Sorting Into Jobs and Labor Supply and Demand at Older Ages

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Abstract
We document considerable heterogeneity in the fraction of older workers across occupations, and show that this is related to occupational characteristics. For example, occupations that have larger fractions of older workers tend to be less physically demanding and more cognitively demanding. Average workers' characteristics such as cognition and health are strongly correlated with these occupational characteristics, although there is considerable within-occupation heterogeneity. Based on these observations, and a Bartik-type argument, we argue that an increase in the employment share of an occupation with a high fraction of older workers implies an increased demand for older workers. This leads to a prediction that the wages of workers in such occupations may have increased in order to lower retirement rates. Using difference-in-difference methods, we do find evidence for the former, but we do not see a direct relation with retirement. However, an indirect effect through wages is consistent with our results.

JEL: J21, J23, J24, J26
keywords: retirement; occupational characteristics; difference-in-differences

1. Introduction

Prolonging individuals' attachment to the labor force is a top priority on policy makers' agendas in most developed economies. The combination of increasing life expectancy and the large cohort of Baby Boomers starting to retire has cast serious doubts on the medium- and long-term financial sustainability of Social Security programs across countries. Extending working lives promises to reduce the risk of insolvency by guaranteeing a larger inflow of payroll taxes in future years. Because of that, a large literature focusing on the determinants of labor supply decisions at older ages has emerged.

Existing studies find that monetary incentives are among the most important drivers of when to exit the labor force. Specifically, the rules governing Social Security eligibility and generosity (Gruber and Wise, 2004), private pension arrangements (Lumsdaine and Mitchell, 1999), and health insurance considerations (French and Jones, 2011) greatly influence the timing of retirement. In recent work, Angrisani et al. (2015, 2017a, 2017b) find that non-monetary job characteristics are strongly associated with labor force transitions at older ages, even after controlling for a broad set of demographics, health, and measures of financial incentives. Examples of such job attributes are physical and cognitive demands, age discrimination in the workplace, work-related stress, interference between work and personal life, and relationships with co-workers and supervisors. Knowledge of which factors determine labor supply decisions of older workers is critical as it provides policy makers with levers to affect retirement outcomes among older workers.

However, while understanding the role of labor supply shifters is crucial, retirement is the result of an interaction between the workers' preferences and the employers' labor demand as reflected in wages and other monetary and non-monetary job characteristics. A lower retirement rate among workers in some types of occupations compared to workers in other types of occupations may be due to supply factors (differential preferences of workers in the different types of jobs) or demand factors.

In this study, we aim to shed more light on this issue by documenting the sorting of older workers into different types of occupations and employers' responses to changes in labor market conditions, especially the age structure of the workforce. Specifically, we study changes in the composition of the workforce across occupations between 1986 and 2016 and identify which occupations have experienced a relative increase in the fraction of older workers. We check the plausibility of the inertia hypothesis, in which workers stay in their jobs and the aging of the workforce should be more apparent in occupations that have shrunk over time, and find little or no support for it. We construct task intensity job demand indexes and document that occupations where the importance of non-routine analytical and interpersonal skills is higher appear to be more suitable for older than younger workers.

Next, we contrast the average characteristics of older workers in terms of cognitive ability, health, and interpersonal skills with the objective job demands and requirements of the occupations they are employed in. We find a correspondence between these, indicating that individuals may sort into jobs that suit them at younger ages (analogous to Krueger and Schkade, 2008) and remain attached to them at older ages. Along these lines, a factor pushing older workers out of the labor force could be an emerging mismatch between individual abilities and job demands; for example, a health shock for workers in physically demanding occupations (Currie and Madrian, 1999). Additionally, we use a Bartik instrument to predict, for each occupation, the fraction of older workers in 2016 as a function of the fraction of older workers in that occupation in 1986 and the increase in the fraction of older workers in the labor force between 1986 and 2016. We observe that, among declining occupations, those with a higher-than expected increase in the fraction of older workers are characterized by low physical demands and accumulated experience, which may make older workers relatively more attractive. Another typology of declining occupations with increasing shares of older workers is represented by occupations where non-routine physical tasks are important. The fact that these tasks may be relatively difficult to automate (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011) alongside supply shifters that have reduced prime-aged workers in these occupations, may explain why older workers have been retained.

Finally, we examine whether a larger share of older workers in certain occupations is a reflection of a larger demand for older workers, which would be manifested in lower retirement rates (compared to other occupations) and higher wages (compared to younger workers in the same occupations). We do not find evidence of demand effects through lower retirement rates and only weak support for higher relative wages. Although not completely comparable, these results are at odds with those of Neumark and Yen (2018), who investigate the extent to which the relative size of age cohorts affects labor force participation and wages of older workers. These authors document that in recent years the large cohort of Baby Boomers relative to a cohort of prime-aged workers has increased labor force participation of among older workers. In contrast, we observe no significant effects on retirement rates. At the same time, Neumark and Yen (2018) find that older workers' wages have not been affected by the relative size of age cohorts, while we do observe an increase in wages. The explanation put forward by Neumark and Yen (2018) for increasing labor force participation of older workers and no change in wages is that when the older cohort is large relative to the prime-aged cohort, demand for older workers increases. However, since workers have a higher extensive margin supply elasticity, no sizable increase in wages is necessary to keep them attached to the labor force.

The remainder of the paper proceeds as follows. Section 2 provides details about the different sources of data used in this study. Section 3 describes the analytical approach. In section 4, we present and interpret the empirical results. Section 5 concludes.

2. Data

We use three data sources: for comparing wages and occupational distributions by age and over time, we use the version of the Current Population Survey (CPS) provided by IPUMS[1]. The CPS is the main source of information about labor force participation in the U.S., and we use it to study the share of individuals in each occupation, by age and year. The IPUMS CPS harmonizes microdata from the monthly CPS; most importantly for our purposes, it provides occupational classifications that are harmonized over time.[2] IPUMS provides three occupational classifications and we use the one based on the 2010 four digit codes, which merges more straightforwardly to the Occupation Information Network (O*NET) database described below. We compare the combined monthly data for 1986 to the combined monthly data for 2016.

We supplement this with the Health and Retirement Study (HRS; Juster & Suzman, 1995; National Institute on Aging, 2007). The HRS is a panel survey that is the leading source of information in the United States on retirement, health, and the economic, personal, and social situation of individuals over the age of 50. The HRS has been used in numerous studies of labor supply, income, assets, consumption, health, medical expenditures, cognitive decline, and other topics. The HRS includes middle-aged and older workers' perceptions of their work environment and allows us to follow individuals over time. Specifically, because the HRS records the current occupation (albeit at a high level of aggregation), we will be able to study differential rates of retirement by occupation. We primarily use the RAND HRS Longitudinal File 2016, V1 (Bugliari et al., 2019), which is a cleaned and user-friendly file that contains a large subset of the HRS data in a single convenient longitudinal file, and we supplement this with additional variables from the RAND-Enhanced FAT files, which are wave-specific files that contain all other variables we use.

Our third data source is the O*NET database of occupational characteristics, maintained by the U.S. Department of Labor (version 19). It contains about 1,100 detailed occupations and, for each one of them, it measures over 250 distinct characteristics, ranging from physical and cognitive demands to social interaction and use of technology, among others. The assessment is carried out by occupational analysts as well as workers, who indicate the extent to which certain

[1] IPUMS-CPS, University of Minnesota, www.ipums.org.

[2] While the coding is harmonized, the original data used different coding schemes, and thus the harmonization is based on necessarily imperfect crosswalks, which implies that the occupational classification used for 1986 is noisier than the one for 2016.

skills are used or possessed by the workforce in each occupation. Generally, the O*NET provides a distribution of the characteristics for an occupation, for example, mean and standard deviation using all available experts' and workers' assessments. We merge occupation-specific information from the O*NET with both the CPS and HRS using occupational codes. This allows us to study various job tasks and characteristics of the occupations and, therefore, to better identify the types of jobs held by older workers.

3. Methods

We limit ourselves to workers age 18 or older. For the purpose of this study, we define an "older worker" as a worker age 50 or older. When studying occupations that have higher or lower fractions of older workers, we limit ourselves to occupations with at least 100 workers in the CPS data we use. We rely on the CPS sampling weights to estimate population fractions of workers in each occupation and fractions of older workers for each occupation. In our analyses using the HRS, we restrict ourselves to workers age 50-79 and we use the respondent-level sampling weights.

Let N_{jt} be the number of individuals who have occupation j in year t, and let O_{jt} be the number of older individuals who have occupation j in year t. Furthermore, let $N_{\cdot t}$ be the total number of workers in year t (the sum of N_{jt} over all occupations j) and let $O_{\cdot t}$ be the total number of older workers in year t (the sum of O_{jt} over all occupations j). All these are conceptually population-level numbers, although in our empirical work, we will of course replace them with (weighted) sample estimates.

We will study the following key concepts:

- The fraction of older workers in occupation j, $P_j(\text{old} \mid t) = O_{jt}/N_{jt}$.
    a. Terciles Terc_{jt}. We take the list of occupations in year t, sort them according to the fraction of older workers and divide them into three categories, with category 1 having the lowest fractions of older workers and category 3 the highest fractions. In some analyses, we only compare the highest to the lowest tercile and ignore the middle one. It is convenient to think of the first tercile as "young" occupations and the third tercile as "old" occupations.
    b. The fraction of older workers in the labor force, $P(\text{old} \mid t) = O_{\cdot t}/N_{\cdot t}$.
- The fraction of all workers who have occupation j, $P(j \mid t) = N_{jt}/N_{\cdot t}$.
    c. Increase of occupation j, Incr_j. This is a dummy indicating whether $P(j \mid 2016) > P(j \mid 1986)$, that is, whether as a share of all workers, the occupation was more common in 2016 than in 1986.

The idea behind some of our analyses is that, if occupations that were in the highest tercile in 1986 saw an increase of their total share of the workforce in 2016, that is, $\text{Terc}_{j,1986} = 3$ and $\text{Incr}_j = 1$, then the demand for older workers is predicted to increase.

We are interested in changes in the labor force between 1986 and 2016 and one aspect of this is whether the fraction of older workers in an occupation has changed. Because of changing demographics, these fractions would change even in the absence of economic or social forces. That is, we would expect the fraction of older workers in an occupation to increase simply because the fraction of older workers in the total labor force increased (we will show some empirical evidence of this in section 4). Therefore, in some of our analyses, we compare the fraction of older workers in an occupation to a hypothetical baseline scenario, which assumes that the demographics have a uniform proportional effect. Specifically, we compute the predicted fractions of older workers by occupation in 2016 as

$$\hat{P}_j(\text{old} \mid 2016) = P_j(\text{old} \mid 1986) \frac{P(\text{old} \mid 2016)}{P(\text{old} \mid 1986)} .$$

This has the same form as a Bartik instrument (e.g., Goldsmith-Pinkham et al., 2019). Occupations in which $P_j(\text{old} \mid 2016) > \hat{P}_j(\text{old} \mid 2016)$ are occupations with a higher-than expected increase in the fraction of older workers.

We define "retiring" between two consecutive waves in the HRS as working for pay in the earlier wave and not working for pay in the subsequent wave. Thus, this includes some patterns that may not strictly be retirement as well, specifically becoming unemployed or disabled. Becoming unemployed is much less common than staying in the workforce or retiring. For example, Angrisani et al. (2015, Table 1) report that 4% of full time employees become unemployed or out of the labor force (conditional on not becoming disabled), compared to 12% retiring. Moreover, "out of the labor force" includes arguably pseudo-retirement such as becoming a homemaker. Qualitatively, the factors affecting demand for older workers should affect retirement, disability, and unemployment in the same direction. For example, if demand for older workers rises, willingness of employers to accommodate disabled older workers should also increase, and incentives to lay off older workers decrease. Hence, our definition of retirement is still meaningful in the context of this paper. We do not study returning to the workforce after unemployment or retirement ("unretirement"; Maestas, 2010), partly because this is still much less common than retirement and partly because we use occupation in the earlier of the two waves as a regressor, which is undefined in this case. The economic incentives for unretirement mirror those for retirement.

Part of our study is descriptive, establishing stylized facts about the occupations older workers hold. To study sorting into different occupations, we compare occupational characteristics and requirements to individual characteristics to assess their match. To study differential retirement rates by occupation, we regress retirement at the individual level on a set of demographic characteristics, economic incentives, health, cognition, and personality, as well as occupational characteristics and indicators of whether the occupation grew or declined and its tercile in the distribution of fractions of older workers. Our main method of analysis for studying wages is difference-in-differences. That is, we compare changes over time by whether an occupation grew or declined and its tercile in the distribution of fraction of older workers, and we study whether this is differentially so for older workers relative to younger workers.

4. Results

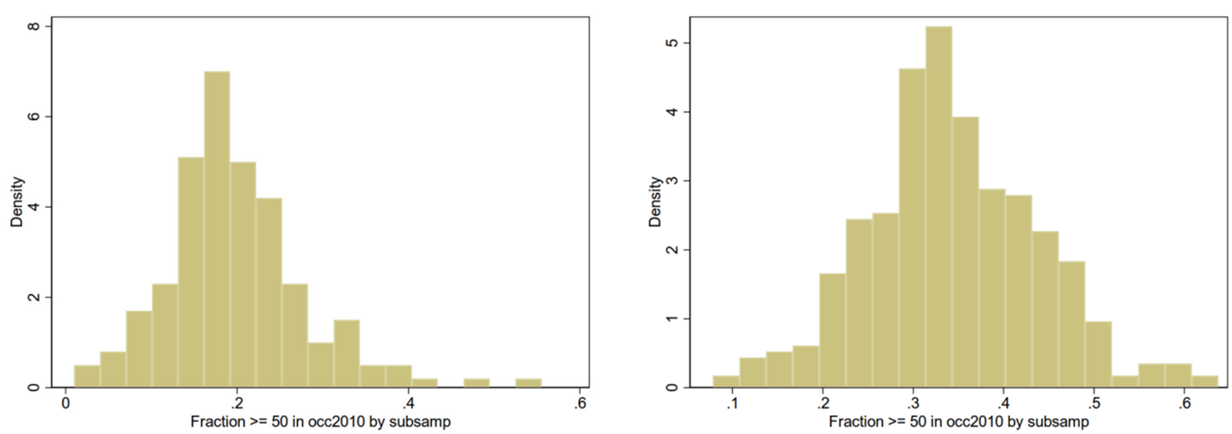
4.1 Heterogeneity in age structure by occupation and vice versa

A basic observation is that older individuals tend to work in different occupations than younger individuals or, correspondingly, that some occupations tend to have more older workers than others. Understanding the differences in occupations that older workers typically work in (McFall et al., 2015; Sonnega et al., 2016) versus occupations younger workers typically work in is the key to understanding differences in labor supply of and labor demand for older workers.

Figure 1, in which the unit of analysis is the occupation and the variable being studied is the fraction of workers age 50+ (i.e., $P_j(\text{old} \mid t)$), shows that there is a large between-occupation variation in the fraction of older workers, both in 1986 and in 2016. The distributions are unimodal and smooth. There is also a noticeable shift to the right in 2016 compared to 1986, which reflects the aging of the workforce.

Figure 1. Distribution of fraction workers age 50+ by occupation in 1986 and 2016.

1986 *2016*



Note: Analysis limited to occupations with at least 100 workers in total.

Table 1 shows the 10 occupations with the highest fractions of older workers and the 10 occupations with the lowest fractions of older workers. Among the occupations with the lowest fractions in 1986, we see lower-level health care occupations and computer programmers. It is not surprising to observe the latter among the "young" occupations in 1986, a time when computer skills were much less common than nowadays. In 2016, we see that occupations that involve serving and assisting customers have relatively low fractions of older workers. In both 1986 and 2016 chief executives and legislators are occupations with a relatively high share of older workers. Also in both years, the highest fractions of older workers are found in traditional crafts occupations. This is a first piece of evidence suggesting occupations with many older workers tend to be declining occupations with little inflow of new workers, which therefore age with their workforce.

Table 1. Occupations with the lowest and highest fractions of workers age 50+

1986		*2016*	
Occupation	Fraction	Occupation	Fraction
	Lowest fractions older workers		
dancers and choreographers	0.010	host and hostesses, restaurant	0.078
dental hygienists	0.026	waiters and waitresses	0.098
law enforcement workers, nec	0.029	residential advisors	0.120
respiratory therapists	0.033	vehicle and mobile equip mechanics	0.126
dental assistants	0.037	helpers, construction trades	0.126
speech language pathologists	0.047	bartenders	0.129
computer programmers	0.052	fence erectors	0.136
announcers	0.054	new account clerks	0.144
physician assistants	0.055	emergency medical tech and paramed	0.146
therapists, nec	0.063	roofers	0.147
	Highest fractions older workers		
precision instr and equipment repair	0.382	tax preparers	0.550
funeral directors	0.391	tool and die makers	0.562
community and social service spec	0.393	chief executives and legislators/publ	0.568
woodworking machine setters, oper	0.399	clergy	0.572
optometrists	0.405	motor vehicle operators, all other	0.592
tailors, dressmakers, and sewers	0.433	bus and ambulance drivers and attend	0.597
farmers, ranchers, and other agric	0.480	tailors, dressmakers, and sewers	0.600
barbers	0.485	agricultural inspectors	0.600
crossing guards	0.552	postal service clerks	0.611
chief executives and legislators/publ	0.555	farmers, ranchers, and other agric	0.637

Note: Analysis limited to occupations with at least 100 workers in total.

To obtain further insights, we divide the occupations in the two different years separately into terciles based on the fraction of older workers in the occupation, as discussed in Section 3 above. Table 2 then looks at the 301 occupations that have at least 100 workers in the CPS in both 1986 and 2016. This shows that there is some relation between the terciles of the 1986 and 2016 distributions, but the relation is far from perfect. For instance, 59 of the 301 occupations are in the bottom one third of the distribution in both years, 49 are in the middle tercile in both years, and 59 are in the top one third of the distribution in both years. Overall, we see that a little more than half (167 out of 301) of the considered occupations lie on the diagonal in Table 2, meaning they are in the same tercile in both years, but 45% (134 out of 301) occupations moved across terciles. The kappa statistic with linear weights (a measure of agreement for tables like these) is 0.4, indicating moderate agreement (Fleiss et al., 2003, p. 604). Thus, while there is some consistency, the age structure by occupation does not appear to be constant over time. Sampling error in the fraction older workers per occupation implies some statistical uncertainty about the classification into terciles, but this is unlikely to fully account for the off-diagonal elements.

Table 2. Number of occupations by terciles of the distributions of fraction older workers in 1986 and 2016

Tercile in 1986	Tercile in 2016: 1	2	3	Total
1	59	30	12	101
2	26	49	30	105
3	13	23	59	95
Total	98	102	101	301

Note: Analysis limited to occupations with at least 100 workers in total in both months.

Table 3. Distribution of aggregated occupational categories among younger and older workers in 1986 and 2016

Aggregated occupational category	1986		2016	
	Age of worker		Age of worker	
	18-49	50+	18-49	50+
Management, business, science, and arts	9.07	13.69	10.21	14.56
Business operations specialists	1.62	1.66	2.64	2.82
Financial specialists	1.90	1.47	2.25	2.53
Computer and mathematical	1.28	0.48	3.46	2.40
Architecture and engineering	2.06	2.29	1.75	1.84
Technicians	0.31	0.28	0.28	0.37
Life, physical, and social science	1.45	1.11	0.93	0.89
Community and social services	0.96	1.24	1.66	1.89
Legal	0.80	0.71	1.10	1.42
Education, training, and library	4.07	4.07	5.62	5.59
Arts, design, entertainment, sports, and media	1.73	1.44	2.09	1.86
Healthcare practitioners and technical	3.78	3.08	5.97	5.87
Healthcare support	1.70	1.54	2.61	1.90
Protective service	1.63	1.69	2.19	1.74
Food preparation and serving	4.45	3.14	6.65	2.87
Building and grounds cleaning and maintenance	3.29	5.66	3.64	4.24
Personal care and service	2.24	2.02	3.91	3.60
Sales and related	11.78	12.54	10.56	10.00
Office and administrative support	16.15	14.81	11.29	12.76
Farming, fishing, and forestry	1.05	1.05	0.76	0.61
Construction	6.00	4.65	5.51	4.46
Extraction	0.18	0.13	0.13	0.08
Installation, maintenance, and repair	4.29	3.89	3.30	3.21
Production	10.73	11.17	5.54	5.93
Transportation and material moving	7.48	6.21	5.95	6.53
Total	100.0	100.0	100.0	100.0

Table 3 shows the distribution of occupational categories by age of the individual. The occupational categories used here are aggregated categories, so that there are 25 categories instead of several hundreds. In this table, the differences for managers do stand out, with older workers substantially more likely to be a manager than younger workers. There are a few other differences that point in the expected direction (e.g., construction workers tend to be younger), but overall it is more striking how similar the distributions are across the age groups. Partly, this may reflect that this (standard) aggregation may not be ideal for our purposes. For example, many of these aggregate categories appear more closely related to industry than to level of occupation within industry. Several of the categories include both supervisor and non-supervisor occupations as subcategories. If workers tend to stay in the same industry, but move up the ranks as they get older, one may expect individuals to move between occupations within the same aggregate category instead of across categories, thus masking differences in the occupations older workers and younger workers have.

4.2 Potential explanations for differences in fractions of older workers

Why would some occupations have more or fewer older workers than others? One explanation might be historical reasons, as alluded to in Section 4.1: If occupation-specific human capital or general inertia reduce movement of workers across occupations, individuals tend to be in occupations for which demand was high when they entered the labor force. Hence, if demand for workers changes over time by occupation – for instance because of automation (Acemoglu and Autor, 2011), outsourcing, or changes in product demand and import competition (Autor, Dorn and Hanson, 2013) – this affects the age structure by occupation. Essentially, this would be a cohort effect rather than an age effect per se, but in any cross-section, this materializes as a difference in the fraction of older workers in the occupation. One implication of this would be that occupations that have shrunk between 1986 and 2016 should have relatively many older workers, whereas occupations that have grown between 1986 and 2016 should have relatively many younger workers. Table 4 shows some evidence for this pattern, indicating that occupations that have become less prevalent over time tend to have higher fractions of older workers in 2016. However, the differences in tercile classifications between the two types of occupations – those that have shrunk and those that grown between 1986 and 2016 – appear too modest to satisfactorily explain the observed age distribution by occupation.

Table 4. Fraction older workers in 2016 by whether occupation has grown or shunk between 1986 and 2016

Change in fraction of workers in occupation	Tercile of fraction older workers in 2016: 1	2	3	Total	Number of occupations
Decrease	25.6	37.5	36.9	100.0	176
Increase	42.4	28.8	28.8	100.0	125
Total	32.6	33.9	33.6	100.0	301

Note. Row-wise percentages based on the number of occupations listed in the last column.

Another way to look at this potential explanation is by thinking of a hypothetical scenario in which younger workers in 1986 do not change occupation and are the older workers in 2016. That is, suppose the occupational distribution of older workers in 2016 equals the occupational distribution of younger workers in 1986, and let the hypothetical occupational distribution of younger workers in 2016 be the residual after subtracting the older workers in 2016 from all workers in 2016. It is easiest to understand this approach by considering the following stylized situation: all workers enter the labor force when they turn 20 and retire when they turn 66, and there is no mortality, immigration, or emigration between these ages. Let O_{jt} be the number of workers age 50-65 in occupation j in year t, and let Y_{jt} be the number of workers age 20-35 in occupation j in year t. The 50-65 year old in 2016 are the 20-35 year old in 1986. Hence, in this scenario, if workers do not change occupation, we would have $O_{j,2016} = Y_{j,1986}$. With N_{jt} the total number of workers in occupation j in year t, the predicted fraction of older workers in occupation j in 2016 in this scenario would be $\tilde{P}_j(\text{old} \mid 2016) = O_{j,2016}/N_{j,2016} = Y_{j,1986}/N_{j,2016}$. In practice, a sizable fraction of workers retire (or otherwise leave the labor force) before age 66, but also a sizable fraction of workers exit the labor force after they turn 66, not everyone enters the labor force at age 20, and there will be immigration and emigration. For this exercise, we ignore these complications, which partially cancel each other out, although probably by no means completely. With this caveat, a strong relation between $\tilde{P}_j(\text{old} \mid 2016)$ as defined in this way and the actual fraction older workers $P_j(\text{old} \mid 2016)$ in the occupation would provide support for the inertia theory, whereas a strong relation between $P_j(\text{old} \mid 2016)$ and $P_j(\text{old} \mid 1986)$ would point at inherent differences between occupations that make occupations more or less suitable for older workers (as discussed below). For easier assessment of the inertia theory, instead of using our earlier definition of "old" as 50+, we look at the age group 50-65 in 2016 here, and compare it to the age groups 20-35 and 50-65 in 1986.

Table 5 shows the results from this exercise. Contrary to the earlier suggestive evidence, it shows no support for the inertia theory. Shrinking occupations have more older workers, but the number of workers in 1986 from the same birth years does not explain this. There is strong support for the hypothesis that some occupations are consistently occupations for older workers. These results do not preclude a modified version of the inertia theory, which would acknowledge that people do change jobs during their working career, but in which transitions to closely related occupations are typical, for example from "police officers and detectives" to "first-line supervisors of police and detectives". Growth or decline of one such occupation may be strongly correlated with the growth or decline of the related occupations, which could explain these patterns. It is difficult to determine empirically what such closely related occupations would be and we have made no attempts to code this up based on our own judgments. However, even if this is part of the story, it is still striking how close to zero the coefficient of the predicted fraction is in Table 5.

Table 5. Regressions of fraction workers age 50-65 by occupation in 2016 on its predicted value and other regressors

Regressor	Formula (j = occupation)	Model (1)	Model (2)	Model (3)
Predicted fraction 50-65	$\tilde{P}_j(\text{50-65} \mid 2016)$	0.009	0.006	0.007
		(0.009)	(0.009)	(0.009)
Fraction 50-65 in 1986	$P_j(\text{50-65} \mid 1986)$		0.560***	0.378***
			(0.073)	(0.111)
Increase	$1[P(j \mid 2016) > P(j \mid 1986)]$		-0.027***	-0.028***
			(0.010)	(0.010)
Fraction 20-35 in 1986	$P_j(\text{20-35} \mid 1986)$			-0.138**
				(0.067)
Constant		0.293***	0.206***	0.304***
		(0.007)	(0.017)	(0.049)
R^2		0.009	0.224	0.234
N		321	321	321

Note. N is the number of occupations. Fractions are computed using sample weights, but regressions at the occupation level are unweighted. Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

As already mentioned, another explanation for the differences in the fraction of older workers by occupation would be that some occupations inherently are more suitable for older workers and others more for younger workers. For example, if a job is physically demanding, it is more suitable for younger workers, as older workers' physical abilities decline. Conversely, if a job requires more experience, older workers are at an advantage. Using the O*NET data, we have created a number of indexes for each occupation. Each index is based on one or (typically) more characteristics in the O*NET data, reflecting characteristics of workers in the occupation, requirements on the workers, or job characteristics. Note that the O*NET data themselves are the same for both years (they were collected in the 2000s, and the implicit assumption we necessarily make is that the characteristics of the detailed occupations themselves have not changed), so any differences across years in the average values of these indexes are due to different occupational distributions.

Table 6 shows the means of these indexes for occupations in the lowest and highest terciles, based on the fraction of older workers. Despite the moderate sample sizes (numbers of occupations with at least 100 workers in the monthly CPS in 1986 and 2016, respectively), many differences are highly statistically significant. Thus there is considerable sorting by age of workers into occupations with different requirements and characteristics. There are a few clear patterns: occupations with many older workers have higher cognitive demands and workers with higher cognitive abilities, lower physical demands and workers with lower physical abilities, and more social interaction and workers with more social skills. Occupations with many older workers also require more experience. However, the sorting by responsibility has decreased.

Table 6. Average worker and job characteristics from the O*NET data, for occupations in the lowest and highest terciles of the fraction workers 50 and over, and *t*-test results for their differences

Characteristic	Highest	Lowest	Diff	p-value	N
			1986		
Worker char: cognition	9.66	8.30	1.35**	0.0489	213
Worker char: psycho-motor ability	3.90	5.62	-1.72**	0.0191	213
Worker char: physical ability	2.37	4.11	-1.73***	0.0087	213
Worker char: eyesight	4.77	5.08	-0.32	0.3057	213
Worker char: sensory-perception	6.76	6.65	0.11	0.7734	213
Worker reqmt: cognition	10.42	8.43	1.99**	0.0194	213
Worker reqmt: social skills	9.58	7.35	2.22***	0.0048	213
Worker reqmt: experience	1.70	0.96	0.73***	0.0087	212
Job char: cognitive demands	13.09	10.91	2.18*	0.0959	213
Job char: physical demands	4.09	5.19	-1.10*	0.0777	213
Job char: working with computer	10.29	9.75	0.53	0.7549	213
Job char: working with equipment	3.53	4.14	-0.61	0.4442	213
Job char: interacting with others	8.65	6.57	2.08**	0.0126	213
Job char: responsibility/lot to say	3.15	2.96	0.19***	0.0095	213
Job char: time pressure	2.53	2.44	0.09	0.1020	213
			2016		
Worker char: cognition	9.93	8.40	1.53***	0.0059	251
Worker char: psycho-motor ability	3.33	4.75	-1.42**	0.0311	251
Worker char: physical ability	1.83	3.76	-1.94***	0.0002	251
Worker char: eyesight	4.80	4.54	0.26	0.4769	251
Worker char: sensory-perception	6.82	6.34	0.48*	0.0816	251
Worker reqmt: cognition	10.83	8.72	2.11***	0.0034	251
Worker reqmt: social skills	9.71	8.33	1.38*	0.0525	251
Worker reqmt: experience	1.67	0.97	0.70***	0.0021	249
Job char: cognitive demands	13.44	10.89	2.55***	0.0083	251
Job char: physical demands	3.56	4.86	-1.30***	0.0061	251
Job char: working with computer	11.56	9.48	2.08	0.1287	251
Job char: working with equipment	2.82	3.48	-0.66	0.2420	251
Job char: interacting with others	8.78	7.27	1.51**	0.0166	251
Job char: responsibility/lot to say	3.09	3.00	0.09	0.1731	251
Job char: time pressure	2.51	2.47	0.04	0.5092	251

Note. N is the number of occupations. Results are weighted by the estimated number of workers in the occupation. Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Most of these patterns point at the explanation that some occupations inherently are more suitable for older workers and others more for younger workers. However, cognition and cognitive demand seems to be an exception. Most cognitive abilities decline at older ages (although more so after typical retirement ages) and based on this alone, we would not expect older workers to sort into occupations with higher cognitive demands. One potential explanation would be that these happen to be occupations for which there was high demand when individuals who were over 50 in 2016 were at the beginning of their careers, say 1986, but the results from Table 5 do not point in that direction. Another potential explanation is comparative advantages of younger workers in the physical domain combined with a negative correlation between physical demands and cognitive demands. The correlation between physical demand and cognitive demand is -0.26, so this could explain part of this. A third explanation would be that to a certain degree experience can substitute for cognitive ability. The correlation between required experience and cognitive demand is 0.51 (and between required experience and physical demand is -0.07), which does suggest that the higher cognitive demand of occupations with many older workers is partly related to experience.

We repeat the same exercise as above, aggregating job demands/requirements according to the indexes proposed by Acemoglu and Autor (2011). Specifically, we create indexes for non-routine analytical skills (analyzing data/information, thinking creatively, interpreting information for others), non-routine interpersonal skills (establishing and maintaining personal relationships; guiding, directing and motivating subordinates; coaching/developing others), routine cognitive skills (repeating the same tasks, being exact or accurate, share of unstructured versus structured work), routine manual skills (pace determined by speed of equipment, controlling machines and processes, spending time making repetitive motions), non-routine physical adaptability (operating vehicles, mechanized devices, or equipment; spending time using hands to handle, control or feel objects/tools; manual dexterity; spatial orientation), and non-routine interpersonal adaptability (social perceptiveness). The results of this exercise, reported in Table 7, confirm the patterns observed above. In particular, they emphasize that occupations requiring manual skills are more suitable for younger workers. This is apparent in both 1986 and 2016, especially for occupations where non-routine manual skills, which are presumably more difficult to automate, are more important. While differences between occupations with the highest and lowest fractions of older workers are not always statistically significant, there is evidence that occupations with an older workforce in both time periods tend to have higher non-routine type of demands. Specifically, in occupations with a higher fraction of older workers, non-routine interpersonal skills and adaptability are relatively more important.

Table 7. Average skills (after Acemoglu and Autor, 2011) from the O*NET data, for occupations in the lowest and highest terciles of the fraction workers 50 and over, and *t*-test results for their differences

Characteristic	Highest	Lowest	Diff	p-value	N
			1986		
Non-routine analytical skills	9.68	8.86	0.82	0.1536	213
Non-routine interpersonal skills	9.94	8.63	1.32***	0.0051	213
Routine cognitive skills	9.13	9.74	-0.60***	0.0079	213
Routine manual skills	7.25	8.06	-0.81	0.1115	213
Non-routine physical adaptability	8.96	10.61	-1.65**	0.0226	213
Non-routine interpersonal adaptability	3.25	3.04	0.21**	0.0430	213
			2016		
Non-routine analytical skills	9.83	9.02	0.80*	0.0693	251
Non-routine interpersonal skills	9.69	9.14	0.55	0.1611	251
Routine cognitive skills	9.20	9.47	-0.27	0.1668	251
Routine manual skills	6.74	7.78	-1.04***	0.0056	251
Non-routine physical adaptability	8.54	10.10	-1.57**	0.0212	251
Non-routine interpersonal adaptability	3.33	3.18	0.14	0.1090	251

Note. N is the number of occupations. Results are weighted by the estimated number of workers in the occupation. Robust standard errors in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

4.3 Match, mismatch, and sorting

The indexes from the O*NET tell us about average worker characteristics by occupation, average worker requirements, and job characteristics. Some of these are related, especially in the cognitive, physical, and social domains. Hence, if the labor market functions efficiently, we would expect the related indexes to tell the same story, and this is indeed what we see: the correlations (at the occupational level used for our CPS analyses) between workers' average cognition and required cognition is 0.98 and the correlations of these with cognitive demands of the job are in the 0.85-0.90 range (depending on year). Analogously, the correlation between physical ability and physical demands is above 0.90. However, these numbers were derived from interviewing experts and workers across all ages, and one could hypothesize that these matches may be weaker for older workers if they sorted into their jobs based on their characteristics many years prior and stayed in their jobs even if their characteristics changed.

We examine the extent to which there is match/mismatch between jobs' attributes and workers' characteristics in the HRS, which has much richer individual-level data than the CPS. A limitation of the HRS is that its public release version only provides occupation in highly aggregate form, based on the CPS detailed occupation codes. Thus, before carrying out the analysis described below, we first aggregate the occupation classification in the IPUMS-CPS to the same categories as used in the HRS.[3] At this more aggregate level, the correlations between the average characteristics from the O*NET (computed as above) are a little higher than at the more detailed level, with the correlation between cognitive demand and cognition and required cognition now being over 0.90 and the correlation between physical demand and physical ability being 0.96.

In the HRS data, we consider related variables at the individual level: a measure of cognition, a measure of physical ability, and a measure of social skills. For cognition, we focus on total word recall, which is a memory measure. The interviewer reads 10 common words to the respondent, and the respondent is then asked to repeat them (in any order) immediately after the list was finished, and again about five minutes later. The total word recall score is the number out of these that the respondent correctly mentioned, and thus it varies from 0 to 20.[4] For physical ability, we consider the standard five point self-reported health variable (1=excellent, ..., 5=poor), and for social skills, we use an extraversion measure from the Big 5 personality test administered every other wave since 2006 in the paper and pencil leave behind questionnaire, which we interpolate for intermediate waves.[5] In addition to these variables, we also consider the job tenure variable as a proxy for experience.

The variation in these individual-level measures can be decomposed into within-occupation variation and between-occupation variation. The latter can then be correlated with the O*NET measures. Table 8 reports the results from the first decomposition. It shows that only 2-8% of the variation can be explained by the occupation dummies. In other words, there is a large amount of within-occupation heterogeneity. Part of this is because the occupations themselves are aggregated from the more detailed CPS coding, thus masking between-occupation variation in the detailed occupations that are combined in the HRS coding. We suspect that this will explain only a limited amount of the within-occupation variation in the table, but we have no empirical evidence about this. Another reason for the relatively low predictive power is likely that the variables themselves are highly imperfect proxies for the relevant concepts, and thus measurement error depresses the explanatory power in this table. For example, when we use the 27-point total cognition score instead of the word recall score, the R^2 goes up to 0.13, suggesting that this may more closely approximate the concept covered by the cognitive requirement variable in the O*NET data. However, total cognition is only available for a selective subset with 6,540 observations, which makes comparisons more difficult.

[3] The Census/CPS coding schemes are updated after each decennial Census, and HRS accordingly updates its schemes. We use the HRS 2010 coding scheme as used in the RAND HRS variable RwJCOCCC, which is available for most respondents in the 2010-2016 waves.

[4] Similar results are obtained when using a total cognition variable that includes additional components (the serial 7s subtraction task and backward counting from 20 to 10), but this is only available for a subset of respondents.

[5] For observations in which the measure is only available in one adjacent wave, we simply copy the value from that adjacent wave.

Table 8. Fraction of the variation in individual-level variables explained by a full set of occupation dummies (HRS, 2010-2016).

Variable	R^2	N
Total word recall	0.0808	15,141
Self-reported health	0.0466	23,355
Extraversion	0.0216	17,597
Job tenure	0.0403	23,061

Shifting focus now to the second part of the comparison, we compute the correlations between the occupation-level averages of the individual-level variables in the HRS and the related occupation-level O*NET variables. Table 9 reports the results. This shows moderate to high, but not perfect, correlations. Taking into account that the HRS variables may measure related dimensions that do not perfectly coincide with the O*NET concepts, we may conclude that there is not much evidence for systematic mismatch. On the other hand, the less than perfect correlations may also indicate a greater scope for mismatch among older workers than in the population as a whole, when the O*NET worker characteristics variable is interpreted as an average for the population as a whole. Furthermore, these correlations indicate relative differences within the population of older workers, which do not address whether absolute levels are sufficient. For example, it says that older workers in occupations with higher physical demands have higher physical ability than older workers in occupations with lower physical demands, but it does not say whether the physical abilities of the former are typically good enough for their occupations. Along these lines, selection mechanisms, by which individuals sort into jobs that suit them at younger ages and only the fittest remain in those jobs at older ages, may also push these correlations upward.

Table 9. Occupation-level correlations of averages of individual-level variables in the HRS (2010-2016) and corresponding occupation-level characteristics in the O*NET.

O*NET Variable	HRS variable			
	Total word recall	Self-reported health	Extraversion	Job tenure
Worker char: cognition	0.78			
Worker reqmt: cognition	0.83			
Job char: cognitive demands	0.67			
Worker char: physical ability		0.72		
Job char: physical demands		0.69		
Worker reqmt: social skills			0.51	
Job char: interacting with others			0.35	
Worker reqmt: experience				0.86

Note. N=22 occupations; results weighted by sum of respondent-level sampling weights.

4.4 Differential changes in the labor market by fraction older workers

In Figure 1, we saw that overall, the fraction of older workers in the labor force has increased between 1986 and 2016. The main reason for this is demographic change, and thus this constitutes an increase in labor supply of older workers, in the sense of the number of older workers relative to the number of younger workers, not necessarily in the sense of the number of employed individuals among older individuals. Here, we intend to understand the economic forces behind increased or decreased labor force participation of older individuals, that is, the fraction of older workers who are still working instead of being retired or otherwise out of the labor force. Specifically, we study changes in the labor market that may indicate changes in labor demand for older workers.

Earlier, we studied the fraction of older workers by occupation and found evidence that some occupations are more typical "older worker" occupations and others more typical "younger worker" occupations. Moreover, in section 4.2, we computed whether the share in total employment of an occupation as a whole increased or decreased (irrespective of the age of the workers in the occupation). Suppose the share of an older worker occupation has increased, then this would suggest that the demand for older workers has increased as well, whereas if an older worker occupation has shrunk, the demand for older workers likely decreased as well. Table 10 shows how many occupations fit each of these scenarios.

Table 10. Overall change in occupation by tercile of fraction older workers in 1986

Tercile of fraction older workers in 1986	Overall change of occupation			Number of occupations
	Decrease	Increase	Total	
1	60.0	40.0	100.0	110
2	62.7	37.3	100.0	110
3	63.6	36.4	100.0	110
Not defined (<100 obs)	5.8	94.2	100.0	121
Total	47.0	53.0	100.0	451

Note. Row-wise percentages based on the number of occupations listed in the last column.

Among the occupations in the lowest, middle, and highest terciles of the distribution of fraction of older workers in 1986, 36-40 percent was held by a higher fraction of (all) workers in 2016 than in 1986. That is, most occupations that were held by at least 100 individuals in 1986 declined. In contrast, 94% of occupations with fewer than 100 observations in 1986 increased. We can view these as "emerging occupations". Because the 36-40 percent range is relatively narrow, there is no indication of a substantial net increase in the demand for older workers. However, it also shows that the demand for some older workers (those in the occupations that increased their market share) likely increased and the demand for other older workers (those in the occupations that decreased their market share) likely decreased.

An example of a declining occupation is "secretaries and administrative assistants". In 1986, 3.8% of workers had this occupation, whereas in 2016, this had decreased to 1.8%. An example of an increasing occupation is "retail salespersons", which went from 1.2% to 2.2%, and an example of an emerging occupation is "personal care aides", which had no observations in the CPS in 1986, but made up 0.9% of the labor market in 2016. In 1986, 19% of the secretaries and 22% of retail salespersons were 50 or older, which puts both of them in tercile 2. An example of an occupation in tercile 3 is "management analysts" with 29% older workers in 1986, which has increased as a share of the total workforce between 1986 and 2016. An example of an occupation in tercile 1 is "computer operators", with 10% older workers in 1986, which has declined as a share of the total workforce between 1986 and 2016.

Of particular interest are declining occupations in which the fraction older workers is higher than predicted. As discussed in section 3, we can compute the predicted fraction of older workers in an occupation in 2016 $\hat{P}_j(\text{old} \mid 2016)$ as the fraction of older workers in that same occupation in 1986, multiplied by a uniform scale factor that accounts for the overall growth of the number of older workers. Table 11 lists all occupations (with at least 100 observations in 1986) in which the actual fraction of older workers in 2016 is at least 15 percentage points higher than predicted, while the occupation declined overall.

Table 11. Declining occupations with a higher than predicted fraction of older workers in 2016

Occupation	N		Percent in occ		Percent older workers		
	1986	2016	1986	2016	1986	2016	Pred 2016
etchers, engravers, and lithographers	371	29	0.049	0.004	22.7	77.7	37.8
flight attendants and transp workers	435	535	0.056	0.083	6.7	45.5	11.2
postal service clerks	2,137	584	0.278	0.079	18.3	61.1	30.5
forest and conservation workers	169	127	0.023	0.014	11.2	47.4	18.7
dental hygienists	463	792	0.056	0.110	2.6	31.5	4.3
respiratory therapists	480	455	0.066	0.056	3.3	32.7	5.5
computer operators	6,075	389	0.839	0.060	10.1	43.0	16.8
meter readers, utilities	298	152	0.037	0.021	14.0	48.9	23.4
buyers and purchasing agents, farm pr	120	71	0.013	0.007	23.4	63.7	39.0
insurance underwriters	486	461	0.067	0.070	9.2	38.4	15.3
cabinetmakers and bench carpenters	403	297	0.055	0.038	15.2	48.0	25.3
computer programmers	3,821	2,039	0.516	0.315	5.2	31.0	8.7
opticians, dispensing	403	275	0.056	0.037	14.2	45.6	23.6
speech language pathologists	443	789	0.053	0.103	4.7	29.2	7.8
adhesive bonding machine operators	260	48	0.033	0.007	19.0	52.4	31.7
announcers	422	274	0.052	0.038	5.4	29.3	9.0
prepress technicians and workers	576	98	0.075	0.015	15.9	46.6	26.6
plating+coating mach, metal and plastic	218	110	0.032	0.013	18.8	51.1	31.3
baggage porters, bellhops, concierges	210	281	0.029	0.045	9.6	35.1	16.0
paralegals and legal assistants	1,274	2,028	0.165	0.291	9.4	34.6	15.6
paper goods machine operators	171	154	0.022	0.022	17.7	48.3	29.4
law enforcement workers, nec	311	718	0.041	0.102	2.9	23.2	4.9
jewelers and precious stone and metal	389	191	0.045	0.026	19.9	51.1	33.2
textile knitting and weaving machine	377	64	0.049	0.009	15.4	43.4	25.6
secretaries and admin assistants	29,501	13,657	3.787	1.840	19.0	49.0	31.7
physical therapists	412	1,390	0.049	0.191	6.9	28.5	11.4
word processors and typists	6,309	383	0.835	0.055	16.1	43.5	26.9
elevator installers and repairers	148	199	0.020	0.030	11.5	35.9	19.2
clinical lab technologists and technician	2,049	1,690	0.267	0.243	9.8	32.3	16.3
computer and office machine repairers	874	961	0.124	0.142	8.1	29.4	13.4
conservation scientists and foresters	272	188	0.029	0.021	11.0	34.3	18.3
lathe+turn mach tool, metal and plastic	599	57	0.082	0.009	17.0	44.0	28.3
environmental scientists and geosci	359	487	0.046	0.060	18.0	45.4	30.0

Looking at this list of occupations, it appears that many of them are manufacturing occupations, so the decline of these occupations corresponds with the decline of manufacturing jobs in general. The actual fractions of older workers among computer programmers and operators are substantially larger than the predicted ones, which seems to be in line with the results in Table 6. This may indicate complementarities between older workers' skills and use of computer/new technologies. While this may be counterintuitive at first sight, it may be related to accumulated experience and low physical demands. To partly support this hypothesis, we observe that in all these occupations the importance of routine manual skills, which in Table 7 are strongly associated with a younger workforce in 2016, is very low. There exist big differences for postal service clerks and forest/conservation workers, with the actual fractions of older workers significantly above the predicted ones. These may be occupations where supply shifters may imply relative scarcity of prime-aged versus older workers, which, in turn, may induce firms to retain an older workforce. Coherent with the results in Table 7, these are also occupations with relatively high importance of non-routine physical adaptability, which reduces the impact of automation (Acemoglu and Autor, 2011).

4.5 Difference-in-difference analyses for wages

Wages are the primary characteristic under employers' control to incentivize workers to stay on the job. If demand has increased, we should see this reflected in increased wages relative to occupations where demand did not increase. Increased demand for older workers would imply that wages increase more for older workers, relative to younger workers. Table 12 presents the results of difference-in-difference analyses investigating this. The dependent variable in these regressions is log hourly wage, but similar results are obtained using log weekly earnings, or hourly wage or earnings in levels. We created an "increased demand" for older workers dummy that is 1 for individuals in occupations that have increased between 1986 and 2016 and were in the highest tercile of the fraction of older workers in 1986.

Models 1 and 2 restrict attention to workers age 50-79 in 1986 and 2016, with the first model only including a few occupation-year level dummy variables and the second adding a full set of age dummies. The key variable of interest here is the interaction between the year 2016 dummy and the "increased demand" dummy. This is statistically significant at the 1% level and its coefficient suggests that the wages in "increased demand" occupations have grown about 9% more than in other occupations. This finding would be consistent with scarcity of prime-aged (25-49) workers relative to older workers, which could stem from relative cohort size and/or supply shifters across cohorts. In this scenario, firms that provide certain occupations may have an incentive to retain or hire older workers and, higher demand would translate in higher wages for older workers. However, this result is at odds with that of Neumark and Yen (2018), who study whether the larger size of older workers cohort relative to prime-aged cohort has had any effect on older workers' wages and find no evidence of that. They speculate that this may be due to a higher extensive margin supply elasticity of older workers. That is, no sizable increase in wages would be necessary to keep them attached to the labor force.

Models 3 and 4 include workers age 18-79 and are triple difference models to study the effects of increased demand on wages by comparing wages of individuals age 50+ in "increased demand" occupations with wages of younger individuals in those same occupations, individuals in non-increased demand occupations, and between 1986 and 2016. The key variable of interest here is the triple interaction between the year 2016 dummy, the "increased demand" dummy, and the dummy for whether the individual is 50+. This is statistically significant only at the 10% level, but it does have the expected sign and a nonnegligible coefficient. So there is weak evidence that older workers' wages have increased more than younger workers' wages in the same occupations.

Table 12. Difference-in-difference analyses of log hourly wage

Regressor	Ages 50-79		Ages 18-79	
	(1)	(2)	(3)	(4)
Year 2016	0.870***	0.879***	0.778***	0.755***
	(0.006)	(0.006)	(0.003)	(0.003)
Increased demand	-0.002	0.020	0.081***	0.059***
	(0.019)	(0.019)	(0.010)	(0.010)
2016 × incr.dem	0.092***	0.083***	0.040***	0.039***
	(0.023)	(0.023)	(0.014)	(0.013)
Age 50+			0.089***	0.399***
			(0.005)	(0.052)
Age 50+ × 2016			0.092***	0.123***
			(0.007)	(0.006)
Age 50+ × Incr.dem			-0.083***	-0.039*
			(0.022)	(0.021)
Age 50+ × 2016 × Incr.dem			0.051*	0.044*
			(0.027)	(0.026)
Age dummies	N	Y	N	Y
R^2	0.399	0.410	0.419	0.489
N	41,443	41,443	175,395	175,395

Note. Weighted regressions. Robust standard errors in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

4.6 Retirement rates by occupation

If there is a large demand for workers in occupations that are typically held by older workers, and by implication a large demand for older workers, then employers will try harder to keep older workers on the job, and we should see lower retirement rates. We study retirement in the HRS data. Table 13 shows the fraction of all workers in each occupational category and the fraction of workers 50 or over in each category, for the HRS occupational classification (but computed in the IPUMS-CPS). Although the variation among the categories is considerably less than among the detailed occupations discussed above, there are still noticeable differences in this classification scheme: Some occupations are more common than others, some have declined whereas others have surged, and the fraction of workers per occupation who are 50 or older also varies. Moreover, the latter fraction has increased for most occupations, consistent with the aging workforce as illustrated in Figure 1 above, but this increase differs across occupational categories, both in relative and in absolute terms. The differences between actual and predicted fractions of older workers in this table, although not always negligible, are also much smaller than in Table 11 (which, among others, selected on large differences), which can also be explained by the aggregation of the occupational categories.

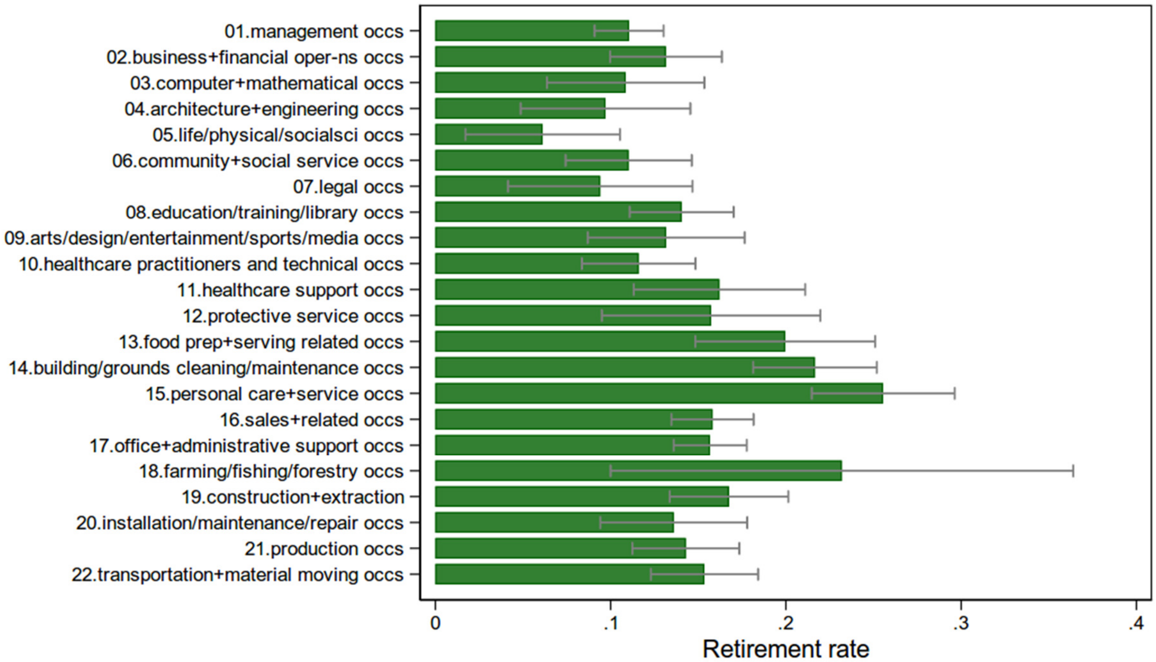
Table 13. Occupational distribution and fraction older workers using HRS 2010 coding

Occupational category (HRS 2010 coding)	N		Percent in occ[a]		Percent older workers[b]		
	1986	2016	1986	2016	1986	2016	Pred 2016
Management, business, science, arts	78,965	84,461	10.0	11.7	27.8	42.2	46.3
Business operations & fin. specialists	25,823	35,032	3.4	5.0	18.5	35.8	30.8
Computer and mathematical	8,251	20,274	1.1	3.1	8.8	26.2	14.6
Architecture and engineering; techn.	17,604	14,442	2.4	2.1	21.6	35.8	35.9
Life, physical, and social science	10,506	6,875	1.4	0.9	16.3	33.1	27.2
Community and social services	7,925	12,758	1.0	1.7	24.8	36.8	41.3
Legal	6,248	9,184	0.8	1.2	18.3	39.7	30.6
Education, training, and library	32,004	40,941	4.1	5.6	20.3	33.7	33.8
Arts, design, entertain, sports, media	12,618	14,050	1.7	2.0	17.5	31.3	29.2
Healthcare practitioners and tech	28,255	42,543	3.6	5.9	17.2	33.5	28.7
Healthcare support	12,649	16,175	1.7	2.4	18.7	27.1	31.2
Protective service	12,286	13,743	1.6	2.0	20.8	28.9	34.8
Food preparation and serving	32,332	36,196	4.2	5.4	15.2	18.1	25.4
Building/grounds cleaning and maint	28,168	26,460	3.8	3.8	30.5	37.3	50.8
Personal care and service	17,373	26,198	2.2	3.8	18.7	32.0	31.1
Sales and related	90,227	70,975	11.9	10.4	21.3	32.6	35.5
Office and administrative support	120,768	83,054	15.9	11.8	18.9	36.6	31.6
Farming, fishing, and forestry	8,513	5,535	1.1	0.7	20.3	29.2	33.9
Construction; extraction	43,824	37,069	5.9	5.3	16.4	29.2	27.4
Installation, maintenance, and repair	31,332	23,161	4.2	3.3	18.8	33.3	31.3
Production	79,339	39,036	10.8	5.7	21.0	35.4	34.9
Transportation and material moving	52,835	41,689	7.2	6.1	17.5	36.0	29.1

Notes. Data are from the IPUMS-CPS with occupations recoded using HRS 2010 coding.
[a]Percent of all workers who have this occupation.
[b]Percent of workers in this occupation who are 50 years old or older.

Figure 2 shows retirement rates across occupations. The lowest retirement rates are observed in "life, physical, and social science," "architecture, engineering," "legal," "computer/mathematics" and "management, business, science, arts." The last three are occupational categories that grew over time as a share of the workforce, which suggests increased labor demand in these categories. Hence, these fit with our theoretical predictions. The first two mentioned categories, however, declined, especially the scientists. Based on anecdotal observation, the explanation for their lower retirement rates that comes to mind would be preference-based, with academics preferring to stay working, much more than workers in other occupations. More empirically based, the lower retirement rates in all these five occupations can be explained by the type of job demands that they entail. In all these cases, we compute very high indexes for non-routine analytical and interpersonal skills, and very low levels of physical demands, which are typically associated with earlier exits from the labor force.

Figure 2. Retirement rates (between waves; approx. two years) by occupation



Note. Health and Retirement Study, 2010-2016; "retirement" as defined in section 3; workers age 50-79.

We have run logit regressions for the probability that a worker retires between two consecutive HRS waves (roughly, a two-year period) as a function of the "increased demand" dummy introduced in section 4.5 (but recomputed for the aggregate occupation classification of the HRS). Table 14 shows weak evidence that this indicator is associated with retirement between the current and next wave in the HRS 2010-2014: the coefficient in the bivariate Model 1 has the expected sign, but is far from statistically significant. Including a complete set of age dummies in these regressions (Model 2) increases the size of the coefficient but not its standard error, and it becomes significant at the 10% level. In Models 3-5, we ran these regressions with a large set of individual-level controls as in Angrisani et al. (2015): demographics (age, sex, couple status, spousal age difference), education (four categories), economic incentives (dummies for reaching age 62 and 65, whether spouse works, log hourly wage, whether enrolled in DB or DC pension or both, health insurance coverage through own or spouse's employer), whether in poor health, cognition (low word recall score, low serial 7s score), personality (Big Five), plus the occupational characteristics from Tables 6 and 7. Again, there is no evidence that the "increased demand" indicator is directly related to retirement. However, higher wages are strongly related to reduced retirement, so the combination of the effect of increased demand on higher wages from section 4.5 and the effect of log wage on retirement in this table is a pathway through which increased demand may affect reduced retirement rates. However, this would rely on strong assumptions without (quasi-)experimental evidence on these mechanisms and therefore should only be viewed as a tentative possibility based on the empirical evidence presented here.

Table 14. Relation between retirement and characteristics of the occupation and the worker (coefficients from logits)

Regressor	Model				
	(1)	(2)	(3)	(4)	(5)
Increased demand for older workers	-0.101	-0.141*	0.005	-0.008	-0.009
	(0.074)	(0.075)	(0.114)	(0.123)	(0.160)
Job char: cognitive demands			-0.032		-0.020
			(0.040)		(0.084)
Job char: physical demands			0.003		0.453
			(0.100)		(0.309)
Job char: working with computer			0.018		0.039
			(0.024)		(0.034)
Job char: working with equipment			-0.012		-0.033
			(0.031)		(0.037)
Job char: interacting with others			-0.069		-0.101
			(0.083)		(0.179)
Job char: responsibility/lot to say			0.883**		0.789
			(0.423)		(0.722)
Job char: time pressure			-0.640		-0.087
			(0.632)		(0.826)
Non-routine analytical skills				-0.014	-0.035
				(0.061)	(0.200)
Non-routine interpersonal skills				-0.098	-0.033
				(0.103)	(0.202)
Routine cognitive skills				-0.080	0.023
				(0.088)	(0.130)
Routine manual skills				-0.008	-0.205
				(0.082)	(0.162)
Non-routine physical adaptability				0.025	-0.236*
				(0.040)	(0.142)
Non-routine interpersonal adaptability				0.131	-0.348
				(0.276)	(0.391)
ln(hourly wage)			-0.113***	-0.112***	-0.116***
			(0.039)	(0.039)	(0.039)
Age dummies	N	Y	N	N	N
Other individual covariates	N	N	Y	Y	Y
Pseudo-R^2	0.000	0.050	0.079	0.077	0.079
Observations (individual-wave)	14,238	14,238	9,617	9,617	9,617
Individuals	6,573	6,573	4,754	4,754	4,754

Note. Weighted regressions. Standard errors clustered at the individual level in parentheses. Individual covariates as discussed in the text.

* p<0.10, ** p<0.05, *** p<0.01

5. Discussion

We have studied patterns in the labor market related to retirement through occupational differences. Some occupations have large fractions of older workers (defined as age 50+ in this paper), whereas others almost entirely consist of younger workers. These differences partially persist over time, although there is some movement in the rank ordering of occupations based on the fraction of older workers. The fraction of older workers is related to occupational characteristics. For example, occupations that have larger fractions of older workers tend to be less physically demanding and more cognitively demanding. This evidence suggests that there are occupations that are specifically suitable for older workers and others that are not. However, there is a considerable amount of variation within occupations, with a full set of occupation dummies explaining less than 10% of the variance of individual characteristics such as cognition and health.

Many of the occupations that have high fractions of older workers are declining occupations. One potential explanation for the differences in the fractions of older workers by occupation could be that individuals enter an occupation that is growing when they are in the initial stages of their career, and then stay in the occupation (we call this the inertia theory). This could explain larger fractions of older workers in declining occupations. However, we have calculated the predicted fractions of older workers in 2016 under this assumption, using 1986 as a baseline, and found the predicted fractions are uncorrelated with the actual fractions in 2016.

Based on these observations, we argue that an increase in the number of workers in an occupation (as a fraction of the total workforce) implies an increased demand for older workers if the occupation tends to have a higher fraction of older workers. This follows from a scenario in which the predicted number of older workers in an occupation in 2016 depends on the fraction of older workers in the same occupation in 1986 and the fraction of all workers in the occupation in 2016. This predicted number has the same form as a Bartik instrument. We also compute a simpler "increased demand for older workers" dummy that is 1 if the occupation as a whole increased between 1986 and 2016 and the occupation was in the upper tercile of occupations in 1986 with respect to the fraction of older workers, and 0 otherwise.

The theory predicts that the wages of workers in such "increased demand" occupations may have increased in order to lower retirement rates. Using difference-in-difference methods, we do indeed find evidence for this. We also estimated logit models for retirement as a function of this "increased demand" indicator, in which we do not see a direct relation with retirement. However, an indirect effect through wages is consistent with our results.

The demand for workers is largely the result of the demand for the products or services an organization offers. This is reflected more by industry than by occupation. Shifts in the demand for the products or services induce shifts in the demand for workers and these shifts are plausibly larger than shifts in workers' preferences and by occupation. Hence, a promising avenue for future research is to repeat the analyses in this paper but with industry instead of occupation. This would also allow one to test a broader version of the inertia theory, in which workers stay in the same industry, but possibly move up the ranks in occupations within the industry.

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