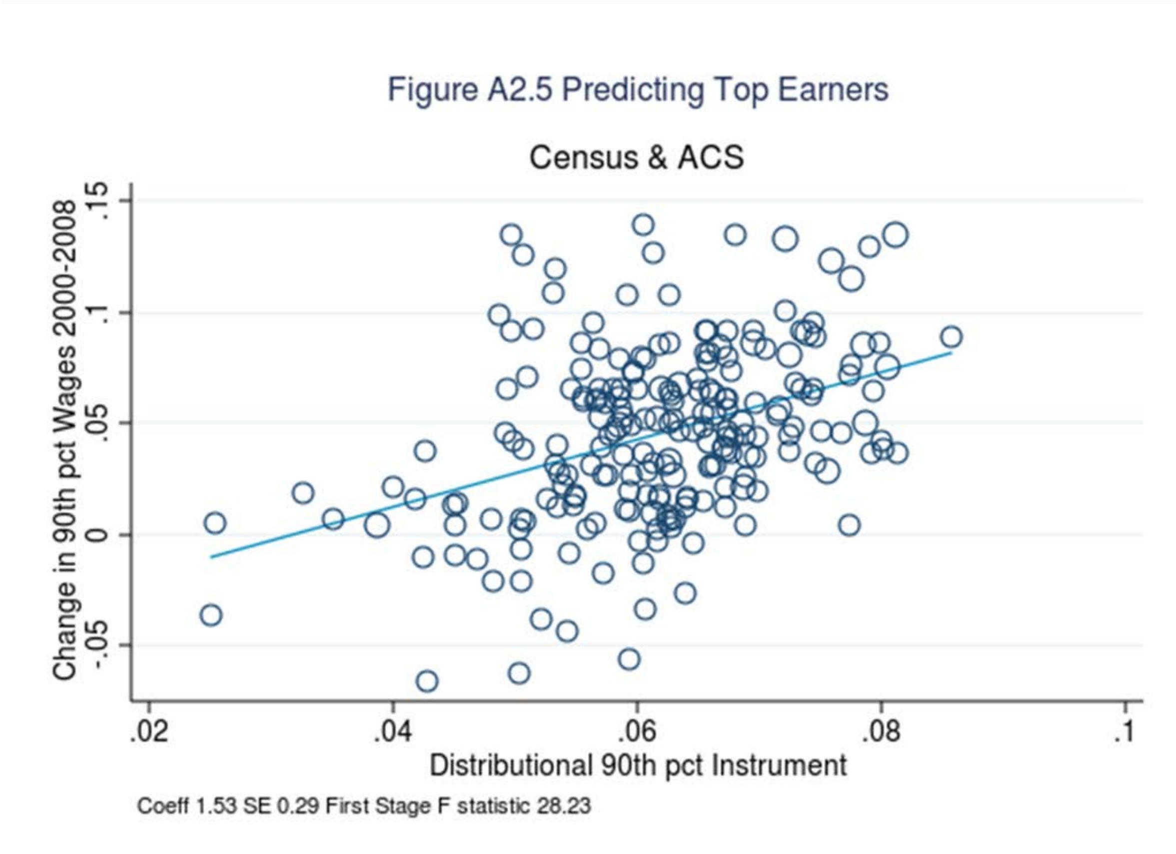
Figure A2.4 Simplified Construction of the Shift-Share Distributional Instrument

		MSA A			MSA B	
	Industry 1	Industry 2	Industry 3	Industry 1	Industry 2	Industry 3
Share	0.8	0.1	0.1	0.5	0.3	0.2

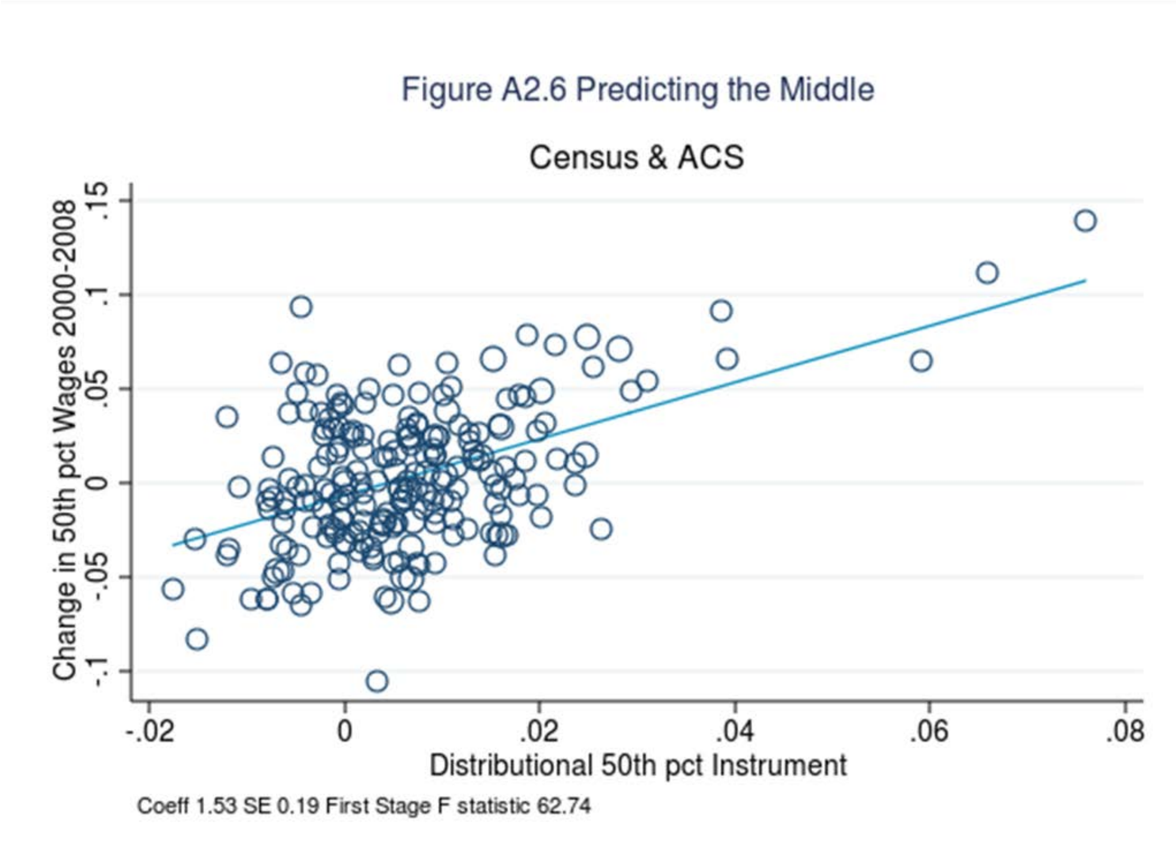
		National Industry1			National Industry 2			National Industry 3	
	<$1	<$5	<$10	<$1	<$5	<$10	<$1	<$5	<$10
Count	0.6	0.85	1	0.33	0.66	1	0.1	0.3	1

	MSA A			MSA B	
<$1	<$5	<$10	<$1	<$5	<$10
0.8*0.6 +.1*0.33+.1* 0.1	0.8*0.85 +.1*0.66 +.1* 0.3	0.8*1 +.1*1+.1* 1	0.5*0.6 +.3*0.33+.2* 0.1	0.5*0.85 +.3*0.66 +.2* 0.3	0.5*1 +.3*1+.2* 1
0.523	0.776	1	0.419	0.683	1

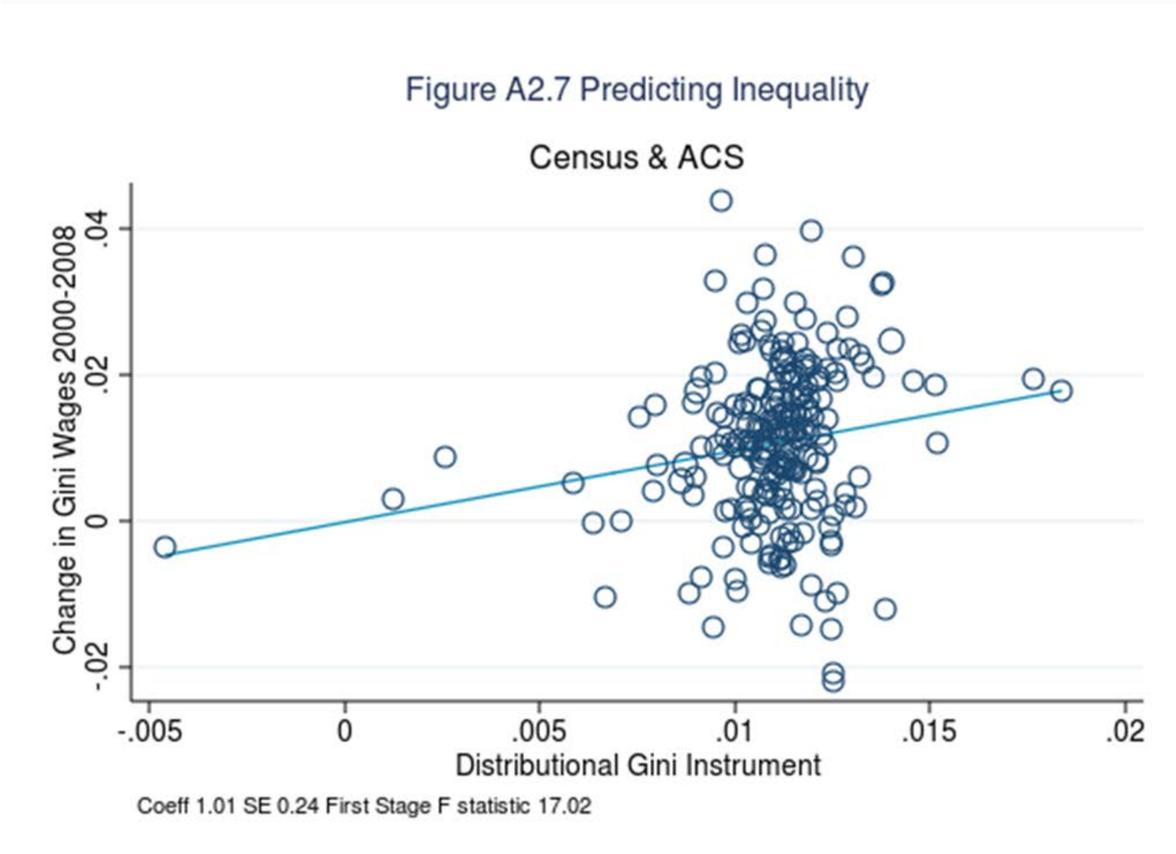
Note: This figure demonstrates the main steps in construction of our distributional shift-share instrument in a sample with two MSAs (A and B) and three industries. This example is provided to guide intuition.



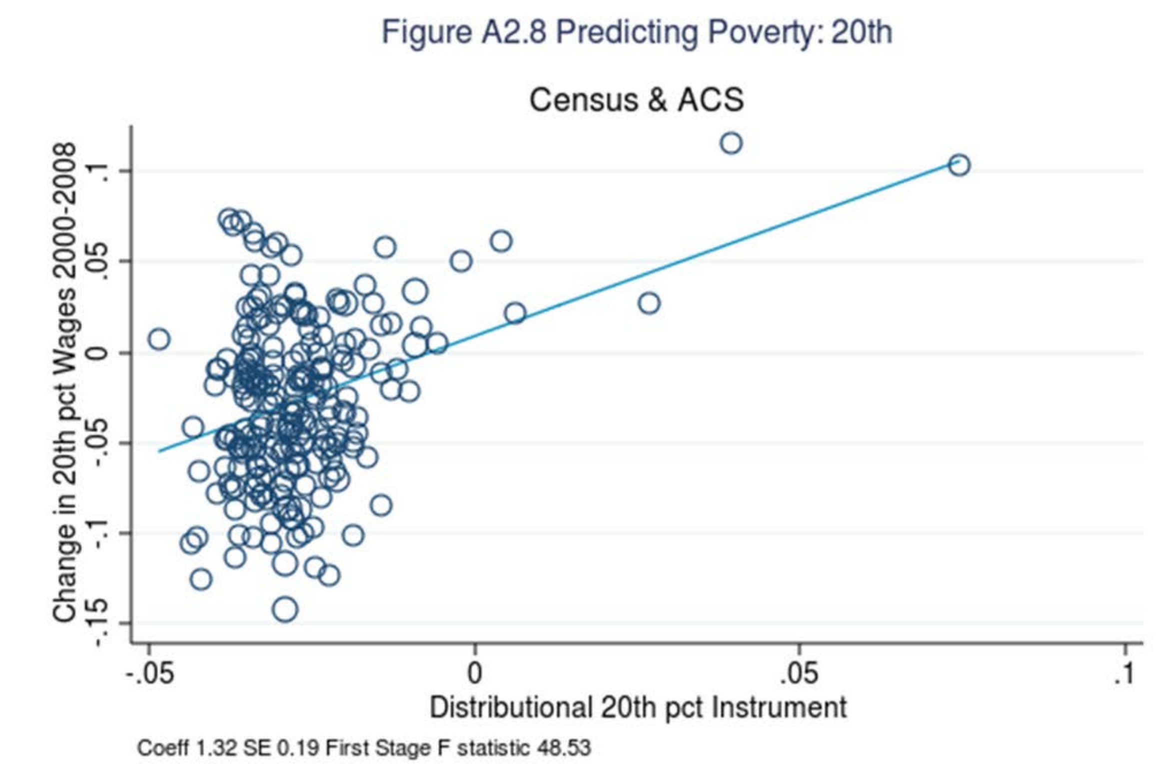
Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of \$5,000 in 2000\$. This figure represents the following regression: change in the 90th percentile of log wages on a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions to predict changes to the 90th percentile. Standard errors are clustered at the state level.



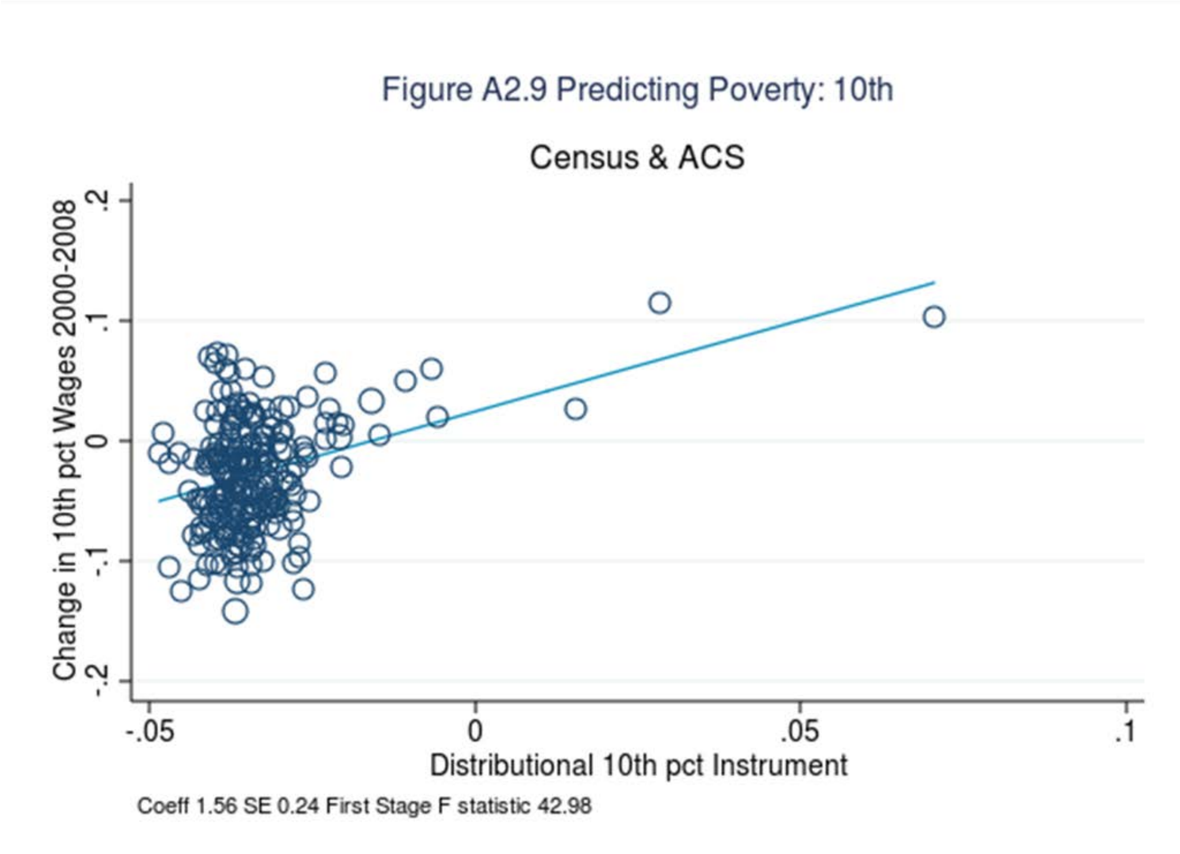
Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. This figure represents the following regression: change in the 50th percentile of log wages on a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions to predict changes to the 50th percentile. Standard errors are clustered at the state level.



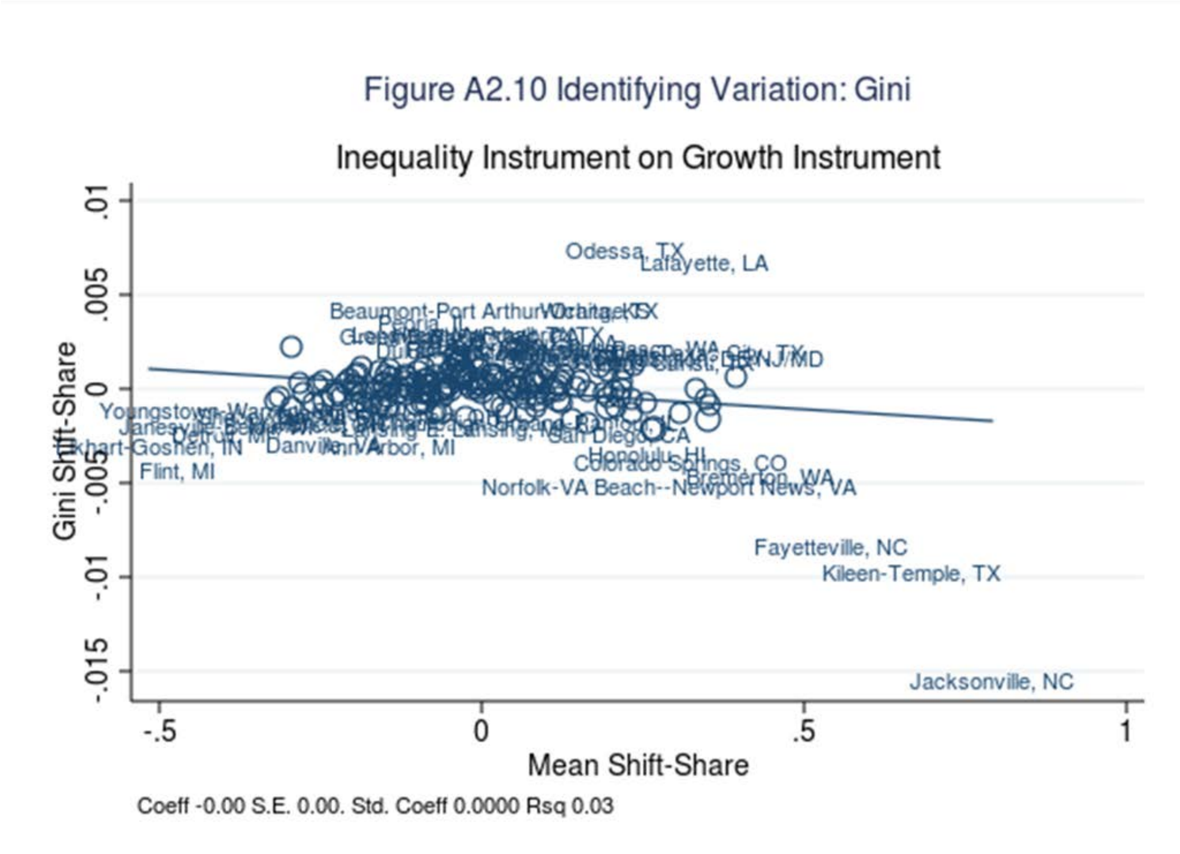
Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. This figure represents the following regression: change in the Gini coefficient of wages on a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions to predict changes to the Gini coefficient. Standard errors are clustered at the state level.



Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. This figure represents the following regression: change in the 20th percentile of log wages on a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions to predict changes to the 20th percentile. Standard errors are clustered at the state level.



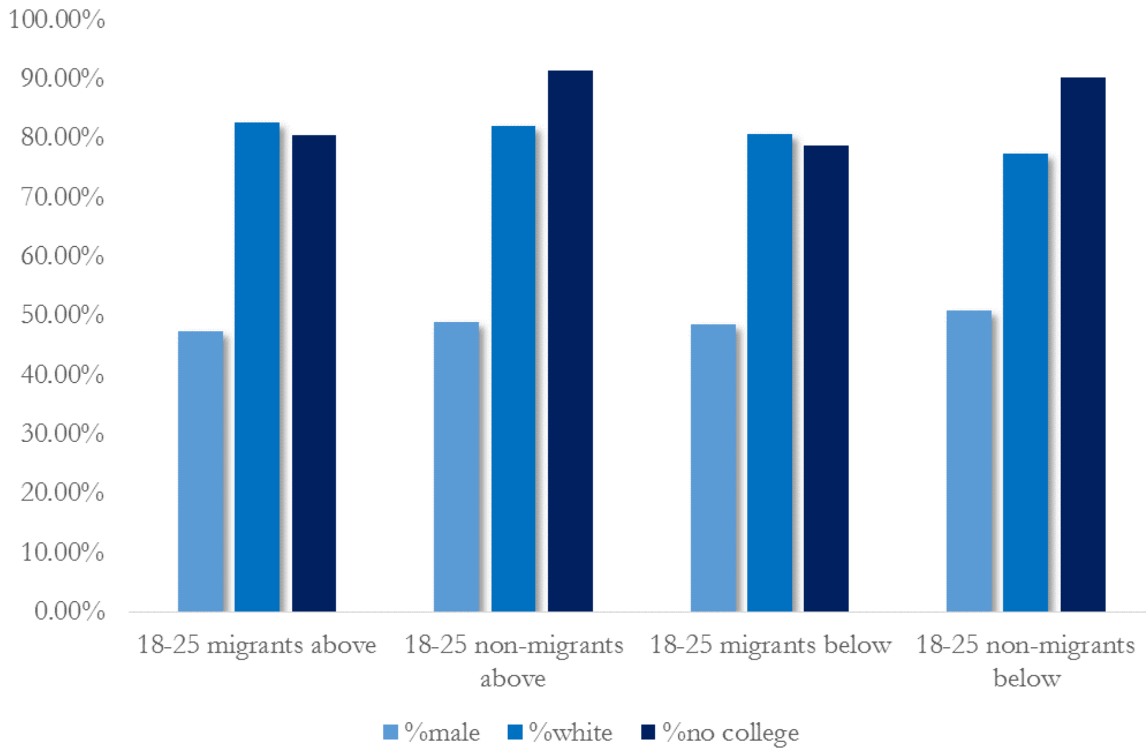
Note: Data is from the 2000 Census and the American Community Survey where the years 2006, 2007 and 2008 represent the year 2008. Each cell is a MSA. Each cell weighted by population in MSA in year 2000. Wages for people age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. This figure represents the following regression: change in the 10th percentile of log wages on a shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions to predict changes to the 10th percentile. Standard errors are clustered at the state level.



Note: Data is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual earnings of $5,000 in 2000$. We include the 192 MSAs from our main analysis. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to the mean wage and the Gini coefficient.

Figure A2.11 Characteristics of Migrants

People Who Lived in Different MSA in Previous Year: Avg 2001 to 2008



Note: Data is from the March CPS 2001-2008. Sample is restricted to non-institutional population age 18-25. We include the 135 MSAs used in analysis of enrollments in the October CPS. Migrants identified as those not living in the same house or the same county in the prior year. "Above" ("below") denotes MSAs with values of the Gini instrument above (below) the median.

Table A2.1 First Stages: Between vs. Within Variance

	Between Industry Variance	Within Industry Variance	Total Variance	Gini	90-50
First-stage					
β Δ Between-industry variance	2.404***	-3.103**	-0.699	0.001*	0.005***
robust standard error	0.667	1.329	1.329	0.000	0.001
F-statistics	12.970	5.460	0.280	2.920	11.930
β Δ Within-industry variance	-0.429*	1.454***	1.025**	0.0002*	0.001
robust standard error	0.241	0.444	0.471	0.000	0.001
F-statistics	3.150	10.740	4.740	2.830	1.030
β Δ **mean wage**	12.001**	-8.701	3.300	-0.009**	-0.034**
robust standard error	5.715	12.913	14.953	0.004	0.015
F-statistics	4.410	0.450	0.050	4.400	4.960

Note: Using shift-share identification, other papers have attempted to predict specific statistics from the wage distribution. Notably, Bertrand, Kamenica and Pan (2014) predict yearly gender-specific income percentiles for each marriage market by weighting national within-industry race- and gender-specific income percentiles by base-year state-level, within-industry, race- and gender-specific employment shares. In contrast, our instrument picks up national trends in *between-industry* dispersion in addition to shocks that tend to *increase within-industry* dispersion of wages. In this table, we explore whether the between and within components have explanatory power. Data is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. Changes to the mean, between-variance, and within-variance are predicted with shift-share instruments. Standard errors are clustered at the state level. This table establishes that: (1) between-variance is best predicted by instrumented between-variance; (2) within-variance is best predicted by instrumented within-variance; (3) total variance is best predicted by within-industry variance; (4) 9050 is best predicted by between-industry variance.

Table A2.2 Predictive Industries

	Gini Coefficient	90-50	Skill Premium
OLS	Transportation, Mining & Energy, Wholesale of Durable & Non-durable Goods, Manufacturing of Inputs & Non-durable Final Goods	Agriculture, Mining & Energy	Manufacturing of Inputs, Nondurable Final Goods & Durable Final Goods
Instrumented	Transportation, Mining & Energy, Wholesale of Durable & Non-durable Goods, Utilities, Health, Legal, FIRE	Mining & Energy, Wholesale of Durable Goods, Utilities, Health, Legal, Retail of Durables, Business and Professional Services, Construction	Manufacturing of Inputs, Nondurable Final Goods & Durable Final Goods, Mining & Energy, Wholesale of Nondurable Goods, Agriculture

Note: In order to identify the predictive industries, we residualize the actual changes in the inequality measure of interest (Gini coefficient, 90-50, skill premium) by the mean. In the OLS specification, we regress actual changes in the inequality measure on actual changes in the mean. In the instrumented specification, we regress the instrument for the inequality measure on the instrument for the mean. Next, we regress the residualized change in inequality on the initial employment share in the MSA by one-digit industry and a vector of controls. The listed "predictive industries" had positive, statistically significant slope coefficients on the industry regressor. Data is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000.

Table A2.3 Effects of Changing Inequality, Growth on Community College Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

	90-50			Gini Coefficient		
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
OLS						
β Δ inequality	0.026	0.266	0.067	-0.056	0.063	-0.363
robust standard error	0.090	0.173	0.103	0.267	0.325	0.341
standardized coefficient	0.001	0.008	0.002	-0.001	0.001	-0.003
β Δ mean wage	-0.009**	-0.016***	-0.015	-0.009*	-0.015**	-0.014
robust standard error	0.005	0.006	0.013	0.005	0.006	0.013
standardized coefficient	-0.005	-0.010	-0.009	-0.005	-0.009	-0.008

Table A2.3 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

		90-50			Gini Coefficient	
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
Instrumental Variables						
β instrument inequality	-0.557*	-0.948	-1.480**	-3.521**	-3.303	-9.228***
robust standard error	0.338	0.746	0.687	1.779	2.184	2.797
standardized coefficient	-0.003	-0.006	-0.008	-0.005	-0.005	-0.013
β instrument mean wages	-0.023	-0.060**	-0.061	-0.017	-0.056**	-0.046
robust standard error	0.015	0.028	0.048	0.014	0.029	0.043
standardized coefficient	-0.004	-0.011	-0.010	-0.003	-0.010	-0.008

Table A2.3 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

		90-50			Gini Coefficient	
	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments	Community College Enrollments	Male Community College Enrollments	Female Community College Enrollments
2SLS						
β Δ predicted inequality	-0.369	-0.871	-0.761**	-2.102***	-2.677*	-4.071***
robust standard error	0.251	0.804	0.360	0.814	1.657	0.977
standardized coefficient	-0.005	-0.013	-0.011	-0.006	-0.008	-0.014
β Δ predicted mean wage	-0.016**	-0.038	-0.035*	-0.011*	-0.029*	-0.035**
robust standard error	0.007	0.026	0.019	0.007	0.018	0.017
standardized coefficient	-0.005	-0.013	-0.012	-0.003	-0.010	-0.012
N	135	101	97	135	101	97

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Education data is from the Historical October Educational Supplement of the Current Population Survey (CPS). The dependent variable is mean enrollment rate for years 2001 to 2008 minus mean enrollment rate for years 1994 to 2000.

Table A2.3 Cont'd Effects of Changing Inequality, Growth on Community College Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

Enrollment rates are calculated by combining information from questions asked about full-time enrollment status, current year in school, and type of institution. We construct first-time, full-year enrollment counts for junior colleges and technical institutions by counting people age 18 to 25 in first-year of school in a community college on a full-time basis and scaling by population of non-institutional people age 18 to 25 from the CPS. We include MSAs with sufficient observations of non-institutional people age 18-25 with complete education information. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3) 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the 90-50 difference, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

Table A2.4 Effects of Changing Inequality, Growth on Four-Year Institution Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

	90-50			Gini Coefficient		
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
OLS						
β Δ inequality	-0.287***	-0.381*	-0.298*	-0.646	-0.843	-0.769
robust standard error	0.106	0.220	0.179	0.406	0.643	0.588
standardized coefficient	-0.009	-0.011	-0.009	-0.006	-0.008	-0.008
β Δ mean wage	0.018	0.086	0.155	0.002	0.005	0.010
robust standard error	0.116	0.151	0.124	0.006	0.009	0.007
standardized coefficient	0.001	0.003	0.005	0.001	0.003	0.006

Table A2.4 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

	90-50			Gini Coefficient		
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
Instrumental Variables						
β instrument inequality	-0.545	-1.154	-0.647	-2.675	-3.680	-1.864
robust standard error	0.573	0.716	0.826	2.282	2.995	2.701
standardized coefficient	-0.003	-0.007	-0.004	-0.004	-0.006	-0.003
β instrument mean wage	0.025	0.007	0.073**	0.028	0.012	0.075**
robust standard error	0.033	0.043	0.031	0.032	0.042	0.033
standardized coefficient	0.004	0.001	0.013	0.005	0.002	0.013

Table A2.4 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

		90-50			Gini Coefficient	
	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments	4 Year College Enrollments	Male 4 Year College Enrollments	Female 4 Year College Enrollments
2SLS						
β Δ predicted inequality	-0.425	-1.035	-0.326	-2.128	-2.889	-0.829
robust standard error	0.548	0.734	0.600	2.121	2.581	2.497
standardized coefficient	-0.005	-0.011	-0.004	-0.005	-0.008	-0.002
β Δ predicted mean wage	0.012	0.001	0.035	0.010	0.002	0.037*
robust standard error	0.022	0.023	0.022	0.021	0.022	0.021
standardized coefficient	0.003	0.000	0.010	0.003	0.001	0.011
N	156	130	137	156	130	137

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. We include the following controls: year 2000 log MSA population, year 2000 female employment share, year 2000 black share of population, share of population with 4-year college attainment in 1980, and year 2000 share of population not born in US with less than 4-year college attainment. Education data is from the Historical October Educational Supplement of the Current Population Survey (CPS). The dependent variable is mean enrollment rate for years 2001 to 2008 minus mean enrollment rate for years 1994 to 2000. Enrollment rates are calculated by combining information from questions asked about full-time enrollment status, current year in school, and type of institution. We construct first-time, full-year enrollment counts for four-year colleges by counting people age 18 to 25 in first-

Table A2.4 Cont'd Effects of Changing Inequality, Growth on Four-Year Institution Enrollments: CPS, Ages 18-25 Aggregate and By Gender: 2000-2008

year of school in a four-year institution on a full-time basis and scaling by population of non-institutional people age 18 to 25 from the CPS. We include MSAs with sufficient observations of non-institutional people age 18-25 with complete education information. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wage, the 90-50, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

Table A2.5 Falsification Test

	Community College Enrollments IPEDS	
2SLS	**Gini**	**90-50**
β predicted change inequality	-0.230	-0.365
robust standard error	2.167	0.377
β predicted change mean wages	0.002	-0.002
robust standard error	0.020	0.018

Note: Data for right-hand side variables is from the 2000 U.S. Census and the American Community Survey where the years 2006, 2007, and 2008 represent the year 2008. Wages computed for those age 21-64 who work 30 hours per week a minimum of 48 weeks/year with minimum annual salary $5,000. Education data is from the Integrated Postsecondary Education Data System (IPEDS). The dependent variable is the change in first-time, full-year enrollment rate from 1990 to 2000. We present 3 estimation strategies in this table: (1) OLS; (2) a specification where we regress change in enrollments directly on our instruments; and (3) 2SLS. A shift-share instrument constructed by interacting initial MSA-level employment shares and national within-industry wage distributions is used to predict changes to mean wages, the 90-50 difference, and the Gini coefficient. Standard errors are clustered at the state level. Standardized coefficients scale the coefficient of interest by the cross-MSA standard deviation of the x variable.

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