Recovering the missing middle: A mesocomparative analysis of within-group inequality, 1970-2011

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Abstract

This research examines a dimension of inequality central to the recent upswing of American wage and income inequality: within-group inequality, or inequality occurring among individuals otherwise similar on observed characteristics. Specifically, this research situates within-group inequality in a mesocomparative analytic framework to examine how contextual characteristics of local labor markets affect the geographical distribution of within-group inequality. A unique dataset is constructed locating within- and between-portions of wage and income inequality from 9 waves of the integrated public use microdata series from the US Census in 722 temporally stable geographical units, commuting zones, which cover the entire contiguous United States. Results from heteroscedastic and multilevel repeated measures regression models on male and female wages and household income reveal that within-group inequality is largely structured by the uneven geographical and temporal distribution of economic development, as well as local institutional configurations. Importantly, this research finds within-group inequality relates to economic development in a u-shaped pattern, initially declining, and then rapidly increasing. Fundamentally, results reveal the crucial missing middle of within-group inequality research, showing within-group inequality to be structured by the mesolevel characteristics of where one lives.

Income inequality growth has become one of the central concerns of American society. Household income inequality began to rise in the 1970s, with wage inequality following shortly thereafter, resulting in contemporary levels of inequality not seen since the early 20th century (Kopczuk et al. 2010, Mishel et al. 2012, Piketty 2014). While renewing scholarly interest in the causes and consequences of inequality (McCall and Percheski 2010), the nature of inequality growth presents a challenge to sociological thinking. Most inequality growth has occurred via *within-group inequality*, or the dispersion of wages and income occurring among individuals and households otherwise similar on observed characteristics which sociologists typically study, such as sex, race, educational attainment, household composition, and occupational characteristics (Levy and Murnane 1992, Juhn et al. 1993, McCall 2000, Lemieux 2006, Autor et al. 2008, Western et al. 2008, Western and Rosenfeld 2011).

Scholars have generally agreed that within-group inequality (henceforth WGI) accounts for the large majority of inequality growth (Levy and Murnane 1992, Autor et al. 2008, Western et al. 2008, Western and Rosenfeld 2011, Mishel et al. 2012). Furthermore, the timing of WGI growth differs from other inequality measures, suggesting that conceptually distinct social processes guide WGI (Katz and Murphy 1992, Levy and Murnane 1992, McCall 2000).[1] These include technologically driven demand for highly skilled workers (Bartel and Lichtenberg 1985, Juhn et al. 1993, Autor et al. 2003, Liu and Grusky 2013), the deinstitutionalization of the American workforce, particularly deunionization (Freeman 1984, Holzer 1990, Levy and Murnane 1992, McCall 2000, Kalleberg 2011, Western and Rosenfeld 2011), and change in population-level human capital and workforce composition (Lemieux 2006, Autor et al. 2008).

In this paper I extend WGI research by connecting it to a mesocomparative analytical framework which has been, with one exception (McCall 2000), absent from analyses (see Hauser and Xie 2005, Sorensen and Sorenson 2007, for similar applications outside the United States). Prior WGI research has either examined individual-level associations and their changes over time, the covariance of national-level WGI and other nation-level characteristics, or the relative proportion of aggregate WGI to its mathematical counterpart, between-group inequality (BGI)

(Levy and Murnane 1992, Juhn et al. 1993, Lemieux 2006, Autor et al. 2005, 2008, Western et al. 2008, Western and Rosenfeld 2011). Such research necessarily overlooks the many inequality-generating processes that operate unevenly across subnational labor markets, from the actual matching of workers and jobs to path dependent patterns of industrial development and clustering (McCall 2001, Fernandez and Su 2004, Lobao et al. 2007, Moller et al. 2009). At a more practical level, situating WGI at the mesocomparative level potentially provides thousands of WGI distributions across a wide range of social contexts, allowing for a systematic analysis of contextual influences.

To motivate the shift of WGI research to the mesocomparative level, Figure 1 displays male logged wage WGI computed for 722 commuting zones (Tolbert and Sizer 1996). The top map shows WGI in 1970 and the bottom shows WGI in 2007-2011, with each map characterizing WGI relative to the period mean (darker shades signify higher relative WGI).[2]

A puzzle is immediately apparent when Figure 1 is considered in relation to the usual suspects of WGI research: unobserved skill, labor market institutions, population composition, and measurement error. High WGI in 1970 was largely concentrated in the South, an exception being the Piedmont region, an area with an historically dense industrial sector. WGI is lowest in the upper Midwest and (now) Rust Belt regions, again areas of historically dense manufacturing concentration as well as high union membership. The top panel of Figure 1 provides an obvious critique of WGI as labor market sorting via unobserved skills. From this perspective, one would need to argue that labor markets in 1970 were most efficient in sorting unobserved talents in the American South, a region and an era of lower economic development and pronounced racial discrimination.

[Figure 1 About Here]

The bottom panel shows WGI in the 2007-2011 period, and one can clearly see that WGI has moved out of the South and into the city. The highest levels of 2007-11 WGI are now concentrated in developed metropolitan centers: New York, Houston, Miami, Atlanta, San Fransisco, Chicago, and Seattle, for example. In fact, regional differences are much less pronounced. This challenges a purely labor-market institutional account, as metropolitan areas in regions with historically high (e.g. Chicago, New York, Newark) and low (e.g. Houston, Atlanta) unionization rates have high WGI. One must argue that the compressing effects of unions are operating outside, but not within, city limits. Furthermore, it is unlikely that measurement error would so closely resemble geographical changes of overall inequality trends, as found by, among others, Moller et al. (2009, Figures 1,2). In sum, prominent accounts of WGI leave many questions at the mesolevel unanswered.

When considered in relation to mesocomparative theories of stratification, Figure 1 suggests a tight connection between WGI and economic development (Lindert and Williamson 1985, Nielsen and Alderson 1997, 2001b, Moller et al. 2009). In the subnational American context, the Kuznets curve has largely petered out, replaced by the acceleration of inequality in highly developed regions (Kuznets 1955, Harrison and Bluestone 1988, Nielsen and Alderson 1997, Korzeniewicz and Moran 2005, Moller et al. 2009). Stated visually, subnational inequality has shifted from following economic development along an inverted-U to a J-shaped pattern. In what follows, I assess how theories of economic development and inequality can be used to make sense of mesolevel WGI.

In summary, locating WGI in geographical space presents an intriguing puzzle for inequality scholars. Previous explanations of WGI—unobserved skills, deinstitutionalization, population composition, and measurement error—cannot adequately explain the patterns of geographically uneven change in WGI from 1970-2011. Therefore, I draw from the rich literature in sociology on inequality and labor market outcomes at the mesocomparative level to develop the crucial "missing middle" of WGI research (Nielsen and Alderson 1997, Tickamyer 2000, Beggs and Villemez 2001, Lobao and Hooks 2003, Lobao et al. 2007, Moller et al. 2009, Wallace et al. 2011).

The following research proceeds in fives stages. First, I discuss WGI in more detail. Second, I extend discussion to mesocomparative inequality theories of economic development and institutional configurations. Third, I discuss the unique dataset created for analysis which uses individual- and household-level data from 9 waves of U.S. Census and the American Community Survey from 1970-2011, extracts within- and between-portions of wages and household income, and sorts them into 722 commuting zones—temporally stable local labor markets which cover the entire contiguous United States. Fourth, I model mesolevel WGI and BGI using a three-level repeated measures regressions model, which shows WGI, but not BGI, to follow the geographically uneven distribution of economic development. Although economic development has not been incorporated into prior WGI research, these results suggest that a standard model of inequality and development goes far in explaining mesolevel WGI. Finally, I discuss the implications of results and suggest future avenues of research.

Within-group inequality

Within-group inequality (WGI) is the variance in wages and income net of socio-demographic, human capital, and occupational characteristics sociologists typically study (Levy and Murnane 1992, Juhn et al. 1993, Card and Dinardo 2002, Lemieux 2006, Autor et al. 2008, Western and Bloome 2009, Mishel et al. 2012). Put differently, WGI is the variation in wages and income that occurs among social strata, rather than between social strata.

One might ask if WGI research yields any insights over more traditional inequality research using one number population summary measures (e.g. Gini coefficient) or regression coefficients measuring average between-group differences of observed characteristics at the micro level. To demonstrate the usefulness of WGI for inequality research, Figure 2 shows simulated data for three populations of 100,000 observations. Each population has a continuous outcome, Y, and has a single binary group contrast, D. Univariate kernel density estimations of Y for each category of D are shown in Figure 2. Gini coefficients, mean between groups group differences measured by regression coefficient β, and the contrast of within-group dispersion of D, as measured by λ, are shown for each population in the top right of each panel.[3]

Although each population has the same Gini coefficient (8.15), the underlying contours of inequality vary strikingly. To claim these populations have equivalent inequality processes is substantively inaccurate. Furthermore, between-group differences, β, do not fully distinguish the three populations. β is 25 in populations A and B. In population A, both categories of D have identical within-group variance, meaning inequality can be sufficiently understood through the simultaneous consideration of β and the Gini coefficient. In population B, dispersion differs *within* the categories. Membership in one group is characterized by high, and the other low, kurtosis. In population C, a regression coefficient of zero may suggest that groups do not differ, but there is in fact a substantial difference in WGI between them. These subtle differences can only be detected by the analysis of WGI.

[Figure 2 About Here]

Explaining WGI

Scholars have examined the distinct reasons for WGI growth, although analysis has almost exclusively occurred at the individual and national levels. The most prominent account is *skill- and routine-biased technological change (SBTC)* (Juhn et al. 1993, Krueger 1993, Autor et al. 2003, 2008, Acemoglu and Autor 2011). Firms have rapidly integrated information and communication technologies, leading to heightened demand and economic rewards for workers with the requisite analytic and abstract skills to use technologies and manage complex organizations (Krueger 1993, Acemoglu and Autor 2011, Liu and Grusky 2013). SBTC has been widely critiqued by economists and sociologists, and three critiques also serve as alternative explanations of WGI. Some claim *labor market institutions*, such as unions, the minimum wage, and internal labor markets, provide economic protection, stabilize wage volatility and constrain top pay, thus lowering WGI (Freeman 1982, Dinardo et al. 1996, Card and Dinardo 2002, Western and Rosenfeld 2011). The minimum wage provides a wage floor, while unions provide workers bargaining power, economic security, and political leverage, both reducing WGI. Others argue that WGI growth is simply *compositional* in nature (Lemieux 2006, Autor et al. 2008). Mincerian theories of human capital suggest that college training amplifies variability of work skills and training quality, while work experience differentiates employees regarding inherent ability, motivation, and training investment (Katz and Murphy 1992, Dinardo et al. 1996). WGI is therefore higher among the more experienced and educated. The third critique paints WGI as *misspecification and error*. Early sociological accounts of WGI attributed it to individual free will, luck, or simply random noise, suggesting it to be inappropriate for study (Blau and Duncan 1967, Jencks 1973). Alternatively, WGI may partially reflect key microlevel between-group characteristics absent from regression models.[4]

The mesocomparative turn

The above debate about WGI does not speak to the geographical puzzle of Figure 1. Thus examination of WGI at the mesolevel of analysis—situating workers in local labor markets which have unique configurations of institutional, political, and social characteristics compared to the United States as a whole (Nielsen and Alderson 1997, McCall 2000)—has the potential to reveal social processes overlooked in WGI research. Only McCall (2000) modeled WGI at the level of local labor markets. However, her results are cross-sectional and cannot speak to the longitudinal changes in WGI which have motivated most research. To motivate my analyses, I draw from the rich sociological literature examining the uneven geographical distribution of economic outcomes across local labor markets (Nielsen and Alderson 1997, Tickamyer 2000, McCall 2001, Lobao and Hooks 2003, Fernandez and Su 2004, Lobao et al. 2007, Moller et al. 2009, Autor and Dorn 2013, Chetty et al. 2013).

As noted in the introduction, a promising mesolevel influence of WGI is economic development, conceptualized as the long term growth of societal prosperity and well-being (Kuznets 1955, Lindert and Williamson 1985, Harrison and Bluestone 1988, Alderson and Nielsen 2002, Moller et al. 2009). In both cross-national and subnational comparative inequality studies, development is routinely found to be associated with inequality (Nielsen and Alderson 2001a, Alderson and Nielsen 2002, Lobao and Hooks 2003, Volscho 2005, Moller et al. 2009). However, an inequality and development framework has not been applied to WGI research. Conceptually, similar social processes guide both economic development and WGI, such as sectoral shifts in employment, human capital development, population aging, technological development, and growing productivity. Empirically, the shift from the inverted-U to the J-shaped relationship between economic development and inequality occurred because of stagnation of lower and middle incomes and takeoff of top pay (Harrison and Bluestone 1988). This closely resembles aggregate WGI trends: high-end residual variance has consistently grown, while low-end residual variance has held constant since the 1980s (Autor et al. 2005, 2008). Considering the patterns of Figure 1, the conceptual linkage, and the empirical similarities, it becomes quite reasonable to expect WGI to be associated with economic development in a predictable pattern: initially declining, and then rising (Nielsen and Alderson 1997, 2001a, Moller et al. 2009).

If WGI relates to economic development as expected, then a natural extension of this association follows the recently modified three-dimension “core model” of economic development and inequality applied to county inequality by Moller et al. (2009). This model was developed by economic historians to explain early American inequality, and has been updated for the great U-turn (Lindert and Williamson 1985, Nielsen and Alderson 1997, 2001a). The first dimension is sector change. Inequality partially results from workforce shifts between economic sectors with different pay structures. Deindustrialization shifted the workforce out of the manufacturing sector, with jobs lost or sent overseas (Tienda et al. 1987, Levy and Murnane 1992, Sassen 2001, Alderson 1999, Browne 2000). Mid-20th century manufacturing generally had egalitarian pay structures and strong labor unions. Its decline can partially be attributed to globalization, which fosters insecure labor relations and highly uneven returns to work. Employment shifted to the service sector, which has a volatile and polarized payment structure (Kalleberg 2011).[5]

Much research has focused on the finance, insurance and real estate (FIRE) industry (Sassen 2001, Moller and Rubin 2008, Moller et al. 2009). Financialization relates to multiple inequality generating processes: a globalized market, pay structures for upper managers not directly dictated by productivity, and winner-take-all markets creating highly uneven worker payoffs. Two expectations follow. First, deindustrialization should increase WGI by a diminishing ability of the manufacturing sector to broadly provide high and egalitarian pay structures. Second, FIRE industry employment should increase WGI, given its connection to uneven payment structures, large payoffs from the global market, and volatile winner-take-all markets.

The second dimension of Moller et al.'s (2009) core model is educational attainment. Two arguments guide expectations. First, skill deepening via educational expansion increases the proportion of highly skilled workers (Lindert and Williamson 1985, Alderson and Nielsen 2002, Moller et al. 2009). A more educated workforce may decrease credential-based rents, countering the pay takeoff of skilled workers. Alternatively, Lemieux (2006) found WGI to grow primarily with college attainment. In contrast to findings from mesocomparative inequality studies of the dampening effect high school attainment (Nielsen and Alderson 1997, 2001a, Moller et al. 2009), the variability of training and skill development of college educated workers may increase WGI. Second, educational expansion corresponds to shifts in educational dispersion, which affects inequality via variable pay structures occurring between different levels of educational attainment (Jacobs 1985, Nielsen and Alderson 2001a, Moller et al. 2009). On the one hand, low education dispersion implies high concentration in a small number of education categories. Credentials and signaling from educational attainment may be less effective in such environments. Unobserved mechanisms—noncognitive skills and personal networks, for example—may be particularly important for workers of similar education credentials. Therefore, low educational heterogeneity would imply increased WGI. Alternatively, heterogeneity in educational attainment should simply correspond to greater differences in the unpredictable component of wages and income across a labor force, thus increasing WGI.

The third and final dimension is population change (Kuznets 1955, Moller et al. 2009, Baum-Snow and Pavan 2013). Some research suggests the takeoff of inequality has been pronounced in urban areas. Urban centers house agglomerated economies where the productivity of skilled workers receives heightened payoffs (Baum-Snow and Pavan 2013), connections to the globalized market are dense (Sassen 2001, Moller et al. 2009), and service sector polarization is pronounced. Together, dense and urbanized areas should be locations of high WGI.

Institutional configuration

Although not the primary focus of this research, an assessment of WGI would be incomplete without considering labor market and political institutional characteristics. Two similar studies find local configurations of labor market institutions—deunionization and deinstitutionalization—to constrain WGI (McCall 2000, Western and Rosenfeld 2011). These build on WGI research examining the nation-level influence of unions and the minimum wage, discussed above (Levy and Murnane 1992, Dinardo et al. 1996, Autor et al. 2008), and mesocomparative studies which examine more generally how labor market and political institutions compress pay structures, increase economic stability, and thus reduce inequality (Lobao and Hooks 2003, Volscho 2005, Moller et al. 2009). McCall finds cross-sectional differences between Public Use Microdata Areas (PUMA) structured by insecure employment relations and shifts in local industrial structure. Western and Rosenfeld find WGI growth to be rooted in union decline.[6] They identify unionization levels in 18 industries across 4 regions, finding an economy-wide influence on WGI growth. I examine mesolevel influences of these labor market institutional effects: unionization, workforce deinstitutionalization, and the minimum wage, expecting to find weak and declining institutional arrangements associated with high WGI.

Additionally, I expand institutional analysis of WGI by drawing from mesocomparative studies which assess the egalitarian effects of political institutions and policies (Lobao and Hooks 2003, Volscho 2005, Moller et al. 2009). I include two main political institutional effects: public employment and social spending. Public employment reflects robustly financed governments, public acceptance of state power, and provides a large sector of secure employment relations to otherwise vulnerable populations (Lobao and Hooks 2003). Therefore, high public employment should signal the utilization of state capacity to shift disadvantaged populations from volatile to secure employment relations, reducing WGI.

Next, social policy is central to egalitarian labor market outcomes. Although most studies examine social policy cross-nationally, some research finds the variability between American states influence labor market outcomes (Lobao and Hooks 2003, Lobao et al. 2007, Moller et al. 2009). Generous social policy is symptomatic of an egalitarian moral economy, potentially lowering WGI through mechanisms akin to those outlined by Western and Rosenfeld (2011). Furthermore, social spending may decrease reliance on extant labor market conditions, reducing economic volatility and providing opportunities to search for more secure employment conditions (Gangl 2004, Western et al. 2012). A relevant dimension is educational spending (Moller et al. 2009). Educational spending can alter human capital attainment and increase educational opportunity for otherwise disadvantaged populations. Educational spending should reduce WGI by reducing education-based rents via a broadened pool of skilled workers.

Data

Data for individual and household wages, incomes, and observed characteristics come from nine waves of integrated public use microdata series (IPUMS) from the US Census (Ruggles et al 2010): 1% samples (1970), 5% samples (1980, 1990, and 2000), and the American Community Survey (ACS) (2007-2011). Census and ACS data use varying geographical identifiers—county groups or public use micro areas (PUMAs)—defined by minimum population levels ensuring respondent confidentiality. I sort these into 722 temporally stable and theoretically meaningful geographical identifiers, commuting zones, used in recent research on earnings, inequality, and labor market outcomes. (Dorn 2009, Autor and Dorn 2013, Chetty et al. 2013).[7] Commuting zones (hereafter CZs), defined by the US Census, are county clusters grouped using hierarchical cluster analysis on Census journey to work data (Tolbert and Sizer 1996). CZs represent the lived experience of local labor markets based on worker residence and occupation locations. Simply put, there is more commuting between counties of a single CZ than between counties of two CZs. I use 1990 definitions of CZs, which can be consistently applied to all nine waves of PUMS data

(Autor and Dorn 2013).

CZs provide a unique opportunity for WGI research. No comparable local labor market definition exists allowing for the micro data required in WGI research to be sorted into temporally stable, fine-grained geographical regions covering the entire contiguous United States. For example, PUMAs have changing boundaries over time and so cannot be used to examine longitudinal change. Metropolitan Statistical Areas (MSAs) cover cities and so provide a partial sample of the American earnings distribution. Current Populatoin Survey (CPS) data only has state identifiers for all respondents, while only half have county identifiers.

CZs do have drawbacks. They cannot be used to examine within-city differences. For example, inequality-generating processes may differ between northern and southern Chicago. CZs aggregate over county-based political constituencies. Counties have distinct political jurisdictions (Lobao et al. 2007), while almost 3% of counties are sorted into CZs which overlap state boundaries.See online supplement section 1.2 for further discussion. Within-CZ county differences in political, policy, and institutional arrangements might cancel out, leading to spurious conclusions of negligible institutional effects. However, this suggests that my research represents a conservative test of institutional effects, as any effect must be large enough to be detected despite these potential drawbacks. Overall, CZs are the best available geographical identifier for situating WGI in local labor markets.

Dependent Variables

I examine inequality of both wages and household income. *Logged wages* are the natural log of respondent pre-tax annual earnings from wages, salaries, commissions, bonuses, and tips from all jobs, divided by the annual hours worked in the past year.[8] I use Acemoglu and Autor's coding scheme for PUMS wages (2011). Wages are adjusted to 2000 dollars using the Personal Consumption Expenditure (PCE) price index. Samples are restricted to full-time, full-year workers aged 16 to 64. Respondents earning under $2.80 / hour (2000 dollars) are excluded from analysis.[9] Top codes are multiplied by 1.5, but restricted to a maximum of the top code multiplied by 1.5, divided by 1,750 (Acemoglu and Autor 2011).[10]

Logged household market income takes the natural log of the summed market income from all household members aged 16 and older, divided by the square root of household members. Households are restricted to those with heads aged between 16 and 64 (Martin 2006). Household income includes wages, salary, commissions, bonuses, and tips from all jobs, net self-employment income from farm and non-farm businesses, and interest, dividends, rental income, royalty income, and income from estates and trusts, representing the large majority of market income for most households (Blank 2011). Government transfers are excluded. Top codes are multiplied by 1.5. Household incomes are adjusted to 2000 dollars using the PCE price index.

I include socio-demographic, human capital, and occupational characteristics commonly used by economists and sociologists in WGI research as independent variables in wage and income equations (McCall 2000, Lemieux 2006, Autor et al. 2008, Western et al. 2008, Western and Rosenfeld 2011, Cha and Weeden 2014).[11] These variables are used to parse total wage and income variance into between (average between-strata differences) and within (variance occurring among strata) group components, allowing for a contextual examination of each. Characteristics include *education* (less than high school; high school or equivalent; some college; four years of college; more than four years of college), *potential experience* (0-9; 10-19; 20-29; 30+ years, following Autor et al. (2008)), a quartic interaction between education and a continuous measure of potential experience (Autor et al. 2008), *race/ethnicity* (non-Hispanic white; black; Asian; white Hispanic; non-white Hispanic; other), *marital status* for wage models (married; divorced or separated; widowed; not married), *overwork status* (working over 50 hours a week), *industry* (agriculture, forestry, and fisheries; mining; construction; manufacturing; transportation, communication, and public utilities; wholesale trade; retail trade; finance, insurance, and real estate (FIRE); services; and pubic administration), *citizenship* (natural born citizens; foreign born citizens; foreign born non-citizens), *industry-region unionization* (matched from the CPS, replicating Western and Rosenfeld (2011)), and household *family / spousal employment status* (ten categories based on spousal employment, (co)habitation status, and the presence of children in the household).[12] Descriptive statistics for microlevel data are in Appendix Tables A1-A4.[13]

Commuting-zone and state variables

The main variables of interest in my analyses capture theoretically important, but under analyzed, aspects of people's lived environment.[14] Descriptive statistics and data sources for each variable are listed in Table 1, and brief descriptions are provided below.[15]

[Table 1 About Here]

Economic Development variables

Nine variables specify the core model of economic development.

Median household income is market income, adjusted to 2000 dollars using PCE price index values, and is a measure routinely used in related studies similar to GDP per capita (Nielsen and Alderson 2001a, Lobao and Hooks 2003, Volscho 2005, Moller et al. 2009). Main and squared terms are included. Substantively similar results are found with per household earnings.

Manufacturing sector size is the percentage employed in the production of durable and nondurable goods. *FIRE sector size* is the percentage employed in finance, insurance, and real estate. *Agriculture sector size* is the percentage employed in the agricultural sector. Following Alderson and Nielsen (2002), *sector dualism* is measured as:

$$R_L = |p - L|, \tag{1}$$

where p is the percentage employed in agriculture, and L is the percentage of total earnings in a CZ from agriculture.

Population density is the logged CZ population per square mile.

Rural-urban continuum code (RUCC) is a 9 category scheme distinguishing metropolitan counties by size, and non-metropolitan counties by urbanization rates and proximity to metropolitan areas. I take an average of the codes weighted by county population. High values represent more urbanized CZs.[16]

College supply is the ratio of adults aged 25+ with a college degree or more to the number of adults aged 25+ with only a high school degree. Higher values indicate a greater relative supply of the adult population with advanced degrees. Results are the same if workers with some college and less than a high school degree are included in the measure.

Educational heterogeneity among CZ adults aged 25+ uses Theil's entropy formula:

$$H = \sum_{e=1}^{4} p_e ln(1/p_e) \tag{2}$$

e has four categories: no high school diploma, high school diploma only, some college, and a college degree or more. p_e is the proportion of a CZ in category e. A high value indicates an even distribution across the 4 categories and thus more educational heterogeneity.

Institutional configuration

Six variables specify local political and labor market institutional configurations. These measures are meant to approximate the variables used in past WGI and mesocomparative research.

Union density is the percent of nonagricultural employees in a state who are trade union members.

Minimum wage is PCE adjusted state minimum wage values not solely targeted to a subset of workers. A binary indicator is included for state-years with no such values.

The *casualization rate* replicates the measure used by McCall (2000) and is the percentage of workers employed part time, as self-employed in unincorporated businesses, or in personnel supply services.

Public employment is the percentage of CZ workers employed in the public sector.

Social spending is operationalized along two dimensions. *Educational spending* is the percentage of total state expenditures on schools, colleges, other educational institutions, and educational programs for adults, veterans, and other special classes. *Public welfare spending* is the percentage of total state expenditures on cash assistance and welfare programs, vendor payments to private purveyors of welfare programs, and miscellaneous welfare payments such as administrative costs.[17]

Methods

The analysis proceeds in three steps. First, I estimate heteroscedastic regression models (HRMs) of individual logged wages and logged total household income separately by time period (see Western and Bloome (2009) for an in-depth discussion of the benefits of HRMs over OLS regression).[18] HRMs estimate parameters for between- and within-portions of an outcome's variance. The first portion of the HRM is a standard linear regression of outcome y_g on independent variables W_{gn}, specified as:

$$y_g = \beta_n W_{gn} + \varepsilon_g \tag{3}$$

The vector of beta coefficients, β_n, represents parameters for mean group differences between values of independent variables: education, potential experience, industry, industry-region unionization, marital (wage model) / household (income model) status, race/ethnicity, and citizenship status. This portion measures between-group variance (BGI), identified by observed characteristics and β_n.

The second portion of the HRM is a gamma regression with a log-link function estimated on the squared residuals, σ^2, from equation (3). This portion estimates systematic trends in residual variance occurring among observed characteristics and is specified as:

$$\log \sigma_g^2 = \pi_n Z_{gn} \tag{4}$$

Predicted values from (4) are used as weights to reestimate y_g on W_{gn} in (3). Squared residuals are recomputed and then (4) is reestimated. The process reiterates until model parameters stabilize. HRMs accounts for heteroscedasticity in the estimation of the covariance of β parameters and provides parametric information for both between- and within-variance. [19]

This first methodological step represents the state-of-the-art for modeling individual wages and household income (Western et al. 2008, Mouw and Kalleberg 2010, Western and Rosenfeld 2011). My main contributions come in the second and third methodological steps. The large sample sizes in each PUMS wave allows computation of individual wage and household WGI and BGI separately in the 722 CZs. The unweighted median number of male wage earners in a CZ is 2,000, 1,300 for women, and 3,000 for households.

In step two, I recover the population-level within- and between-group variances, V_{it}^{W} and V_{it}^{B}, for each CZ i in time t from step one using the following formula (Western and Bloome 2009):

$$\begin{aligned} V_{it}^{W} &= \sum_{c=1}^{C} \phi_{itc}\sigma_{itc}^{2} \\ \sigma^{2}{}_{itc} &= exp(Z'_{itc}\pi_t) \end{aligned} \tag{5}$$

ϕ_{itc} is the weighted cell proportion of the combination of observed characteristics Z_{itc} in CZ i at time t. V_{it}^{B} is simply the local variance of the predicted values from the final iteration of (3). This second step yields wage and income WGI and BGI at the CZ level, conditional on HRM results from methodological step 1.[20] In total, 10,830 CZ-year variances are computed for male wages, female wages, and household income, for both WGI and BGI.[21]

In step three, I analyze how wage and income WGI and BGI are affected by CZ- and state-contextual effects by estimating multilevel repeated-measures regression models (Moller et al. 2009, Fitzmaurice et al. 2004).[22] I follow the logic of Moller et al. (2009) and use three-level regression models. The unit of analysis is the CZ-year. Samples are comprised of five repeated observations from 722 CZs, yielding 3,610 CZ-year observations. Independent variables are decomposed into two dimensions: cross-sectional means and longitudinal deviations from these means. Both are estimated *simultaneously* in a single regression model.

The first level of the model is specified as:

$$
\begin{aligned}
y_{tij} = {} & \gamma_{0ij} + \gamma_{1ij} t1980_{tij} + \gamma_{2ij} t1990_{tij} + \gamma_{3ij} t2000_{tij} + \gamma_{4ij} t2007-2011_{tij} \\
& + \sum_{k=5}^{K+5} \gamma_{kij}(X_{ktij} - \bar{X}_{kij}) + \sum_{m=K+5}^{M+5} \gamma_{mj}(X_{mtj} - \bar{X}_{mj}) + \varepsilon_{tij}
\end{aligned}
\tag{6}
$$

y_{tij} is logged income or wage WGI in CZ i in state j at time t. γ_{0ij} is the model intercept, and γ_{1ij} through γ_{4ij} are time-period effects. 1970 is the omitted category. γ_{kij} are longitudinal effects for the $k = 1...K$ CZ independent variables operationalized as deviations from the CZ specific mean centered effects. γ_{nij} are the same but for deviations of state level effects, $n = 1...N$, from state means. The error term, ε_{tij}, is unstructured, allowing for any level of correlation between time periods.[23]

The second and third model portions include parameters for cross-sectional CZ and state effects:

$$
\gamma_{0ij} = \zeta_{000} + \sum_{k=5}^{K+5} \zeta_{0kj}\bar{X}_{kij} + \sum_{m=K+5}^{M} \zeta_{00m}\bar{X}_{mnj} + \mu_{00j} \tag{7}
$$

ζ_{0kj} and ζ_{00m} represent CZ- and state-mean effects for sets of variables k and m. $\bar{X}_{kij}$ and $\bar{X}_{mnj}$ are mean values from the 5 time periods for CZ- and state-level variables. ζ_{000} is the WGI grand mean across states, and μ_{00j} is the state-level random effect.[24]

Results

WGI trends

Figures 3 and 4 show nation- and CZ-level trends in WGI. The three panels of Figure 3 show the growth of nation-level male wage, female wage, and household income variance decomposed into within- and between-components, computed from Eq. (3) and (4). Results in the three panels share some broad similarities. WGI is primarily responsible for both cross-sectional levels and longitudinal change of wage and household income inequality. Cross-sectionally, WGI accounts for between 62% (male wages 2007-11) and 72% (household income 1980) of total inequality. Also, WGI accounts for most of the longitudinal change in inequality. Even when considering the recent spike in BGI in the 2007-11 period for male and female wages, WGI change accounts for approximately 60% of the total change in inequality for each of the three outcomes.[25]

There are also some notable differences across the three outcomes. First, the importance of WGI for female wages has diminished over time, from 73% to 66% of cross-sectional levels. That female wages have become more predictable is unsurprising, considering the rapid incorporation into the labor force, the general upward occupational mobility, and the smoothing of labor force participation over the life course by women over the period of study (Percheski 2008, Kopczuk et al. 2010). It remains to be seen whether WGI will continue to drop for female wages, or if it will converge on male wage trends. Second, WGI plays a larger, and growing, role for household income than it does for wages. Third, note the variable changes in WGI and BGI across the three outcomes. A decade change associated with negligible BGI change has led to large WGI change, and vice versa, which is suggestive of distinct social processes influencing each dimension.

Figure 4 shows the 10,830 moments of CZ WGI computed from methodological step 2 as a series of boxplots. Each boxplot represents the quartile distribution of the 722 CZ WGI moments for a single outcome in a single time period. WGI varies considerably in cross-sectional geographic space. For example, the variance of nation-level male wage WGI increased from 0.156 to 0.266, or a change of 0.110. In any cross-sectional wave, the geographical variability is approximately 2/3 of the total longitudinal change. This is less the case for female wages and more for household income. Simply put, in any time period, there is a wide range of WGI across local labor markets.

To transition to the next phase of analysis, I note a limitation of analysis based on aggregate trends. Nation-level trends belie wide geographical variability occurring in any cross-sectional period. These cross-sectional slices in turn belie the radical restructuring of where WGI occurs

(Figure 1). Therefore, my analysis now shifts to multivariate models designed to test my main expectations of the connection between WGI and economic development.

[Figure 3 About Here]

[Figure 4 About Here]

Multivariate regression

Economic Development

Tables 2 through 5 include results from multilevel repeated measures models of methodological step three, estimated on CZ-year inequality.

[Table 2 About Here]

I first examine how WGI and BGI relate to the well-established curvilinear relationship between economic development and inequality. Table 2 shows results for simple models regressing WGI and BGI on median household income, its squared term, and period indicators. Models 1, 2, and 3 show results for male wage, female wage, and household income WGI, respectively.

Results show a curvilinear relationship between development and WGI. In all six cross-sectional and longitudinal instances, WGI follows economic development along a u-shaped pattern. Cross-sectionally, economic growth initially decreases WGI. Then, at approximately $31,000 for wages and $45,000 for household income, higher development corresponds with increasing WGI. The pattern also holds longitudinally within CZs. The inflection point occurs at $1,000 above the CZ-mean for wages and $6,000 for household incomes. Conceptually, economic growth has an initial stabilizing effect, making wages and incomes more predictable. Then, economic growth amplifies wage and income instability and unpredictability.[26] This is the first empirical connection between WGI and economic development, showing that it follows the tail-end of the Kuznets curve and ensuing J-shaped takeoff. Most WGI research cannot detect this curvilinear pattern due to reliance on individual and aggregate inequality trends, neither of which has the necessary sampling variability to detect this association. Figure 5 shows the association between economic development and period mean-centered WGI, plotting CZ WGI against median household income and fitting locally weighted univariate regression lines.[27] It confirms the u-shaped pattern and shows that the relationship for wages nears a linear increase in 2007-11.

To what extent does the u-shape pattern between inequality and development simply occur for *any* inequality indicator? It is possible that the WGI results in Models 1-3 also occur for BGI, in which case the parsing of total inequality into WGI and BGI would do little to develop the mesocomparative understanding of development and inequality. To examine this possibility, models 4, 5, and 6 replicate models 1 through 3 using BGI instead of WGI.

Unlike WGI, BGI has no consistent curvilinear relationship to development. Cross-sectionally, more developed CZ have higher BGI—e.g. more inequality occurring between observed social strata.[28] Longitudinally, unlike the consistent results of WGI, no clear pattern exists. The longitudinal growth of development has at best a weak effect on male wage BGI, a positive effect on female wage BGI, and a dampening effect on household BGI.

Taken together, my results clearly indicate that the nonlinear relationship between economic development and inequality regularly observed in prior research is generated by the within portion of wages and incomes: variation occurring among, rather than between, observable social strata.[29] Simply put, the scholarly examination of the great u-turn of inequality since Harrison and Bluestone (1988) *has largely been an implicit examination of WGI*. As I am unaware of any research explicitly bridging these literatures, this finding is central not only for the current research, but for stratification research more generally. I now shift to the next phase of analysis to examine the mechanisms guiding the u-shaped relationship between economic development and WGI.

[Figure 5 About Here]

Sector change

Models 7, 8, and 9 of Table 3 show cross-sectional and longitudinal effects of the modified core model of economic development. The top portion of the table shows cross-sectional, and the bottom portion longitudinal, effects.

Results clearly demonstrate that WGI is affected by the presence, and loss, of the manufacturing sector. On average, CZs with a lower concentration of manufacturing have higher WGI across each outcome. A legacy of dense employment in the relatively egalitarian manufacturing sector has a compressing effect on wage volatility. Longitudinally, deindustrialization increases WGI, shown by the inverse of the coefficient of the longitudinal change in manufacturing. The loss of manufacturing employment in CZs increases WGI across outcomes. The broadly shared increase in WGI runs in contrast to the limited research finding gender differences in deindustrialization (McCall 2001). However, my expanded data show deindustrialization to have an economy wide destabilizing effect on wages and income.

[Table 3 About Here]

In contrast, FIRE employment has little effect on CZ-level WGI. CZs with legacies of greater FIRE employment have higher male wage WGI, but longitudinal change in FIRE employment does not affect any of the three outcomes, and FIRE concentration has no cross-sectional effects for female wages or household income. Thus, in contrast to large individual-level effects of FIRE employment (see online appendix), the story of sector change and WGI at the meso-level appears to be one of deindustrialization, not financialization.

Education

Education effects generally occur as expected. Longitudinally, the growth in the relative supply of college educated workers increases male wage and household income WGI. These longitudinal results support the compositional findings of Lemieux (2006). Yet human capital growth has no effect for female wages once other dimensions of economic development are added to the model.

In contrast to Lemieux's aggregate findings, I find unmeasured skills associated with educational attainment are less important for female wages than sector change and urbanization. Cross-sectionally, college supply is excluded because it is highly correlated with educational heterogeneity, the latter strongly preferred by BIC statistics. While college supply has the expected cross-sectional amplifying effect, this is removed when cross-sectional educational heterogeneity is added to the model. Thus WGI is not simply the manifestation of high education, but of the diversity of educational attainment in local labor markets.

Cross-sectionally, educational heterogeneity has a positive effect across outcomes. CZs that on average have more educationally diverse populations have higher WGI, confirming the importance of variable levels of WGI across levels of educational attainment. In contrast to cross-sectional effects, educational heterogeneity decreases WGI for each outcome. Because educational heterogeneity is on average highest in 1980 and 1990, effects are curvilinear over time. WGI initially decreases with educational heterogeneity growth (i.e. individuals moving out of low-educational attainment) and then increases with its decline (individuals moving into high-education groups). This curvilinear relationship is confirmed in models run separately by year. In total, more educationally heterogeneous CZs have higher WGI, whereas longitudinal change in educational heterogeneity decreases, then increases, WGI.

Urban agglomeration

Results for urbanization initially receive only partial support. The rural-urban continuum code (RUCC) has no effect on male wage WGI, although more metropolitan regions have higher household income WGI and *lower* female wage WGI. Growing population density increases female wage and household income WGI.

However, RUCC results are an average across the five time periods. If the geography underlying WGI is fundamentally shifting, the simple average of RUCC effects over time is inadequate to capture real longitudinal change in metropolitan status. Furthermore, change in population density is not fully equivalent to changing cross-sectional metropolitan status; the correlation between population density change and RUCC is 0.13. Thus, any movement of WGI into urban areas has not been modeled. To examine geographical change, I interact RUCC with time period indicators. Results are shown in Table 4.

[Table 4 About Here]

Models 10 through 12 in Table 4 show a dramatic geographical realignment of wage WGI (not found in equivalent models for BGI, in models 13-15).[30] In 1970 and 1980, wage WGI was lower in metropolitan and higher in rural CZs. By 2000 and beyond, the relationship reversed. In these later time periods, higher wage WGI occurs in more metropolitan areas. Note that these effects are detected net of two education measures and (in sensitivity analyses) union density and the minimum wage, Thus, the geographical change is not simply a proxy of local human capital attainment or institutional configurations. WGI change in recent time periods corresponds with the growing importance of metropolitan agglomerated economies with tight connections to global markets, net of the composition of the labor supply of these areas. Importantly, the inclusion of interactions between RUCC and period indicators reduces the magnitude of the squared component of longitudinal economic development. The coefficient for male wage WGI is reduced by about 25%, and female wage and household income coefficients are reduced by 13% (available upon request). Simply put, a sizeable portion of the longitudinal growth or WGI via development is guided by the relocation of WGI into metropolitan areas.

Institutional configuration

I next examine the effects of labor market and political institutions. Models 16 through 18 of Table 5 include six institutional characteristics: union density, minimum wage rates, workforce casualization, public employment, and two measures of social spending.

As found by Western and Rosenfeld, trade unions have a clear negative effect on WGI. States with on average higher unionization rates have lower WGI across all outcomes, while union decline increases WGI for male wage and household income WGI.

Union decline coexists with other dampening institutional effects. Casualization expectations receive partial support. Cross-sectionally, all effects are positively signed, but are only significant for male wage WGI. Longitudinal effects are excluded because they are highly correlated with other institutional variables. However, results show high within-CZ casualized employment relations have higher WGI for each outcome (available upone request).[31] The minimum wage partially influences WGI. These results reinforce findings from Autor et al which deemphasize the importance of the minimum wage on WGI (2008). However, both cross-sectionally and longitudinally, public employment reduces WGI across all outcomes, although the effects are more scattered than developmental characteristics. Thus, the presence of an public sector which absorbs otherwise vulnerable populations into an egalitarian wage structure reduces WGI. Finally, both social spending has a longitudinal dampening effect on household income WGI. The growth of social spending over time has reduced WGI, while the longitudinal decline of educational spending has increased household WGI. Kenworthy (2004) noted the central linkage of social policy to household-level inequality, and so it is unsurprising to find social policy effects at this level of analysis compared to wage outcomes. Importantly, the decline of educational spending has female wage WGI, suggesting that heightened wage dispersion associated with human capital models can be partially mediated by state educational policy.

[Table 5 About Here]

I note two main points of this section. First, even in a strenuous test of market (pre-tax, pre-transfer) incomes located in local labor markets agglomerated across political constituencies, I find a system of labor market and state institutional compressing effects of WGI. This clearly demonstrates the importance of the local institutional configuration on providing stable and secure labor relations, manifest as low WGI. It further shows the findings of Western and Rosenfeld (2011) to be robust to a multivariate set of controls and verifies that the findings of McCall (2000) extend longitudinally.

Second, institutional effects neither remove nor dramatically change results of the development model discussed above. The curvilinear patterns of development remain, as do the main mechanisms of sector change, educational attainment, and urban agglomeration. That the results of the developmental model of inequality remain even with the inclusion through set of institutional characteristics suggests that the two explanations have independent effects on WGI. It further demonstrates the robust effects of the uneven geographical distribution of economic development on WGI. These results have hitherto been absent from WGI research, but Table 5 clearly demonstrates the importance of a developmental model of inequality for mesolevel WGI.

Conclusion

In this paper, I set out to assess how contextual features of local labor markets affect within-group inequality (WGI). To do so, I create a unique dataset locating within- and between-components of inequality in 722 commuting zones covering the entire contiguous United States across 40 years using Census and American Community Survey data. These data are unique and reveal striking patterns rooted in mesocomparative theories of economic development.

What is learned by situating WGI at the mesocomparative level? I find WGI follows the uneven geographical distribution of economic development. Most importantly, WGI, but not BGI, relates to economic development in a u-shaped pattern. This shows that the famous shift from the Kuznets Curve to the Great-U turn is fundamentally a WGI phenomenon (Harrison and Bluestone 1988, Moller et al. 2009). This mesolevel developmental association can be detected in individual-level associations, but show up as residual variance. Thus previous research examining individual and national-level associations of WGI and BGI have missed a crucial underlying process. This finding is particularly important given the strenuous methodological requirements of counterfactual analyses used in much WGI research (Lemieux 2006, Western and Bloome 2009, Western and Rosenfeld 2011). Future inequality research on WGI and BGI need to incorporate a developmental model to accurately assess the two inequality components.

Furthermore, my findings suggest that development is channelled into inequality change through the mechanisms of WGI, such as economic volatility, insecurity, and winner-take-all markets (Hacker 2006, Frank 2007, Western et al. 2012). My results suggest that future research on development and inequality would benefit by carefully incorporating these characteristics into analyses. Additionally, the link between economic development and WGI suggests that WGI may be particularly important in future inequality growth. As more labor markets grow in prosperity and well-being, I anticipate inequality growth to occur within-social strata. This expectation can be tests on future ACS data.

Why does WGI follow economic development in a u-shaped pattern? Foremost is the dramatic geographical realignment of WGI. Until 2000, WGI was concentrated in rural areas. Since then, WGI has moved to the city, with high of WGI shifting to metropolitan areas. This geographical shift can explain upwards of 25% of the longitudinal growth associated with economic development. This finding provides a targeted focus for future WGI research. Global cities should be of central importance to future WGI research to examine how urban processes have changed in recent decades to amplify the within-portion of inequality. Moreover, a main priority of WGI research should be generating micro data with more precise geographical identification. For example, to what extent is the growth of metropolitan WGI an indication of increased neighborhood effects on wages and income? My unique data offers the best available place-based examination of WGI that currently exists, but many place-based questions are still unanswered.

The two other components of the modified core model of economic development affect WGI as expected. Deindustrialization consistently amplifies WGI, and labor markets with a greater concentration of manufacturing have lower WGI. And growth in the supply of college educated workers increases WGI, although the effect for women is much weaker than suggested in previous research (Lemieux 2006). College attainment coexists with the heterogeneity of educational attainment in local labor markets. Cross-sectionally, high educational heterogeneity increases WGI, while longitudinal change in educational heterogeneity decreases, then increases, WGI. These results show that WGI is partially a predictable outcome of a developmental model of inequality.

Local institutional configurations have the anticipated compressing effect on WGI.

Unionization, work casualization, public employment, and (for households) social education and welfare spending relate to WGI as expected, even in a strenuous test of pre-tax and transfer outcomes situated in local labor markets that aggregate over multiple political jurisdictions. However, these institutional effects occur jointly with developmental effects and do not remove the main effects of development. This finding clarifies that local institutional and developmental characteristics are independent sources of WGI change.

Of course, the relationship between inequality and economic development is primarily a descriptive pattern, and the effects of development were not fully explained by the core model of economic development or institutional characteristics. This suggests that further research is needed on mesolevel WGI. Although it is beyond the scope of the current research to provide an exhaustive account of contextual factors influencing WGI, I highlight two promising avenues. First, in a similar Danish study of corporate demography, Sorensen and Sorenson (2007) found that local patterns of industrial concentration and differentiation influence WGI. Corporate demography could similarly affect subnational American WGI patterns. Second, the growth of WGI may be an outcome of globalization. This has been argued previously by McCall (2000). Development patterns could mirror findings in cross-national research linking the U-turn of inequality to global trade and investment (Alderson and Nielsen 2002). Further, the rapid growth of urban WGI could signal connections to global markets, leading both to volatile and insecure labor relations (McCall 2000) and lavish winner-take-all payoffs (Frank 2007).

Any study moving beyond the first distributional moment can be critiqued by asking to what extent are the findings simply representative of change in between-group characteristics not available in the Census, or just noise? It is unlikely that my findings reduce to either of these. In reference to Figure 3, most growth of inequality over time occurs within social strata of standard wage and income regression models, and there is no theoretical reason to suspect why the modelling of wages and incomes should become worse over time. To suggest WGI is simply measurement error or noise implicitly either refutes the dramatic growth of inequality (i.e. better measurement would reduce measurement error, thus inequality) or relinquishes the ability of social scientists to assess reasons for its growth. And although more narrow and targeted studies can incorporate fine-grained observed micro characteristics, such studies will inevitably have difficulty situating these effects in the broader temporal and geographical changes associated with the current inequality upswing. WGI analysis is part of a broader scholarly movement in understanding subtle distributional properties crucial to present inequality, to which my research contributes.

My research makes three major contributions to understanding the increase in United States inequality. First, I find WGI to be grounded in place-based social contexts. The geographical underpinnings and mesolevel mechanisms I find are undetectable by any alternative data. CPS data cannot locate workers in units smaller than states, confounding high and low developed labor markets. Metropolitan Statistical Areas cannot detect the great flip in urbanized WGI. Geographical identifiers provided by the Census sacrifice longitudinal analysis. Because of the unique data created for this project, debates about WGI as unobserved skill, the aftermath of deinstitutionalization, nation-level population composition, and noise now face a fifth explanation. WGI is also due to the developmental characteristics of where one lives. Two otherwise labor forces can expect different degrees of pay unpredictability depending on the developmental characteristics of their local labor markets.

Second, my research provides the most thorough evidence of distinct social processes guiding WGI and BGI. Through the use of thousands of BGI and WGI observations instead of the 30 nation-level observations of most studies, I find that the two components of inequality have fundamentally different relationships to economic development and one of the main mechanisms of development, urban agglomeration. Previous research frequently situates WGI and BGI in competition, with analyses leading to claims of one or the other being more important for moving overall inequality trends (Lemieux 2006, Mouw and Kalleberg 2010). Yet my more flexible data allows for a more nuanced examination of the two components of inequality. WGI and BGI need not be in a horserace, but rather can be critically examined in relation to multiple local features of social contexts. An intriguing avenue of future research would be to further examine the degree to which WGI and BGI follow different social processes.

Third, my research is the first to bridge the inequality literatures of WGI and development. When understood through a developmental model of inequality, WGI appears less chimerical, as it responds to well-trodden mechanisms of inequality: prosperity, sector change, education, and urban agglomeration. When understood through this theoretical lens, WGI can be further decoupled from unobservable characteristics of the individual—thus risking reasons of WGI to be left to speculations of the researcher—and grounded in macrosociological inequality theories of the social context occurring above the individual.

In summary, when situated in a mesocomparative analytic framework, WGI tracks quite closely with the geographically uneven distribution of economic development. Thus, the unpredictability of personal earnings are not simply due to unobserved capacities of the individual or the nation-level decline of protective labor market institutions, but also the developmental characteristics of where one lives. Not only does this finding fundamentally connect WGI to the great U-turn of inequality, but it also establishes a promising mesolevel avenue to examine the relative importance of between- and within-portions of inequality to total inequality trends.

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Endnotes

[1]For example, WGI began growing in the late 1960s and early 1970s prior to between-group inequality (BGI), and WGI growth slowed in comparison to BGI following the great recession (Katz and Murphy 1992, Mishel et al. 2012).

[2]I describe inequality as relative to the period mean to clarify that dark shades do not represent change in inequality levels over time.

[3]Categorical, continuous variables, and multivariate analysis are simply expansions of the processes shown in Figure 2.

[4]Some overcome this issue by shifting attention from individual wages to occupational payoffs (Weeden et al. 2007, Mouw and Kalleberg 2010, Liu and Grusky 2013).

[5]Shifts from agricultural to manufacturing sectors affected inequality (Alderson and Nielsen 2002). Because my research focuses on an era with low agricultural employment, I simply include farm employment and sector dualism as controls.

[6]For space reasons, I do not go into great detail of deinstitutionalization or deunionization and WGI. See McCall (2000) and Western and Rosenfeld (2011) for extended discussion of these effect.

[7]See the online supplement section 1.1 for further discussion of sorting respondents into CZs.

[8]Economists have debated a similar measurement of wages in the CPS, which is potentially relevant for the current research. Lemieux (2006) argued that the May/MORG CPS should be used instead of the March CPS. The latter has a wage measure constructed as above, potentially inflating WGI, while the May/MORG CPS has wage data from the previous week for hourly workers. Hourly pay—i.e. measurement error—has grown over time in the March CPS, not WGI. Yet the debate is not settled. Autor et al. (2005, 2008) note a *downward* bias in May/MORG WGI.

Crucially, May/MORG CPS wage data misses contingent, performance, and transitory pay for hourly workers which accumulate over the year (Hacker 2006, Lemieux et al. 2009, Western et al. 2012). Most importantly, they note that differences in March and May/MORG CPS wage data are minimal when samples are restricted to full-time, full-year workers, as I do with my sample.

[9]I test results against imputing such cases with a random value between \$2.80 and the year-specific minimum wage, which does not change results.

[10]This topcoding decision affects a very small number of respondents. Note that the restriciton necessarily reduces WGI, and so my results are a conservative estimate of WGI. Refer to the online supplement (section 1.3 for more coding details.

[11]Census and ACS data are cross-sectional and I therefore cannot test whether local WGI is driven by individuals self-selecting into labor markets. Although developmental and institutional characteristics included in analysis should capture much of the effect that inter-CZ migration patterns has on inequality patterns (Moller et al. 2009), future longitudinal research on WGI and migration patterns is warranted.

[12]In sensitivity analyses, I included 368 occupational contrasts when fitting my models. The results were substantively identical.

[13]See the online supplements sections 1.4 and 1.5 for discussion of missing data and survey weights.

[14]Some effects discussed below have corresponding individual effects. CZ-level variables measure distinct, contextual effects of these characteristics on CZ-level WGI. Individual effects are used to parse individual wages into between- and within-components based on individual-level associations. Including each dimension of these characteristics accurately captures relevant individual and contextual dimensions. I test results by estimating 90/10 residual variances following OLS regressions, where WGI levels are less conditioned on individual covariates (Autor et al. 2008). Conclusions are

substantively similar.

[15]I test results against additional compositional and institutional variables: unemployment, female labor force participation, proportion single mothers, proportion black, proportion Hispanic, percent foreign born, percent aged 65 and older. These characteristics do not change main results. It is beyond the scope of the current research to fully justify and describe these effects, but future research on such compositional and institutional features is warranted.

[16]Cross-sectional population density has a correlation of 0.8 with RUCC and so is excluded. It yields the same results as RUCC. There is virtually no change over time of RUCC codes and so only the mean value is used.

[17]I test measures which divide educational and social spending by state GDP and find similar results.

[18]ACS waves from 2007 to 2011 are estimated jointly. The Census changed PUMA definitions beginning with the 2008 wave and so the 2008-2012 sample is not currently compatible with 1990 CZ definitions.

[19]β and π are not of primary interest. They are included in the online supplement (Tables A5-A7).

[20]Computation conditions WGI on equation (4). Western and Bloome (2009) note this smooths the data and reduces influence of outlying cells. Comparisons to similar results following OLS regression reveal smaller HRM residual variances. The results in this paper therefore represent conservative estimates of place effects.

[21]I follow the logic of Autor and Dorn (2013) by estimating individual and place effects separately. This approach is desirable as it is more substantively interesting to examine place effects on population level spreads of residual wages and incomes. I also include individual and place characteristics simultaneously in supplemental HRM, and draw substantively similar conclusions.

See online supplement 2.1 for further discussion.

[22]In sensitivity analyses, I include a spatial correlation term to account for the similarity of neighboring CZs. Main results are substantively identical.

[23]LR tests confirm an unstructured residual covariance is preferred over simpler residual covariance structures. Results using simpler residual covariance structures are substantively similar, but with inflated statistical significance.

[24]Note that I test results using state fixed effects and lagged differences of the dependent variables in an instrumental variable regression. Neither changes main results below.

[25]HRM estimated separately for single years of 2007-2011 reveal stable cross sectional levels of WGI for each outcome. WGI contributed slightly higher proportions of change to inequality following the recession for each outcome (e.g. 31% for men rather than 27%).

[26]Note that slight the exception is the main term for longitudinal female wages. However, it is correctly signed and the two terms are jointly significant.

[27]WGI is mean-centered to ease comparisons of the non-parametric relationship between WGI and development across time periods.

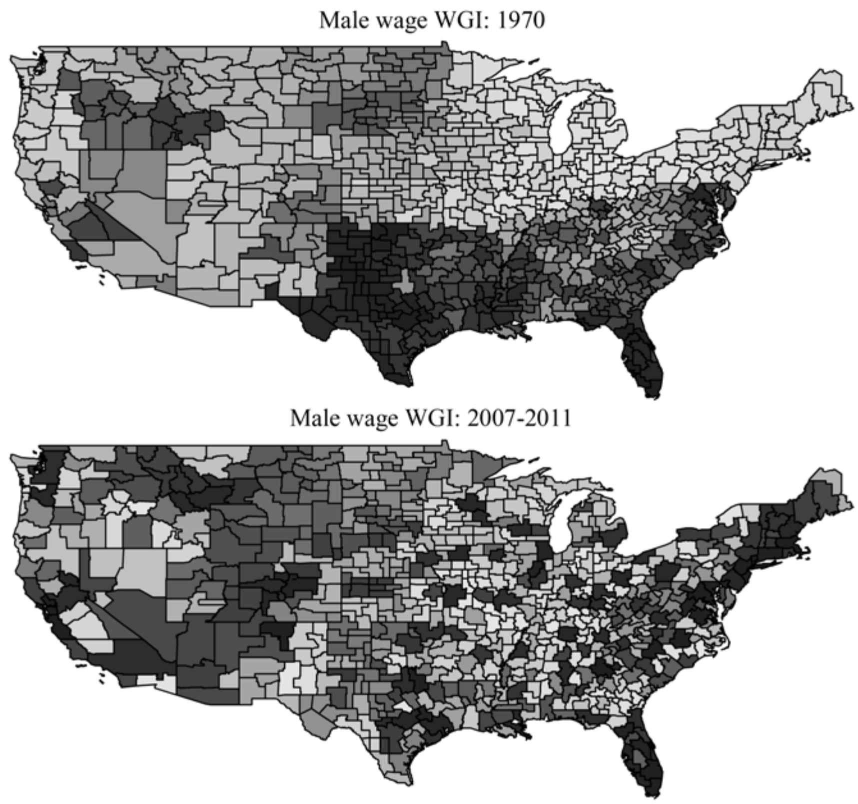
[28]Although the signs for cross-sectional household income are correct and the terms are jointly significant, the plotted function shows that the negative main coefficient simply indicates no effect of development on household income BGI until approximately $30,000. This is in contrast to a distinct curvilinear pattern for all WGI effects.

[29]Sensitivity analyses reveal a u-shaped pattern for overall inequality also.

[30]There are few significant effects for household income. Thus, household WGI is better understood using the average over the 5 time periods showing higher WGI in urban areas.

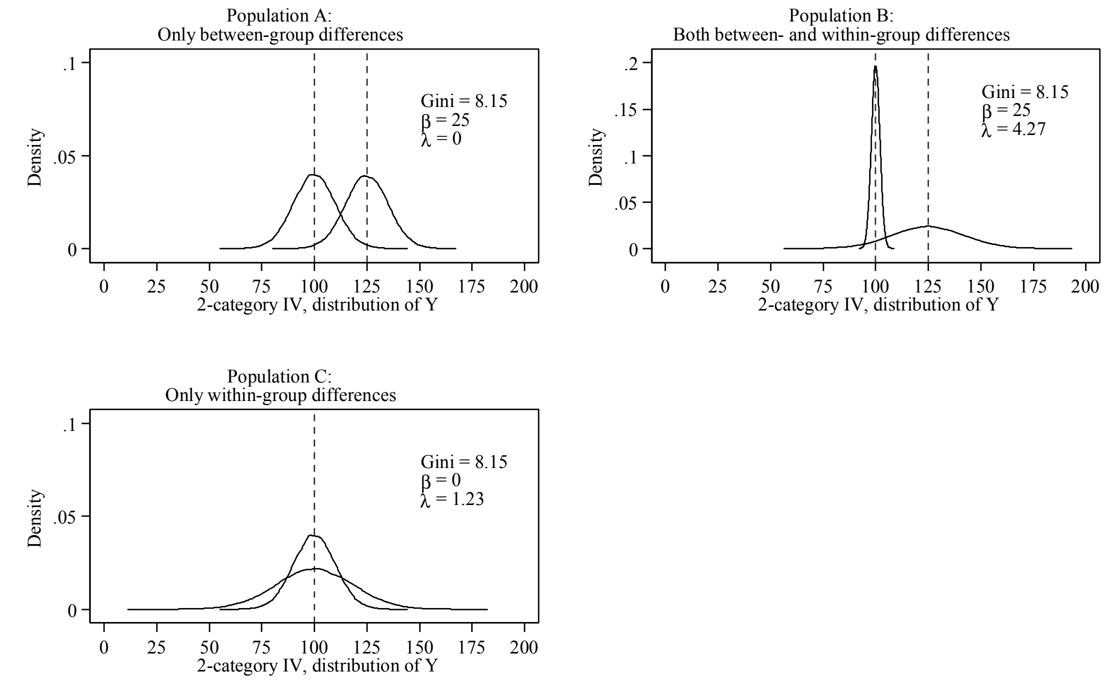
[31]Note that casualization rates are highest in 1970. This is because most casualized workers are

part-time, meaning some of the results are confounded by the entrance of female workers into the labor force.



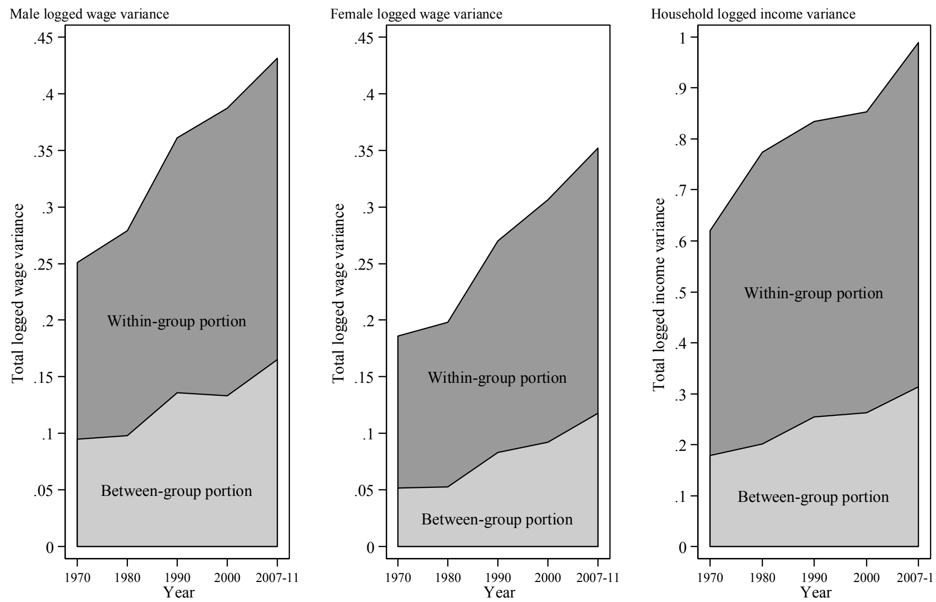
Darker shade indicate higher WGI relative to time period mean. See data and methods section for the procedure to compute WGI locally in 722 commuting zones.

Figure 1: Male wage within-group inequality (WGI) over time



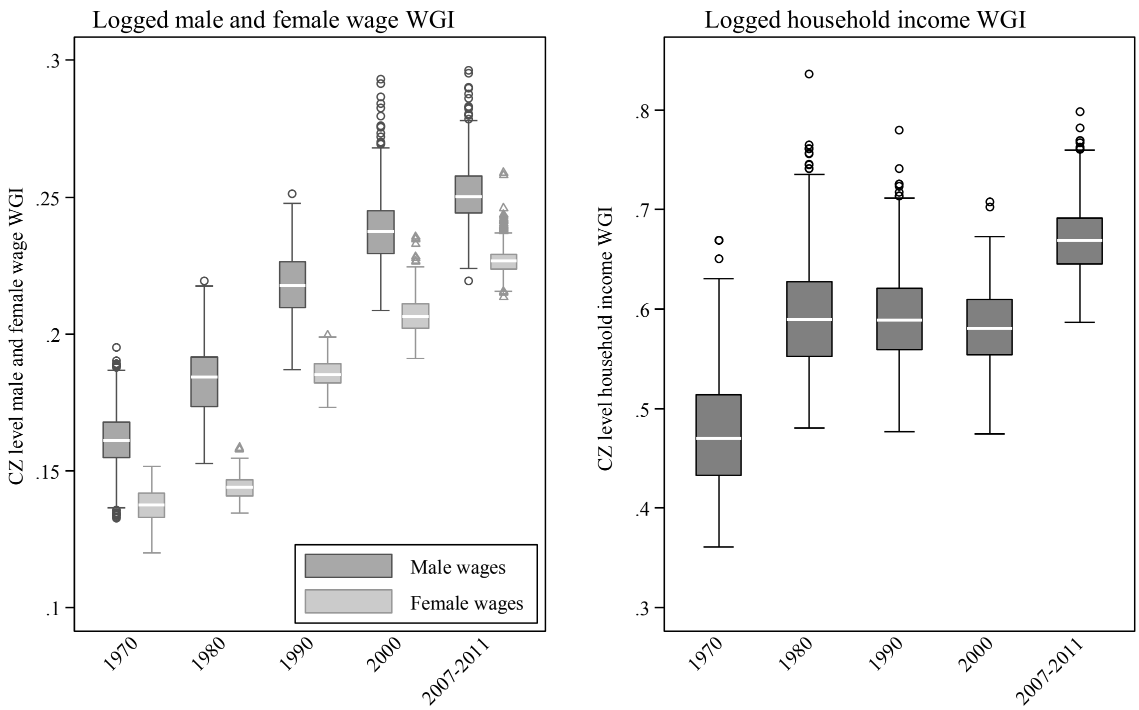
Gini=population-level inequality: β=between-group inequality: λ=within-group inequality (see Methods section for more detail).
Each simulated population is composed of 100,000 observations

Figure 2: Within- and Between group inequality: conceptual visualization



Within- and between-group inequality computed from IPUMS data

Figure 3: Aggregate inequality trends



CZ level WGI computed from equation (5). Each boxplot represents the quartile distribution of 722 commuting zone-year moments, per survey time period. Middle 50% of commuting zone level distribution of WGI occur in shaded box

Figure 4: Commuting zone (CZ) distribution of within-group inequality (WGI), 1970-2011

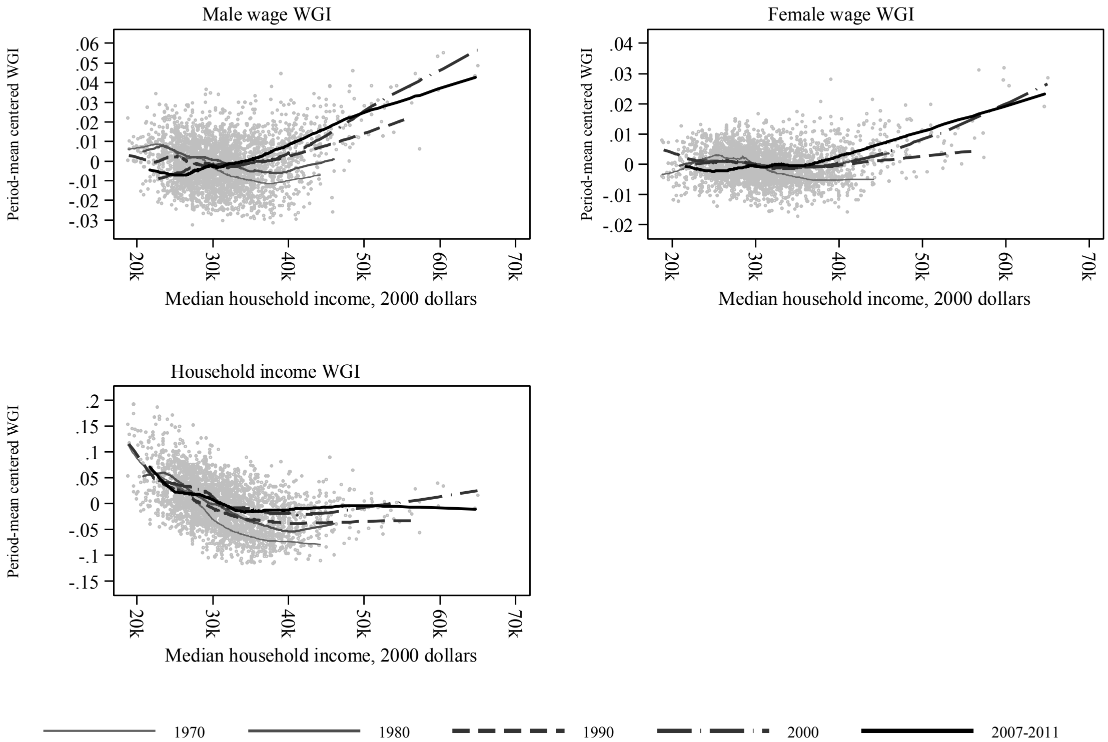


Figure 5: Scatterplot and locally weighted regression of within-group inequality (WGI) and economic development

Table 1: Variable Means, Deviations from the Mean by Period, Data Sources

Name	Mean	Period deviances 1970	1980	1990	2000	2007-11	Sources
Dependent Variables							
Male wage within-group inequality[a]	0.210	-0.050	-0.027	0.008	0.028	0.041	PUMS 1970, 1980, 1990, 2000, ACS 2007-2011
Female wage within-group inequality[a]	0.180	-0.043	-0.036	0.005	0.027	0.047	PUMS 1970, 1980, 1990, 2000, ACS 2007-2011
Household income within-group inequality[b]	0.583	-0.106	0.011	0.010	-0.001	0.087	PUMS 1970, 1980, 1990, 2000, ACS 2007-2011
Independent Variables							
Economic development							
Median household income	0.311	-0.029	-0.003	-0.012	0.026	0.018	PUMS 1970, 1980, 1990, 2000, ACS 2007-2011
Manufacturing sector size	0.130	0.032	0.025	0.008	-0.012	-0.053	BEA REIS 2014
FIRE sector size	0.055	-0.008	-0.001	-0.003	-0.002	0.013	BEA REIS 2014
Agriculture sector size	0.097	0.048	0.014	-0.006	-0.021	-0.035	BEA REIS 2014
Sector dualism	0.041	-0.001	0.004	-0.002	-0.001	0.000	BEA REIS 2014
Rural Urban Continuum Code	3.582	-0.361	-0.193	-0.054	0.250	0.358	Beale 2004; U.S. Bureau of the Census (various years)
Population density	3.454	-0.151	-0.029	-0.009	0.074	0.116	U.S. Bureau of the Census (various years)
College supply	0.896	-0.040	-0.007	0.013	0.007	0.027	U.S. Bureau of the Census (various years); NHGIS 2014
Educational heterogeneity	1.239	-0.137	0.001	0.074	0.029	0.033	U.S. Bureau of the Census (various years); NHGIS 2014
Institutional configuation							
Unionization rate	15.758	7.671	4.643	-2.005	-4.193	-6.117	Hirsch and Macpherson 2013
Minimum wage	3.288	-2.030	0.154	0.168	0.506	1.202	U.S. Department of Labor 2014
Casualization rate	0.360	0.031	0.013	0.008	-0.022	-0.030	PUMS 1970, 1980, 1990, 2000, ACS 2007-2011
Public sector size	0.173	0.009	-0.001	0.000	-0.006	-0.002	BEA REIS 2014
Education spending	0.363	0.037	0.010	-0.003	-0.013	-0.031	U.S. Bureau of the Census (various years)
Social welfare spending	0.171	-0.048	-0.026	-0.016	0.034	0.057	U.S. Bureau of the Census (various years)

[a] Estimated from HRM (equations 4 and 5) using the following independent variables: education (5 categories), potential experience (4 categories), quartic interaction between education and continuous potential experience (Autor et al 2008), race (6 categories), marital status (4 categories), overwork status, industry (10 categories), citizenship status (3 categories), industry-region unionization rate

[b] Estimated from HRM (equations 4 and 5). Household head's characteristics from footnote a (above) used as independent variables. 10 categories of household composition / spousal employment status included in lieu of marital status.

Table 2: Multilevel repeated measures model predicting commuting zone wage/income within-group inequality and between-group inequality

	Within-group inequality (WGI)					
	Model 1: Male wage WGI[a]		Model 2: Female wage WGI		Model 3: Household income WGI	
	Estimate	t	Estimate	t	Estimate	t
Cross-Sectional Effects[d]						
Median income	-0.0996**	(-2.96)	-0.0666***	(-4.23)	-1.1628***	(-8.12)
Median Income^2	0.1549**	(3.14)	0.1066***	(4.64)	1.2653***	(6.07)
Longitudinal Effects						
Median income	-0.0152***	(-4.01)	-0.0024	(-1.03)[c]	-0.3865***	(-28.21)
Median Income^2	0.4416***	(7.26)	0.2996***	(6.79)	3.0809***	(13.09)
	Between-group inequality (BGI)					
	Model 4: Male wage BGI		Model 5: Female wage BGI		Model 6: Household income BGI	
	Estimate	t	Estimate	t	Estimate	t
Cross-Sectional Effects[e]						
Median income	0.0390	(0.58)[f]	0.0327	(1.06)[f]	-0.2189	(-1.76)[f]
Median Income^2	0.0333	(0.34)	0.0145	(0.32)	0.4199*	(2.32)
Longitudinal Effects						
Median income	0.0131*	(2.09)	0.0276***	(7.57)[f]	-0.0784***	(-9.55)[f]
Median Income^2	-0.1518	(-1.37)	0.1094	(1.52)	-0.0730	(-0.45)
Observations	3,610[b]		3,610		3,610	

* p<0.05 ** p<0.01 *** p<0.001, two-tailed test

[a]WGI estimated from HRM of equations (4) and (5) of logged wages on 5 education categories, 4 potential experience categories, a quartic interaction between education categories and a continuous version of potential experience, 6 race categories, marital status, 10 industry categories, citizenship status, industry-region union density rates, and household type. Variance of resulting residual wages was computed locally in 722 commuting zones (CZ), using equation (6). BGI is estimated locally by computing the variance of predicted values from methodological step 1 in 722 CZ.

[b]722 commuting zones and 48 states

[c] Main and squared terms jointly significant ($\chi^2_{(df=2)} = 46.91$, $p<0.001$)

[d] Models estimated with period indicator variables and an indicator variable for commuting zones crossing state boundaries

[e] BGI results are tested with polynomial terms included. In none of the six cases are polynomial terms significant

[f] Main and squared terms jointly significant (all p<0.001)

Table 3: Multilevel repeated measures model predicting commuting zone wage/income within-group inequality (WGI)

	Male wage WGI[a]		Female wage WGI		Household income WGI	
	Model 7		Model 8		Model 9	
	Estimate	t	Estimate	t	Estimate	t
Cross-Sectional Effects[c]						
Economic development effects						
Median income	-0.1593***	(-5.46)	-0.0795***	(-5.25)	-1.3927***	(-9.97)
Median Income^2	0.2428***	(5.83)	0.1302***	(6.04)	1.4476***	(7.30)
Manufacturing sector size	-0.0212***	(-8.07)	-0.0088***	(-6.44)	-0.1096***	(-8.71)
FIRE sector size	0.0705***	(6.66)	0.0024	(0.44)	0.0267	(0.53)
Farm sector size	0.0199***	(5.31)	0.0027	(1.40)	0.0703***	(3.97)
Sector dualism	-0.0196*	(-2.48)	-0.0082*	(-1.99)	-0.0924*	(-2.43)
Rural Urban Continuum Code (RUCC)	-0.0002	(-1.70)	-0.0003***	(-4.30)	0.0014*	(2.48)
Ed heterogeneity	0.0504***	(12.56)	0.0165***	(8.06)	0.0766***	(4.07)
Longitudinal Effects						
Economic development effects						
Median income	-0.0025	(-0.63)	-0.0015	(-0.63)	-0.3676***	(-25.92)
Median Income^2	0.3992***	(6.25)	0.2968***	(6.65)	3.1480***	(13.19)
Manufacturing sector size	-0.0394***	(-11.64)	-0.0115***	(-5.55)	-0.1346***	(-9.89)
FIRE sector size	-0.0205*	(-2.26)	0.0021	(0.35)	-0.0437	(-1.26)
Farm sector size	0.0290***	(5.78)	0.0202***	(5.87)	0.2040***	(9.58)
Sector dualism	0.0006	(0.21)	-0.0064***	(-3.58)	-0.0227*	(-2.26)
Population density (log)	0.0001	(0.05)	0.0038***	(7.51)	0.0317***	(9.03)
College supply	0.0624***	(9.50)	0.0076	(1.75)	0.0767**	(3.03)
Ed heterogeneity	-0.0251***	(-10.30)	-0.0074***	(-4.88)	-0.0912***	(-9.49)
1980	0.0248***	(47.53)	0.0078***	(21.38)	0.1417***	(68.09)
1990	0.0606***	(78.53)	0.0499***	(98.42)	0.1435***	(47.60)
2000	0.0791***	(99.54)	0.0706***	(137.63)	0.1395***	(46.97)
2010	0.0908***	(95.15)	0.0902***	(148.88)	0.2205***	(58.53)
Constant	0.1175	(18.17)	0.1266	(38.58)	0.6645	(22.24)
Observations	3,610[b]		3,610		3,610	

* p<0.05 ** p<0.01 *** p<0.001

[a]WGI estimated from HRM of equations (4) and (5) of logged wages on 5 education categories, 4 potential experience categories, a quartic interaction between education categories and a continuous version of potential experience, 6 race categories, marital status, 10 industry categories, citizenship status, industry-region union density rates, and household type. Variance of resulting residual wages was computed locally in 722 commuting zones, using equation (6)

[b]722 commuting zones and 48 states

[c] Models estimated with an indicator variable for commuting zones crossing state boundaries

Table 4: Change in the effect of Rural Urban Continuum Code (RUCC) over time

	Within-group inequality (WGI)					
	Model 10[a] Male wage WGI[b]		Model 11 Female wage WGI		Model 12 Household income WGI	
	Estimate	t	Estimate	t	Estimate	t
RUCC by time period[c]						
1970	-0.0004*	(-2.50)	-0.0007***	(-6.22)	-0.0002	(-0.21)
1980	-0.0006***	(-4.24)	-0.0001	(-1.67)	-0.0012	(-1.47)
1990	-0.0005**	(-2.66)	-0.0001	(-1.45)	-0.0001	(-0.13)
2000	0.0014***	(7.14)	0.0006***	(6.31)	0.0031***	(4.68)
2007-11	0.0014***	(6.51)	0.0003**	(3.05)	0.0010	(1.30)
	Between-group inequality (BGI)					
	Model 13 Male wage BGI		Model 14 Female wage BGI		Model 15 Household income BGI	
	Estimate	t	Estimate	t	Estimate	t
RUCC by time period						
1970	-0.0002	(-0.57)	-0.0002	(-1.01)	0.0005	(0.85)
1980	-0.0001	(-0.25)	0.0003**	(2.62)	0.0024***	(4.73)
1990	0.0010**	(3.26)	0.0007***	(4.63)	0.0025***	(4.64)
2000	0.0017***	(5.86)	0.0009***	(5.70)	0.0035***	(6.44)
2007-11	0.0028***	(7.71)	0.0011***	(6.07)	0.0041***	(6.89)
Observations	3,610[d]		3,610		3,610	

* p<0.05 ** p<0.01 *** p<0.001, two-tailed tests

a Multilevel repeated measures regression models include all independent variables from Table 3. Per findings from Table 2, BGI include only main term for economic development. Results are the same if all independent variables from Table 5 are included.

b WGI and BGI estimated from HRM of equations (4) and (5) of logged wages on 5 education categories, 4 potential experience categories, a quartic interaction between education categories and a continuous version of potential experience, 6 race categories, marital status, 10 industry categories, citizenship status, industry-region union density rates, and household type. Variance of resulting residual wages was computed locally in 722 commuting zones (CZ), using equation (6). BGI is estimated locally by computing the variance of predicted values from methodological step 1 in 722 CZ.

[c] Displayed coefficients, t-statistics and statistical significance are for the combined main and interaction effects.

[d] 722 commuting zones and 48 states across 5 periods

Table 5: Multilevel repeated measures model predicting commuting zone wage/income within-group inequality (WGI)

	Model 16		Model 17		Model 18	
	Male wage WGI[a]		Female wage WGI		Household income WGI	
	Estimate	t	Estimate	t	Estimate	t
Cross-Sectional Effects[c]						
Economic development						
Median income	-0.1391***	(-4.73)	-0.0888***	(-5.86)	-1.4033***	(-9.72)
Median Income^2	0.2359***	(5.77)	0.1462***	(6.93)	1.4743***	(7.35)
Manufacturing sector size	-0.0255***	(-8.58)	-0.0135***	(-8.75)	-0.1213***	(-8.26)
FIRE sector size	0.0520***	(4.42)	-0.0153*	(-2.52)	-0.0222	(-0.38)
Farm sector size	0.0137***	(3.57)	-0.0011	(-0.58)	0.0593**	(3.18)
Sector dualism	-0.0158*	(-2.06)	-0.0074	(-1.86)	-0.0902*	(-2.37)
Rural Urban Continuum Code (RUCC)	0.0001	(0.05)	-0.0002**	(-3.28)	0.0016*	(2.54)
Ed heterogeneity	0.0462***	(11.31)	0.0177***	(8.45)	0.0776***	(3.90)
Institutional configuration						
Union density	-0.0007***	(-3.89)	-0.0002**	(-3.05)	-0.0012*	(-2.00)
Minimum wage	-0.0018**	(-2.92)	-0.0002	(-0.74)	-0.0036	(-1.74)
Casualization rate	0.0379***	(4.34)	0.0054	(1.23)	0.0168	(0.40)
Public sector size	-0.0071*	(-2.46)	-0.0088***	(-5.88)	-0.0214	(-1.50)
Education spending	0.0122	(0.59)	0.0142	(1.92)	-0.0453	(-0.63)
Social welfare spending	-0.0045	(-0.16)	-0.0021	(-0.21)	-0.0303	(-0.32)
Longitudinal Effects						
Economic development						
Median income	-0.0048	(-1.15)	-0.0035	(-1.39)	-0.3740***	(-25.57)
Median Income^2	0.4143***	(6.45)	0.2886***	(6.40)	3.1244***	(12.98)
Manufacturing sector size	-0.0403***	(-11.30)	-0.0126***	(-5.89)	-0.1443***	(-10.40)
FIRE sector size	-0.0203*	(-2.21)	-0.0005	(-0.08)	-0.0395	(-1.14)
Farm sector size	0.0256***	(4.80)	0.0195***	(5.45)	0.2002***	(9.21)
Sector dualism	0.0011	(0.39)	-0.0065***	(-3.67)	-0.0238*	(-2.37)
Population density (log)	0.0003	(0.37)	0.0035***	(6.76)	0.0319***	(9.03)
College supply	0.0609***	(9.03)	0.0088*	(2.01)	0.0612*	(2.40)
Ed heterogeneity	-0.0236***	(-9.14)	-0.0075***	(-4.78)	-0.0779***	(-7.95)
Institutional configuration						
Union density	-0.0003***	(-4.53)	0.0001	(1.58)	-0.0010***	(-5.10)
Minimum wage	-0.0010***	(-7.32)	0.0001	(1.31)	-0.0005	(-1.19)
No minimum wage	-0.0047***	(-7.13)	0.0004	(1.01)	-0.0049*	(-2.16)
Public sector size	-0.0134**	(-2.98)	-0.0019	(-0.69)	-0.0451**	(-2.67)
Education spending	-0.0053	(-1.26)	-0.0066**	(-2.94)	-0.0267*	(-1.96)
Social welfare spending	0.0046	(0.98)	-0.0020	(-0.72)	-0.0700***	(-4.48)
1980	0.0234***	(38.11)	0.0078***	(19.47)	0.1367***	(59.23)
1990	0.0574***	(55.25)	0.0500***	(80.66)	0.1316***	(35.13)
2000	0.0753***	(65.12)	0.0709***	(103.90)	0.1291***	(32.41)
2010	0.0868***	(63.91)	0.0905***	(112.95)	0.2095***	(43.20)
Constant	0.1254	(9.72)	0.1270	(24.20)	0.7297	(14.54)
Observations	3,610[b]		3,610		3,610	

* p<0.05 ** p<0.01 *** p<0.001, two-tailed tests

aWGI computed by conducting variance function regression of logged wages on 5 education categories, 4 potential experience categories, a quartic interaction between education categories and a continuous version of potential experience, 6 race categories, marital status, 10 industry categories, citizenship status, industry-region union density rates, and household type. Variance of resulting residual wages was computed locally in 722 commuting zones.

[b] 722 commuting zones and 48 states

[c] Models estimated with an indicator variable for commuting zones crossing state boundaries

Online Supplement:
Recovering the missing middle: A mesocomparative analysis of within-group inequality, 1970-2011

1 Data Management

1.1 Commuting Zones

PUMS data include geographical identifying information, either in the form of county groups (1970 and 1980 waves) or public use micro areas (PUMAs) (1990, 2000, and ACS). I follow the strategy developed by Dorn (2009) to sort country groups and PUMAs to the 1990 commuting zone. Data from Alaska and Hawaii are excluded due to inconsistent definitions of county boundaries over the study period.

Geographical unit $j = 1, 2, ..., J$ is matched to commuting zone CZ $k = 1, 2, ..., 722$ by computing the probability that a resident of geographical unit j lives in CZ k in PUMS wave $t = 1970, 1980, 1990, 2000, 2007-2011$. The probability, α_{jkt}, is defined as:

$$\alpha_{jkt} = \sum_{c=1}^{C} \frac{r_{jct}}{r_{jt}} \frac{r_{ckt}}{r_{ct}} \tag{1}$$

where c is a United States county. Individuals in the minority of geographical units that overlap CZs are split into multiple observations and re-weighted via equation (1). Although this introduces some noise to the data, it provides the best currently available procedure to examine within-group inequality and place effects. As noted by Dorn (2009), most cases can be matched without this partitioning. For example, about 80% of respondents in the 2000 PUMS wave can be exactly assigned to a commuting zone. While the weighted partitioning of observations necessarily includes noise into results, it represents the best, and only, option for conducting longitudinal analysis of within-group inequality in fine grained geographical space.

1.2 State Allocation

I follow the practice of Autor and Dorn (2013) and Chetty et al. (2013) in assigning CZs to states. However, 98 of the 722 CZs have a single county that is in a different state than the assigned state. One commuting zone is comprised of three counties, each in a different state. In total, this means that 99 of over 3,000 counties are assigned to a neighboring state. I test results using only a sample of CZs that do not cross state boundaries. Results are substantively similar. Furthermore, all regression models include a dummy variable indicating whether a commuting zone crosses a state boundary. In no case is this variable close to statistically significant. It is therefore not presented in main tables for the sake of parsimony.

1.3 Dependent Variables

The 2000 and 2007-2011 samples have multiple top codes for market income sources. These top codes are determined by state residence and represent the 99.5^{th} percentile of that state income's source. I follow procedures similar to Acemoglu and Autor (2011), who provide a uniform top code near the minimum topcode value, by applying a topcode equal to the minimum topcode. While this has the effect of truncating certain high incomes, it does not risk artificially inflating between-state place effects.

"Other" income is excluded because it is an indistinguishable mix of both government transfers (e.g. veterans benefits) and market income (e.g. child support payments). In waves 1990, 2000, and 2007-2011, respondents indicate their retirement income. However, public and private retirement income cannot be distinguished. Income from this source is therefore excluded. In 1970, income from interest, dividends, rental income, royalty income, and income from estates and trusts is lumped into other income. Main analyses include all "other" incomes in 1970. I test results excluding this other income component from 1970. Results are substantively the same. For household income, households with no income are excluded from analysis. Results are the same if analysis includes households with zero income.

1.4 Survey Weights

Results from methodological step 1 use individual and household survey weights provided by the IPUMS. These weights are combined with weights created for assigning individuals to CZs, following Dorn (2009) and Acemoglu and Autor (2011). For male and female wage results, observations are further weighted by standardized annual hours worked, following Acemoglu and Autor (2011).

I additionally test results which fully incorporate stratification and clustering information provided by IPUMS. These results yield substantively identical conclusions.

1.5 Missing Data

The PUMS provides imputed wage and income data for respondents with missing values. Imputed values are created by the US Census. These imputation methods occur in numerous forms: logical edits of inconsistent or incorrectly filled out forms, hot deck allocation of wages and income, and cold deck allocation of wages and income. Hot deck procedures vary between census data sets, but are typically based on such characteristics as sex, race, ethnicity, household relationship, years of school completed, geographical area, age, disability status, presence of children, veteran status, work experience, occupation, class-of-worker, level of earnings, and value of property or monthly rent. The Census documentation of missing imputation procedures are often nebulous, but the IPUMS website claims that results following imputed values are more valid than results excluding these values.

To the best of my knowledge, much recent scholarship on earnings, inequality, and labor market outcomes by sociologists and economists using PUMS does not explicitly address the handling of Census-imputed data (McCall, 2000, 2001; Cohen and Huffman, 2003; Levanon et al., 2009; Dorn, 2009; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Lee, 2013; Kim and Sakamoto, 2014).

Examination of data made publicly available suggests that imputed cases are treated as non-missing (Dorn, 2009, Acemoglu and Autor, 2011; Autor and Dorn 2013).

Given the above observation, I follow standard practice by including imputed wage data in main analyses. However, Western and Rosenfeld (2011) and Mouw and Kalleberg (2010) note that hot deck imputation of wages in CPS data may distort results. Therefore, I also conduct sensitivity analyses excluding wages imputed by either hot or cold deck imputation. I also replicate the detailed occupational hot deck imputation method used by Mouw and Kalleberg (2010). CZ level WGI rates are very similar and yield identical substantive results.

2 Modeling sensitivity analyses

2.1 Multilevel HRM

I test main multilevel results by including individual (or household), CZ, and state information simultaneously in HRMs. I conduct these analyses in two ways: separately by time period, and with the five time periods included simultaneously, with period indicator variables fully interacted with individual (or household) characteristics. Main meslevel results are found with these modeling strategies.

Several computational problems lead me to consider results from a simultaneous HRM as a sensitivity analysis. Survey weights are not allowed for mixed effects multilevel generalized linear models in the statistical computing environment used for analyses (Stata 13.1). As discussed above, survey weights are crucial for accurately sorting respondents into CZs. Additionally, the residual covariance structure cannot be correctly specified to allow for correlated errors between years, an intuitive approach that LR tests prefer in main results. I therefore fit single level models with standard errors clustered by CZs for these sensitivity analyses. However, this is not an optimal modeling strategy, given that the central argument of this research is the importance of mesolevel characteristics on local WGI. Given that main conclusions are drawn from both main analyses and these sensitivity analyses, I contend that modeling decisions of the main paper are appropriate.

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Table A1: Male wage earners descriptive statistics

	1970	1980	1990	2000	2007-2011
Education					
LT HS	0.36	0.22	0.11	0.09	0.08
HS	0.36	0.38	0.33	0.39	0.35
Some college	0.13	0.19	0.29	0.23	0.24
4 year degree	0.08	0.11	0.17	0.19	0.21
4+ years college	0.07	0.10	0.09	0.10	0.12
Potential Experience					
0 to 9 years	0.20	0.29	0.24	0.20	0.19
10 to 19 years	0.25	0.27	0.34	0.30	0.26
20 to 29 years	0.23	0.19	0.23	0.29	0.27
30 or more years	0.32	0.25	0.19	0.21	0.28
Marital Status					
Married	0.86	0.75	0.69	0.66	0.63
Divorced	0.04	0.08	0.10	0.11	0.11
Widowed	0.01	0.01	0.00	0.01	0.01
Never maried	0.09	0.16	0.20	0.22	0.25
Citizenship status					
Natural citizen	0.95	0.94	0.91	0.87	0.83
Foreign born citizen	0.03	0.03	0.04	0.05	0.07
Foreign born non-citizen	0.02	0.03	0.05	0.08	0.10
Race					
White	0.88	0.85	0.81	0.75	0.69
Black	0.08	0.08	0.09	0.09	0.10
Other	0.01	0.01	0.01	0.01	0.01
Asian	0.00	0.01	0.02	0.04	0.05
White Hispanic	0.03	0.05	0.07	0.11	0.15
Non-white Hispanic	0.01	0.01	0.01	0.01	0.01
Works 50+ hours	0.26	0.23	0.31	0.36	0.33
IR union	0.33	0.32	0.21	0.17	0.12
Industry					
Agriculture, Forestry, Fishing	0.02	0.02	0.02	0.02	0.02
Mining	0.02	0.02	0.01	0.01	0.01
Construction	0.08	0.08	0.09	0.10	0.10
Manufacturing	0.35	0.33	0.26	0.23	0.18
TCPU	0.12	0.11	0.11	0.11	0.11
Wholesale trade	0.06	0.06	0.06	0.05	0.04
Retail Trade	0.11	0.11	0.12	0.13	0.13
FIRE	0.04	0.04	0.05	0.05	0.06
Services	0.14	0.16	0.19	0.23	0.26
Public Administration	0.06	0.07	0.09	0.08	0.08
Observations	671,893	2,843,533	3,269,289	3,593,061	3,499,088

Table A2: Female wage earners descriptive statistics

	1970	1980	1990	2000	2007-2011
Education					
LT HS	0.30	0.17	0.08	0.06	0.05
HS	0.47	0.46	0.35	0.38	0.31
Some college	0.13	0.21	0.33	0.26	0.27
4 year degree	0.06	0.09	0.16	0.20	0.23
4+ years college	0.04	0.07	0.08	0.10	0.14
Potential Experience					
0 to 9 years	0.25	0.34	0.27	0.21	0.21
10 to 19 years	0.17	0.24	0.31	0.27	0.23
20 to 29 years	0.23	0.18	0.23	0.29	0.26
30 or more years	0.35	0.24	0.19	0.22	0.30
Marital Status					
Married	0.59	0.56	0.56	0.55	0.53
Divorced	0.13	0.18	0.19	0.20	0.19
Widowed	0.08	0.05	0.03	0.02	0.02
Never maried	0.20	0.22	0.22	0.23	0.26
Citizenship status					
Natural citizen	0.95	0.94	0.92	0.89	0.86
Foreign born citizen	0.03	0.03	0.04	0.06	0.08
Foreign born non-citizen	0.02	0.03	0.04	0.05	0.06
Race					
White	0.86	0.81	0.77	0.73	0.67
Black	0.10	0.12	0.13	0.14	0.14
Other	0.00	0.01	0.01	0.01	0.01
Asian	0.01	0.02	0.03	0.04	0.05
White Hispanic	0.03	0.05	0.06	0.09	0.12
Non-white Hispanic	0.01	0.01	0.01	0.01	0.01
Overwork status					
Works 50+ hours	0.06	0.06	0.13	0.18	0.18
IR union	0.17	0.20	0.14	0.13	0.13
Industry					
Agriculture, Forestry, Fishing	0.01	0.01	0.01	0.01	0.01
Mining	0.01	0.01	0.01	0.01	0.01
Construction	0.01	0.01	0.01	0.01	0.01
Manufacturing	0.26	0.23	0.17	0.14	0.09
TCPU	0.06	0.06	0.06	0.06	0.05
Wholesale trade	0.03	0.03	0.04	0.03	0.02
Retail Trade	0.14	0.13	0.13	0.14	0.14
FIRE	0.09	0.10	0.11	0.10	0.10
Services	0.35	0.36	0.40	0.45	0.51
Public Administration	0.06	0.07	0.06	0.06	0.07
Obs	278,818	1,634,389	2,223,988	2,692,391	2,871,879

Table A3: Household income descriptive statistics

	1970	1980	1990	2000	2007-2011
Education					
LT HS	0.39	0.24	0.13	0.09	0.08
HS	0.33	0.36	0.32	0.37	0.34
Some college	0.13	0.19	0.29	0.24	0.25
4 year degree	0.08	0.11	0.17	0.19	0.21
4+ years college	0.07	0.11	0.10	0.11	0.12
Potential Experience					
0 to 9 years	0.17	0.24	0.18	0.16	0.15
10 to 19 years	0.21	0.26	0.32	0.27	0.23
20 to 29 years	0.23	0.19	0.24	0.30	0.27
30 or more years	0.39	0.31	0.26	0.28	0.35
Famiy type					
Married w kids under 18 in hh, no dual employment	0.35	0.22	0.15	0.14	0.12
Married w/o kids under 18 in hh, no dual employment	0.15	0.13	0.10	0.09	0.10
Single woman with kids under 18 in hh	0.05	0.06	0.07	0.08	0.08
Single woman no kids under 18 in hh	0.08	0.11	0.12	0.13	0.14
Single man with kids under 18 in hh	0.01	0.01	0.01	0.02	0.02
Single man w/o kids under 18 in hh	0.06	0.11	0.12	0.13	0.14
Married w kids under 18 in hh, dual employment	0.18	0.20	0.22	0.20	0.18
Married w/o kids under 18 in hh, dual employment	0.12	0.14	0.16	0.15	0.15
Cohabitating, no dual employment	0.01	0.02	0.03	0.04	0.05
Cohabitating, dual employment	0.01	0.01	0.02	0.02	0.03
Citizenship status					
Natural citizen	0.95	0.94	0.92	0.88	0.84
Foreign born citizen	0.03	0.03	0.04	0.05	0.07
Foreign born non-citizen	0.02	0.03	0.05	0.07	0.08
Race					
White	0.87	0.84	0.80	0.75	0.69
Black	0.09	0.10	0.10	0.11	0.12
Other	0.01	0.01	0.01	0.01	0.01
Asian	0.01	0.01	0.02	0.03	0.04
White Hispanic	0.03	0.05	0.07	0.09	0.13
Non-white Hispanic	0.01	0.00	0.00	0.00	0.01
IR union	0.30	0.29	0.19	0.16	0.13
Works 50+ hours	0.18	0.18	0.23	0.27	0.24
Industry					
Agriculture, Forestry, Fishing	0.04	0.03	0.03	0.02	0.03
Mining	0.01	0.02	0.01	0.01	0.01
Construction	0.09	0.09	0.09	0.10	0.10
Manufacturing	0.30	0.27	0.21	0.19	0.14
TCPU	0.10	0.10	0.09	0.09	0.09
Wholesale trade	0.05	0.05	0.05	0.04	0.04
Retail Trade	0.12	0.12	0.12	0.13	0.13
FIRE	0.04	0.05	0.06	0.06	0.06
Services	0.19	0.22	0.26	0.30	0.33
Public Administration	0.05	0.06	0.07	0.06	0.07
Obs	1,109,360	4,356,752	4,946,263	5,460,229	5,611,173

Table A4: Logged wage and household income descriptive statistics

	Year	Mean	Std. dev.	Min	Max
Men	1970	2.65	0.50	1.03	5.11
	1980	2.72	0.53	1.03	4.90
	1990	2.68	0.60	1.03	5.02
	2000	2.76	0.62	1.03	5.01
	2007-2011	2.77	0.66	1.03	4.93
Women	1970	2.22	0.43	1.03	5.11
	1980	2.30	0.44	1.03	4.90
	1990	2.40	0.52	1.03	5.02
	2000	2.54	0.55	1.03	5.01
	2007-2011	2.60	0.59	1.03	4.93
Household	1970	9.88	0.80	3.95	13.31
	1980	9.97	0.89	1.37	13.47
	1990	10.08	0.93	-0.66	13.45
	2000	10.20	0.93	0.29	13.52
	2007-2011	10.14	1.01	-1.64	13.51

Table A5: Mean and variance regressions on male logged hourly wages

	Between					Within				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	1970	1980	1990	2000	2007-2011	1970	1980	1990	2000	2007-2011
Education[1]										
HS	0.0768***	0.163***	0.0294***	0.0245***	-0.0307***	0.0842	-0.104***	-0.136***	-0.109***	-0.0907***
	(7.97)	(37.94)	(4.86)	(4.15)	(-4.17)	(1.72)	(-5.37)	(-5.68)	(-4.62)	(-3.36)
Some college	0.145***	0.290***	0.106***	0.124***	0.0424***	0.0800	-0.0245	-0.0528*	-0.0131	0.0717*
	(13.64)	(61.46)	(17.21)	(19.39)	(5.52)	(1.49)	(-1.16)	(-2.17)	(-0.51)	(2.56)
4 year degree	0.424***	0.514***	0.527***	0.512***	0.453***	0.198***	-0.168***	-0.144***	-0.00158	0.154***
	(34.47)	(98.31)	(79.62)	(76.55)	(58.13)	(3.38)	(-7.05)	(-5.56)	(-0.06)	(5.54)
4+ years college	0.764***	0.655***	0.812***	0.744***	0.789***	-0.0509	0.0277	0.142***	0.284***	0.261***
	(65.20)	(122.84)	(98.59)	(87.16)	(88.45)	(-0.89)	(1.17)	(4.71)	(9.46)	(8.55)
LT HS * potential experience	0.0661***	0.0599***	0.0533***	0.0469***	0.0410***	-0.0380***	0.00869*	-0.0262***	-0.0465***	-0.0418***
	(36.02)	(62.42)	(40.40)	(34.44)	(25.53)	(-4.08)	(2.04)	(-5.15)	(-8.77)	(-7.24)
HS * potential experience	0.0951***	0.0709***	0.0879***	0.0754***	0.0772***	-0.107***	0.00244	0.00416	-0.0113***	0.00187
	(65.54)	(114.28)	(122.56)	(108.44)	(101.85)	(-13.83)	(0.83)	(1.40)	(-4.00)	(0.68)
Some college * potential experience	0.112***	0.0622***	0.105***	0.0860***	0.0901***	-0.0991***	-0.0345***	-0.00201	-0.0333***	-0.0311***
	(54.13)	(70.79)	(129.53)	(86.65)	(91.61)	(-9.23)	(-8.64)	(-0.62)	(-8.53)	(-8.96)
4 year degree * potential experience	0.107***	0.0431***	0.0962***	0.0775***	0.0799***	-0.161***	-0.0209***	-0.00444	-0.00738	-0.0364***
	(35.65)	(35.03)	(82.10)	(62.62)	(69.61)	(-11.68)	(-3.80)	(-1.01)	(-1.69)	(-9.95)
4+ years * potential experience	0.0599***	0.0565***	0.0733***	0.0779***	0.0653***	-0.0382**	-0.0174**	0.0138*	-0.00572	0.00409
	(18.84)	(41.43)	(36.89)	(37.11)	(35.88)	(-2.63)	(-3.02)	(2.09)	(-0.88)	(0.76)
LT HS * potential experience^2	-0.00257***	-0.00234***	-0.00219***	-0.00192***	-0.00132***	0.00227***	0.000251	0.00300***	0.00440***	0.00420***
	(-20.94)	(-33.32)	(-22.60)	(-18.62)	(-11.22)	(3.61)	(0.81)	(8.08)	(11.08)	(10.04)
HS * potential experience^2	-0.00485***	-0.00293***	-0.00427***	-0.00339***	-0.00329***	0.00777***	0.000290	0.000943***	0.00212***	0.00165***
	(-37.74)	(-50.05)	(-64.01)	(-53.16)	(-48.06)	(11.29)	(1.06)	(3.51)	(8.40)	(6.83)
Some college * potential experience^2	-0.00624***	-0.00191***	-0.00549***	-0.00382***	-0.00368***	0.00738***	0.00400***	0.000610*	0.00408***	0.00403***
	(-30.93)	(-21.74)	(-70.86)	(-41.78)	(-41.17)	(7.20)	(10.16)	(2.02)	(11.64)	(13.08)
4 year degree * potential experience^2	-0.00552***	0.000511***	-0.00579***	-0.00301***	-0.00272***	0.0158***	0.00599***	0.00345***	0.00438***	0.00636***
	(-17.77)	(3.86)	(-48.06)	(-24.17)	(-23.86)	(11.28)	(10.57)	(7.96)	(10.32)	(18.01)
4+ years * potential experience^2	-0.00198***	-0.000535***	-0.00296***	-0.00329***	-0.000996***	0.00532**	0.00529***	0.000644	0.00365***	0.00205***
	(-5.32)	(-3.36)	(-14.32)	(-15.44)	(-5.38)	(3.22)	(8.20)	(0.96)	(5.65)	(3.85)
LT HS * potential experience^3	0.0000452***	0.0000488***	0.0000513***	0.0000417***	0.0000211***	-0.0000469**	-0.0000174*	-0.0000867***	-0.000122***	-0.000119***
	(14.00)	(24.98)	(18.81)	(13.82)	(6.33)	(-2.83)	(-2.01)	(-8.31)	(-10.65)	(-10.08)
HS * potential experience^3	0.000112***	0.0000586***	0.000107***	0.0000764***	0.0000691***	-0.000206***	-0.0000103	-0.0000448***	-0.0000739***	-0.0000670***
	(25.78)	(28.91)	(46.02)	(35.00)	(30.04)	(-8.95)	(-1.10)	(-4.90)	(-8.71)	(-8.38)
Some college * potential experience^3	0.000158***	0.0000230***	0.000144***	0.0000823***	0.0000724***	-0.000164***	-0.000120***	-0.00000827	-0.000134***	-0.000134***
	(21.67)	(7.10)	(51.88)	(25.75)	(23.64)	(-4.54)	(-8.39)	(-0.78)	(-11.17)	(-12.90)
4 year degree * potential experience^3	0.000132***	-0.0000626***	0.000179***	0.0000470***	0.0000385***	-0.000479***	-0.000230***	-0.000132***	-0.000196***	-0.000237***
	(11.01)	(-12.07)	(38.72)	(9.99)	(9.13)	(-9.07)	(-10.71)	(-8.18)	(-12.56)	(-18.54)
4+ years * potential experience^3	0.0000193	-0.0000466***	0.0000569***	0.0000598***	-0.0000417***	-0.000153*	-0.000231***	-0.0000436	-0.000180***	-0.000100***
	(1.22)	(-6.91)	(6.95)	(7.27)	(-5.86)	(-2.25)	(-8.73)	(-1.67)	(-7.31)	(-5.00)
LT HS * potential experience^4	-0.000000326***	-0.000000431***	-0.000000484***	-0.000000360***	-0.000000154***	0.000000336*	0.000000214**	0.000000782***	0.00000109***	0.00000108***
	(-11.20)	(-23.64)	(-18.63)	(-12.19)	(-4.82)	(2.24)	(2.66)	(7.91)	(9.82)	(9.54)
HS * potential experience^4	-0.000000990***	-0.000000489***	-0.00000104***	-0.000000685***	-0.000000587***	0.00000199***	0.000000155	0.000000600***	0.000000825***	0.000000759***
	(-20.36)	(-21.42)	(-39.66)	(-27.94)	(-23.15)	(7.84)	(1.47)	(5.87)	(8.78)	(8.71)
Some college * potential experience^4	-0.00000151***	-0.000000100**	-0.00000145***	-0.000000701***	-0.000000590***	0.00000118**	0.00000122***	4.91e-08	0.00000148***	0.00000145***
	(-17.53)	(-2.58)	(-44.45)	(-18.96)	(-16.99)	(2.83)	(7.20)	(0.40)	(10.89)	(12.50)
4 year degree * potential experience^4	-0.00000125***	0.000000830***	-0.00000206***	-0.000000234***	-0.000000239***	0.00000481***	0.00000269***	0.00000157***	0.00000258***	0.00000275***
	(-8.21)	(12.63)	(-35.27)	(-3.98)	(-4.66)	(7.38)	(10.11)	(7.95)	(13.64)	(18.02)
4+ years * potential experience^4	1.81e-08	0.000000868***	-0.000000473***	-0.000000413***	0.000000909***	0.00000137	0.00000314***	0.000000770*	0.00000256***	0.00000141***
	(0.08)	(9.35)	(-4.39)	(-3.88)	(10.04)	(1.50)	(8.88)	(2.28)	(8.17)	(5.62)

Table A5 continued: Mean and variance regressions on male logged hourly wages

	Between					Within				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	1970	1980	1990	2000	2007-2011	1970	1980	1990	2000	2007-2011
Potential Experience[2]										
10-19 years	-0.0211***	-0.0181***	-0.00840***	-0.00657***	-0.0237***	0.0418**	0.00314	0.0181***	0.0263***	0.0129*
	(-8.08)	(-14.35)	(-6.52)	(-4.64)	(-15.53)	(2.79)	(0.52)	(3.50)	(4.72)	(2.42)
20-29 years	-0.00559	-0.0183***	0.00726***	-0.00563*	-0.0177***	0.00725	-0.00294	0.0192*	0.0253**	-0.0115
	(-1.31)	(-8.23)	(3.44)	(-2.55)	(-7.21)	(0.30)	(-0.28)	(2.31)	(2.99)	(-1.38)
30+ years	-0.00608	-0.00813**	-0.0120***	0.00325	-0.0168***	0.000298	0.00275	0.0240*	0.0523***	-0.00412
	(-1.13)	(-2.71)	(-4.07)	(1.14)	(-5.47)	(0.01)	(0.20)	(2.13)	(4.93)	(-0.41)
Marital status[3]										
Divorced	-0.105***	-0.0914***	-0.113***	-0.129***	-0.118***	0.172***	0.172***	0.112***	0.0525***	0.0627***
	(-41.18)	(-94.31)	(-126.83)	(-155.53)	(-133.19)	(13.39)	(40.76)	(33.60)	(17.06)	(21.77)
Widowed	-0.0983***	-0.0957***	-0.0937***	-0.129***	-0.114***	0.00294	0.140***	0.0913***	0.0816***	0.0962***
	(-19.23)	(-29.08)	(-23.97)	(-33.31)	(-30.49)	(0.11)	(10.21)	(6.55)	(6.07)	(8.28)
Never married	-0.190***	-0.162***	-0.145***	-0.148***	-0.147***	0.228***	0.173***	0.105***	0.0676***	0.0822***
	(-102.58)	(-207.15)	(-199.66)	(-209.17)	(-202.73)	(24.32)	(48.80)	(36.79)	(25.13)	(33.71)
Citizenship status[4]										
Foreign born citizen	0.0631***	0.00953***	0.0216***	-0.000371	-0.0253***	0.0134	0.0505***	0.0544***	0.0765***	0.0801***
	(21.58)	(6.09)	(13.80)	(-0.27)	(-20.01)	(0.89)	(7.36)	(9.50)	(16.00)	(20.25)
Foreign born non-citizen	-0.0332***	-0.0841***	-0.0904***	-0.110***	-0.158***	0.120***	0.192***	0.179***	0.202***	0.138***
	(-8.68)	(-49.10)	(-62.42)	(-89.62)	(-140.46)	(6.31)	(27.23)	(34.77)	(47.64)	(38.87)
Race[5]										
Black	-0.235***	-0.150***	-0.136***	-0.132***	-0.152***	0.0746***	0.126***	0.0420***	0.0463***	-0.00416
	(-130.26)	(-158.75)	(-150.91)	(-146.98)	(-164.52)	(7.76)	(29.73)	(11.73)	(13.55)	(-1.33)
Other	-0.172***	-0.137***	-0.150***	-0.140***	-0.124***	0.174***	0.269***	0.114***	0.161***	0.128***
	(-17.68)	(-36.23)	(-44.45)	(-43.61)	(-36.53)	(3.60)	(17.49)	(8.89)	(13.96)	(11.83)
Asian	-0.109***	-0.0776***	-0.0844***	-0.0380***	-0.00332*	0.111**	0.0899***	0.0902***	0.143***	0.114***
	(-14.02)	(-29.33)	(-40.73)	(-21.07)	(-2.10)	(2.94)	(8.09)	(12.27)	(24.10)	(24.03)
White Hispanic	-0.144***	-0.102***	-0.0991***	-0.110***	-0.0985***	0.0533***	0.0394***	0.0172***	0.000589	-0.0366***
	(-51.50)	(-85.24)	(-89.67)	(-111.17)	(-107.93)	(3.63)	(7.31)	(4.06)	(0.16)	(-12.08)
Non-white Hispanic	-0.213***	-0.169***	-0.125***	-0.111***	-0.103***	0.201**	0.118***	0.0196	0.118***	0.00962
	(-15.75)	(-27.90)	(-26.07)	(-27.29)	(-28.58)	(3.00)	(4.53)	(1.05)	(7.98)	(0.79)
Works 50+ hours	-0.272***	-0.180***	-0.168***	-0.108***	-0.0836***	0.210***	0.350***	0.312***	0.232***	0.209***
	(-239.25)	(-274.21)	(-282.10)	(-192.44)	(-138.36)	(36.07)	(128.49)	(143.48)	(113.71)	(108.49)
IR union	0.529***	0.449***	0.455***	0.375***	0.222***	-0.744***	-0.659***	-0.237***	-0.291***	-0.174***
	(128.59)	(206.28)	(189.61)	(138.85)	(89.22)	(-32.68)	(-63.89)	(-24.28)	(-27.90)	(-20.48)
Industry[6]										
Mining	0.220***	0.377***	0.330***	0.301***	0.347***	-0.167***	-0.0432***	-0.195***	-0.150***	0.171***
	(39.49)	(133.18)	(109.91)	(90.57)	(109.70)	(-5.85)	(-3.62)	(-16.84)	(-11.43)	(16.27)
Construction	0.318***	0.272***	0.252***	0.249***	0.233***	0.228***	0.156***	0.0198*	0.0494***	0.148***
	(66.99)	(112.09)	(113.14)	(115.80)	(112.55)	(10.25)	(16.02)	(2.43)	(6.06)	(20.35)
Manufacturing	0.278***	0.267***	0.276***	0.271***	0.206***	-0.125***	-0.154***	-0.235***	-0.112***	-0.0280***
	(62.50)	(115.27)	(130.74)	(131.49)	(102.07)	(-6.01)	(-16.58)	(-30.69)	(-14.41)	(-3.96)
TCPU	0.209***	0.252***	0.230***	0.228***	0.202***	-0.0708**	-0.0477***	-0.135***	0.0164	0.126***
	(44.00)	(101.24)	(99.47)	(101.36)	(90.62)	(-3.10)	(-4.64)	(-15.77)	(1.93)	(16.31)
Wholesale trade	0.382***	0.318***	0.307***	0.267***	0.248***	-0.0817***	-0.0954***	-0.0645***	-0.00626	0.0699***
	(83.57)	(132.53)	(136.57)	(118.90)	(115.94)	(-3.85)	(-9.94)	(-7.93)	(-0.74)	(9.46)
Retail trade	0.280***	0.197***	0.158***	0.148***	0.0833***	-0.0545**	-0.0862***	0.0137	0.126***	0.186***
	(64.00)	(85.51)	(74.24)	(71.00)	(44.61)	(-2.72)	(-9.48)	(1.79)	(16.10)	(28.50)

Table A5 continued: Mean and variance regressions on male logged hourly wages

	Between					Within				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	1970	1980	1990	2000	2007-2011	1970	1980	1990	2000	2007-2011
FIRE	0.466***	0.356***	0.402***	0.411***	0.410***	0.0109	0.0838***	0.239***	0.297***	0.302***
	(95.81)	(138.06)	(164.77)	(170.12)	(188.10)	(0.49)	(8.37)	(28.50)	(34.70)	(42.12)
Services	0.258***	0.127***	0.133***	0.172***	0.176***	-0.0147	0.00685	0.0557***	0.136***	0.187***
	(58.98)	(54.97)	(62.32)	(83.02)	(95.54)	(-0.74)	(0.75)	(7.30)	(17.62)	(29.18)
Public administration	0.299***	0.149***	0.0727***	0.105***	0.226***	-0.268***	-0.220***	-0.338***	-0.164***	-0.125***
	(65.27)	(60.55)	(32.53)	(45.73)	(112.54)	(-12.31)	(-21.75)	(-40.44)	(-18.71)	(-17.57)
Constant	1.597***	1.697***	1.652***	1.802***	1.834***	-1.604***	-1.724***	-1.696***	-1.731***	-1.813***
	(168.50)	(377.51)	(275.55)	(305.14)	(254.05)	(-34.32)	(-88.68)	(-73.09)	(-74.49)	(-69.03)
N	671,893	2,843,533	3,269,289	3,593,061	3,499,088	671,893	2,843,533	3,269,289	3,593,061	3,499,088

t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

[1] Less than high school = reference

[2] 0-9 years = reference

[3] Married = reference

[4] Natural born citizen = reference

[5] White = reference

[6] Agriculture, Forestry, and Fishing = reference

Table A6: Mean and variance regressions on female logged hourly wages

	Between					Within				
	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) 2007-2011	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) 2007-2011
Education[1]										
HS	0.0416**	0.0554***	0.0280***	0.0307***	-0.0302**	-0.432***	-0.340***	-0.112***	-0.252***	-0.256***
	(2.89)	(9.83)	(3.48)	(3.80)	(-2.94)	(-5.91)	(-11.58)	(-3.33)	(-7.57)	(-6.68)
Some college	0.151***	0.193***	0.100***	0.0931***	0.0323**	-0.163*	-0.0860**	-0.0262	-0.175***	-0.103**
	(9.79)	(32.59)	(12.52)	(11.27)	(3.14)	(-2.09)	(-2.80)	(-0.79)	(-5.14)	(-2.68)
4 year degree	0.521***	0.425***	0.483***	0.467***	0.430***	-0.145	-0.0901**	-0.0129	-0.191***	0.0210
	(31.36)	(66.72)	(58.35)	(56.32)	(41.94)	(-1.75)	(-2.72)	(-0.38)	(-5.63)	(0.56)
4+ years college	0.828***	0.678***	0.810***	0.774***	0.807***	-0.313**	-0.0738*	0.0779*	-0.128***	0.0200
	(41.92)	(101.27)	(84.26)	(84.80)	(76.06)	(-3.14)	(-2.12)	(1.99)	(-3.45)	(0.51)
LT HS * potential experience	0.0446***	0.0457***	0.0399***	0.0378***	0.0362***	-0.0785***	-0.0220***	-0.00526	-0.0447***	-0.0375***
	(14.56)	(34.58)	(22.42)	(19.81)	(16.23)	(-5.06)	(-3.30)	(-0.73)	(-5.76)	(-4.56)
HS * potential experience	0.0845***	0.0781***	0.0736***	0.0647***	0.0721***	-0.0470***	0.00677	-0.00781*	-0.0201***	0.00647
	(56.44)	(124.38)	(90.86)	(83.22)	(82.68)	(-5.51)	(1.89)	(-2.26)	(-5.83)	(1.90)
Some college * potential experience	0.0966***	0.0836***	0.0992***	0.0864***	0.0953***	-0.0759***	-0.0397***	-0.0179***	-0.0378***	-0.0100**
	(37.65)	(92.97)	(125.36)	(91.96)	(101.90)	(-5.59)	(-8.22)	(-5.40)	(-9.16)	(-2.83)
4 year degree * potential experience	0.0896***	0.0795***	0.104***	0.0911***	0.0938***	-0.113***	-0.0480***	-0.0258***	-0.0315***	-0.0511***
	(23.15)	(57.09)	(88.25)	(85.22)	(95.89)	(-5.96)	(-6.67)	(-5.53)	(-7.11)	(-14.76)
4+ years * potential experience	0.0315***	0.0679***	0.0716***	0.0678***	0.0681***	0.0593*	-0.0155	0.0356***	0.0322***	-0.0116*
	(5.15)	(39.90)	(35.03)	(38.84)	(48.79)	(2.07)	(-1.81)	(4.51)	(4.71)	(-2.39)
LT HS * potential experience^2	-0.00211***	-0.00218***	-0.00187***	-0.00174***	-0.00155***	0.00565***	0.00299***	0.00113*	0.00386***	0.00341***
	(-10.15)	(-22.31)	(-14.36)	(-12.01)	(-9.66)	(5.30)	(6.11)	(2.16)	(6.56)	(5.74)
HS * potential experience^2	-0.00569***	-0.00479***	-0.00380***	-0.00310***	-0.00350***	0.00638***	0.00259***	0.00287***	0.00393***	0.00187***
	(-37.35)	(-75.19)	(-51.12)	(-43.92)	(-45.57)	(7.55)	(7.41)	(9.24)	(12.88)	(6.42)
Some college * potential experience^2	-0.00691***	-0.00535***	-0.00552***	-0.00435***	-0.00501***	0.00702***	0.00628***	0.00369***	0.00563***	0.00292***
	(-26.26)	(-55.80)	(-70.15)	(-48.79)	(-57.71)	(5.04)	(12.41)	(11.47)	(14.79)	(9.12)
4 year degree * potential experience^2	-0.00720***	-0.00501***	-0.00694***	-0.00502***	-0.00500***	0.0142***	0.00917***	0.00594***	0.00762***	0.00853***
	(-16.65)	(-30.42)	(-53.24)	(-43.49)	(-48.36)	(6.78)	(11.12)	(11.76)	(16.50)	(23.94)
4+ years * potential experience^2	-0.00167*	-0.00463***	-0.00415***	-0.00335***	-0.00300***	-0.00355	0.00671***	-0.00278***	0.000877	0.00498***
	(-2.37)	(-21.83)	(-18.71)	(-17.77)	(-19.81)	(-1.11)	(6.54)	(-3.31)	(1.21)	(9.65)
LT HS * potential experience^3	0.0000446***	0.0000486***	0.0000430***	0.0000375***	0.0000305***	-0.000144***	-0.000101***	-0.0000350*	-0.000106***	-0.000101***
	(8.07)	(17.71)	(11.76)	(8.92)	(6.76)	(-5.06)	(-7.39)	(-2.39)	(-6.24)	(-6.03)
HS * potential experience^3	0.000158***	0.000126***	0.0000884***	0.0000713***	0.0000795***	-0.000224***	-0.000124***	-0.000116***	-0.000143***	-0.0000778***
	(29.43)	(55.47)	(34.73)	(29.95)	(31.63)	(-7.61)	(-10.16)	(-11.10)	(-14.10)	(-8.32)
Some college * potential experience^3	0.000202***	0.000145***	0.000135***	0.000102***	0.000123***	-0.000202***	-0.000235***	-0.000140***	-0.000202***	-0.000103***
	(21.19)	(40.36)	(47.00)	(32.51)	(41.30)	(-4.03)	(-12.48)	(-12.07)	(-15.27)	(-9.50)
4 year degree * potential experience^3	0.000231***	0.000133***	0.000197***	0.000119***	0.000120***	-0.000544***	-0.000374***	-0.000257***	-0.000330***	-0.000325***
	(13.59)	(19.78)	(37.54)	(26.40)	(30.60)	(-6.72)	(-11.32)	(-12.89)	(-18.65)	(-24.39)
4+ years * potential experience^3	0.0000481	0.000144***	0.000103***	0.0000734***	0.0000541***	0.000117	-0.000334***	0.0000879**	-0.000125***	-0.000239***
	(1.67)	(15.52)	(11.39)	(9.72)	(9.00)	(0.92)	(-7.67)	(2.61)	(-4.33)	(-11.85)
LT HS * potential experience^4	-0.000000355***	-0.000000411***	-0.000000374***	-0.000000300***	-0.000000227***	0.00000121***	0.00000102***	0.000000314*	0.000000966***	0.000000964***
	(-7.09)	(-15.83)	(-10.76)	(-7.30)	(-5.29)	(4.69)	(7.95)	(2.27)	(5.87)	(6.07)
HS * potential experience^4	-0.00000151***	-0.00000117***	-0.000000753***	-0.000000633***	-0.000000679***	0.00000244***	0.00000152***	0.00000133***	0.00000154***	0.000000847***
	(-24.97)	(-45.11)	(-26.54)	(-24.06)	(-25.02)	(7.39)	(11.08)	(11.48)	(13.92)	(8.48)
Some college * potential experience^4	-0.00000205***	-0.00000139***	-0.00000121***	-0.000000922***	-0.00000114***	0.00000187**	0.00000263***	0.00000157***	0.00000223***	0.00000106***
	(-18.39)	(-32.31)	(-35.70)	(-25.24)	(-33.61)	(3.20)	(11.73)	(11.59)	(14.77)	(8.78)
4 year degree * potential experience^4	-0.00000252***	-0.00000127***	-0.00000202***	-0.00000107***	-0.00000112***	0.00000668***	0.00000456***	0.00000334***	0.00000422***	0.00000375***
	(-11.74)	(-14.43)	(-29.55)	(-18.53)	(-22.95)	(6.60)	(10.76)	(13.05)	(18.99)	(23.07)
4+ years * potential experience^4	-0.000000561	-0.00000163***	-0.000000940***	-0.000000649***	-0.000000350***	-0.00000140	0.00000477***	-0.000000847	0.00000234***	0.00000324***
	(-1.47)	(-12.55)	(-7.78)	(-6.48)	(-4.47)	(-0.86)	(8.04)	(-1.90)	(6.18)	(12.43)

Table A6 continued: Mean and variance regressions on female logged hourly wages

	Between					Within				
	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) 2007-2011	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) 2007-2011
Potential Experience[2]										
10-19 years	-0.0370***	-0.00746***	-0.0197***	-0.0133***	-0.0187***	0.107***	0.0321***	0.0248***	0.0341***	-0.00563
	(-8.18)	(-4.57)	(-12.99)	(-8.25)	(-11.17)	(4.17)	(3.62)	(3.94)	(4.93)	(-0.91)
20-29 years	-0.0159*	0.00129	-0.000924	-0.0109***	-0.0107***	-0.00260	-0.0112	0.00287	-0.0124	-0.0333***
	(-2.13)	(0.44)	(-0.37)	(-4.30)	(-3.88)	(-0.06)	(-0.73)	(0.28)	(-1.18)	(-3.41)
30+ years	-0.0296***	0.000263	-0.00368	0.000122	-0.00769*	-0.000788	0.0334	0.0181	0.0173	-0.0312**
	(-3.31)	(0.07)	(-1.08)	(0.04)	(-2.30)	(-0.02)	(1.66)	(1.34)	(1.34)	(-2.67)
Marital status[3]										
Divorced	0.0467***	0.0288***	0.0114***	-0.00957***	-0.0334***	0.0674***	0.0228***	-0.00839**	0.00746*	0.0113***
	(22.15)	(35.18)	(14.81)	(-12.93)	(-43.51)	(5.90)	(5.27)	(-2.71)	(2.47)	(4.22)
Widowed	0.0432***	0.000224	-0.0197***	-0.0315***	-0.0721***	0.178***	0.0356***	0.0207**	0.0289***	0.0404***
	(14.87)	(0.14)	(-10.74)	(-16.22)	(-35.59)	(12.21)	(4.44)	(2.90)	(3.77)	(5.87)
Never married	0.0571***	0.0397***	0.0243***	-0.000764	-0.0316***	0.175***	0.0836***	0.0168***	0.0295***	0.0338***
	(29.75)	(49.51)	(31.20)	(-1.01)	(-41.98)	(16.67)	(19.05)	(5.21)	(9.31)	(12.49)
Citizenship status[4]										
Foreign born citizen	0.0470***	0.0240***	0.0435***	0.0186***	-0.00236	0.0989***	0.0691***	0.0375***	0.0862***	0.0758***
	(11.05)	(13.04)	(25.28)	(12.70)	(-1.85)	(4.46)	(7.43)	(5.59)	(15.17)	(17.66)
Foreign born non-citizen	-0.0342***	-0.0577***	-0.0659***	-0.0956***	-0.153***	0.0353	0.101***	0.125***	0.195***	0.145***
	(-7.02)	(-29.34)	(-38.88)	(-63.35)	(-112.82)	(1.34)	(10.22)	(19.30)	(34.28)	(31.85)
Race[5]										
Black	-0.114***	-0.0322***	-0.0451***	-0.0442***	-0.0686***	0.135***	0.114***	0.0463***	0.0702***	0.0104***
	(-47.43)	(-33.50)	(-50.78)	(-52.35)	(-81.36)	(10.68)	(22.92)	(12.86)	(20.14)	(3.46)
Other	-0.0805***	-0.0825***	-0.112***	-0.101***	-0.101***	0.0807	0.122***	0.0489***	0.0851***	0.0514***
	(-6.18)	(-20.37)	(-31.04)	(-31.60)	(-31.62)	(1.14)	(5.85)	(3.36)	(6.54)	(4.56)
Asian	0.0190	0.0149***	0.00657**	0.0332***	0.0755***	0.229***	0.0584***	0.0895***	0.135***	0.205***
	(1.85)	(5.45)	(3.01)	(17.81)	(45.93)	(4.58)	(4.22)	(10.78)	(19.36)	(39.24)
White Hispanic	-0.0846***	-0.0495***	-0.0433***	-0.0576***	-0.0594***	-0.0146	0.0380***	0.0265***	0.0231***	-0.0240***
	(-19.69)	(-33.63)	(-33.87)	(-52.49)	(-61.76)	(-0.61)	(4.89)	(5.14)	(5.10)	(-6.97)
Non-white Hispanic	-0.0137	-0.0293***	-0.0363***	-0.0379***	-0.0404***	-0.0542	0.0560	0.0597**	0.0647***	0.0429**
	(-0.90)	(-4.84)	(-7.02)	(-8.93)	(-10.67)	(-0.63)	(1.79)	(2.92)	(3.73)	(3.20)
Works 50+ hours	-0.260***	-0.187***	-0.166***	-0.0822***	-0.0698***	0.321***	0.480***	0.424***	0.343***	0.294***
	(-77.42)	(-124.11)	(-163.61)	(-98.82)	(-83.88)	(20.63)	(74.73)	(122.05)	(112.87)	(111.42)
IR union	0.505***	0.560***	0.616***	0.396***	0.360***	-0.200***	-0.190***	-0.395***	-0.582***	-0.212***
	(74.46)	(185.68)	(177.54)	(112.60)	(119.42)	(-5.31)	(-12.12)	(-28.11)	(-40.24)	(-19.65)
Industry[6]										
Mining	0.344***	0.317***	0.324***	0.322***	0.406***	-0.303**	-0.123***	-0.158***	-0.0730*	0.0838***
	(20.59)	(51.81)	(52.31)	(41.64)	(54.21)	(-3.26)	(-3.86)	(-6.09)	(-2.24)	(3.31)
Construction	0.321***	0.182***	0.221***	0.219***	0.268***	0.0399	-0.0780**	-0.0350*	0.0452**	-0.0409**
	(23.41)	(36.46)	(51.87)	(52.43)	(67.98)	(0.58)	(-3.11)	(-2.05)	(2.58)	(-2.86)
Manufacturing	0.0944***	0.0843***	0.149***	0.191***	0.127***	-0.215***	-0.124***	-0.0285*	0.0151	-0.0144
	(8.01)	(19.68)	(41.11)	(53.51)	(38.31)	(-3.60)	(-5.86)	(-1.99)	(1.01)	(-1.20)
TCPU	0.165***	0.214***	0.198***	0.229***	0.196***	-0.162**	0.00119	0.0625***	0.149***	0.0335**
	(13.60)	(47.50)	(51.30)	(60.77)	(56.73)	(-2.63)	(0.05)	(4.06)	(9.43)	(2.68)
Wholesale trade	0.205***	0.187***	0.245***	0.228***	0.231***	-0.193**	-0.166***	-0.0334*	0.00511	-0.00215
	(16.86)	(41.92)	(63.97)	(59.20)	(63.53)	(-3.11)	(-7.44)	(-2.19)	(0.32)	(-0.16)
Retail trade	-0.00382	0.000809	0.00417	0.0284***	-0.0143***	0.00215	-0.00570	0.0859***	0.148***	0.117***
	(-0.32)	(0.19)	(1.15)	(7.94)	(-4.43)	(0.04)	(-0.27)	(6.00)	(9.91)	(10.06)

Table A6 continued: Mean and variance regressions on female logged hourly wages

	Between					Within				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	1970	1980	1990	2000	2007-2011	1970	1980	1990	2000	2007-2011
FIRE	0.255***	0.184***	0.265***	0.293***	0.309***	-0.275***	-0.225***	-0.0469**	0.0238	0.00504
	(21.55)	(43.09)	(73.17)	(81.47)	(94.93)	(-4.60)	(-10.63)	(-3.27)	(1.58)	(0.43)
Services	0.107***	0.0213***	0.0538***	0.0863***	0.0978***	-0.0262	-0.144***	0.0276	0.0838***	0.00644
	(9.16)	(5.00)	(14.94)	(24.31)	(31.02)	(-0.44)	(-6.88)	(1.93)	(5.64)	(0.56)
Public administration	0.284***	0.121***	0.112***	0.171***	0.241***	-0.251***	-0.251***	-0.218***	-0.0954***	-0.141***
	(23.76)	(27.69)	(29.75)	(45.92)	(72.76)	(-4.14)	(-11.52)	(-14.46)	(-6.09)	(-11.69)
Constant	1.583***	1.598***	1.566***	1.691***	1.726***	-1.750***	-1.885***	-1.857***	-1.693***	-1.700***
	(87.29)	(233.71)	(185.50)	(198.79)	(166.23)	(-19.20)	(-54.46)	(-53.52)	(-48.64)	(-44.50)
N	278,818	1,634,389	2,223,988	2,692,391	2,871,879	278,818	1,634,389	2,223,988	2,692,391	2,871,879

t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

[1] Less than high school = reference

[2] 0-9 years = reference

[3] Married = reference

[4] Natural born citizen = reference

[5] White = reference

[6] Agriculture, Forestry, and Fishing = reference

Table A7: Mean and variance regressions on household logged income

	Between					Within				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	1970	1980	1990	2000	2007-2011	1970	1980	1990	2000	2007-2011
Education[1]										
HS	0.151***	0.297***	0.218***	0.204***	0.138***	-0.436***	-0.459***	-0.354***	-0.401***	-0.362***
	(9.73)	(31.47)	(16.76)	(16.28)	(8.70)	(-6.28)	(-11.66)	(-7.48)	(-10.01)	(-6.92)
Some college	0.0832***	0.223***	0.153***	0.0421***	-0.0329*	-0.548***	-0.321***	-0.263***	-0.281***	-0.220***
	(5.37)	(23.44)	(11.97)	(3.32)	(-2.09)	(-7.98)	(-8.23)	(-5.76)	(-6.96)	(-4.28)
4 year degree	0.440***	0.568***	0.692***	0.624***	0.646***	-0.544***	-0.558***	-0.385***	-0.479***	-0.417***
	(27.08)	(58.71)	(53.93)	(49.62)	(41.32)	(-7.42)	(-13.54)	(-8.27)	(-11.83)	(-8.08)
4+ years college	0.845***	0.803***	1.088***	1.011***	1.081***	-0.882***	-0.574***	-0.613***	-0.786***	-0.652***
	(51.95)	(82.33)	(79.39)	(75.75)	(67.01)	(-11.78)	(-13.75)	(-11.73)	(-17.41)	(-11.91)
LT HS * potential experience	0.0933***	0.0835***	0.102***	0.0914***	0.0865***	-0.169***	-0.0703***	-0.0790***	-0.111***	-0.132***
	(33.12)	(44.65)	(41.20)	(36.27)	(28.93)	(-13.31)	(-8.99)	(-8.77)	(-13.40)	(-12.79)
HS * potential experience	0.127***	0.103***	0.139***	0.119***	0.126***	-0.177***	-0.0843***	-0.104***	-0.122***	-0.121***
	(63.46)	(97.95)	(109.82)	(104.29)	(95.51)	(-17.02)	(-15.98)	(-18.15)	(-27.14)	(-23.69)
Some college * potential experience	0.180***	0.150***	0.197***	0.197***	0.203***	-0.148***	-0.129***	-0.141***	-0.171***	-0.161***
	(82.93)	(129.53)	(172.13)	(155.36)	(155.09)	(-13.07)	(-23.41)	(-27.87)	(-34.04)	(-33.02)
4 year degree * potential experience	0.151***	0.118***	0.170***	0.161***	0.154***	-0.211***	-0.158***	-0.178***	-0.149***	-0.166***
	(53.41)	(84.50)	(130.11)	(124.67)	(118.46)	(-13.95)	(-21.40)	(-29.02)	(-27.75)	(-31.76)
4+ years * potential experience	0.0745***	0.0922***	0.114***	0.117***	0.113***	-0.0849***	-0.0848***	-0.0545***	-0.0245**	-0.0849***
	(23.42)	(59.68)	(56.51)	(59.68)	(61.61)	(-5.01)	(-10.50)	(-5.70)	(-2.99)	(-10.91)
LT HS * potential experience^2	-0.00520***	-0.00435***	-0.00558***	-0.00502***	-0.00436***	0.0106***	0.00422***	0.00478***	0.00690***	0.00788***
	(-28.92)	(-34.55)	(-34.13)	(-28.93)	(-22.18)	(12.88)	(7.93)	(7.84)	(11.79)	(11.24)
HS * potential experience^2	-0.00852***	-0.00654***	-0.00894***	-0.00739***	-0.00755***	0.0131***	0.00683***	0.00833***	0.0100***	0.00956***
	(-51.37)	(-72.49)	(-87.80)	(-80.10)	(-73.21)	(14.72)	(15.03)	(17.97)	(27.08)	(23.32)
Some college * potential experience^2	-0.0128***	-0.00991***	-0.0133***	-0.0130***	-0.0128***	0.0108***	0.0104***	0.0109***	0.0137***	0.0120***
	(-60.65)	(-88.55)	(-132.56)	(-118.22)	(-115.73)	(9.64)	(18.84)	(23.87)	(30.49)	(27.87)
4 year degree * potential experience^2	-0.0105***	-0.00753***	-0.0128***	-0.0113***	-0.0103***	0.0182***	0.0161***	0.0158***	0.0140***	0.0150***
	(-36.01)	(-50.87)	(-99.74)	(-90.23)	(-83.71)	(11.46)	(20.48)	(25.88)	(26.47)	(29.61)
4+ years * potential experience^2	-0.00357***	-0.00480***	-0.00712***	-0.00804***	-0.00692***	0.00875***	0.00898***	0.00551***	0.00464***	0.00924***
	(-9.87)	(-27.25)	(-34.99)	(-40.94)	(-37.97)	(4.57)	(9.84)	(5.71)	(5.69)	(11.96)
LT HS * potential experience^3	0.000135***	0.000120***	0.000153***	0.000134***	0.000107***	-0.000269***	-0.000118***	-0.000128***	-0.000177***	-0.000191***
	(29.57)	(36.24)	(35.52)	(28.37)	(20.65)	(-12.86)	(-8.43)	(-7.93)	(-10.98)	(-10.10)
HS * potential experience^3	0.000252***	0.000198***	0.000266***	0.000216***	0.000211***	-0.000381***	-0.000227***	-0.000270***	-0.000319***	-0.000293***
	(47.12)	(66.80)	(82.12)	(73.87)	(66.38)	(-13.29)	(-15.42)	(-18.42)	(-27.24)	(-23.08)
Some college * potential experience^3	0.000389***	0.000295***	0.000394***	0.000374***	0.000355***	-0.000299***	-0.000323***	-0.000330***	-0.000418***	-0.000352***
	(51.63)	(72.90)	(115.56)	(101.56)	(97.92)	(-7.48)	(-16.27)	(-21.30)	(-27.80)	(-24.52)
4 year degree * potential experience^3	0.000327***	0.000235***	0.000418***	0.000344***	0.000302***	-0.000556***	-0.000562***	-0.000510***	-0.000473***	-0.000488***
	(29.34)	(40.81)	(86.84)	(74.32)	(68.52)	(-9.28)	(-18.70)	(-22.48)	(-24.46)	(-26.93)
4+ years * potential experience^3	0.0000969***	0.000130***	0.000209***	0.000257***	0.000196***	-0.000299***	-0.000343***	-0.000211***	-0.000223***	-0.000349***
	(6.50)	(17.68)	(26.52)	(34.24)	(28.38)	(-3.85)	(-9.19)	(-5.71)	(-7.26)	(-12.12)
LT HS * potential experience^4	-0.00000129***	-0.00000125***	-0.00000155***	-0.00000131***	-0.000000979***	0.00000242***	0.00000123***	0.00000129***	0.00000164***	0.00000165***
	(-32.16)	(-41.97)	(-39.46)	(-29.71)	(-20.72)	(13.25)	(9.88)	(8.80)	(10.94)	(9.51)
HS * potential experience^4	-0.00000264***	-0.00000219***	-0.00000286***	-0.00000233***	-0.00000218***	0.00000395***	0.00000273***	0.00000310***	0.00000359***	0.00000318***
	(-45.62)	(-67.65)	(-82.45)	(-74.09)	(-65.35)	(12.82)	(17.20)	(20.05)	(28.97)	(24.04)

Table A7 continued: Mean and variance regressions on household logged income

	Between					Within				
	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) 2007-2011	(1) 1970	(2) 1980	(3) 1990	(4) 2000	(5) 2007-2011
Some college * potential experience[4]	-0.00000415***	-0.00000318***	-0.00000419***	-0.00000390***	-0.00000358***	0.00000296***	0.00000363***	0.00000365***	0.00000458***	0.00000372***
	(-47.25)	(-66.45)	(-108.16)	(-93.80)	(-89.65)	(6.41)	(15.64)	(20.94)	(27.33)	(23.59)
4 year degree * potential experience[4]	-0.00000363***	-0.00000274***	-0.00000481***	-0.00000379***	-0.00000329***	0.00000580***	0.00000664***	0.00000577***	0.00000559***	0.00000558***
	(-26.09)	(-37.64)	(-80.72)	(-66.83)	(-62.41)	(7.89)	(17.84)	(20.93)	(24.04)	(26.09)
4+ years * potential experience[4]	-0.00000112***	-0.00000149***	-0.00000241***	-0.00000313***	-0.00000220***	0.00000345***	0.00000463***	0.00000301***	0.00000352***	0.00000469***
	(-5.62)	(-15.02)	(-23.52)	(-32.49)	(-25.14)	(3.38)	(9.37)	(6.41)	(9.15)	(13.11)
Potential Experience[2]										
10-19 years	-0.0747***	-0.0426***	-0.0427***	-0.0278***	-0.0472***	0.123***	0.0574***	0.0647***	0.0492***	0.0675***
	(-22.48)	(-25.56)	(-26.54)	(-16.26)	(-25.84)	(6.06)	(5.99)	(7.44)	(5.92)	(7.70)
20-29 years	-0.0303***	-0.0176***	-0.00273	-0.00685**	-0.0181***	0.0817*	0.0279	0.0342*	0.0131	0.0271*
	(-5.74)	(-6.24)	(-1.11)	(-2.72)	(-6.60)	(2.56)	(1.72)	(2.56)	(1.07)	(2.03)
30+ years	-0.0339***	-0.0289***	-0.0412***	-0.0199***	-0.0304***	0.0778*	0.0348	0.0481**	0.0433**	0.0350*
	(-5.25)	(-7.80)	(-12.69)	(-6.43)	(-9.22)	(2.02)	(1.65)	(2.77)	(2.92)	(2.22)
Household composition[3]										
Married w/o kids under 18 in hh, no dual employment	0.308***	0.283***	0.301***	0.259***	0.241***	0.108***	0.125***	0.0797***	0.151***	0.165***
	(146.05)	(196.95)	(188.46)	(162.27)	(143.82)	(10.22)	(18.70)	(11.83)	(25.33)	(27.10)
Single woman with kids under 18 in hh	-0.572***	-0.591***	-0.520***	-0.470***	-0.411***	0.830***	0.569***	0.539***	0.355***	0.311***
	(-126.23)	(-272.64)	(-251.46)	(-269.54)	(-228.02)	(52.80)	(69.57)	(73.33)	(57.88)	(49.06)
Single woman no kids under 18 in hh	0.0991***	0.137***	0.214***	0.151***	0.179***	0.270***	0.0535***	-0.0441***	0.0612***	0.122***
	(33.95)	(93.20)	(152.73)	(108.50)	(118.81)	(20.43)	(7.70)	(-7.10)	(11.31)	(21.69)
Single man with kids under 18 in hh	0.0190*	0.0562***	0.0613***	0.0350***	0.0663***	0.279***	0.130***	0.0421**	0.0181	0.0891***
	(2.37)	(14.44)	(18.59)	(13.16)	(23.91)	(7.75)	(7.42)	(2.98)	(1.72)	(8.60)
Single man w/o kids under 18 in hh	0.343***	0.363***	0.386***	0.319***	0.355***	0.386***	0.244***	0.131***	0.180***	0.243***
	(112.06)	(254.20)	(277.68)	(238.23)	(245.62)	(28.20)	(37.38)	(21.88)	(34.80)	(45.58)
Married w kids under 18 in hh, dual employment	0.239***	0.268***	0.326***	0.340***	0.477***	-0.514***	-0.631***	-0.705***	-0.699***	-0.822***
	(168.43)	(290.59)	(321.43)	(336.81)	(434.25)	(-57.21)	(-118.94)	(-138.07)	(-152.38)	(-167.07)
Married w/o kids under 18 in hh, dual employment	0.622***	0.644***	0.699***	0.678***	0.787***	-0.623***	-0.774***	-0.799***	-0.825***	-0.964***
	(372.92)	(633.73)	(636.75)	(621.54)	(670.64)	(-57.99)	(-127.52)	(-139.99)	(-161.87)	(-180.90)
Cohabitating, no dual employment	0.427***	0.475***	0.533***	0.489***	0.589***	-0.133*	-0.358***	-0.497***	-0.514***	-0.687***
	(40.33)	(209.70)	(314.05)	(325.91)	(393.51)	(-2.33)	(-27.20)	(-54.70)	(-70.79)	(-94.48)
Cohabitating, dual employment	-0.0369**	-0.106***	-0.137***	-0.0498***	-0.154***	0.463***	0.375***	0.376***	0.264***	0.263***
	(-2.61)	(-25.89)	(-40.50)	(-18.69)	(-59.26)	(8.35)	(23.32)	(31.26)	(28.35)	(29.60)
Citizenship status[4]										
Foreign born citizen	0.0747***	0.0272***	0.0724***	0.0244***	0.00557***	0.0388*	0.0315**	-0.0510***	-0.0150*	-0.0535***
	(22.49)	(14.09)	(41.98)	(16.61)	(4.31)	(2.19)	(3.14)	(-5.92)	(-2.34)	(-9.16)
Foreign born non-citizen	-0.0614***	-0.108***	-0.0821***	-0.109***	-0.130***	0.210***	0.228***	0.142***	0.167***	0.00365
	(-12.85)	(-46.89)	(-45.85)	(-73.19)	(-100.30)	(8.91)	(21.05)	(17.45)	(27.57)	(0.65)
Race[5]										
Black	-0.285***	-0.179***	-0.143***	-0.145***	-0.159***	0.329***	0.268***	0.155***	0.135***	0.00988*
	(-121.02)	(-140.04)	(-126.39)	(-140.63)	(-157.27)	(29.32)	(44.44)	(29.51)	(31.23)	(2.31)
Other	-0.290***	-0.222***	-0.278***	-0.228***	-0.177***	0.386***	0.321***	0.364***	0.237***	0.155***
	(-23.68)	(-45.24)	(-62.37)	(-60.48)	(-45.96)	(6.99)	(14.41)	(19.78)	(15.85)	(10.01)
Asian	-0.110***	-0.0705***	-0.0921***	-0.0455***	0.00824***	0.250***	0.161***	0.211***	0.171***	0.0887***
	(-12.04)	(-21.34)	(-37.66)	(-22.74)	(4.90)	(5.53)	(9.48)	(18.13)	(20.57)	(11.98)

Table A7 continued: Mean and variance regressions on household logged income

	Between					Within				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	1970	1980	1990	2000	2007-2011	1970	1980	1990	2000	2007-2011
White Hispanic	-0.207***	-0.134***	-0.102***	-0.103***	-0.0836***	0.164***	0.101***	0.00119	-0.0485***	-0.141***
	(-56.28)	(-79.52)	(-73.89)	(-86.58)	(-80.32)	(8.83)	(12.08)	(0.18)	(-9.25)	(-29.91)
Non-white Hispanic	-0.255***	-0.235***	-0.145***	-0.145***	-0.124***	0.418***	0.370***	0.141***	0.144***	0.0270
	(-14.29)	(-27.10)	(-22.46)	(-28.46)	(-28.45)	(5.26)	(9.94)	(4.86)	(7.14)	(1.48)
IR union	0.433***	0.338***	0.366***	0.223***	0.0986***	-0.579***	-0.473***	-0.355***	-0.320***	-0.00208
	(87.39)	(117.12)	(127.07)	(73.41)	(35.29)	(-20.11)	(-29.71)	(-22.84)	(-22.02)	(-0.16)
Works 50+ hours	0.0959***	0.161***	0.191***	0.227***	0.259***	0.0359***	-0.00828	-0.105***	-0.184***	-0.217***
	(66.25)	(196.81)	(282.27)	(367.92)	(397.10)	(4.29)	(-1.77)	(-27.87)	(-59.31)	(-66.05)
Industry[6]										
Mining	0.232***	0.363***	0.307***	0.303***	0.383***	-0.543***	-0.437***	-0.455***	-0.522***	-0.427***
	(35.91)	(103.29)	(83.94)	(75.31)	(101.47)	(-16.52)	(-25.19)	(-25.77)	(-27.82)	(-24.02)
Construction	0.316***	0.227***	0.256***	0.277***	0.201***	-0.391***	-0.312***	-0.335***	-0.333***	-0.249***
	(65.52)	(83.47)	(102.22)	(110.17)	(81.20)	(-18.38)	(-25.83)	(-31.28)	(-33.77)	(-24.31)
Manufacturing	0.353***	0.311***	0.349***	0.349***	0.265***	-0.688***	-0.566***	-0.636***	-0.597***	-0.525***
	(77.89)	(119.77)	(147.56)	(145.52)	(109.61)	(-35.12)	(-49.38)	(-63.62)	(-64.10)	(-51.99)
TCPU	0.300***	0.300***	0.307***	0.326***	0.271***	-0.594***	-0.436***	-0.473***	-0.457***	-0.424***
	(60.22)	(104.61)	(117.18)	(125.04)	(103.30)	(-25.59)	(-32.57)	(-40.32)	(-43.40)	(-38.09)
Wholesale trade	0.467***	0.373***	0.400***	0.361***	0.306***	-0.615***	-0.544***	-0.544***	-0.512***	-0.432***
	(99.60)	(138.69)	(159.17)	(139.14)	(121.18)	(-29.73)	(-44.36)	(-49.03)	(-48.28)	(-39.43)
Retail trade	0.330***	0.197***	0.201***	0.202***	0.0928***	-0.428***	-0.320***	-0.279***	-0.258***	-0.182***
	(75.15)	(76.98)	(83.51)	(82.68)	(40.79)	(-24.04)	(-29.34)	(-28.24)	(-27.64)	(-19.83)
FIRE	0.556***	0.420***	0.491***	0.500***	0.442***	-0.594***	-0.515***	-0.421***	-0.400***	-0.326***
	(114.54)	(153.21)	(192.25)	(192.38)	(182.39)	(-27.77)	(-41.67)	(-38.54)	(-39.23)	(-32.82)
Services	0.329***	0.167***	0.206***	0.238***	0.196***	-0.413***	-0.311***	-0.289***	-0.288***	-0.236***
	(75.29)	(65.89)	(87.38)	(99.71)	(88.92)	(-23.51)	(-28.70)	(-29.65)	(-31.57)	(-26.73)
Public administration	0.390***	0.223***	0.226***	0.270***	0.329***	-0.758***	-0.492***	-0.710***	-0.628***	-0.617***
	(82.80)	(78.95)	(88.89)	(102.01)	(136.44)	(-35.05)	(-37.59)	(-61.39)	(-57.21)	(-59.77)
Constant	8.457***	8.499***	8.297***	8.522***	8.462***	0.607***	0.550***	0.640***	0.667***	0.708***
	(579.37)	(933.83)	(669.87)	(702.39)	(554.69)	(9.69)	(14.93)	(14.64)	(17.47)	(14.17)
N	1,109,360	4,356,752	4,946,263	5,460,229	5,611,173	1,109,360	4,356,752	4,946,263	5,460,229	5,611,173

t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

[1] Less than high school = reference

[2] 0-9 years = reference

[3] Married w kids under 18 in hh, no dual employment = reference

[4] Natural born citizen = reference

[5] White = reference

[6] Agriculture, Forestry, and Fishing = reference