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Abstract

The fraction of workers who are self-employed increases with age, but the types of self-employment that older workers do and the effects of this work on their well-being is not well understood. This project examines such heterogeneity by considering how differing investment and managerial responsibilities in self-employment contribute to disparities in characteristics and measures of economic, physical, and mental well-being. The paper first uses internal narrative descriptions of industry and occupation in the 1994 to 2018 Health and Retirement Study and machine learning methods to classify self-employment reports into a useful framework of self-employment roles. The project then uses these roles to examine self-employment heterogeneity and finds substantial differences in demographic characteristics, work characteristics, income, benefits, quality of life, and retirement expectations across self-employment roles. Further work finds distinctive patterns in role changes with the transition to retirement such that large shares of workers in all roles transition into independent self-employment at the time of retirement. Work linking to administrative records suggests substantial discrepancies, which vary across roles, between survey responses and administrative records and finds the most prominent discrepancies for post-retirement independent self-employment. The paper's findings motivate future research exploring the work trajectories leading to these roles and their consequences on financial, physical, and mental well-being into retirement.

Citation

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1. **Introduction**

A longstanding question is the extent to which workers prefer self-employment or choose self-employment as a result of limited wage employment opportunities, and, relatedly, whether self-employment makes them better off compared to their alternative employment options. This question has become more pertinent with the rise in electronically-mediated gig work, which lowers the entry barriers to certain forms of self-employment.

The question is particularly salient for older workers because they are more likely to be self-employed. Estimates from the 2016 wave of the Health and Retirement Study (HRS) suggest that the fraction of workers who are self-employed increases with age from 15.4%of workers younger than 55, to 17.1%of workers ages 55 to 65, and 33.8%of workers 65 and older. This could come about through staying employed longer or switching to self-employment later in life. On the one hand, self-employment can provide flexibility desired by older workers and can act as a bridge between career jobs and retirement. On the other hand, workers may turn to self-employment only because they cannot get hired as wage employees, for example, because of changing demands for skills or ageism.

One barrier to answering these questions is that, generally speaking, a number of different roles comprise self-employment and such choices and differences in well-being may vary systematically across these roles. For example, an individual pursuing self-employment in the transportation sector could choose to drive for an app-based ride-sharing service, advertise their own chauffeur services, drive on a contract basis for an established business, or manage their own or someone else's established business. For each role within the same line of work, the barriers to entry, work stresses, and compensation vary. Furthermore, it is hard to find data that identify these roles and examine well-being.

To fill this gap, this paper presents an approach using existing data from a large-scale and long-running survey, the HRS, and leverages narrative survey information to develop a rich data source capturing the breadth of alternative work arrangements and their effects on the individuals who pursue them, which is critical for informing sound policy. The approach identifies three dimensions of self-employment, hereafter referred to as self-employment roles, using internal data on self-employed respondents' narratives on industry and type of work collected in the 1994 to 2018 HRS. This approach is particularly useful because the HRS does not collect measures of business ownership.

This paper uses this approach to take first steps to answer big questions about self-employment and the retirement transition by examining, pre- and post-retirement: (1) self-employment roles among older workers; (2) the characteristics of individuals engaged in different self-employment roles; (3) measures of well-being of individuals engaged in different self-employment roles. The paper also examines transitions across roles at the time of retirement and compares survey reports of self-employment to administrative records to identify reporting discrepancies across self-employment roles. This research lays the groundwork for future analysis examining individuals' movement between different self-employment roles and wage employment and how these are associated with different levels of economic, physical, and psychological well-being over the life course.

2. Measuring self-employment

As discussed in the recent National Academies of Sciences, Engineering, and Medicine (2020) report on measuring alternative work arrangements, existing data sources have limitations in their usefulness in understanding the changing nature of work and developing appropriate policy. Furthermore, discrepancies appear across different data sources — administrative records, electronic transaction records, and survey data — in identifying trends in contingent and gig employment (Abraham et al. 2013, 2018; Allard and Polivka 2018; Jackson et al. 2017; Katz and Krueger 2019). While administrative records and electronic transaction records provide valuable information on alternative work arrangements (Jackson et al. 2017; Farrell et al. 2018; Hall and Krueger 2018; Garin et al. 2020), they lack information on many demographic, health, and family characteristics of interest. In addition, they do not capture employment taking place outside of their own purviews— for example, work not reported on tax filings or not electronically mediated, respectively. This points to the need to better understand survey data on self-employment as a complement to administrative and electronic transaction data sources. At the same time, traditional survey data are limited in their ability to accurately capture how respondents think about work, especially when limited to brief survey questions. Household surveys, such as the American Community Survey and Current Population Survey (CPS), ask about self-employment, but do not provide detailed employment characteristics. More focused surveys, such as the Bureau of Labor Statistics' Contingent Worker Supplement (CWS), collect data on alternative work arrangements and some demographic characteristics, but they do not include the full breadth of individual and household characteristics of interest and are generally cross-sectional.

Given the benefits and limitations of using survey data to better understand alternative work arrangements, recent research has used two main approaches: utilizing existing measures in large-scale, publicly available data as proxies for different elements of work, or conducting independent telephone or internet-based surveys to capture specific information of interest. Examining differences in individuals engaged in incorporated self-employment and unincorporated self-employment, Levine and Rubinstein (2017) aimed to distinguish between "entrepreneurs" and other business owners. Using the 1991 U.S. Department of Labor's Dictionary of Occupational Titles, the 1995 to 2012 Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) on workers 25 to 55 years old, and the 1982-2012 National Longitudinal Survey of Youth (NLSY), they found that the incorporated self-employed perform activities demanding comparatively strong nonroutine cognitive skills. They also found that people who become incorporated business owners tend to be more educated and, as teenagers, score higher on learning aptitude tests, exhibit greater self-esteem, and engage in more illicit activities than others. Boeri et al. (2020) consider differences among the solo self-employed and the self-employed with employees. Using online surveys of self-employment and alternative work arrangements among individuals in Italy, the United Kingdom, and the United States, as well as 2016 to 2017 monthly CPS data, they found that the solo self-employed have lower hourly earnings, work fewer hours, are more likely to report being underemployed, report lower job satisfaction, greater liquidity constraints, are less likely to have health insurance coverage and tax-deferred retirement savings accounts, and are more likely to transition into and out of unemployment than the employed with employees. Focusing on older workers, Abraham et al. (2020) examine this question focusing specifically on independent contractor work. Using data from a Gallup telephone survey module, they found that work as an independent contractor is the most common type of self-employment and that approximately one-quarter of independent contractors 50 and older work for a former employer. They further found that self-employment generally and work as an independent contractor specifically were more common among the highly educated at older ages.

Most similar to this work, Moulton and Scott (2016) used publicly-available variables in the 1992 to 2010 HRS to identify push and pull factors into more and less desirable self-employment. To do this, they disaggregated self-employment into four types through an interaction along two dimensions: first, defining jobs as "knowledge-based" and "nonknowledge-based" using broad occupation codes; second, defining jobs as entrepreneurial if they meet at least one of two criteria: reporting having more than two workers at the employer as a proxy for supervisory responsibilities or reporting nonzero household business assets. They find large differences between individuals in these alternative measures of self-employment and that there are distinctive factors influencing entry into these types.

The present study adds to this recent literature by focusing on older workers and exploring self-employment heterogeneity by entrepreneurial role based on respondents' descriptions of their work responsibilities. This contributes to a more thorough understanding of the determinants and outcomes of investment and managerial responsibilities associated with different entrepreneurial roles. By using HRS data, this work benefits from a higher survey response rate, as well as the HRS' breadth of information collected both contemporaneously and longitudinally and its ability to link to administrative records.

This work builds on the work of Moulton and Scott (2016) and augments their approach by using internal HRS data on industry and occupation narratives to classify self-employment across a different dimension, examining ownership/management/independent activities as compared to Moulton and Scott's (2016) knowledge-based and entrepreneurship proxies. This approach provides a valuable additional aspect that can be examined in conjunction with occupation, number of workers, and business assets variables to construct a more complete picture of self-employment heterogeneity among older workers.

While the existing creative survey-based approaches provide valuable insights into alternative work arrangements and entrepreneurship, they underscore the potential benefit of having better data on these arrangements in large-scale, long-running surveys. This study's approach fills the existing gap by leveraging narrative survey information to capture the breadth of alternative work arrangements and their links with individual well-being.

3. Methods

3.1 Data

To examine self-employment heterogeneity, this analysis uses internal information in the 1994-2018 HRS. The HRS is a longitudinal study of a representative sample of approximately 20,000 Americans older than 50 and their spouses. Since 1992, it has been conducted every two years with new cohorts added every six. The HRS asks questions on a breadth of topics, including work history, current employment, disability, retirement plans, net worth, income, health insurance and health status. For the purposes of this analysis, all measures of dollar amounts have been converted to 2016 dollars.

In addition to publicly available HRS data, the analysis leverages internal narrative descriptions of industry and occupation collected in the 1994 to 2018 HRS to classify self-employment reports into a useful framework.[1] The narratives include

[1] Narratives were collected as part of the 1992 survey wave, but were unable to be located for the purposes of this analysis.

answers to the following open-ended questions: “What industry do you work in? That is, what does your company do or make?” and “What sort of work do you do?” Responses tend to be four to five sentences long. The HRS collects this information only for respondents’ current main jobs. Nearly all respondents who report self-employment provide answers to the open-ended industry and type of work questions.

3.2 Data classification approach

To classify the HRS self-employment reports into a useful framework, narrative responses to the open-ended industry and type of work questions were each coded as one of three self-employment roles (own, manage, independent) based on a more detailed classification by Light and Munk (2018). Jobs were classified as “own” when a respondent explicitly claimed to own the business by using such terms as own, co-own, owner, proprietor, president, or chief executive officer (CEO), or to run the business by using such terms as director, officer, or “I run the business.” Jobs were classified as “manage” when a respondent explicitly claimed a managerial or executive role by using such terms as boss, manager, supervisor, executive, chief financial officer (CFO), or vice president, or indicated engaging in managerial or supervisory activity. Jobs were classified as “independent” when a respondent did not express owning or managing a business or managing or supervising people (all other cases). The classification aims to distinguish between those who own a business (requiring investment and managerial responsibilities), manage (but do not own) a business (requiring managerial, but not necessarily investment responsibilities), and work independently (requiring varying degrees of investment, but no managerial responsibilities). This work builds on that of

Abramowitz (2020), who hand-coded narratives in the 2016 HRS according to this schema.

The present study used machine learning to automate the classification of alternative work arrangements depicted in narrative responses on industry and type of work according to the described schema, expanded the classification to earlier waves of the HRS, and permitted an increased sample size for inference along additional dimensions, as well as a better understanding of self-employment over time and respondents' lives. The machine learning approach used manual classifications of a data subset into self-employment roles to automate classification of the remaining data. Two reviewers categorized the same subset of the data, and the set of records on which they agreed was used to train the machine learning approach. Using these manual classifications, the machine learning approach performed several tasks: (1) preprocessed the raw data, (2) trained candidate machine learning models, (3) validated of the candidate models, and (4) implemented the optimal model. These tasks followed common procedures conducted in previous, similar studies of predicting occupational or demographic classes using text data (Boselli et al. 2018; Ikudo et al. 2019; Lampos et al. 2016; Mac Kim et al. 2017; Preoţiuc-Pietro et al. 2015; Preoţiuc-Pietro and Ungar 2018). Abramowitz and Kim (2021) provide more detail on the machine learning approach.

Applying these methods, approximately 5,000 self-employment reports were initially hand-coded, with agreement on approximately 4,500. Applying the machine learning approach to the remainder of the reports resulted in a total of 17,854 classified narratives. Of these, approximately an additional 2,300 were flagged for manual review by the two initial reviewers, with approximately 35% requiring adjudication by a third reviewer. Since respondents did not provide narratives in all survey waves, roles for missing narratives were imputed as the role in the previous wave for jobs identified as being the same job as in the previous wave.

3.3 Analysis

Using this classification, the analysis examines the prevalence of older workers' different self-employment roles, the characteristics of individuals engaged in different roles, and measures of well-being and retirement expectations across different work roles, pre- and post-retirement. The analysis also compares survey reports of self-employment to administrative records to identify reporting discrepancies across self-employment roles pre- and post-retirement. The approach estimates means for each self-employment role as well as for employees, and presents results from significance tests of differences between independent self-employed workers and all other groups. The paper also examines transitions across roles at the time of retirement.

4. Results

4.1 Share of workers and job tenure by self-employment role

Knowing that the share of workers who are self-employed increases with age, the analysis lays the groundwork to better understand the forces driving workers to stay in or enter different kinds of self-employment. First examining the distribution of self-employed workers in the HRS across self-employment roles overall and by five-year age groups, Figure 1 shows that, overall, 83.9% of self-employed HRS respondents reported independent roles, 5.6% reported managerial roles, and 10.6% reported ownership roles. Figure 1 further shows the shift toward independent roles with age.

To better understand how these different self-employment roles function as bridge jobs, Figure 2 shows the distribution of job tenure by self-employment roles and for the wage-employed. The figure shows stark differences across roles. The wage-employed and, less so, the independent self-employed, are more likely to recently have transitioned into their current job than other roles. This suggests that, while some independent self-employed workers are employed in long-tenure career jobs and some self-employed workers of all roles have recently transitioned into their current employment, the independent self-employed are more likely to have higher turnover or be engaged in bridge employment. In contrast, business managers and owners have longer job tenure on average and appear less likely to have made recent transitions into these roles. Taken together, these findings suggest meaningful differences in work characteristics across the studied roles.

4.2 Worker characteristics and quality of life

Having found differing patterns of employment dynamics across roles, Table 1 presents characteristics across self-employment roles and for employees, and shows significant differences in socioeconomic characteristics, well-being, retirement expectations, and job characteristics across roles.

First examining demographic characteristics in Table 1, self-employment in general and management and ownership in particular are associated with being male, white, and non-Hispanic, as well as more years of education. Self-employment in general and independent self-employment in particular is associated with older age.

Considering differences in economic outcomes across roles, Table 1 further shows self-employment in general is associated with having less labor income and more pension income. Among the self-employed, management and ownership are associated with working more hours and having greater labor income compared to independent workers. Self-employment in general and management and ownership in particular are associated with greater household wealth, savings, and business assets. While self-employment in general is associated with a lower likelihood of having own employer-sponsored insurance, among the self-employed, managers and owners are more likely to have their own employer-sponsored health insurance compared to independent workers.

Next examining the extent to which different roles are associated with differential well-being, Table 1 shows substantial variation in quality of life and retirement expectations by role. Self-employment in general and management and ownership in particular are associated with being more likely to report excellent or very good health and are less likely to say they are depressed compared to employees. Self-employment, especially independent self-employment, is associated with being more likely to say they are at least partially retired, but managers and owners are less likely to be fully retired. Self-employment is generally associated with expecting to work longer compared to employees.

Table 1 further shows differences in job characteristics across roles. In general, independent self-employment appears to be the most physically demanding, but involves the least stress. Managers and owners have the least physically demanding, but most stressful, jobs.

4.3 Worker characteristics and quality of life by retirement status

While examining characteristics by roles reveals considerable differences, it masks differences along a key dimension: retirement status. While the labor force status of all respondents reporting any employment in the HRS is considered to be working, respondents are also asked whether they consider themselves to be retired.

Given the dynamics of a shift to independent self-employment as workers age, it is important to consider how preretirement self-employment in different roles may fundamentally differ from post-retirement self-employment. To explore this question, Table 2 and Table 3 separately present characteristics for respondents who say they are not retired and for respondents who say they are at least partially retired, respectively. While the main patterns across roles persist pre- and post-retirement, there are some notable differences between the pre- and post-retirement respondents. In particular, across all employee and self-employment roles, post-retirement respondents are more likely to be white, non-Hispanic, and male. They work, on average, half as many hours as preretirement respondents and earn correspondingly less labor income. They are less likely to say they are depressed and their jobs tend to be less physically demanding and less stressful. These findings suggest that retirement represents a fundamental shift in the nature of work, but that the general characteristics of roles are consistent pre- and post-retirement.

4.4 Retirement transitions across of self-employment roles

Wanting to understand how the transition to retirement is driven by changes in self-employment roles, Table 4 presents a transition matrix across wage employment, the three self-employment roles, and nonemployment for respondents who appear in the data both pre- and post-retirement. Roles are identified as the modal role in each of the pre- and post-retirement periods. The preretirement roles are represented vertically while the post-retirement roles are represented horizontally. Panel A presents the percentage of each preretirement role for each transition, and Panel B presents the number of respondents for each transition.

Panel A shows that the majority of employees and those not working preretirement transition to not working post-retirement. In contrast, most engaged in independent self-employment preretirement continue to do so post-retirement. The majority of managers transition to independent self-employment or become employees, while owners tend to stay in their ownership roles or transition to independent self-employment.

Observing the magnitudes of these transitions in Panel B sheds light on the finding that the share of workers engaged in self-employment increases with age. While only 7.9% of employees transition to independent self-employment, they represent many more individuals than the 13.1% of the independent self-employed, 27.2% of managers, and 9.5% of owners who transition to wage employment. These findings warrant further research to understand how transitions across roles at the time of retirement affect emotional, physical, and financial well-being.

4.5 Comparison to administrative records

In addition to better understanding the nature of self-employment, the self-employment role classification is also useful for examining discrepancies across survey and administrative record self-employment measures. Given that, as previously mentioned, these discrepancies are large and may suggest differing policy actions, considering the source of discrepancies and potential ways to address them is valuable. To examine such discrepancies, the analysis next compares survey employment reports to reported wage and self-employment earnings across roles. To do this, I link the 1994 to 2016 HRS data to Social Security Administration (SSA) administrative earnings records. The analysis is limited to 2016 since that this is the most recent year that the linked earnings records are available. These records are compiled from information provided to SSA by employers and the Internal Revenue Service (IRS) through IRS Form W-2, quarterly earnings records, and annual income tax forms. SSA uses this information to calculate benefit amounts for all beneficiary types (Olsen and Hudson 2009).

This analysis links HRS respondents to their earnings information in SSA's Summary Earnings File (SER) and Detail Earnings File (DER). The self-employment earnings information examined in this analysis comes from IRS Form 1040 Schedule SE (self-employment tax). For this exercise, the HRS classifies respondents as self-employed if they indicate their main employment as self-employment or if they report self-employment earnings. The administrative records classify respondents as self-employed if they either have self-employment earnings in the DER or have self-employment quarters of coverage in the SER.

Results comparing survey and administrative reports are presented in Table 5 with Panel A showing results for all respondents, Panel B showing results for respondents who say they are not retired, and Panel C showing results for respondents who say they are at least partially retired. For all respondents in Panel A, across all roles, workers reporting self-employment were much more likely to have only self-employment earnings: 34.6% of independent roles, 27.9% of managing roles, and 33.5% of ownership roles. They were also more likely to have both self-employment and wage earnings: 8.4% of independent roles, 7.8% of managing roles, and 8.3% of ownership roles. These compare to 4.5% of employees that had self-employment and wage earnings and 1.5% that had only self-employment earnings and to 0.4% of nonworkers that had self-employment and wage earnings and 1.3% that had only self-employment earnings.

Nonetheless, a substantial share of the self-employed had only wage earnings: 18.1% of independent roles, 42.1% of managing roles, and 31.7% of ownership roles. These compare to 89.2% of employees and 10.2% of nonworkers having only wage earnings.

In addition, a substantial share of the self-employed had no self-employment or wage earnings: 39.7% of independent roles, 22.5% of managing roles, and 27.4% of ownership roles. These compare to 4.8% of employees and 88.1% of nonworkers having no self-employment or wage earnings. Differences in the shares of earnings types across roles, particularly in the share having only wage earnings and the share having no reported earnings suggest meaningful differences in the nature of jobs across roles.

Comparing results in Panel B and Panel C suggests that across all respondents, those who say they are at least partially retired are substantially less likely to have any earnings appear in administrative records. This is most pronounced for the independent self-employed, with 51.1% of respondents who say they are at least partially retired having no reported earnings. This finding is useful in identifying the roles not identified in tax records in order to better understand discrepancies in survey reports and administrative records of self-employment.

Discussion

This paper presents an approach using novel data and machine learning methods to consider a new dimension of self-employment heterogeneity based on respondents' descriptions of their work responsibilities and to identify differing investment and managerial activities. In conjunction with the HRS' breadth of information, the approach provides complementary measures of older workers' self-employment arrangements, permitting better understanding of the arrangements' effects on the well-being of the individuals who pursue them. The classification will be made available publicly to enhance core HRS data.

This approach allows me to take first steps to answer big questions about self-employment by examining (1) the roles of self-employment older workers do, (2) the characteristics of individuals engaged in different work roles; and (3) measures of well-being and views toward work of individuals engaged in different work roles. Using the paper's classification of self-employment roles along with the breadth of information collected in the HRS, this work finds substantial differences in demographic characteristics, work characteristics, income, and benefits, as well as substantial variation in quality of life and retirement expectations by role, pre- and post-retirement. This project also adds insight into the nature of self-employment transitions at the time of retirement. Finally, linking to administrative records suggests substantial discrepancies between survey responses and administrative records, in line with the findings of Abraham et al. (2018). The paper finds the most pronounced discrepancies among the independent self-employed who say they are at least partially retired. Future work exploring ways to better capture earnings of these individuals and others at the labor market's margins, and the effect of their exclusion on analyses using administrative records, would be valuable.

While the paper's approach is valuable, it does have limitations. The results are limited in that the classification can only be used to the extent that the respondents provide sufficiently detailed narratives. The results are further limited in that there is some degree of subjectivity and error in coding the narratives. For example, Abramowitz (2020) identifies substantially more self-employed managers in the 2016 HRS. Despite this difference, the findings' implications are qualitatively similar. Future work will continue to evaluate the coding schema.

This study adds to the existing literature by developing a new measure of self-employment heterogeneity and examining disparities across roles. While previous work has found such disparities across incorporated and unincorporated self-employment (Levine and Rubinstein 2017); the solo self-employed and self-employed with employees (Boeri et al. 2020); independent contractor work and other self-employment (Abraham et al. 2020); and public HRS variables on occupation, number of employees, and business assets (Moulton and Scott 2016), this work considers a new dimension of self-employment heterogeneity based on respondents' descriptions of their work responsibilities to identify differing investment and managerial activities. In conjunction with the HRS' breadth of information, the findings add to the understanding of older workers' self-employment arrangements.

The results of this study provide greater insight into the nature of self-employment and permit future work more thoroughly considering the causes and implications of differences in self-employment roles. This work lays the groundwork for future research examining individuals' work trajectories leading to these roles, movement between different self-employment roles and wage employment, and how these are associated with different levels of economic, physical, and psychological well-being over the life course including the transition to retirement.

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Tables

Table 1: Characteristics by self-employment role

	Employee		Self-employed: Independent		Self-employed: Manage		Self-employed: Own/Run	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Individual Characteristics								
Percent male	43.7***	0.2	58.3	0.4	68.7***	1.4	70.6***	1.0
Percent white	73.5***	0.2	81.9	0.3	85.1***	1.1	83.4*	0.8
Percent Hispanic	11.9***	0.1	10.6	0.2	6.1***	0.7	6***	0.5
Age	58.9***	0.0	62.3	0.1	60.4***	0.2	61.4***	0.2
Years of education	13.1***	0.0	13.3	0.0	14***	0.1	13.7***	0.1
Weekly hours worked at main job	36.8***	0.1	32.0	0.2	44.3***	0.6	42.3***	0.5
Labor income (000's)	47.6***	0.2	17.8	0.7	42.6***	6.0	29***	2.3
Pension income (000's)	2.5***	0.0	4.4	0.2	2.2***	0.3	4.1	0.5
Household wealth (000's)	310.9***	3.5	812.9	19.6	1576.1***	94.2	1532.3***	67.6
Household savings (000's)	51.8***	1.7	114.1	5.2	159.2***	11.2	166.2***	13.4
Household business assets (000's)	27.7***	1.7	198.8	10.7	643.3***	67.3	617.3***	41.6
Percent with nonzero business assets	7***	0.1	34.8	0.4	68.4***	1.4	66.9***	1.0
Percent with any health insurance	90.4***	0.1	81.9	0.3	88.7***	1.0	87***	0.7
Percent with own employer health insurance	61.1***	0.2	23.1	0.3	39.1***	1.5	33.8***	1.1
Well-being and retirement expectations								
Percent says excellent or very good health	51.2***	0.2	54.7	0.4	62.1***	1.5	57**	1.1
Percent says they're depressed	10.3***	0.1	9.4	0.2	7***	0.8	7.9**	0.6
Percent says they're at all retired	17.3***	0.1	39.5	0.4	22.1***	1.3	26.8***	1.0
Percent says they're fully retired	2.4***	0.1	6.4	0.2	1.1***	0.3	2.6***	0.4
Prob. working at 62	51.2***	0.2	56.2	0.4	63.4***	1.4	64.8***	1.1
Prob. working at 70	14.6***	0.2	22.7	0.5	21.7	1.6	25.4*	1.3
Job characteristics								
Lots of physical effort	35.4***	0.2	38.4	0.4	31.4***	1.4	34.8***	1.1
Lifting heavy loads	15	0.1	14.8	0.3	11.9***	1.0	13.1**	0.8
Stooping/kneeling/crouching	26.4***	0.2	29.0	0.4	19.3***	1.2	25.9***	1.0
Good eyesight	89.1***	0.1	85.5	0.3	82.5**	1.2	86.6	0.8
Involves much stress	56.5***	0.2	47.6	0.4	66.3***	1.4	59.5***	1.1

Source: 2018 RAND HRS Longitudinal File and 1994 to 2018 HRS self-employment industry and occupation narratives; *** p<0.01, ** p<0.05, * p<0.1 for t-test of difference in means with Independent role.

Table 2: Characteristics by self-employment role for respondents who say they are not retired

	Employee		Self-employed					
			Independent		Manage		Own/Run	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Individual characteristics								
Percent male	40.7***	0.2	53.2	0.5	65.9***	1.7	65.9***	1.3
Percent white	72.1***	0.2	80.6	0.4	84.8***	1.3	83.2**	1.0
Percent Hispanic	12.9*	0.1	13.6	0.4	7***	0.9	7.6***	0.7
Age	57.1***	0.0	59.0	0.1	58.8	0.3	59.3	0.2
Years of education	13.2**	0.0	13.2	0.0	14.1***	0.1	13.7***	0.1
Weekly hours worked at main job	40.1***	0.0	39.0	0.2	48.7***	0.6	47.9***	0.5
Labor income (000's)	52.9***	0.2	21.7	1.1	50***	8.3	26.9**	2.0
Pension income (000's)	1.1***	0.0	1.9	0.2	0.9***	0.2	2.6	0.5
Household wealth (000's)	293.1***	4.1	770.1	29.4	1463.4***	113.1	1304.6***	74.0
Household savings (000's)	47.4***	2.2	103.2	7.4	147.3***	11.6	132.8*	15.8
Household business assets (000's)	27.2***	2.0	207.8	16.3	595.1***	82.4	529.3***	43.3
Percent with nonzero business assets	7.1***	0.1	37.8	0.5	69.6***	1.6	67.9***	1.3
Percent with any health insurance	89.6***	0.1	76.2	0.4	86.3***	1.2	84.8***	1.0
Percent with own employer health insurance	66.8***	0.2	22.4	0.4	39.2***	1.8	33.7***	1.3
Well-being and retirement expectations								
Percent says excellent or very good health	51.7***	0.2	57.1	0.5	64.5***	1.7	60.2**	1.3
Percent says they're depressed	10.6*	0.1	10.1	0.3	6.5***	0.9	8.4**	0.7
Prob. working at 62	53***	0.2	62.9	0.4	66.2**	1.4	68.7***	1.1
Prob. working at 70	15.3***	0.2	27.4	0.6	22.2***	1.8	26.5	1.4
Job characteristics								
Lots of physical effort	36.5***	0.2	41.3	0.5	32***	1.7	37.6***	1.3
Lifting heavy loads	15.9	0.2	16.6	0.4	11.6***	1.1	14.7*	1.0
Stooping/kneeling/crouching	27.4***	0.2	31.3	0.5	19***	1.4	28.7**	1.2
Good eyesight	89.5***	0.1	86.1	0.4	84.2	1.3	88.4**	0.9
Involves much stress	62***	0.2	56.2	0.5	73***	1.6	65.7***	1.3

Source: 2018 RAND HRS Longitudinal File and 1994 to 2018 HRS self-employment industry and occupation narratives; *** p<0.01, ** p<0.05, * p<0.1 for t-test of difference in means with Independent role.

Table 3: Characteristics by self-employment role for respondents who say they are at least partially retired

			Self-employed					
	Employee		Independent		Manage		Own/Run	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Individual characteristics								
Percent male	48.8***	0.5	61.7	0.6	68.6**	3.1	75.3***	1.9
Percent white	79.8***	0.4	84.0	0.5	84.8	2.4	82.7	1.7
Percent Hispanic	6.5***	0.2	5.4	0.3	3.2*	1.2	2.4***	0.7
Age	66.8***	0.1	67.3	0.1	66.6	0.5	67.3	0.3
Years of education	13.2***	0.0	13.5	0.0	14.1***	0.2	13.8***	0.1
Weekly hours worked at main job	20.9***	0.1	20.1	0.2	28.4***	1.3	24.4***	0.8
Labor income (000's)	20.4***	0.3	10.9	0.7	16.6	3.5	24.8**	6.8
Pension income (000's)	9.5*	0.2	8.6	0.4	6.4*	1.2	9.4	1.8
Household wealth (000's)	384.4***	7.8	874.5	26.6	1880.9***	211.9	1942.9***	155.4
Household savings (000's)	70.8***	2.2	133.9	8.5	209.8**	35.3	228.8***	26.2
Household business assets (000's)	29.2***	2.5	179.4	13.8	709.9***	134.2	725.5***	108.4
Percent with nonzero business assets	6.8***	0.2	28.9	0.6	59.2***	3.3	62.9***	2.2
Percent with any health insurance	95.1***	0.2	91.1	0.4	93.7	1.6	92.8	1.2
Percent with own employer health insurance	32.7***	0.4	23.9	0.6	34.9***	3.2	28.4**	2.1
Wellbeing and retirement expectations								
Percent says excellent or very good health	50.8**	0.5	52.5	0.6	59.2**	3.3	52.8	2.2
Percent says they're depressed	8.7	0.3	8.2	0.4	9	1.9	6.8	1.1
Prob. working at 62	22.3***	0.6	28.8	0.9	37	4.9	37**	3.5
Prob. working at 70	8.6***	0.4	11.4	0.7	19.6*	4.3	20.5**	3.4
Job characteristics								
Lots of physical effort	28.3***	0.4	32.5	0.6	25.5**	2.9	25.9***	2.0
Lifting heavy loads	9***	0.3	10.9	0.4	10	2.0	8**	1.2
Stooping/kneeling/crouching	19.9***	0.4	23.9	0.6	16.4***	2.5	18.5***	1.8
Good eyesight	87***	0.3	84.2	0.5	75.9***	2.9	82.1	1.7
Involves much stress	30.6*	0.4	32.0	0.6	41.4***	3.3	38.3***	2.2

Source: 2018 RAND HRS Longitudinal File and 1994 to 2018 HRS self-employment industry and occupation narratives; *** p<0.01, ** p<0.05, * p<0.1 for t-test of difference in means with Independent role.

Table 4: Retirement transitions by self-employment role

Panel A: % of Preretirement role

	Post-retirement				
Preretirement	**Employee**	**Independent**	**Manager**	**Owner**	**Not working**
Employee	38.2%	7.9%	0.2%	0.2%	53.5%
Independent	13.1%	51.6%	1.2%	3.1%	31.1%
Manager	27.2%	33.6%	6.9%	0.9%	31.4%
Owner	9.5%	35.4%	2.0%	21.2%	31.9%
Not Working	8.3%	3.8%	0.0%	0.0%	87.8%

Panel B: Number of respondents

	Post-retirement				
Preretirement	**Employee**	**Independent**	**Manager**	**Owner**	**Not working**
Employee	33,340	6,887	162	214	46,690
Independent	1,929	7,578	172	450	4,566
Manager	153	189	39	5	177
Owner	95	354	20	212	319
Not working	1,196	543	0	6	12,609

Source: 2018 RAND HRS Longitudinal File and 1994 to 2018 HRS self-employment industry and occupation narratives

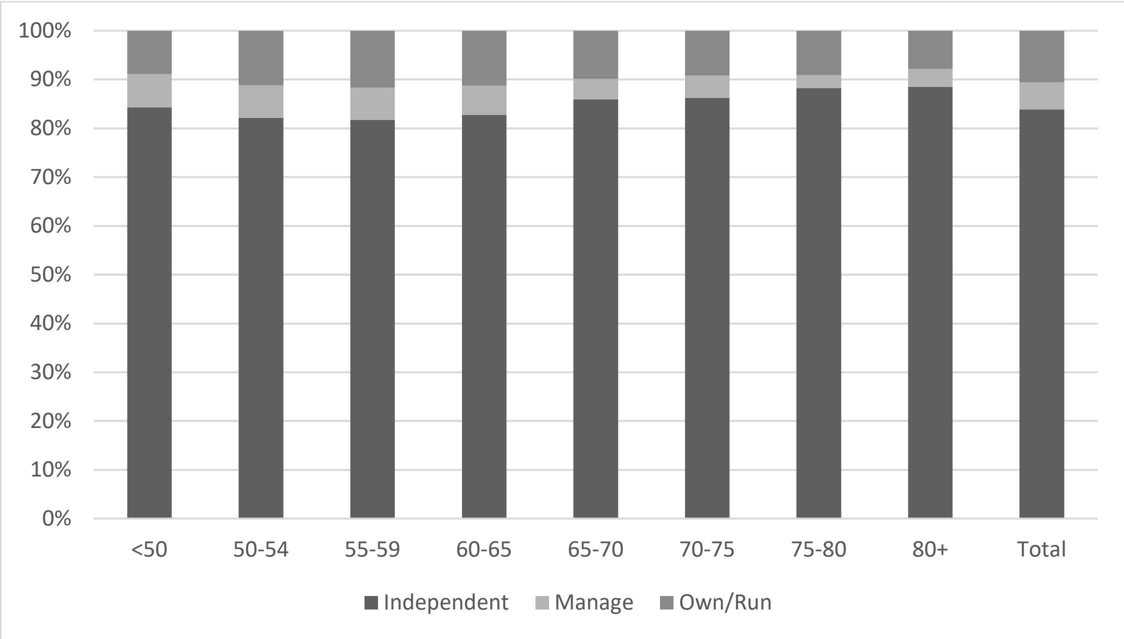
Table 5: Comparison of survey reports and administrative records by self-employment role

	Panel A: All respondents									
	Employee		Independent		Manage		Own/Run		Nonworker	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Only self-employment earnings	1.5***	0.1	34.6	0.5	27.9***	1.8	33.5	1.4	1.3***	0.0
Self-employment and wage earnings	4.5***	0.1	8.4	0.3	7.8	1.1	8.3	0.8	0.4***	0.0
Only wage earnings	89.2***	0.2	18.1	0.4	42.1***	2.0	31.7***	1.4	10.2***	0.1
No self-employment or wage earnings	4.8***	0.1	39.7	0.5	22.5***	1.7	27.4***	1.4	88.1***	0.1
	Panel B: Respondents who say they are not retired									
	Employee		**Independent**		**Manage**		**Own/Run**		**Nonworker**	
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
Only self-employment earnings	1***	0.1	38.6	0.7	30.9***	2.2	35.6	1.8	2.5***	0.2
Self-employment and wage earnings	4.4***	0.1	9.4	0.4	7*	1.2	8.4	1.0	1.7***	0.2
Only wage earnings	91.2***	0.2	21.0	0.6	43.1***	2.4	34***	1.7	31.6***	0.7
No self-employment or wage earnings	3.4***	0.1	32.0	0.7	19.4***	1.9	22.6***	1.5	64.4***	0.7
	Panel C: Respondents who say they are at least partially retired									
	Employee		**Independent**		**Manage**		**Own/Run**		**Nonworker**	
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
Only self-employment earnings	3.8***	0.2	29.1	0.8	19***	3.7	30	2.8	1.2***	0.0
Self-employment and wage earnings	4.8***	0.3	6.7	0.4	8.6	2.6	6.5	1.5	0.3***	0.0
Only wage earnings	80.7***	0.5	13.6	0.6	35.3***	4.5	22.7***	2.6	9.2***	0.1
No self-employment or wage earnings	10.7***	0.4	51.1	0.8	37.9***	4.5	42.3***	3.1	89.2***	0.1

Source: 1994 to 2016 RAND HRS Fat Files, 1994-2016 HRS self-employment industry and occupation narratives, and 2016 Social Security Administration Summary Earnings File and Detail Earnings File; *** p<0.01, ** p<0.05, * p<0.1 for t-test of difference in means with Independent role.

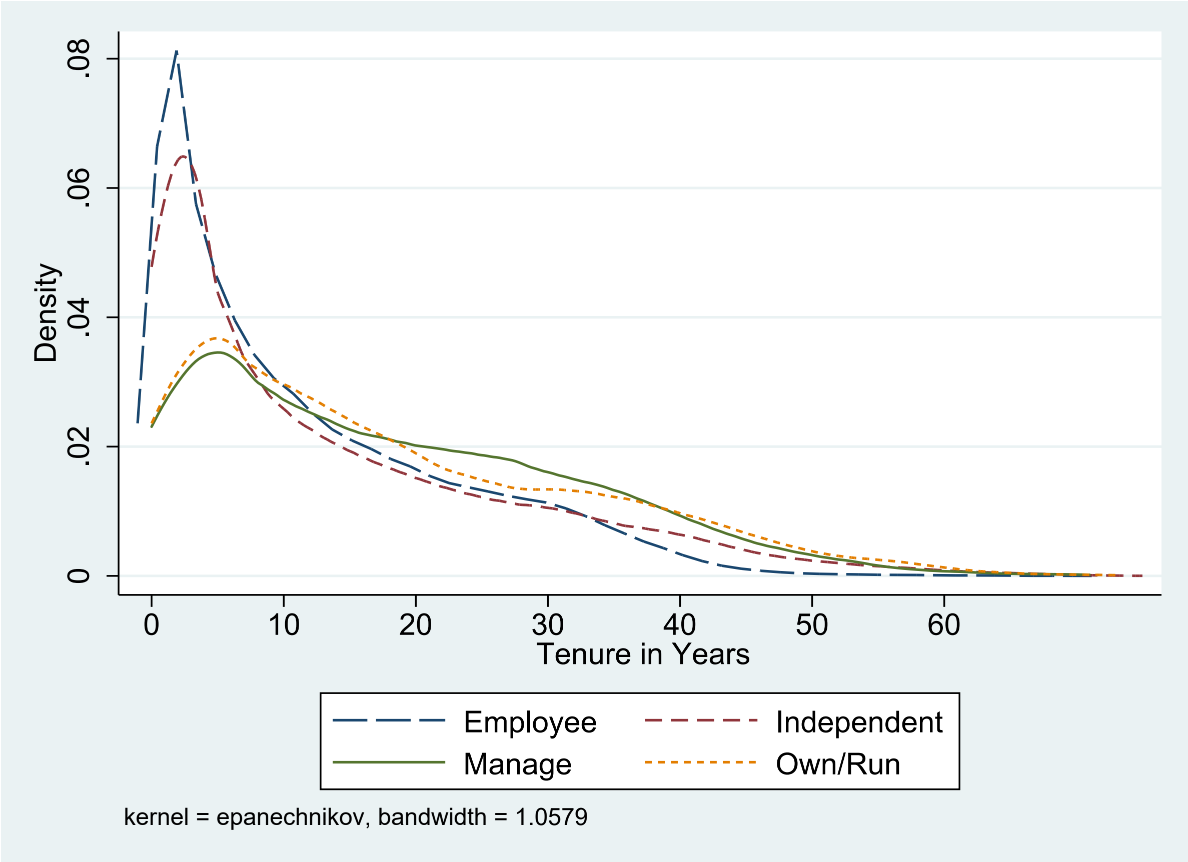
Figures

Figure 1: Share of workers by self-employment role and age group



Source: 2018 RAND HRS Longitudinal File and 1994 to 2018 HRS self-employment industry and occupation narratives

Figure 2: Kernel density of job tenure by self-employment role



Source: 2018 RAND HRS Longitudinal File and 1994 to 2018 HRS self-employment industry and occupation narratives