CENTER *for* RETIREMENT RESEARCH *at* BOSTON COLLEGE

IS DEMAND FOR OLDER WORKERS ADJUSTING TO AN AGING LABOR FORCE?

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Abstract

This paper analyzes the demand for older workers, their substitutability with younger workers, and how well the demand for older workers tracks changes in the age composition of the labor force. The main data source for the analysis is the *Quarterly Workforce Indicators* from 2000 to 2018, which provides earnings and employment by sector and metropolitan statistical area. The analysis also uses KLEMS national data to estimate the sector-specific price and quantity of capital and the *Annual Social and Economic Supplement* of the *Current Population Survey* to estimate educational attainment and annual hours worked by age group and sector. The paper posits a translog production function using capital and three types of labor as inputs – young workers (ages 16 to 34), mature workers (ages 35 to 54), and older workers (55 and older) – to estimate partial cross-elasticities of factor demand and factor price as measures of the substitutability between labor categories.

The paper found that:

- There is some evidence that the substitutability between older and younger workers increased over the past two decades, but the finding is not robust. One specification shows an increasing trend in the substitutability, but two alternative specifications do not.
- There is a substantial amount of sector-level heterogeneity of the trends in the substitutability between older and younger workers.

The policy implications of the findings are:

- Understanding the demand side of the labor market is a key to understanding and projecting trends in employment.
- Although our findings do not offer robust results that can be directly applied in policy making, they point to the need for future research into employer demand for older workers.

Introduction

The U.S. labor force has been aging rapidly, a trend that is likely to continue as the population grows older and the labor force participation of older adults increases. According to U.S. Bureau of Labor Statistics data, the share of workers ages 55 and older in the U.S. labor force has doubled over the past three decades and now exceeds 23 percent. However, previous research has shown that many employers either appear reluctant to hire older workers or might encourage their older employees to retire in the face of increased competitive pressures (Bello and Galasso 2020; Johnson and Gosselin 2018; Neumark, Burn, and Button 2019; and Perron, 2018). These findings suggest that employers do not perceive older workers as perfect substitutes for their younger counterparts. If this perception persists and suppresses the demand for older workers despite their growing supply, unemployment for this population might increase and their wages might fall. Moreover, supply-side policies designed to increase employment at older ages by encouraging work might prove to be misplaced. If employers remain reluctant to employ older workers, policies that bolster labor demand instead of supply might more effectively increase employment at older ages (Kondo and Shigeoka, 2017).

The present study aims to extend the existing literature on the demand for older workers by providing insight into employers' views of worker substitutability and how well these views track changes in the age composition of the labor force. Our approach relies on estimating a production function that, in addition to capital, uses three types of labor input: young (ages 16 to 34), mature (ages 35 to 54), or old (55 and older). Our measures of substitutability between labor categories are cross-elasticities of factor demand and factor price, calculated based on our estimates of the production function. We posit the translog production function, an approach previously used in a number of studies of labor demand with heterogeneous labor, including some studies that focus on how labor demand varies by age group. Our principal data source is the *Quarterly Workforce Indicators* (QWI) from 2000 to 2018, which we use to compile a panel dataset consisting of information on factor prices, compensation shares, and factor quantities by sector and metropolitan statistical area.

Our estimates demonstrate that substitutability between older and younger workers could plausibly have increased over time, but we fail to find convincing evidence. The main challenge in estimating labor demand based on a production function is identification. Because only the equilibrium employment is observed, any identification of labor demand must be based on simplifying assumptions. We estimated three specifications, which rely on mutually exclusive assumptions. One set of estimates indicates that older workers have become somewhat more substitutable with both mature and younger workers over our analysis period, but the other two estimates do not show such a trend.

Background

For many years, researchers have recognized and studied a complex dynamic between employers and workers as workers age. Workers' value to employers, most commonly measured as productivity, generally increases with age as they improve their skills by accumulating experience and learning on the job. Later in life, aging might reverse some gains for older workers who experience physical and cognitive decline. The timing of this inflection point varies by person and occupation. A worker in poor physical health with excellent cognitive skills is likely to exhibit low productivity in a physically demanding occupation and high productivity in an occupation that requires only strong cognitive skills.

Another part of this equation is the compensation workers receive. In general, compensation increases or stagnates with tenure, but very rarely does it decrease for a worker who remains on the same job (Dustmann and Meghir, 2005). The cost of employing an older worker is higher not only because earnings generally increase with tenure, but also because the cost of some fringe benefits increases with age. For example, Mermin, Johnson, and Toder (2008) argue that the cost of providing health benefits increases with age because older workers use more health services than younger workers. They also note that the cost of defined-benefit pension plans generally increases with age as well.

Because a worker's cost profile generally increases monotonically and her productivity profile is parabolic, workers are generally underpaid relative to their productivity early in their careers and are generally overpaid as they get older. Two hypotheses have emerged to explain this discrepancy: the tilted wage profile could be a device for retaining workers[1] (Salop and Salop, 1976) or, alternatively, for deterring workers from shirking (Lazear, 1979). Either way, workers reach a point at which their cumulative cost to the employer exceeds their cumulative value, reducing the incentive for employers to retain them. Some researchers viewed mandatory retirement, which was outlawed in the United States by the 1967 Age Discrimination in

[1] Ippolito (1991) found that a tilted wage profile did not have a significant effect on tenure.

Employment Act, as a mechanism that limits the length of employment and thus prevents overall labor costs from exceeding worker productivity. Consistent with this explanation, Clark and Ogawa (1992) found that increases in the mandatory retirement age in Japan reduced earnings growth. In the absence of a mandatory retirement age, employers may find other ways to induce older workers to separate, although empirical evidence for this is scarce.

This theoretical framework provides a way to think about labor demand for older workers, but it is not always suitable for quantitative analysis. One way to assess the demand for older workers is to look at hiring and firing rates for this population. Johnson and Gosselin (2018) estimated the incidence of employer-related involuntary separations and earnings on subsequent jobs for workers who are in their 50s and early 60s. They found that more than one-half of older full-time workers experienced at least one involuntary job separation and only one-tenth of those who lost their jobs ever earned as much after their separation as they did before. Johnson and Mommaerts (2011) compared older and younger workers and found that, when controlling for job tenure, older workers are as likely to become displaced as their younger counterparts, but reemployment was much more challenging for older workers. When older workers found a new job, they were more likely to earn less than at the previous job. These findings are consistent with the wage tilt theory. Although wages rarely fall as tenure increases, older workers who are newly hired receive lower wages.

Another common approach for quantifying labor demand, which we use in this paper, is to estimate a production function and use it to calculate measures of labor demand. The canonical form of the production function has only two inputs—capital and labor—but researchers often posit production functions with more than two inputs when labor is assumed to be heterogenous. For example, Johnson and Blakemore (1979) estimated a production function with 14 labor inputs classified by age; Merrilees (1982) used two age and two sex groups to create four labor inputs, as did Costrell, Duguay, and Treyz (1986) and Lewis (1985). Estimating a production function with heterogeneous labor allows researchers not only to quantify the demand for each labor group, but also to analyze substitutability among labor groups. This is particularly relevant to our study, which seeks to understand if and how this substitutability changed as the composition of the workforce changed.

The two main measures of substitutability are the cross elasticity of factor demand and, its dual form, the cross elasticity of factor prices. The cross-elasticity of factor demand between inputs *i* and *j* is defined as the percentage change in the demand X for *i* caused by a one-percent increase in the price *w* of *j*:

$$\eta_{ij} = \frac{\partial \ln X_i}{\partial \ln w_j}$$

The elasticity η_{ij} can be positive or negative. A positive value means that if *j* becomes more costly, the demand for *j* would fall and it would be partially substituted by *i*, indicating that the inputs are *p-substitutes*; a negative value indicates that they are *p-complements*. When $i = j$, the expression represents own demand elasticity.

Analogously, the cross-elasticity of factor price is defined as the percentage change in the price *w* of *i* that would be caused by a one-percent increase in the supply X of *j*:

$$\epsilon_{ij} = \frac{\partial \ln w_i}{\partial \ln X_j}$$

In this case, a positive value means that an increase in the supply of *j* causes the price of *i* to increase, indicating complementarity, and the inputs are said to be *q-complements*. A negative value indicates that the inputs are *q-substitutes*.

Both elasticities are defined under the assumption that the quantities and prices of other inputs are held constant. In addition, demand elasticities assume that output is held constant, and price elasticities assume that marginal cost is held constant. These assumptions make direct estimation of the elasticities extremely difficult, but they can be estimated indirectly from a production function.

The assumed form of a production function is crucial. The commonly used *constant elasticity of substitution* production function and its special case, *Cobb-Douglas*, are not suitable for this kind of investigation because they impose the same technological parameters on all pairs of inputs, resulting in the same degree of substitutability between inputs. The elasticities of factor demand and factor price vary only when factor shares differ. The two functional forms that are typically used when studying heterogenous labor demand—*generalized Leontief* and *translog* functions—allow much richer interactions between factors. The generalized Leontief function defines a firm's output in terms of a weighted sum of the geometric means of pairs of factor quantities. It was used by Borjas (1983, 1986) to study the substitutability between workers of different racial and ethnic backgrounds and between native-born and immigrant workers.

In this paper, we use the translog function, which has been used much more frequently in the literature on the demand for heterogeneous labor (see, for example, Grant, 1979; Grant and Hamermesh, 1986; Hamermesh, 1993; Ferguson, 1986). It defines a firm's output in terms of the logarithms of factor quantities, which enter the expression as a sum of individual factors and as a sum of products of each pair of factors. Like generalized Leontief, the translog function has its dual form that defines the cost of production in terms of factor-price logarithms. Both forms can be transformed into a system of equations that define factor shares as linear functions of log-quantities, in the case of the production function, and log-prices, in the case of the cost function. This system of linear equations is most commonly estimated in empirical studies.

The present study is similar to a paper by Levine and Mitchell (1988) that used a factor-share system of equations in log-quantities to project changes in relative wages over time caused by a projected change in the age composition of the labor force. They relied on the 1985 demographic projections from the Bureau of Economic Activity and Social Security Administration, which anticipated a surge in the number of workers ages 55 and older by 2020. The authors reasoned that such a dramatic change in the composition of the labor force must affect relative wages. An increase in the supply of older workers would reduce their wages, which would decrease the demand for age groups that are viewed as their substitutes, driving down wages for those age groups. Age groups that complement older workers, on the other hand, should experience an increase in demand and receive higher wages.

Levine and Mitchell (1988) divided workers into eight sex-age groups. Both female and male workers were classified into teens (ages 16 to 19), young workers (ages 20 to 34), mature workers (ages 35 to 54) and older workers (ages 55 and older). In addition to these eight labor types, their production function also used capital. They used national aggregate data on wages, employment, the price of capital, and the capital stock from 1955 to 1984 to estimate the production function coefficients, which allowed them to project changes in wages resulting from the anticipated demographic changes. They projected that wages in 2020 would be higher for all sex-age groups, but older workers of both sexes would receive the smallest increase.

While the projected increase in the supply of older workers did materialize, it is difficult to find evidence of the prediction about the change in relative wages. Over our analysis period from 2000 to 2018, which is only about half as long as Levine and Mitchell's, the US labor force grew by 28.6 million workers, almost two-thirds of which, or 18 million, were people ages 55 and older. The number of workers in this age group almost doubled, increasing from 18.8 million to 37.0 million (Figure 1). In contrast, the number of mature workers ages 35 to 54 grew by only 2.5 million (4 percent) over the same period, and the number of young workers ages 16 to 34 grew by 7.9 million (15 percent). Based on the model estimated by Levine and Mitchell (1988), this dramatic shift in the age-composition of the labor force should cause changes in wages that are negatively correlated with changes in labor supply. In other words, we would expect the smallest increase (or largest decrease) in wages for older workers. However, older workers, whose wages increased by 7.5 percent, received the largest increase in wages over this period, while wages for younger and mature workers increased by between 5 and 6 percent.[2] Even though this comparison is not based on a rigorous application of the model, it raises questions about its validity.

One likely reason for the discrepancy between the model prediction and historical data is that the parameters of the model changed over time. Levine and Mitchell (1988) estimated their production function using data from 1955 to 1984 assuming that the function is time-invariant and will not change over the following 35 years. But there is no obvious reason why this would be the case. Employers can react to demographic changes not only by substituting between different age groups according to a given substitutability, but also by changing that substitutability due to changes in their views of different age groups or changes in some characteristics of these groups. For example, an increase in the automation of production processes has reduced physical demands on workers, thus making older workers more likely substitutes for workers in younger age groups. Similarly, the educational attainment of older workers increased substantially over the observation period, which is also likely to affect the degree of their substitutability with younger age groups.

In this paper, we adopt this dynamic view of ever-evolving employers and their production functions by allowing the substitutability between various labor types to change over time. We estimate production functions at multiple times and separately for each sector. This allows us to track changes in the substitutability between older workers and their younger counterparts and to isolate the labor-supply contribution to wage changes from the contribution of changes in the production function.

[2] These results are based on simple averages, but results are similar when we controlled for changes in educational attainment.

Data

Our econometric approach requires data on compensation shares and quantities of factor inputs by sector and metropolitan statistical area (MSA). Because no single data source contains this information, we combined several of them. Our main data source, Quarterly Workforce Indicators (QWI), contains the quantity and compensation of labor. It is a publicly available data set compiled by the U.S. Census Bureau (2020) through its Longitudinal Employer-Household Dynamics program, which links administrative and survey data to create a longitudinal employee-employer dataset. Each quarter, QWI report the numbers of employees and their average earnings aggregated by employer characteristics (sector and MSA) and employee characteristics (gender, age group, race, and education).

The QWI data start as early as 1990 for some states, but other states enter the dataset later (Figure 2). In selecting our analysis period, we considered the tradeoff between length and the number of states that could be included in the sample. Another constraint on our choice was the availability of other data needed for the analysis. Finally, because labor demand varies with business cycles, it was important to compare demand at the same phase of the business cycle. Considering these requirements, we use data from 2000, 2006, and 2018, the peaks of the last three business cycles. We also include data from 2012 to equalize the time between observations. Our sample includes all MSAs that are available in the QWI data in those four years.

We use *Emp*, a variable that contains employment at the beginning of a quarter, and *EarnBeg*, the average monthly earnings for those who were employed at the beginning of a quarter. We convert quarterly employment to annual data by averaging it over four quarters. We multiply monthly earnings by three times quarterly employment to obtain total quarterly earnings and then sum total quarterly earnings over a year and divide the sum by the average annual employment to obtain average annual earnings. We used total annual earnings by age group to calculate labor cost shares for each group by sector and MSA. Even though earnings do not account for the full labor cost, which also includes fringe benefits and the employer's portion of the payroll tax, we believe that this discrepancy does not significantly bias the estimation of the elasticity of substitution between two labor inputs. While this would represent a critical issue if we were interested in the substitutability between labor and capital, the measurement of cost for each labor input is affected by a similar error and their effects should cancel out.

We use three age categories: young workers (Y), defined as ages 16 to 34; mature workers (M), ages 35 to 54; and older workers (O), ages 55 and older. Levine and Mitchell (1988) had a separate group for teenage workers (T) for ages 16 to 18, but this group represents an extremely small share of workers in most industries (Figure 3). The small sample generated imprecise estimates, so we merge teenage workers into our group of young workers. In addition, Levine and Mitchell (1988) classified workers by sex. This was important for a model estimated with aggregate data, because substitutability between women and men varies by sector. However, considering that we estimate our model separately for each sector, we believe that the benefits of having separate sets of estimates for each sex would be too small to justify the additional analytical complexity that would result.

QWI uses the North American Industry Classification System (NAICS), which classifies industries into 20 two-digit sectors. Two of these sectors may be less suitable for our estimation, but we decided to keep them in the sample. The real estate sector, which includes leasing of buildings and houses, counts these buildings as capital resulting in an extremely small labor share. Dividing labor into three groups produced even smaller shares, which is likely to result in imprecise parameter estimates. The government sector is usually excluded from this kind of analysis because input-output accounting uses a different methodology from what is used for other sectors. In particular, the output of private companies is valued at market prices, while the output of the government is valued at its cost of production. This difference, however, does not play a significant role in our case because our key variables are inputs and their costs, and they are accounted in the same way across sectors.

To calculate age-group compensation shares as shares of total compensation, rather than shares of only labor compensation, we need to know how compensation is split between labor and capital. Unfortunately, this information is not available at the MSA level, which forced us to make an assumption of fixed industry-specific labor and capital shares across MSAs. The best available data is KLEMS national data from the integrated industry-level production account jointly produced by the Bureau of Economic Activity and Bureau of Labor Statistics (BEA, 2011). It contains information on quantity and compensation for main types of production inputs (i.e., labor, capital, energy, materials, and services) as well as quantity of output by industry. We used this data to estimate total compensation shares for labor and capital inputs by industry. We combined these shares with the age-group shares of labor compensation calculated from the QWI data to estimate the age-group shares of total compensation under the assumption of constant capital and labor shares across MSAs for any given industry.

Having information on labor compensation by industry and MSA, and information on labor and capital shares allowed us to estimate capital compensation by industry and MSA. Finally, the quantity of capital used in the production, the last missing piece of data, was obtained by dividing the compensation to capital by the capital price index, which we obtained from the KLEMS. The KLEMS data provide quantities of five types of capital (art, R&D, IT, software, and other) in the form of an index that equals 100 in 2012. We created an aggregate capital index as a weighted average of indices for individual capital types weighted by their compensation.

The main shortcoming of the QWI data is that they cannot be disaggregated by both the age and education of employees, but only by one characteristic at a time. Because age is our explanatory variable of interest and education is a key determinant of worker productivity, this is a significant limitation. In addition, QWI provides only the number of workers employed in a given quarter, rather than the actual labor supplied in days or hours. This is also a significant shortcoming because the distribution of the number of hours workers spend on the job in a given quarter varies across age groups. We worked around these measurement problems by using the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), which was harmonized by Flood, King, Rodgers, Ruggles, and Warren (2020), to adjust the quantity of labor for education and annual hours worked by industry and age group. Because CPS does not use the NAICS, we mapped the industry variable from the Census's classification system to NAICS.

Methods

Our main goal is to understand the degree of substitutability between workers in different age groups and how that substitutability changes over time. We adopt an approach based on estimating a production function with heterogeneous labor—or its dual form, a cost function—and using these estimates to calculate cross-partial elasticities between workers in different age groups, which relate wages of one age group with the quantity of another. The cross-elasticity of factor demand represents the percentage change in the demand for workers in one age group caused by a one-percent change in the wages of another group. A positive value indicates that the workers in two age groups are viewed as substitutes, and a negative value indicates complementarity. Conversely, the cross-elasticity of factor price shows the percentage change in wages of one age group caused by a one-percent increase in supply of workers in another group. In this case, a positive value indicates complementarity and a negative value indicates substitutability. In this paper, we are interested in changes in this relationship over time. In particular, we are interested in whether older workers have become more substitutable with workers in other age groups as their relative supply increased. In addition, we used the estimated production function to predict changes in earnings over time. We decompose these changes into a component caused by changes in the quantity of inputs and a component caused by changes in the demand for inputs.

We posit a *translog* production function with four inputs—one capital input and three labor inputs (young, mature, and old workers)—for each economic sector. This functional form allows a high degree of heterogeneity in substitutability between inputs. Unlike the Cobb-Douglas or constant-elasticity-of-substitution functions, which impose the same parameters for each pair of inputs, the translog function allows any degree of substitutability (or complementarity) between any two inputs. In addition, under commonly made assumptions, the function can be transformed into a system of linear equations that can be easily estimated using standard econometric techniques. Denoting output as Y and input *i* as X_i, the translog production function can be written as:

$$Y = \alpha_0 + \sum_i \alpha_i \log X_i + 0.5 \sum_i \sum_j \beta_{ij} \log X_i \log X_j$$

Assuming constant returns to scale[3] imposes the constraints $\sum_i \alpha_i = 1$ and $\sum_i \beta_{ij} = 0$ for each *j*, and the symmetry of second partial derivatives implies $\beta_{ij} = \beta_{ji}$. Under the assumption of competitive factor markets, a system of equations for cost shares can be derived.[4] Using s_{ik} to denote the cost share of input *i* in MSA *k*, and adding a residual term ε_{ik}, we can write our econometric model as a system of four linear equations with factor shares as dependent variables and logarithms of factor quantities as independent variables:

[3] Constant returns to scale are commonly assumed in the literature. We also tested this assumption and were not able to reject it for most sectors in the sample.
[4] For a derivation of the cost shares system in the case of three inputs, see Hamermesh and Grant (1979).

$$s_{ik} = \alpha_i + \sum_j \beta_{ij} \log X_{jk} + \varepsilon_{ik}, i = 1, \ldots, 4 \quad (1)$$

We obtained labor quantity X_{jk} directly from QWI and adjusted it for annual hours worked and quality of labor based on the CPS ASEC data. We calculated the national average number of hours worked by age group and sector and multiplied the QWI number of employees by it. Adjustment for quality of labor took into account differences in educational attainment among age groups in each sector. We used the CPS ASEC to create a labor quality index similar to the one constructed by Harper and Field (1983), who used wage as a proxy for labor productivity to adjust state-level labor quantity for differences in education, race, and sex. Because research shows that differences in wages by race and sex are driven more by discrimination than by differences in productivity (Paul et al., 2018; Weinberger and Joy, 2007), we use only education to make this adjustment. Our index q_{is} is calculated for each age group *i* and sector *s* by weighting the quantity of labor in each age-education group L_{ies} by a sector-wide, education-specific, hourly wage, w_{es}, and normalizing it by the sectoral mean wage w_s and sector-age labor quantity L_{is}:

$$q_{is} = \frac{\sum_e w_{es} L_{ies}}{w_s L_{is}}$$

Assuming that residual terms in (1) are correlated across inputs but not across MSAs[5], we estimated this system of equations as seemingly unrelated regressions (SUR) for the economy as a whole and for each of the 20 sectors at four points in time: 2000, 2006, 2012, and 2018. Ordinary least squares (OLS) can yield efficient estimates when all equations have the same regressors, but not in the presence of restrictions on coefficients, in which case SUR is necessary to obtain efficient estimates (see Greene, 2002, p. 344). Because our assumptions about the production function coefficients make the system overdetermined, we drop the capital equation and estimate only three labor-shares equations. The estimated parameters allow us to calculate cross-price elasticities of demand that indicate the degree of substitutability between two inputs. In addition, this functional form is suitable for predicting changes in wages caused by changes in labor supply.

[5] We assume that $E[\varepsilon_{it}\varepsilon_{js}|X_1, \ldots, X_N] = \sigma_{ij}$ if t=s, and 0 otherwise.

While this model is useful for our purpose, it requires some strong identifying assumptions. The main source of identification is the implicit assumption that labor supply is infinitely inelastic (or at least much less elastic than labor demand), and therefore all the observed variation in wages, and consequently labor compensation shares, comes from variation in labor demand. If labor supply was not infinitely inelastic, a shock to labor demand would also cause a change in employment, making factor quantities endogenous. While a case for inelastic supply at the MSA level can be made, it is much more difficult to do so at the sector-MSA level. The cost of switching industries within an MSA is low, and workers frequently switch industries in response to a change in an industry's labor demand. Consequently, the effects of changes in labor supply on wages based on this assumption are most likely overestimated and represent only the upper bound.

One way to address this problem is to use the MSA, rather than the sector-MSA, as a unit of observation and make the assumption of inelastic labor supply at the MSA level. Although the labor supply curve is still not vertical, this would represent a significant improvement. The main downside is that we lose the heterogeneity across sectors because we have to assume that all sectors have the same production function. We use this estimate as one of our robustness checks.

Another way to assess the robustness of our results is to estimate the dual functional form that requires making the opposite assumptions. This functional form is derived from the firm's cost function and defines factor compensation shares as linear functions of logarithms of factor prices w_{jk}:[6]

$$s_{ik} = a_i + \sum_j b_{ij} \log w_{jk} + \varepsilon_{ik}, i = 1, \dots, 4 \tag{2}$$

In this case, the identifying assumption requires factor prices, rather than quantities, to be exogenous, or equivalently, that labor supply can be considered infinitely elastic. In other words, each sector within an MSA takes wages as given. This proposition is easier to defend at the sector-MSA level. All MSAs in our sample contain multiple sectors and very few of them have a high sector-level concentration. We show this by calculating the Herfindahl–Hirschman Index (HHI) index for sector-level labor compensation. The index is generally used for assessing

[6] For derivation, see Hamermesh and Grant (1979).

market concentration of sellers in markets for goods and services, but it can also be used to assess the market concentration of buyers in the labor market (Azar et al., 2020). Calculated as the sum of squared market shares expressed as percentages, its maximum value is 10,000 for a market dominated by a single entity. The US Department of Justice and Federal Trade Commission consider values between 1,500 and 2,500 as indicators of moderately concentrated markets and values greater than 2,500 as indicators of highly concentrated markets.[7] These ranges should be interpreted only as rough guides because they are defined with respect to firms rather than sectors, and for the case of sellers, rather than buyers. Figure 4 shows that the majority of MSAs in our sample exhibit a low sector-level concentration and only a small fraction is highly concentrated.

We use the estimated production-function coefficients to calculate factor price elasticities, which in this case are wage elasticities. A cross-wage elasticity ϵ_{ij} indicates the percentage change in the wage of workers in group *i*, w_i, due to a one-percent increase in the quantity of workers in group *j*. Own wage elasticity ϵ_{ii} indicates the percentage change in the wage caused by a one-percent increase in the quantity of workers in the same group.

$$\epsilon_{ij} = \frac{\partial \ln w_i}{\partial \ln X_j} = s_j + \frac{\beta_{ij}}{s_i} \tag{3a}$$

$$\epsilon_{ii} = \frac{\partial \ln w_i}{\partial \ln X_i} = s_i + \frac{\beta_{ii}}{s_i} - 1 \tag{3b}$$

The expressions for factor demand elasticity parallel those above but use the coefficient from the cost function:

$$\eta_{ij} = \frac{\partial \ln X_i}{\partial \ln w_j} = s_j + \frac{b_{ij}}{s_i} \tag{4a}$$

$$\eta_{ii} = \frac{\partial \ln X_i}{\partial \ln w_i} = s_i + \frac{b_{ii}}{s_i} - 1 \tag{4b}$$

The expressions for variances of these estimates were derived by Levine and Mitchell (1988) in the working paper version of their study.

As the last step, we use estimated production function coefficients to predict changes in wages over the analysis period. We then decompose these predicted changes into components

[7] "Horizontal Merger Guidelines", U.S. Department of Justice and Federal Trade Commission, accessed on 20 March 2021, https://www.justice.gov/atr/horizontal-merger-guidelines-08192010.

that can be attributed to the changes in coefficients and those that can be attributed to changes in input quantities. We start with the definition of the cost share $s_i = \frac{w_i X_i}{Y}$, where Y is output, and we log-differentiate it to obtain:

$$\text{dlog}\, w_i = \frac{\text{d}s_i}{s_i} - \text{dlog}\, X_i + \text{dlog}\, Y$$

We then differentiate equation (1) to obtain an expression for $\text{d}s_i$, which we substitute in the equation above, and use the approximation $\text{dlog}\, Y \approx \sum_i s_i \text{dlog}\, X_i$ to obtain an expression for predicting changes in wages of workers in age group *i* due to changes in production function coefficients and factor quantities:

$$\begin{aligned} \text{d}\log w_i = & \frac{1}{s_i}[\text{d}\alpha_i + \sum_j \text{d}\beta_{ij} \log X_j + \sum_j \beta_{ij} \text{d}\log X_j] - \text{d}\log X_i \\ & + \sum_j s_j \text{d}\log X_j \end{aligned} \tag{5}$$

The expression on the right-hand side contains 13 terms, which we group into three groups: terms with differentials in coefficients α_i and β_{ij} where *j* is another age group; terms with differentials in quantities of labor; and terms with differentials related to capital in coefficients or quantity. We are mostly interested in the first group, which represents changes in wages due to changes in labor demand and substitutability between age groups, and the second group, which represents changes in wages due to changes in the composition of the labor force. We use expression (5) to predict wages of workers in the three age groups by sector and to decompose these changes into the above three groups.

Results

Because the approximate value and trend of many of our estimates are more interesting than their precise values, we rely mostly on visual presentation of our results rather than tables. All estimates are presented with their 95-percent confidence intervals. We start with estimates of cross-wage elasticities, which represent the percent change in wages of one group caused by a 1-percent increase in the labor supply of another group. We first present our estimates by sector and then show aggregate results. In the interest of space and considering that we are most interested in the substitutability between older workers and those in the other two younger age groups, we present sector-specific estimates only of the elasticity of wages of mature and younger workers with respect to older workers. Aggregate estimates are presented for all combinations of age groups. We then present the estimates of cross-demand elasticity, which are based on our estimates of the cost function. These results are used as an indirect test of our identifying assumptions.

Most of our estimates pass the basic validity check in that they have the expected sign and fall in the expected range. All estimates of own-wage elasticity are negative, which is consistent with theory. Our estimates of cross-wage elasticity fall between -0.4 and 0.2, which is very similar to the range of estimates by Levine and Mitchell (1988) for groups that do not involve teenagers (who tend to have higher values of elasticities), which falls between -0.4 and 0.3. Elasticities that are based on an aggregate production have similar values to those obtained by aggregating sector-specific elasticities. Own demand elasticities are also mostly negative: only 3 of 240 estimates (20 sectors over 4 years and 3 age groups) are positive and statistically significant.

The estimates of the cross-elasticity of wages of mature and younger workers with respect to older workers are shown by sector for years 2000, 2006, 2012, and 2018 in figures 5 and 6. Mature and older workers start the period as complements in many sectors including accommodation and food, agriculture, arts and entertainment, business services, health care, management, and professional services, although some of these estimates are statistically indistinguishable from zero at the 95-percent significance level. In other sectors, they were viewed as weak substitutes, as indicated by a cross-wage elasticity in the range between 0 and -0.1. Over our analysis period, the cross-wage elasticity for mature workers with respect to older workers declined in most sectors, indicating increasing substitutability between these two groups. In 2018, the estimates were non-negative only in management and retail. Our estimates of the substitutability between younger and older workers shown in Figure 6 have been lower and more stable, but patterns across the sectors are similar.

This decrease in the cross-wage elasticity of mature and younger workers with respect to older workers could indicate that older workers at any age have become more substitutable with their younger counterparts. For example, a technological advance that reduces physical demands on workers could increase the demand for older workers. However, it could also be caused by a rightward shift in the age-productivity profile consistent with an increasing capacity for work at older ages due to improved health and an increasing life expectancy. Even over this relatively short time period, average life expectancy increased by more than 2.1 years for women and 2.5 years for men.[8] A 55-year-old woman in 2000 had the same life expectancy as a woman aged 57.4 in 2018. If we used an alternative measure of age, like the one constructed by Cosic and Steuerle (2018) that controls for life expectancy, workers ages 56 and 57 would be categorized as mature rather than old in 2018. If this shift occurred in employers' perception but not in our classification, it would cause an increase in measured substitutability. Our data do not allow us to disentangle the effect of an across-the-board increase in substitutability from a shift in the threshold between mature and older workers, but it is worth considering it as a potential factor.

This sector-specific view is useful because it highlights the sector-level heterogeneity in substitutability between age groups. However, sectors also vary by employment and this view does not provide any information about the overall trend. To do that, we aggregated these elasticities by calculating a weighted mean, in which we use sector-specific employment shares as weights.[9] We aggregated both point estimates and confidence intervals in the same way. In addition, we estimated an aggregate production function and used it to obtain an alternative set of cross-wage elasticities, which provide a reference for our robustness check. Both sets of estimates are shown in Figure 7; those based on sector-specific production functions are in yellow and those based on the aggregate production function are in blue.

The aggregated sector-specific estimates indicate that mature and older workers have become more substitutable over the observed period. The weighted mean of cross-wage elasticity for mature workers with respect to older workers decreased from -0.01 and statistically insignificant in 2000 to -0.06 and statistically significant in 2018. The 95-percent confidence intervals estimated in these two years do not overlap. The substitutability between younger and older workers increased as well but by a smaller amount and with less statistical significance. The cross-wage elasticity for young workers with respect to older workers decreased from -0.02 and statistically insignificant in 2000 to -0.04 and statistically significant in 2018, but there is a substantial overlap between the two confidence intervals. The substitutability between younger and mature workers remained relatively stable over the observed period.

[8] "Period Life Tables," Social Security Administration, https://www.ssa.gov/oact/HistEst/PerLifeTablesHome.html.
[9] The aggregate elasticity represents a mean percentage change in wages in all sectors. A mean percent change for the sample can be calculated as a weighted mean of percent changes of its parts.

The estimates of cross-wage elasticity that are based on the aggregate production function show a lower degree of substitutability between age groups and smaller changes over time. These estimates were higher in absolute value than those based on sector-specific production functions in all but two cases. The two sets of estimates are relatively close, which gives us some confidence in our estimation methods, but the systematic differences between the two bring our identifying assumptions into question. We can think of three reasons for these differences. First, the sector-specific estimates were aggregated by weighting them by sectoral employment shares, but the estimates based on the aggregate production function do not take sector size into account. If the cross-wage elasticities in large sectors were lower than in small sectors, a non-weighted average would bias it upwards. However, we were able to reject this hypothesis by estimating non-weighted means of sector specific elasticities, which were even lower than the weighted means.

The other two potential reasons for differences between estimates based on aggregate and sector-specific production functions are related to the identifying assumptions. As discussed in the previous section, the main weakness of our identifying strategy is the assumption of an infinitely inelastic labor supply at the sector-MSA level. This assumption is much more likely to hold at the MSA level, which is the unit of observation for our estimation of the aggregate production function. Consequently, if the sector-specific estimates yielded the upper bound on substitutability, the aggregate estimates should be closer to the true values. On the other hand, the assumption of a homogenous production function across sectors might be too strong. Imposing the same production function on sectors with very different technologies and labor and capital shares could lead to a misspecified model, and consequently to biased elasticity estimates.

Although we do not have a direct way of distinguishing between the last two reasons for the discrepancy, we can consider another measure of substitutability, which requires less problematic assumptions, to shed some additional light on this question. As discussed in the previous section, the dual specification (2) that is based on the cost function is more likely to be well identified at the sector-MSA level than specification (1) that is based on the production function. We estimated model (2) and used the estimated parameters to estimate cross-demand elasticities between age groups. This elasticity represents the percentage change in demand for labor in one group caused by a 1-percent increase in wages of another group. It is positive when two groups are substitutes and negative when they are complements. Our sector-specific estimates aggregated as weighted means are shown in Figure 8.

A surprising result from this figure is that the cross-demand elasticity between mature and older workers is negative, indicating that the two groups are complements rather than substitutes. These elasticities (the right-most chart in both rows of Figure 8) are negative for all four years, although they are statistically indistinguishable from zero at the period's ends (i.e., years 2000 and 2018). Equally surprising is the lack of a trend in these estimates. Our hypothesis was that employers' views would change with the composition of the workforce and that older workers would become more substitutable, or at least less complementary, to other workers, but these results show that elasticities changed little over the analysis period. These estimates put our results based on cross-wage elasticities in doubt. They are not only showing different magnitudes, but they are indicating the opposite type of relationship between older and mature workers. Estimates of the cross-wage elasticity between young and old workers and between young and mature workers are positive in all years, indicating net-substitutability, but statistically insignificant and equally flat over the observed period.

We also show estimates of own-wage and own-demand elasticity in figures 9 and 10. These elasticities represent the relationship between changes in wages and employment for the same group of workers. As with cross-wage elasticities, we estimated two sets of own-wage elasticities in two ways: weighted averages of sector-specific elasticities and aggregate elasticities based on the aggregate production function. And as with cross-wage elasticity estimates, the averaged elasticities have larger magnitudes than those based on the aggregate function. Somewhat surprisingly, the averaged estimates indicate that the demand for mature workers is more elastic than the demand for younger and older workers. However, the aggregate estimates have similar values for all three groups. Moreover, they exhibit similar trends. At the beginning of the period, elasticities are between -0.15 and -0.18. They increase (i.e., fall in absolute value) in 2006 and 2012 reaching about -0.12, and then fall in 2018. Estimates of own demand elasticities, shown in Figure 11, are closer to what we expected. In particular, the labor demand is most elastic (i.e., the elasticity is the lowest) for young people. This result is consistent with theory and was found in previous empirical studies (see Bazen and Martin, 1991; Grant, 1979; Hamermesh, 1986).

Finally, we discuss the changes in wages predicted by equation (5) and the components of these changes, with the caveat that this analysis is based on our estimates of the production function that did not pass the robustness check. Figure 11 shows actual and predicted changes in wages from 2000 to 2018 by age group and sector. Actual changes in wages were demeaned by subtracting the mean change in wages for all workers over this period. The results are mixed. Comparing only the signs of our predictions with actual changes, our success rate is just barely higher than 50 percent. Predicted wages for older workers fell in most sectors and increased in only six of them. They did increase in five out of predicted six sectors, but they also increased in seven others for which we predicted decreasing wages for older workers. We predicted that wages for younger workers would increase in 10 sectors, but they actually increased in only 4 of those and one other for which we predicted a decrease. For mature workers, we predicted increases in 16 sectors; they occurred in 10 of those and 2 others for which we predicted decreases.

Figure 12 shows results of the decomposition of the predicted changes in wages into components caused by changes in the production function, changes in the age composition of the labor force, and changes related to capital, both its role in the production process and quantity. As expected, the changes in age composition alone would have reduced wages for older workers, whose number increased dramatically, in almost all sectors. However, age composition had a negative contribution in most sectors for workers in the other two age groups whose numbers increased much less than for older workers. A possible explanation is that the increase in the number of younger and mature workers was large relative to the increase in the quantity of capital and that this relationship dominated in some sectors. The changes in the production function also had a negative impact on older workers' wages, even though we expected them to counteract the effects of changes in age composition. The estimated contribution of capital is positive across the board, for virtually all ages and sectors.

Conclusion

The aging of the labor force, improvements in worker health conditional on age, and technological advances in production processes are likely to change the relative demand for workers of different ages. In this paper, we searched for evidence of such demand shifts from 2000 to 2018 based on MSA-level QWI data on employment and earnings. We found some evidence that points in the expected direction, but it is far from conclusive. Our estimates of the cross-wage elasticity of demand, which are based on a translog production function with three labor inputs corresponding to three age categories, show that older workers have become more substitutable in the production process with their younger counterparts. But these estimates are based on the assumption of an infinitely inelastic labor supply at the sector-MSA level, which is unlikely to hold. Our alternative models show little or no trend in the substitutability between older and younger workers.

Although this outcome is somewhat disappointing, it poses a new question that future research should address. Our paper failed to provide evidence of a trend in substitutability between workers in different age groups, but it also has not provided evidence of the lack of a trend. Our alternative models that did not show a trend are also based on assumptions that are unlikely to hold. Because the assumption of a production function that is homogenous across sectors and the assumption of an infinitely elastic labor supply are likely to be violated, it is important to keep in mind that they represent different but not necessarily more correct models. The present study showed that identifying assumptions matter and that these estimates are sensitive to them. We leave it to future research to find a "more correct" model that can provide evidence of changes in relative labor demand with less ambiguity.

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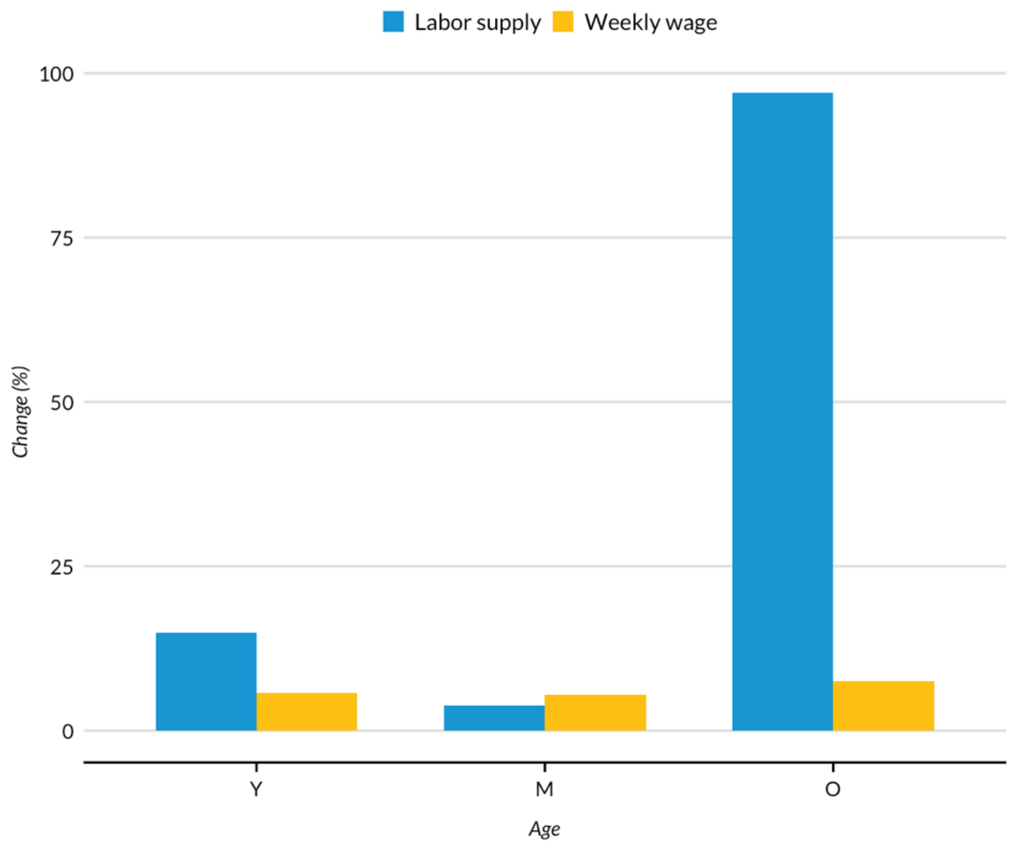
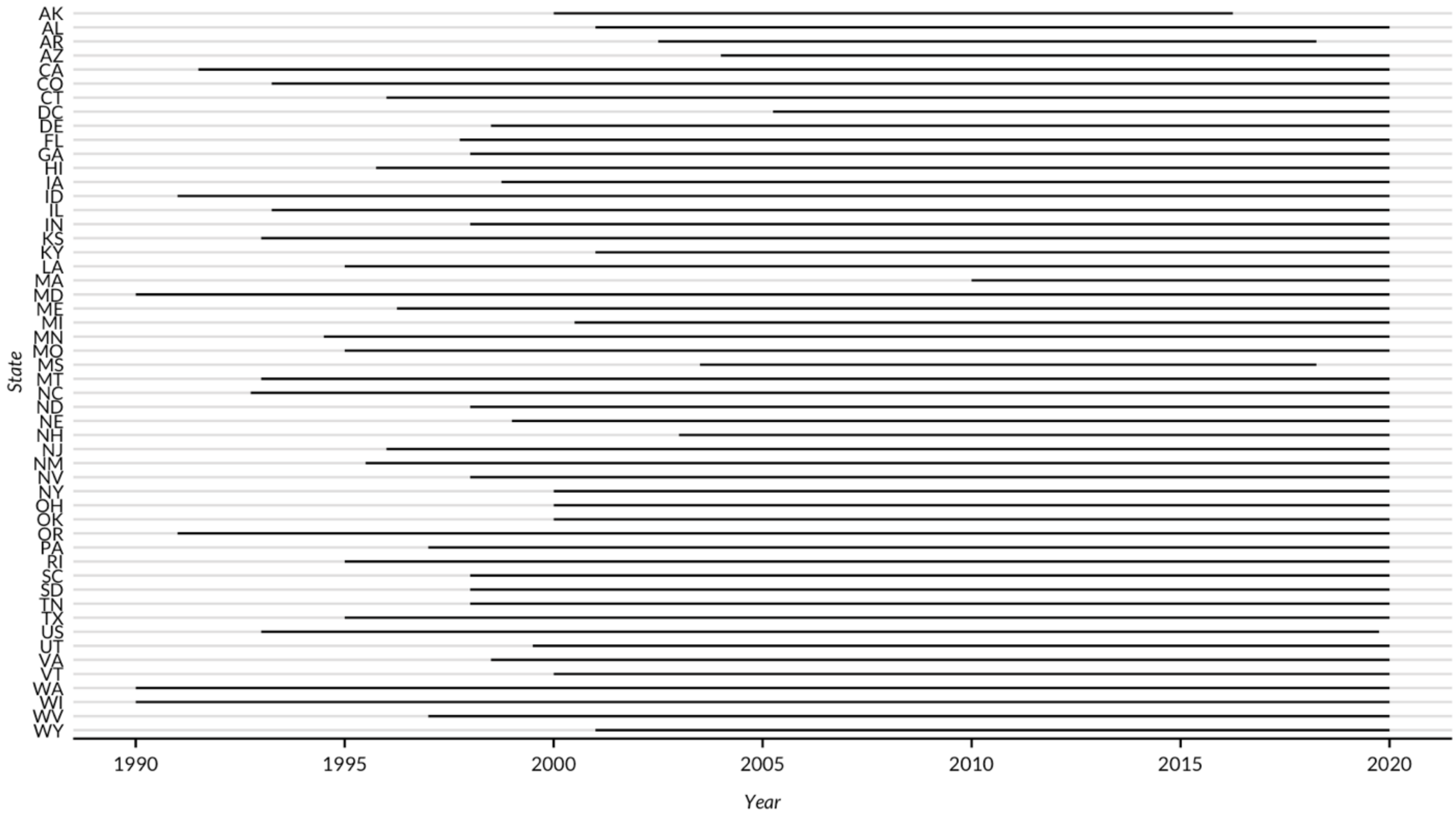
Figures

Figure 1. *Percent-Change in Weekly Wages and Labor Force by Age Group, 2000 and 2018*



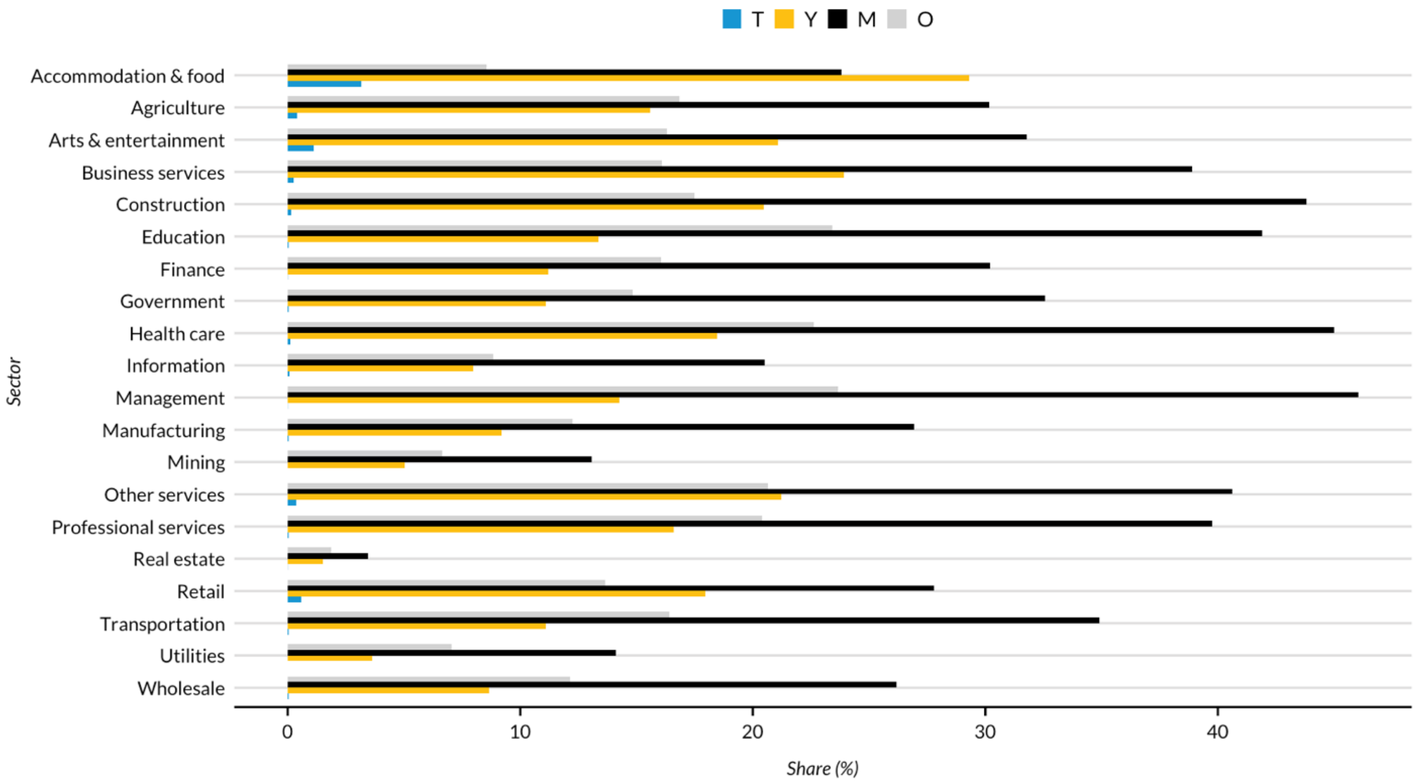
Notes: The analysis groups workers into young (Y) ages (16 to 34), mature (M) ages (35 to 54), and older (O) ages (55 and older). Labor force size was estimated as the number of people who participated in the labor force. Weekly wages were estimated as annual earnings divided by weeks worked for full-time, full-year workers (35 or more hours per week, 40 or more weeks per year) whose hourly wages were between \$3 and \$300 in 2019 inflation-adjusted dollars.
Sources: Authors' computations from the *Annual Social and Economic Supplement of the Current Population Survey* (2001, 2019) and *American Community Survey* (2000, 2018).

Figure 2. *QWI Observation Periods by State*



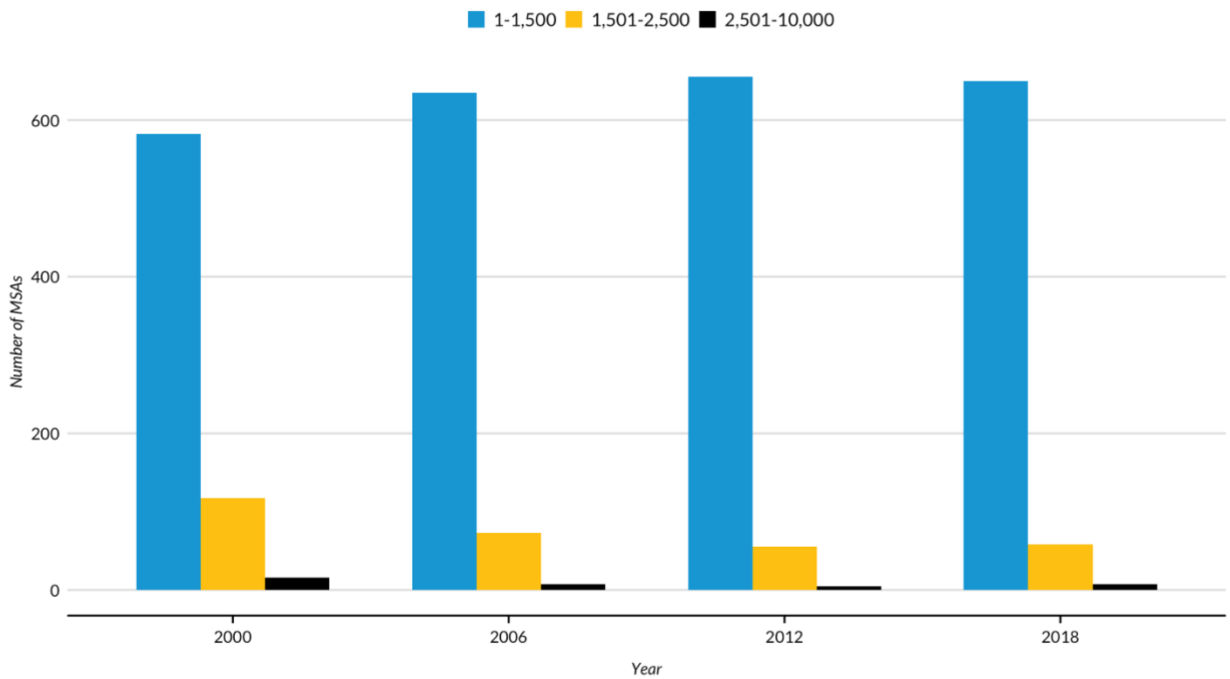
Source: "QWI loading status" https://lehd.ces.census.gov/applications/help/qwi_explorer.html#!loading_status

Figure 3. *Shares of Workers by Age Group and Sector, 2012*



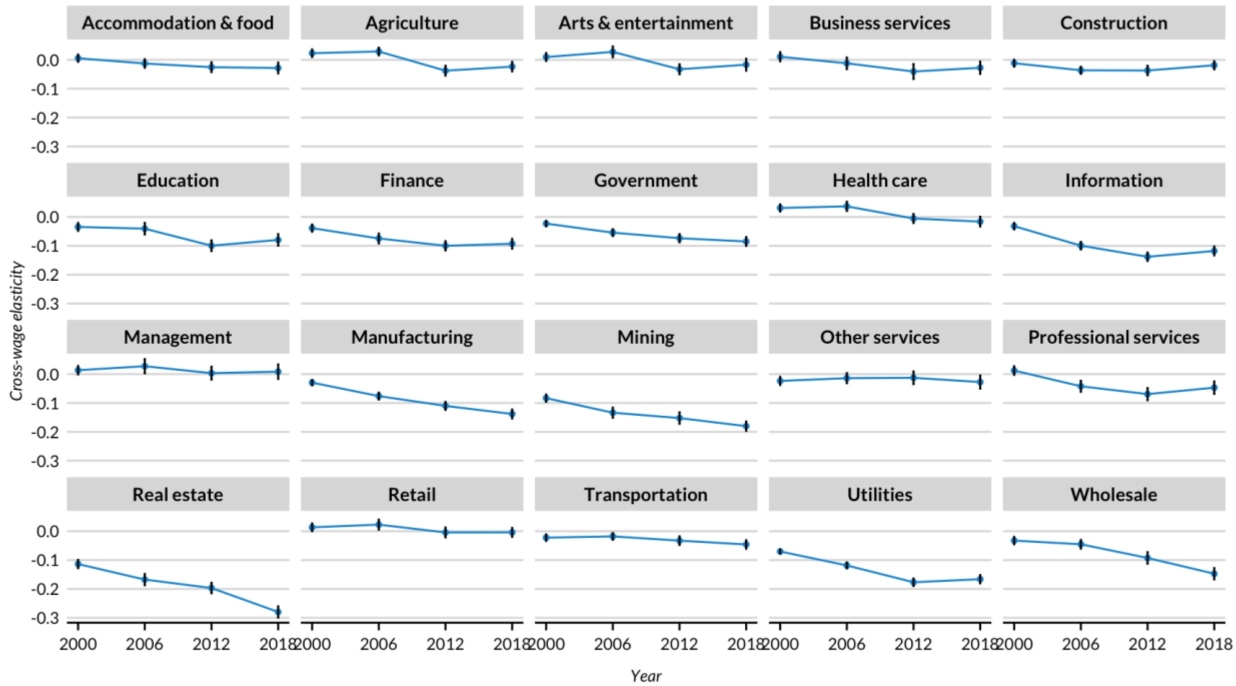
Notes: The analysis groups workers into teenagers (T) (ages 16 to 18), young (Y) ages (19 to 34), mature (M) ages (35 to 54), and older (O) ages (55 and older).
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

Figure 4. *Distribution of Herfindahl–Hirschman Index for Sector-Level Employment*



Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

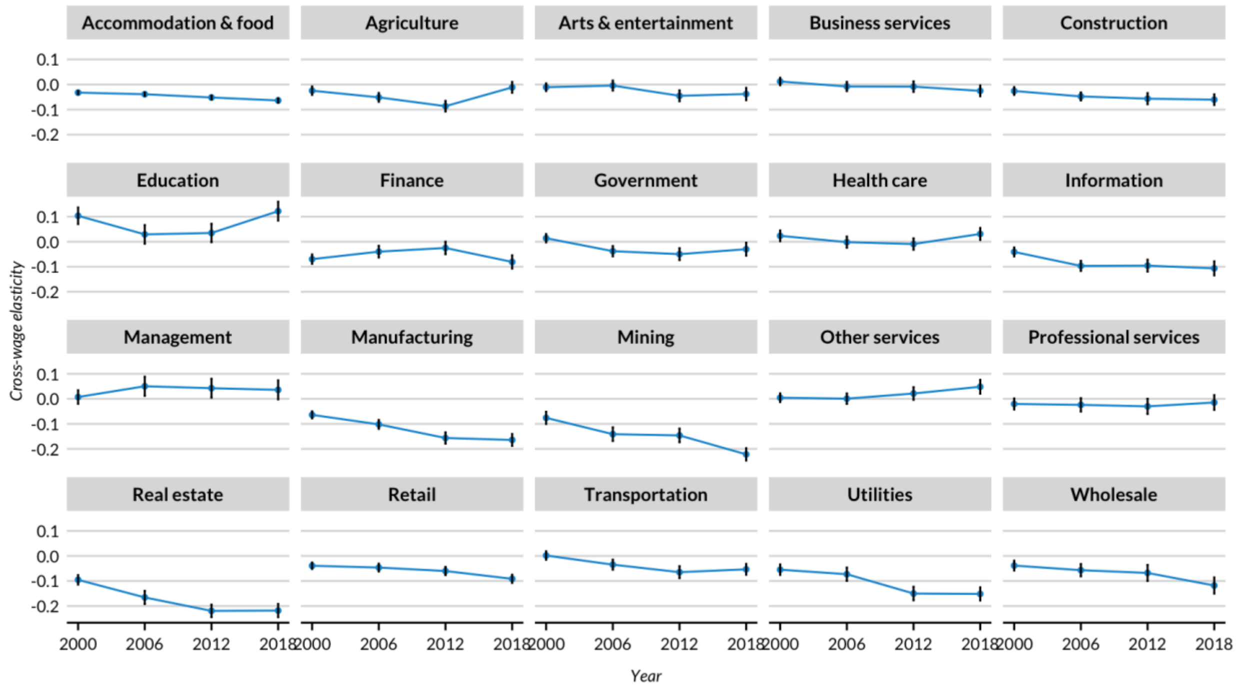
Figure 5. *Cross-Wage Elasticity of Demand for Mature Workers with Respect to Older Workers*



Notes: This elasticity represents the percent change in the wages of mature workers (ages 35 to 54) caused by a one-percent increase in supply of older workers (ages 55 and older). It was calculated using equation (3a) and estimated coefficients from equation (1). Standard errors, estimated by the delta method, were used to construct confidence intervals.

Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

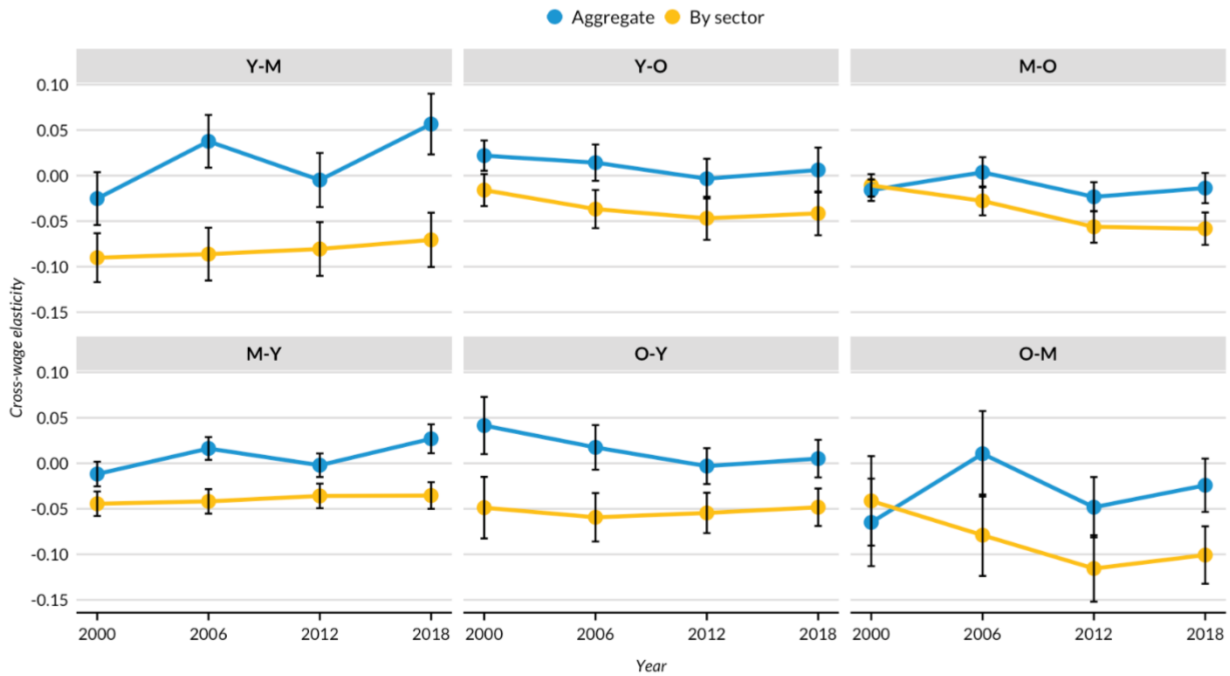
Figure 6. *Cross-Wage Elasticity of Demand for Young Workers with Respect to Older Workers*



Notes: This elasticity represents the percent change in the wages of young workers (ages 16 to 34) caused by a 1 percent increase in the supply of older workers (ages 55 and older). It was calculated using equation (3a) and estimated coefficients from equation (1). Standard errors, estimated by the delta method, were used to construct confidence intervals.

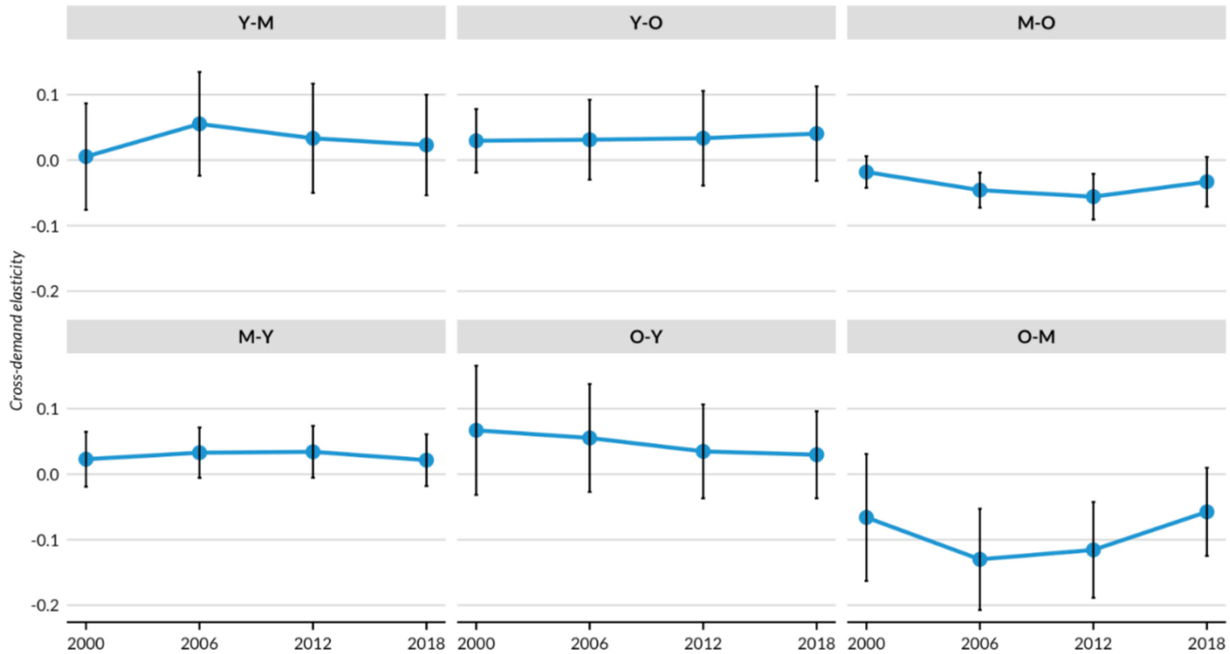
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

Figure 7. *Cross-Wage Elasticity Based on the Aggregate Production Function and Sector-Specific Production Functions*



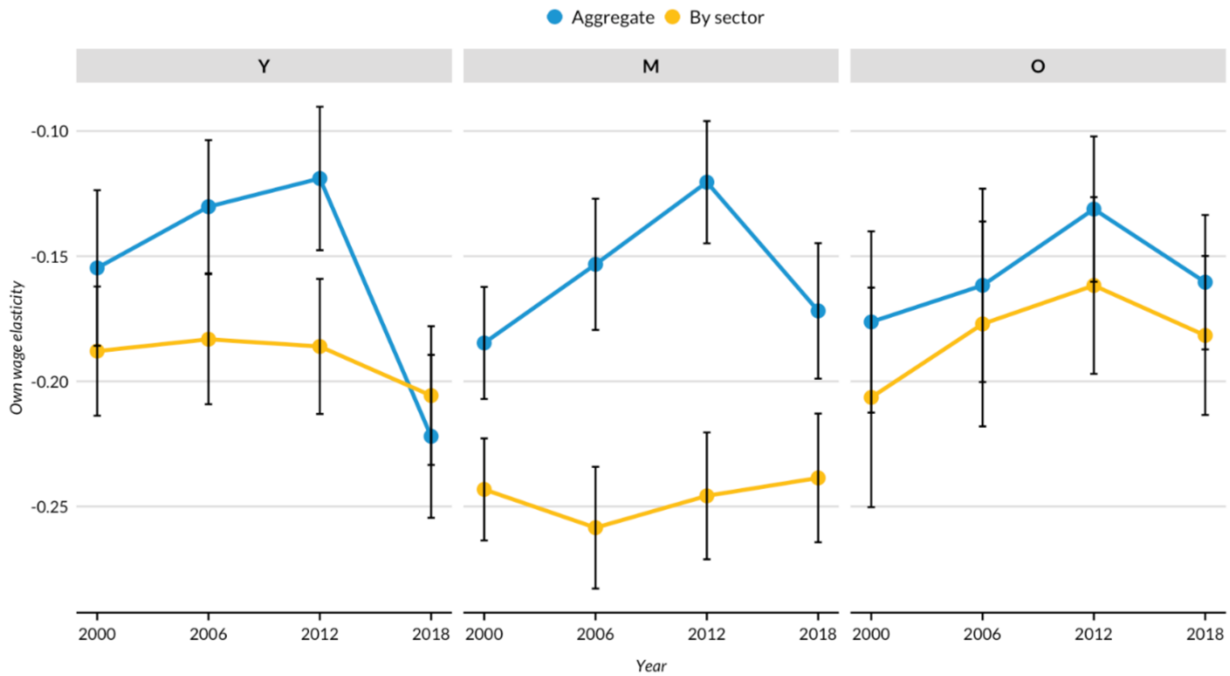
Notes: Elasticities were calculated using equation (3a) and estimated coefficients from equation (1). The aggregate estimates shown in blue were estimated using a single production function. The "by sector" estimates shown in yellow were calculated as a weighted mean of sector-specific elasticities. Standard errors, estimated by the delta method, were used to construct confidence intervals. Y indicates young workers (ages 16 to 34), M indicates mature workers (ages 35 to 54), and O indicates older workers (ages 55 and older).
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

Figure 8. *Cross-Demand Elasticity Estimates*



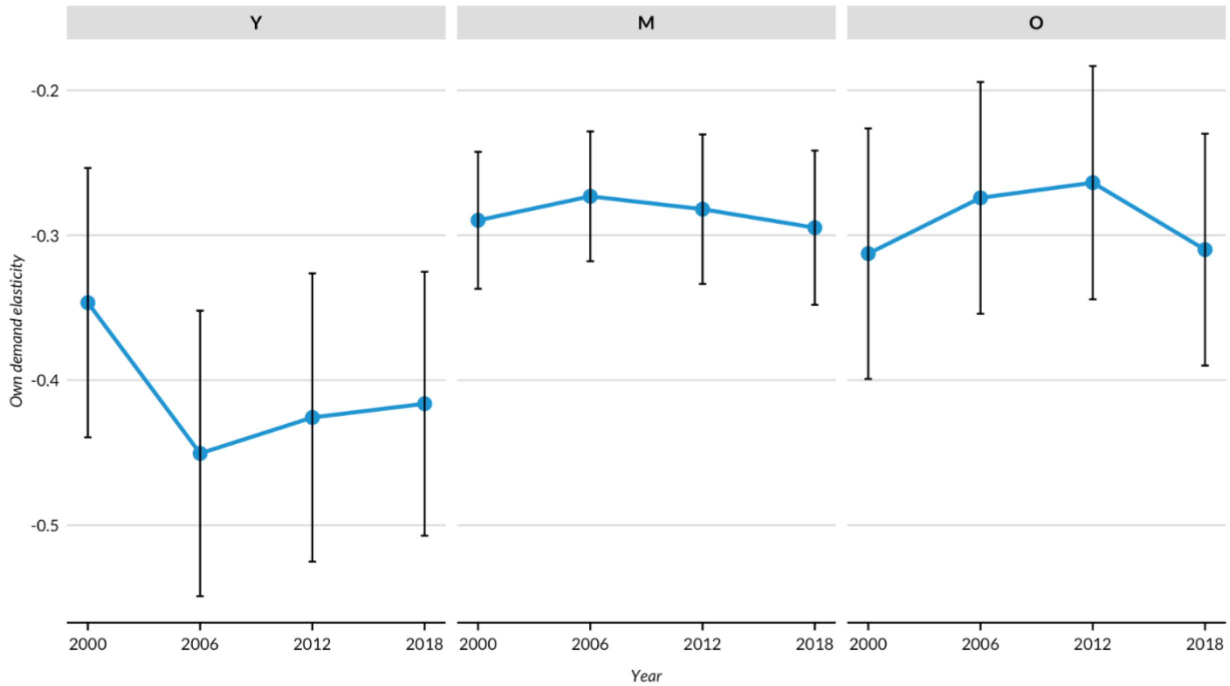
Notes: Elasticities were calculated using equation (4a) and estimated coefficients from equation (2). The estimates were calculated as a weighted mean of sector-specific elasticities. In the two-letter shorthand for elasticities, the first letter is the age group demand changes as a result of an increase in wages of the group represented by the second letter. Standard errors, estimated by the delta method, were used to construct confidence intervals. Y indicates young workers (ages 16 to 34), M indicates mature workers (ages 35 to 54), and O indicates older workers (ages 55 and older).
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

Figure 9. *Own Wage Elasticity Based on the Aggregate Production Function and Sector-Specific Production Functions*



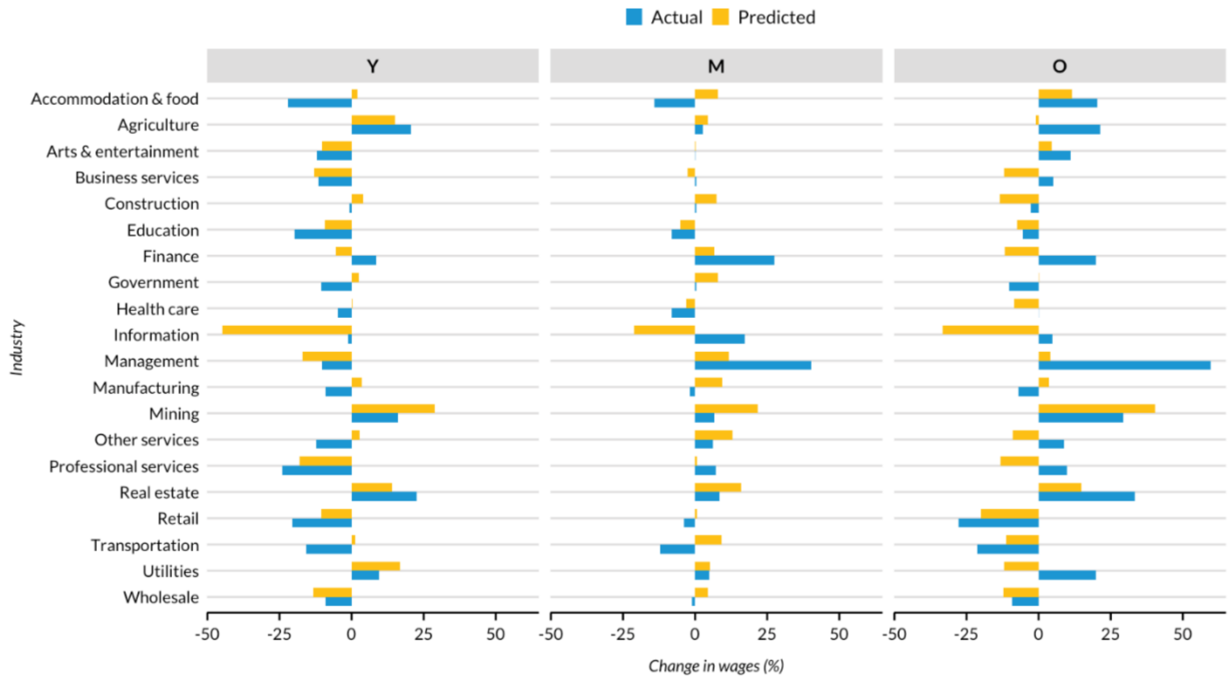
Notes: Elasticities were calculated using equation (3b) and estimated coefficients from equation (1). The aggregate estimates shown in blue were estimated using the aggregate production function. The "by sector" estimates shown in yellow were calculated as a weighted mean of sector-specific elasticities. Standard errors, estimated by the delta method, were used to construct confidence intervals. Y indicates young workers (ages 16 to 34), M indicates mature workers (ages 35 to 54), and O indicates older workers (ages 55 and older).
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

Figure 10. *Own Demand Elasticity Based on Sector-Specific Cost Functions*



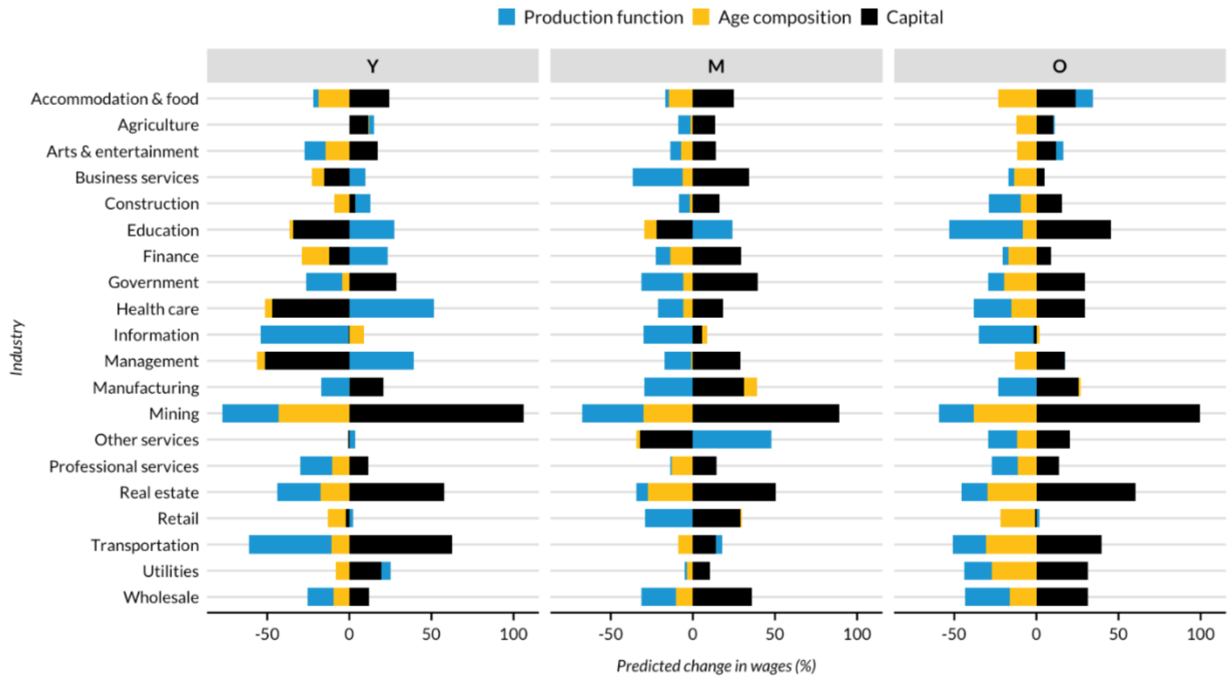
Notes: Elasticities were calculated as a weighted mean of sector-specific elasticities, which were calculated using equation (4b) and estimated coefficients from equation (2). Standard errors, estimated by the delta method, were used to construct confidence intervals. Y indicates young workers (ages 16 to 34), M indicates mature workers (ages 35 to 54), and O indicates older workers (ages 55 and older).
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

Figure 11. *Actual and Predicted Changes in Wages, 2000 to 2018*



Notes: Actual changes are based on hourly wages, which were calculated by dividing total earnings by total employment adjusted for labor quality and hours worked. Percent changes in wages by age and sector were demeaned by subtracting the average percent change in all wages. The predicted changes in wages were estimated using equation (5). Y indicates young workers (ages 16 to 34), M indicates mature workers (ages 35 to 54), and O indicates older workers (ages 55 and older).
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

Figure 12. *Decomposition of Predicted Changes in Earnings, 2000 to 2018*



Notes: The predicted changes in wages were estimated using equation (5). The production function component includes terms $\mathrm{d}\alpha_i$ and $\log X_j\, \mathrm{d}\beta_{ij}$ where *j* represents labor age groups. The age composition component includes terms $\mathrm{d}\log X_j$ where *j* represents labor age groups. The capital component includes all other terms. Y indicates young workers (ages 16 to 34), M indicates mature workers (ages 35 to 54), and O indicates older workers (ages 55 and older).
Source: Authors' computations from Quarterly Workforce Indicators, U.S. Census Bureau (2020).

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