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Abstract

We use the 2014 and 2018 panels of the Survey of Income and Program Participation to create a schema of earnings that come from employee and nonemployee sources. Traditional earnings are from a job or incorporated business, while nontraditional earnings are from an unincorporated business or other work arrangement. We then create a typology of workers based on their experience with traditional and nontraditional earnings, describe workers of each type along dimensions of demographics, financial well-being, and beneficiary status, and use regressions to identify key predictors of earnings sources. Among prime-age workers, we find that workers with nontraditional earnings vary significantly based on whether the nontraditional earnings were the only source of wage income or in conjunction with traditional earnings. Among older workers, we find that receipt of Social Security benefits is a key predictor of nontraditional earnings. We discuss both findings and their research and policy implications.

Citation

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"Employment" in the United States spans colloquial and technical definitions. Employment broadly refers to the relationship in which a person sells their labor in exchange for compensation. Employment is also a specific work arrangement in which the person selling labor is legally recognized as an "employee" of the employing firm. Nonemployee employment covers an array of work arrangements, from individuals self-employed in an incorporated business to independent contractors. Explicitly underlying employee and nonemployee employment is the jurisdiction and application of labor law and whether earnings are subject to employer-paid or employee-paid payroll taxes. Implicitly underlying employee and nonemployee employment is the concern that employers are "misclassifying" employees as contractors in order to save money and reduce liability (Buscaglia 2008). And in the background is the secular increase in the number and availability of online platforms for work arrangements, often referred to as "gig work," such as Uber or TaskRabbit. This poses problems of both language (i.e., how to describe employee versus nonemployee employment) and analysis (i.e., how to measure and monitor employee and nonemployee employment trends), especially given that most individuals likely describe each situation equivalently: a job.

Or possibly: a side job. Following (Abraham et al. 2021), one definition of traditional employment is a job that pays a wage or salary, is expected to continue, has a predictable work schedule, predictable earnings, and is supervised by the employing firm; an alternative work arrangement is an employment scenario that diverges in at least one respect from traditional. Under this definition, the share of U.S. workers reporting earnings from alternative work arrangements has increased in the past 20 years (Collins et al. 2019; Katz and Krueger 2019; Mas and Pallais 2020). But research has identified that this increase does not come from workers solely employed in alternative work arrangements, but is instead driven by workers whose earnings from alternative arrangements supplement traditional earned income (Abraham and Houseman 2022; Collins et al. 2019; Farrell, Greig, and Hamoudi 2019; Katz and Krueger 2019; Mas and Pallais 2020)

However, identifying trends in nonemployee employment and the extent to which earnings are primary or supplemental is thwarted by inconsistent survey data. Early estimates of “moonlighting,” or taking a side job in addition to a primary job, date back to the 1960s, though they were not necessarily intended to capture details of the secondary job’s work arrangements (Amuedo-Dorantes and Kimmel 2009). The Contingent Worker Supplement in the Current Population Survey (CPS-CWS) captures key aspects of work arrangements, thus enabling clear estimates of employee and nonemployee employment, but it is fielded irregularly: 1995, 1997, 1999, 2001, 2005, and 2017. Moreover, workers may not understand what constitutes an “alternative” arrangement, or for whom certain arrangements would be considered “alternative” (Abraham and Houseman 2022). Nor are measurement issues limited to survey data; tax data may also underestimate nonemployee employment if people do not fully report their supplemental income on their tax returns.

Finally, the individual motivation for pursuing nonemployee work arrangements, as well as its downsides, are well-documented (Katsnelson and Oberholzer-Gee 2021; Mas and Pallais 2017; Scott, Edwards, and Stanczyk 2020): Nonemployee work arrangements can offer certain benefits, such as flexible scheduling, diversity in tasks, ability to work from home, and key supplemental income, but often lack employer-provided health insurance or retirement benefits, protection under labor regulations, or access to paid time off. Moreover, evidence of cyclicality in second-job holding — earning supplemental income outside of a primary job is more common when the economy is weak — muddles the reasoning for why people might pursue supplemental income from work arrangements (Amuedo-Dorantes and Kimmel 2009).

Hence, the study of employee and nonemployee employment is a tangle of contemporary economic questions: survey measurement, technological advances, employer preferences, labor law, and worker preferences. Inseparable from the study of nonemployee employment is the study of secondary job holding.

Our motivating research question is to understand which workers have nonemployee employment, and the insight that the characteristics of workers in nonemployee employment gives about those work arrangements. To do that, we define a dichotomous classification of work arrangements of “traditional” and “nontraditional” (it does not align with employee and nonemployee, or with prior uses of traditional and alternative). We show the prevalence of traditional and nontraditional work arrangements in the 2014 and 2018 panels of Survey of Income and Program Participation (SIPP), which were fielded after a large redesign of the survey following the 2008 panel. We discuss why the redesigned SIPP is (and is not) well suited to study work arrangements. We then classify workers into types based on their experience in traditional and nontraditional work arrangements over a one-year period. To our knowledge, we are the first to study work arrangements using this newly redesigned SIPP survey and the first to produce a coincidental study of work arrangements and multiple job holding.

Between 2013 and 2019, we find that the share of workers ages 19 and older working solely in nontraditional arrangements increased from 2.9% to 3.4% while the share of workers working in both traditional and nontraditional arrangements increased from 0.8% to 1.3%. As a final contribution, we conduct a series of regression analyses to predict worker type based on demographic characteristics (such as age, sex, race-ethnicity, education, marital status), household economic characteristics (such as poverty status and beneficiary status), and economic context (such as the unemployment rate and state minimum wage). We have two key findings. First, workers with any nontraditional earnings are highly heterogeneous; individuals who work solely in nontraditional jobs versus a mix of traditional and nontraditional jobs have different age, race, education, income, and beneficiary characteristics. Second, one of the strongest predictors of nontraditional earnings is being a Social Security beneficiary. We discuss our findings and implications at the close of the paper.

Data

The Survey of Income and Program Participation (SIPP) is a household survey that collects data on the nation's economic well-being including measures of wealth, employment, program participation (e.g., Supplemental Nutrition Assistance), child care, health insurance, and much else. Following the most recent redesign, each household in the SIPP is followed over the course of four years, inclusive of each member that joins or leaves the household. Households are interviewed once per year. Our analysis utilizes the SIPP 2014 and SIPP 2018 panels, which to date covers a period of seven calendar years. We restrict our analysis to individuals ages 19 and older at the time of entering the survey and to those individuals observed in every month for the first three years of each SIPP panel. In Table 1, we show the raw, person-month sample sizes for each panel in each year for both the unbalanced and balanced analytic sample.[1]

Table 1: SIPP panels and sample size in study by wave

Year	**2014 Panel**		**2018 Panel**	
	Unbalanced (raw)	**Balanced analytic sample**	**Unbalanced (raw)**	**Balanced analytic sample**
2013	870,352	441,744		
2014	676,105	441,744		
2015	556,943	441,744		
2016	492,776			
2017			763,186	250,164
2018			422,860	250,164
2019			395,834	250,164

Source: U.S. Census Bureau, Survey of Income and Program Participation. Sample counts are person-month. Unbalance sample makes no restriction for inclusion; balanced analytic sample requires individuals to begin the panel at 19 years of age and be observed in each of the first three years of the panel.

Our research question explores the extent of employee and nonemployee employment in the U.S. labor market. The SIPP collects data on up to seven jobs per individual and identifies the type of work arrangement: work for an employer, self-employed (owns a business), or another type of work arrangement. Additionally, in the case of self-employment, it identifies whether the individual's business is incorporated or not; self-employment without an incorporated business is interpreted here as

[1] As of the writing of this analysis, the final year of the 2018 SIPP is not yet available. In addition, beginning in 2018, the subsequent SIPP panels overlap, so that the 2019 SIPP has panel years 2018 to 2021, the 2020 SIPP has panel years 2019 to 2022, and so on. With overlapping panels in a single year, the sample size of the SIPPs from 2018 onward is slightly smaller. Hence, in 2014 the panel n=441,744 and in 2018 the n=250,164. In Technical Appendix Table A1, we show a balancing regression to note where the larger, earlier sample differs.

independent contracting. As such we can split employment and earnings into two types: earnings from traditional work arrangements and earnings from nontraditional work arrangements. **Traditional work** arrangements are work for an employer and work for a self-incorporated business. **Nontraditional work** arrangements span all other types of work arrangements and unincorporated self-employment.[2]

The possible earnings combinations in each month (of 36 total) span three source types — no earnings, traditional earnings, nontraditional earnings. Each source can have single or multiple arrangements. From these combinations, we create a schema of four earner types: traditional earners with one job, traditional earners with multiple jobs, nontraditional earners, and straddlers — workers who have both traditional and nontraditional earnings. The latter three can be thought of as types of deviations from the classical one-worker, one-job type. Table 2 below lays out our schematic for classifying individuals into one of these four categories (plus a fifth category for nonearners, i.e., individuals that never work through the entirety of the time period). The schematic flows left to right based on conditional response, starting with whether the individual earned traditional earnings, multiple sources of earnings, or nontraditional earnings.

[2] Appendix Table A2 lists the specific SIPP variables used in identifying traditional and nontraditional earnings, their description, response code, and universe.

Table 2: Definition of earner types based on monthly aggregates of work arrangements

<table>
<tr><td rowspan="5">Traditional earnings in at least one month</td><td rowspan="3">Yes</td><td rowspan="3">Nontraditional earnings in at least one month</td><td>Yes</td><td colspan="3">STRADDLER</td></tr>
<tr><td rowspan="2">No</td><td rowspan="2">Earnings from more than one traditional source in at least one month</td><td>YES</td><td>TRADITIONAL, MULTIPLE JOBS</td></tr>
<tr><td>NO</td><td>TRADITIONAL, ONE-JOB</td></tr>
<tr><td rowspan="2">No</td><td rowspan="2">Nontraditional earnings in at least one month</td><td>Yes</td><td colspan="3">NONTRADITIONAL</td></tr>
<tr><td>No</td><td colspan="3">NONEARNER</td></tr>
</table>

There are three potential timeframes under which we can impose this schema: person-month, person-year, or person-panel (three years). An analysis at the person-month level may be inadequate in this context, as individuals may switch between types of earnings arrangements and this dynamic would not be identified in a single month. However, too long of a window for classifying into worker types might pool together workers who have very different patterns of earnings and arrangements, such as workers who had nontraditional earnings in half the months and traditional earnings in the other half and a worker who had traditional earnings in all but one month over those three years. This is particularly relevant for straddlers. In a person-month timeframe, a straddler is someone with coincidental traditional and nontraditional earnings, perhaps suggesting a supplemental income arrangement. In a person-year or person-panel, a straddler is someone who has had both traditional and nontraditional earnings, but not necessarily at the same time, and could be switching between them. In subsequent analysis, we will perform a series of regressions to predict inclusion into types based on demographic, policy, and economic characteristics at the person-year level. Hence, we highlight person-year means in the paper.[3]

Work-related variables in the SIPP are available at the person-month level as described in our Table 2 definitional schematic. To conduct our analyses at the person-year level, we aggregate the monthly categorizations up to an annual level and sort individuals into the four, mutually exclusive and exhaustive earner types using the following criteria:

- **one job, traditional earner**: the individual held a single job in every working month[4] in a year and only earned income from traditional work arrangements;
- **multiple jobs, traditional earner**: an individual had at least two in jobs in at least one working month in a year and only earned income from traditional work arrangements;[5]

[3] Person-month and person-panel type distribution is available in Tables A3 and A4 of the Technical Appendix.

[4] An individual need not work every month in a year, so we restrict these classifications to working months, otherwise we might over-inflate the nonearner subgroup.

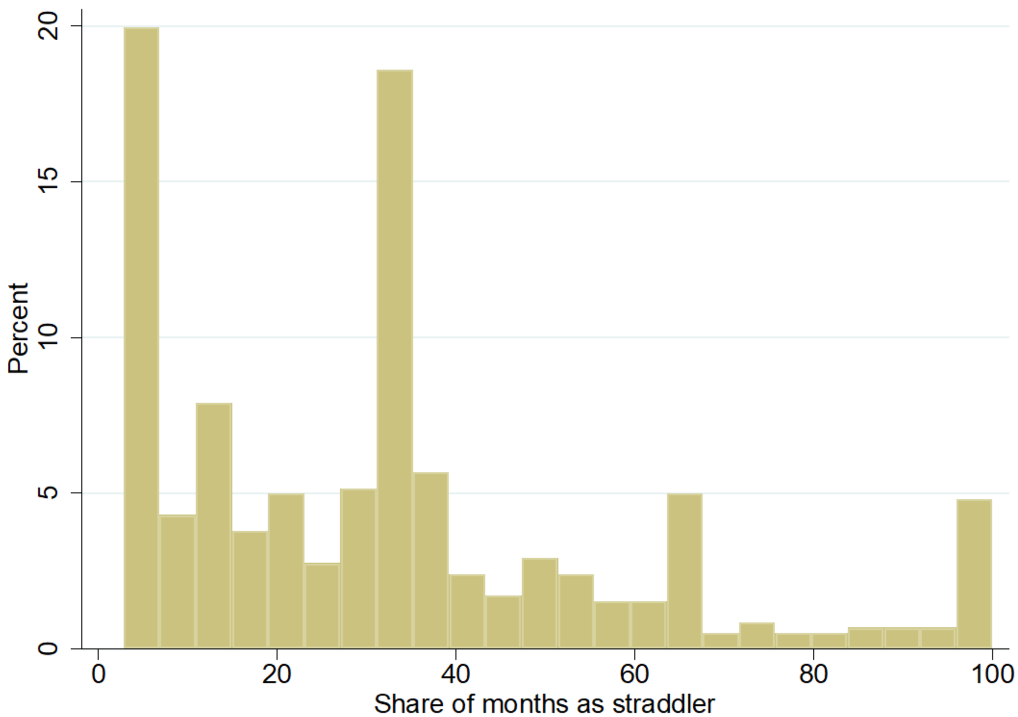
[5] A discussion of how to identify a job switch versus a concurrent job is in the Technical Appendix.

- **nontraditional earner**: an individual only earned income from nontraditional work arrangements throughout their working months in a single year; and
- **straddler**: an individual earned income from both traditional and nontraditional work arrangements in the working months of a given year.

The "straddler," though the smallest category, has a relatively broad definition. Being classified as a straddler may take different forms. For instance, we consider an individual a straddler at the yearly level if they move between earnings income from traditional sources in one month to income from nontraditional sources in another month. And an individual is classified as a straddler if in a specific month they had more than one job, with at least one job contributing income from a traditional source and another job contributing income from a nontraditional source (e.g., moonlighting, side-hustles, etc.). Straddler classification is more about the source of earnings, rather than the timing. This differs from our classification of "multiple jobs, traditional earners," because we require those individuals to have worked at least two jobs in a single month (to differentiate from job switching). In other words, straddling encompasses not only a side hustle of nontraditional earnings, but also a job switch from traditional to nontraditional earnings.

To further explore the notion of straddling, we examine the frequency of having both traditional and nontraditional earnings in a single month, which we call a straddler month. In Figure 1, we show the distribution of straddler months as a share of total work months (months in which the individual had positive earnings from traditional or nontraditional sources). The distribution is conditional on ever being observed straddling. Workers who do not straddle, or who do not work, are not included. The tendency is for straddling to be less, as opposed to more, common. About 20% of straddlers only earned coincidental income in a single month. The majority straddle fewer than half the time. Only a small share (5%) consistently have both traditional and nontraditional sources in a month.

Figure 1: Histogram of the share of work-months with both traditional and nontraditional earnings, conditional on at least one month



Source: U.S. Census Bureau, Survey of Income and Program Participation. A straddler is a worker who earns traditional and nontraditional earnings in a single month. The figure shows the distribution of straddlers (individuals must have at least one straddler month to be included in distribution) by frequency of straddling as expressed as the share of all work months the worker straddled.

From Figure 1, we conclude that our preferred definition of straddling — earning income from both sources in a calendar year, and not necessarily in the same month — is generous, but appropriate. Requiring straddling in each month would be too rigid, given how few workers exhibit this behavior. If straddling is seen as the phenomenon in which workers supplement traditional earning with nontraditional earnings, we allow that supplement to occur in months spent away from traditional work.

In Table 3, we show the person-year distribution of individuals across earner types. In the first column, we show the characteristic as a percent of the total sample (i.e., the first column sums to 100 within groups) and in each row of the subsequent columns, we show the distribution across types (i.e., each row sums to 100). For example, starting in the first row: 67.7% of our sample is white, non-Hispanic; of those white, non-Hispanic individuals, 43.5% are nonearners, 48.2% are traditional earners in a single job, 6% are traditional earners in multiple jobs, 1.6% are nontraditional earners, and 0.7% are straddlers.

Table 3: Distribution of earner types within demographic by person-year

	Share of total sample	***Share of demographic group***				
Demographic		**Nonearner**	**Traditional earner (one job)**	**Traditional earner (multiple jobs)**	**Non-traditional earner**	**Straddler**
Race-ethnicity						
White, non-Hispanic	67.7% (91479)	43.5% (39783)	48.2% (44089)	6.0% (5474)	1.6% (1463)	0.7% (670)
Black, non-Hispanic	11.5% (15552)	45.3% (7040)	47.3% (7352)	5.5% (858)	1.4% (220)	0.5% (82)
Hispanic	13.9% (18744)	36.6% (6869)	55.2% (10351)	4.9% (918)	2.6% (485)	0.6% (121)
All Other, non-Hispanic	6.9% (9381)	40.4% (3789)	52.1% (4888)	5.1% (475)	1.9% (177)	0.6% (52)
Education						

Less than high school	12.9% (17400)	62.3% (10840)	32.9% (5730)	2.2% (378)	2.3% (393)	0.3% (59)
High school & equivalent	29.1% (39318)	48.8% (19197)	45.1% (17749)	3.9% (1523)	1.6% (645)	0.5% (204)
Some college	27.9% (37644)	39.5% (14882)	51.8% (19493)	6.4% (2396)	1.7% (637)	0.6% (236)
Bachelors	18.2% (24567)	30.9% (7600)	58.5% (14367)	8.0% (1955)	1.6% (392)	1.0% (253)
Graduate/professional	12.0% (16227)	30.6% (4962)	57.6% (9341)	9.1% (1473)	1.7% (278)	1.1% (173)
Sex						
Male	46.7% (63132)	37.0% (23344)	54.4% (34344)	5.9% (3720)	1.9% (1229)	0.8% (495)
Female	53.3% (72024)	47.4% (34137)	44.9% (32336)	5.6% (4005)	1.5% (1116)	0.6% (430)
Age Group						
Age: [18, 20)	1.3% (1704)	36.7% (625)	54.6% (931)	7.6% (130)	0.6% (11)	0.4% (7)
Age: [20, 29)	12.6% (17034)	21.8% (3717)	66.2% (11272)	9.9% (1678)	1.3% (215)	0.9% (152)
Age: [30, 39)	14.8% (20070)	20.3% (4068)	68.5% (13757)	8.2% (1639)	2.0% (406)	1.0% (200)
Age: [40, 49)	15.5% (20934)	22.5% (4716)	66.9% (13997)	7.7% (1611)	2.0% (415)	0.9% (195)
Age: [50, 59)	19.3% (26118)	32.3% (8443)	58.5% (15269)	6.4% (1660)	2.1% (548)	0.8% (198)
Age: [60, 65)	10.2% (13788)	48.6% (6695)	44.8% (6183)	3.9% (536)	2.1% (284)	0.7% (90)
Age: [65, inf)	26.3% (35508)	82.3% (29217)	14.8% (5271)	1.3% (471)	1.3% (466)	0.2% (83)

Source: U.S. Census Bureau, Survey of Income and Program Participation. The first column expresses distribution across demographic groups within demographic category (e.g., distribution among age groups), the subsequent columns express distribution of a distinct demographic group across earner types (e.g., distribution of women among earner types). Distribution is presented as percentage with number of observations in parentheses.

With the exception of those individuals (of any age) with less than a high school degree, or those individuals (of any education) who are 65 or older, the majority of individuals work, and conditional on working, work a traditional job. In general, just under 2% of individuals have solely nontraditional earnings, and an even smaller share — less than 1% — have both sources. We include the count of nonearners in Table 3 for completeness. In Table 4, we recreate Table 3 but drop those nonearners so that the shares across worker types are limited to the sample of workers, making it easier to discern patterns among workers (as opposed to individuals).

There a few key comparisons of note. First, traditional multiple job holders have educational patterns more similar to straddlers than straddlers have to nontraditional earners. That is, the two groups with multiple sources of earnings have more similar educational correlates than the two groups with nontraditional earnings. Multiple traditional job earning increases with education, from 5.8% for workers with less than a high school degree to 13.1% for workers with a graduate degree. Straddling similarly increases from 0.9% to 1.5%. By contrast, solely nontraditional earnings decreases with education, from 6.0% among those without a high school degree to 2.5% among those with a graduate degree. Together, these two patterns of secondary and nontraditional earnings across educational groups suggest a low-wage/high-wage split in nontraditional earnings, from being the sole option versus a supplemental source of income. Second, and unlike education, nontraditional earnings, both alone and straddling, increase with age. That is, the two groups with nontraditional earnings have more similar age correlates than the two groups of multiple earners. Solely nontraditional earners increase from 1.6% of workers ages 20 to 29 to 7.4% of workers 65 and older; straddlers similarly increase from 1.1% to 1.3%. The latter is such a small change that it is not necessarily significant.

Table 4: Distribution of earner types within demographic by person-year, workers only

Demographic	Share of Demographic Group			
	Traditional earner (one job)	Traditional earner (multiple jobs)	Non-traditional earner	Straddler
Race-ethnicity				
White, non-Hispanic	85.3% (44089)	10.6% (5474)	2.8% (1463)	1.3% (670)
Black, non-Hispanic	86.4% (7352)	10.1% (858)	2.6% (220)	1.0% (82)
Hispanic	87.2% (10351)	7.7% (918)	4.1% (485)	1.0% (121)
All Other, non-Hispanic	87.4% (4888)	8.5% (475)	3.2% (177)	0.9% (52)
Education				
Less than high school	87.3% (5730)	5.8% (378)	6.0% (393)	0.9% (59)
High school & equivalent	88.2% (17749)	7.6% (1523)	3.2% (645)	1.0% (204)
Some college	85.6% (19493)	10.5% (2396)	2.8% (637)	1.0% (236)
Bachelors	84.7% (14367)	11.5% (1955)	2.3% (392)	1.5% (253)
Graduate/ professional	82.9% (9341)	13.1% (1473)	2.5% (278)	1.5% (173)
Sex				
Male	86.3% (34344)	9.3% (3720)	3.1% (1229)	1.2% (495)
Female	85.3% (32336)	10.6% (4005)	2.9% (1116)	1.1% (430)
Age Group				
Age: [18, 20)	86.3% (931)	12.0% (130)	1.0% (11)	0.6% (7)
Age: [20, 29)	84.6% (11272)	12.6% (1678)	1.6% (215)	1.1% (152)
Age: [30, 39)	86.0% (13757)	10.2% (1639)	2.5% (406)	1.2% (200)
Age: [40, 49)	86.3% (13997)	9.9% (1611)	2.6% (415)	1.2% (195)
Age: [50, 59)	86.4% (15269)	9.4% (1660)	3.1% (548)	1.1% (198)
Age: [60, 65)	87.2% (6183)	7.6% (536)	4.0% (284)	1.3% (90)
Age: [65, inf)	83.8% (5271)	7.5% (471)	7.4% (466)	1.3% (83)

Source: U.S. Census Bureau, Survey of Income and Program Participation. The first column expresses distribution across demographic groups within demographic category (e.g., distribution among age groups), the subsequent columns express distribution of a distinct demographic group across earner types (e.g., distribution of women among earner types). Distribution is presented as percentage with number of observations in parentheses.

Finally, we note that in terms of education and age, it is the groups with lowest overall participation, or highest share of nonworkers, that have the highest share of nontraditional earnings. However, in terms of race and ethnicity, it is Hispanics who have both the lowest share of nonworkers (36.6 percent from Table 3) but the highest share of nontraditional earners (4.1%, Table 4). All of these patterns suggest, if nothing else, a high level of diversity in the quality of nontraditional earnings sources, preferences for them, and access to them. We explore this further through regression analysis.

Methods

Our primary method is to use regression analysis to explore what predicts inclusion into the earner types presented in Tables 3 and 4, with a particular emphasis on workers with nontraditional earnings. The basic approach regresses earner type on a set of characteristics. However, even within this frame, there are several options of how to approach the specific regression method. For example, an analysis of the overall typology of individuals would lend itself to a multinomial or ordered logit (or probit) regression. Or, as noted before, the typology could be based on classification in a month, year, or three-year period.

We defer to the motivating research question of this paper, which is to understand who has nontraditional earnings, in determining our method. We test three dependent variables, each binary: straddler, sole nontraditional earner, or either (any nontraditional earnings). Our period of analysis is a calendar X^E year. As for independent variables, we test the demographic characteristics listed in Table 3, and add measures of household financial strength as well as economic context. We also perform our regressions on the sample limited to workers only. Formally:

$$W_{it} = X_{it}^D \beta^D + X_{it}^E \beta^E + \varepsilon_{it}$$

where *W* is the worker type, X^D are individual characteristics, and X^E are economic characteristics for worker *i* in year *t*. We include in X^D all the characteristics from Table 3.

Some of the individual characteristics are time invariant, but we do not pursue a fixed effects approach. We are not estimating the change in behavior or any treatment. Further, we want to be as inclusive as possible in producing coefficient estimates, especially for characteristics such as race and educational level.

Our method is not causal. We do not have identifying variation; our use of "predict" in this context is a statistical, but not causal, relationship. There are some variables that are more exogenous to the dependent variables than others, such as the unemployment rate versus race, but we do not assert or emphasize these over others. The contribution of this paper is to provide a landscape — inclusive of as many descriptors as possible — of nontraditional workers that serves as a base of, and motivation for, future research. For that reason, we opt for a linear probability model because of ease in interpreting coefficients (relative to an ordered logit, for example). We note in presenting the results what we think are the biggest research questions raised by our analysis, and in our discussion note various approaches to exploring that further.

Results

We test three dependent variables: being a nontraditional type, being a straddler type, or being either type. The sample includes all workers but excludes nonearner types. The time period of worker type classification is a calendar year. In interpretation, we consider the relationship between the coefficient and the dependent variable, as well as the coefficient's pattern across all three dependent variables. Our motivation is to understand who engages in nontraditional work and how those individuals differ based on their overall (traditional and nontraditional) earning patterns. Hence, we refer here to "types" rather than "work" to emphasize those different patterns. In general, the regression had more precision in coefficients predicting nontraditional type, as opposed to straddler type, likely because the sample mean of the latter is so low. By construction, the final column in Table 5 is a sum of the prior two and we do not discuss it, but provide it for reference to the general features of workers with nontraditional earnings, and for comparison with prior research that examined any nontraditional earnings (and does not follow our typology).

The means of sample demographic characteristics presented in Tables 3 and 4 cohere with the regression results in Table 5. Black workers are less likely (-0.006) to be a nontraditional type relative to the omitted white workers, while Hispanic workers are more likely (0.007), results that hold for predicting any nontraditional earnings, but not predicting straddlers. For the residual "Other" category of nonwhite, non-Black, non-Hispanic workers, the nontraditional type is more likely (0.005) and the straddler type less (-0.004). Workers with less than a high school degree are much more likely to be a nontraditional type (0.018) relative to the omitted high school graduate workers, while workers with a bachelor's (-0.005) or graduate (-0.006) degree are less likely to be nontraditional type. In contrast, higher-educated workers are more likely to be straddler type (0.004 and 0.005, respectively). Finally, nontraditional type likelihood grows with age, from being less likely for workers 19 to 24 or 25 to 34 relative to the omitted category of 35 to 44 year old workers (-0.021 and -0.008, respectively), to more likely for workers 55 to 64 (0.011) and 65 and older (0.021). We also include marital status. Relative to never married workers, being married, widowed, or divorced is associated with a lower likelihood of nontraditional type or straddler type.

Table 5: Results from regression worker types on demographic and economic characteristics, full sample

	Worker Type: Nontraditional	Worker Type: Straddler	Worker Type: Nontraditional or Straddler
White, non-Hispanic			
Black, non-Hispanic	-0.0060**	-0.0022	-0.0082***
	(0.0019)	(0.0012)	(0.0023)
Hispanic	0.0073***	-0.0016	0.0058*
	(0.0020)	(0.0012)	(0.0023)
All Other, non-Hispanic	0.0055*	-0.0044**	0.0011
	(0.0025)	(0.0014)	(0.0028)
Less than High School	0.0181***	-0.0014	0.0167***
	(0.0034)	(0.0015)	(0.0037)
High School & Equivalent			
Some College	-0.0017	-0.0004	-0.0021
	(0.0017)	(0.0010)	(0.0019)
Bachelor's	-0.0046**	0.0042***	-0.0005
	(0.0018)	(0.0012)	(0.0021)
Graduate/Professional	-0.0056**	0.0052***	-0.0004
	(0.0020)	(0.0014)	(0.0024)
Male			
Female	-0.0019	-0.0011	-0.0030*

	(0.0012)	(0.0008)	(0.0015)
19-24	-0.0207***	0.0013	-0.0194***
	(0.0023)	(0.0019)	(0.0030)
25-34	-0.0080***	-0.0008	-0.0088***
	(0.0018)	(0.0013)	(0.0022)
35-44			
45-54	0.0008	0.0006	0.0014
	(0.0018)	(0.0012)	(0.0021)
55-64	0.0108***	0.0002	0.0111***
	(0.0020)	(0.0012)	(0.0023)
65+	0.0207***	-0.0013	0.0194***
	(0.0044)	(0.0022)	(0.0049)
Never Married			
Married	-0.0035*	-0.0033**	-0.0068***
	(0.0017)	(0.0012)	(0.0020)
Widowed	-0.0012	-0.0082***	-0.0093
	(0.0052)	(0.0022)	(0.0056)
Divorced or separated	-0.0055*	-0.0019	-0.0074**
	(0.0023)	(0.0015)	(0.0027)
Not Social Security Recipient			
Social Security Recipient	0.0355***	0.0045	0.0399***
	(0.0048)	(0.0023)	(0.0053)
No Social Security Recipient in Household			
Social Security Recipient in Household	0.0012	0.0006	0.0017
	(0.0019)	(0.0012)	(0.0023)
Household in Poverty			
Household Income 100-200% Poverty	-0.0258***	-0.0019	-0.0277***
	(0.0043)	(0.0019)	(0.0047)
Household Income 200% Poverty or more	-0.0427***	-0.0010	-0.0437***
	(0.0039)	(0.0018)	(0.0043)
Unemployment Rate	-0.0003	-0.0017***	-0.0020***
	(0.0004)	(0.0003)	(0.0005)
State Min Wage < Federal Min Wage			
State Min Wage > Federal Min Wage	0.0022	0.0020*	0.0043**
	(0.0013)	(0.0008)	(0.0015)

State Per Capita < Federal Per Capita			
State Per Capita > Federal Per Capita	0.0022	0.0012	0.0034*
	(0.0013)	(0.0008)	(0.0016)
Constant	0.0673***	0.0217***	0.0891***
	(0.0051)	(0.0028)	(0.0058)
N	77489	77489	77489

Source: U.S. Census Bureau, Survey of Income and Program Participation. Table shows the result of three regressions of three binary dependent variables: being a nontraditional worker type in a year, being a straddler worker type in a year, being a nontraditional or straddler worker type in a year. For mutually exclusive and exhaustive groups of independent variables, one variable is omitted. These include: race (white non-Hispanic), Education (High School and Equivalent), Sex (Male), Age (35 to 44), Marital Status (Never Married), Social Security Recipiency (Not a Recipient, Not a Recipient Household), Household Poverty Status (In Poverty), State Status (Minimum Wage less than or equal to Federal, Per Capita Income less than or equal to Federal). Standard errors in parentheses. Significance level: * = 10%; ** = 5%; *** = 1%

We also tested various measures of household financial status and broader economic context, which are presented in the bottom half of Table 5. Given the higher rates of nontraditional type among older workers form Tables 3 and 4, we included a variable whether the individual receives Social Security, or if there is a Social Security recipient in the household. The former is strongly predictive of nontraditional type: Being a recipient is associated with a higher likelihood of being a nontraditional type (0.036) but has an insignificant relationship with the straddler type. Having a Social Security household member is predictive of neither.

In addition, we examined household income relative to poverty: in poverty, the omitted category; near poverty, with income 100% to 200% of the poverty rate; and those with income more than twice poverty. Higher income, whether near poverty

(-0.026) or twice above (-0.043) reduces the likelihood of being a nontraditional type. These income levels were not a significant predictor of straddling.

The unemployment rate is one of the few significant straddler type predictors. Although it seems to have a neutral relationship with nontraditional type (near zero and insignificant), a higher unemployment rate is associated with a reduction in the likelihood of straddling (-0.002). This could be because earnings from nontraditional arrangements are less desirable, or attainable, when the economy is weak. But intuitively, it is more likely that straddling drops because traditional job holding declines (which the unemployment rate approximates). Lastly, we looked at two measures of state economic circumstances: whether the minimum wage is higher than the federal wages, and whether per capita income in the state is higher than per capita income in the country. The results indicated that straddler type is more likely in states with higher wages and income lower than the country overall (0.004 and 0.003, respectively).

Because of the strong age trends, and in order to explore these main results further, we performed additional regressions on separate groups of workers: prime-age workers 25 to 54 years old and older workers 55 and older. We use the same set of independent variables. The results are presented in Table 6; for parsimony we do not show the results for the summary category (being nontraditional or straddler). The left two columns of results show nontraditional type, the right two straddler type. In terms of significance, coefficients may change because the underlying population estimate is different, or because the smaller sample size affords less precision. We attempt to not conflate the two.

By race, the overall differences in the likelihood of being a nontraditional type are driven, for Black workers, by older workers (-0.011) instead of younger, but for Hispanic workers by younger (0.093) instead of older workers. The results for both age groups move in the same direction, but one age group has a smaller, imprecise estimate. The results for nonwhite, non-Black, and non-Hispanic are similar to the full sample: They are more likely to be nontraditional type and less likely to be straddler type, but only precise for the younger group.

For both age groups, having a less than high school education is strongly and significantly associated with nontraditional type (0.016 and 0.021 for young and older workers), with no relationship to straddler type. Among higher-educated workers with a bachelor's or graduate/professional degree, nontraditional type is less likely and straddler type more likely. However, the coefficients are only large enough to be precise in predicting nontraditional type among younger workers (-0.006 and -0.009) and straddler type among older workers (0.007 and 0.011). This suggests that there may be more nontraditional types among older, highly educated workers and fewer straddler types among young, highly educated workers.

When the sample is divided into prime age and older workers, most of the age trends by smaller age bands become imprecise, meaning that while there is a large difference in nontraditional and straddler types across these two age groups, there is less difference within them. An exception is that workers 65 and older, relative to the omitted 55- to 64-year-old group, are more likely to be nontraditional type (0.011). The effect of marital status does not differ much by age; for both groups, each marital status that indicates marital experience (whether married, widowed, or divorced) is associated a lower likelihood of nontraditional or straddler type, relative to never married (omitted) individuals.

Table 6: Results from regression worker types on demographic and economic characteristics, prime-age workers versus older workers

	Worker Type: Nontraditional Prime Age	Worker Type: Nontraditional Older	Worker Type: Straddler Prime Age	Worker Type: Straddler Older
White, non-Hispanic				
Black, non-Hispanic	-0.0034	-0.0113*	-0.0011	-0.0027
	(0.0022)	(0.0045)	(0.0016)	(0.0021)
Hispanic	0.0093***	0.0048	-0.0011	0.0018
	(0.0023)	(0.0056)	(0.0014)	(0.0028)
All Other, non-Hispanic	0.0070*	0.0008	-0.0036*	-0.0024
	(0.0028)	(0.0063)	(0.0017)	(0.0030)
Less than High School	0.0162***	0.0212**	-0.0028	-0.0002
	(0.0041)	(0.0071)	(0.0018)	(0.0027)
High School & Equivalent				
Some College	-0.0023	-0.0012	-0.0014	0.0007
	(0.0020)	(0.0036)	(0.0013)	(0.0017)
Bachelor's	-0.0061**	-0.0058	0.0025	0.0070**
	(0.0020)	(0.0038)	(0.0015)	(0.0022)
Graduate/ Professional	-0.0089***	-0.0015	0.0022	0.0106***
	(0.0022)	(0.0042)	(0.0018)	(0.0025)
Male				
Female	-0.0011	-0.0034	-0.0013	-0.0014
	(0.0014)	(0.0028)	(0.0010)	(0.0015)
25-34	-0.0070***		-0.0008	
	(0.0018)		(0.0013)	
35-44				
45-54	0.0006		0.0005	
	(0.0018)		(0.0012)	

55-64				
65 and older		0.0110*		-0.0032
		(0.0046)		(0.0022)
Never Married				
Married	0.0007	-0.0157**	-0.0030*	-0.0041
	(0.0018)	(0.0057)	(0.0013)	(0.0031)
Widowed	-0.0089	-0.0102	-0.0018	-0.0103**
	(0.0073)	(0.0081)	(0.0047)	(0.0036)
Divorced or separated	-0.0036	-0.0162**	-0.0011	-0.0036
	(0.0025)	(0.0062)	(0.0018)	(0.0033)
Not A Social Security Recipient				
Social Security Recipient	0.0320*	0.0403***	-0.0050	0.0050
	(0.0134)	(0.0055)	(0.0043)	(0.0029)
No Social Security Recipient in Household				
Social Security Recipient in Household	0.0054*	-0.0045	-0.0014	0.0029
	(0.0026)	(0.0034)	(0.0016)	(0.0022)
Household in Poverty				
Household Income 100-200% Poverty	-0.0294***	-0.0437**	-0.0007	-0.0019
	(0.0053)	(0.0137)	(0.0023)	(0.0046)
Household Income 200% Poverty or more	-0.0427***	-0.0719***	-0.0011	-0.0012
	(0.0049)	(0.0125)	(0.0021)	(0.0043)
Unemployment Rate	-0.0014**	0.0015	-0.0020***	-0.0012*
	(0.0005)	(0.0010)	(0.0004)	(0.0005)
State Min Wage < Federal Min Wage				
State Min Wage > Federal Min Wage	0.0010	0.0050	0.0022*	0.0011
	(0.0015)	(0.0028)	(0.0010)	(0.0015)
State Per Capita < Federal Per Capita				

State Per Capita > Federal Per Capita	0.0031*	0.0007	0.0013	0.0002
	(0.0015)	(0.0029)	(0.0010)	(0.0016)
Constant	0.0703***	0.1079***	0.0245***	0.0191**
	(0.0061)	(0.0147)	(0.0034)	(0.0058)
N	47686	23943	47686	23943

Source: U.S. Census Bureau, Survey of Income and Program Participation. Table shows the result of four regressions of two binary dependent variables: being a nontraditional worker type in a year and being a straddler worker type in a year. The four regressions span samples of prime age (25 to 54) and older (55+) workers. For mutually exclusive and exhaustive groups of independent variables, one variable is omitted. These include: race (white non-Hispanic), Education (High School and Equivalent), Sex (Male), Age (35 to 44; 55 to 64), Marital Status (Never Married), Social Security Recipiency (Not a Recipient, Not a Recipient Household), Household Poverty Status (In Poverty), State Status (Minimum Wage less than or equal to Federal, Per Capita Income less than or equal to Federal). Standard errors in parentheses. Significance level: * = 10%; ** = 5%; *** = 1%

Social Security recipiency at any age is associated with a higher likelihood of nontraditional type; the coefficients are both fairly large, 0.032 for younger workers and 0.040 for older workers. Interestingly, having a Social Security member in one's household also increases the likelihood of nontraditional type for younger workers (0.005). Our household definition did not exclude the individual respondent; an individual recipient is also, by their own participation, in a recipient household. It could be that those have a closer overlap for younger recipients. Social Security has no predictive relationship with straddler type at any age.

Consistent across age groups is that individuals in households above poverty, whether they are near poverty or twice above it, are much less likely to be nontraditional types relative to individuals in poor households. And for both age groups, near poverty (-0.029 for younger and -0.044 for older) has a smaller coefficient than more than twice poverty (-0.043 and -0.072 respectively). In contrast, younger workers appear more sensitive to the unemployment rate. A higher rate is associated with a reduced likelihood of nontraditional type (-0.001) and straddler type (-0.002). For the former, the relationship with older worker is slightly positive and imprecise and, for the latter, about half the size (-0.001). There is not a clear relationship for workers of either age in state wages or income.

We tested numerous independent variables not shown in Tables 5 and 6, including cash on hand, value of held assets, debt, presence of children, the state minimum wage, state per capita GDP, state median income, among others. We also tested numerous measures of self-reported program participation. We found that many of these estimators were close substitutes (e.g., SNAP participation and low-income household), and picked a set that was lean and nonoverlapping, while also easy to interpret. We also tested using year fixed effects, interacting different variables with education or age, and did not see strong or consistent findings. We specifically tested numerous variables interacted with Social Security recipiency — education, race, unemployment rate, cash on hand, debt — but without precise results or any informative patterns.

Discussion

We developed a typology of workers based on their observed experience with nontraditional earnings. We then used regression analysis to understand which demographic or economic factors are predictive of the two types that span any nontraditional earnings: nontraditional and straddler. We summarize those findings in Table 7. We present the coefficients that had significant estimates in the regressions, grouped by whether they were positive, negative, and whether they were significant for all workers, just younger, or just older. Given that these are still relatively rare types of workers, and that we used a linear probability model, we put less weight on the exact point estimates and more on the direction.

Table 7: Summary of predictive variables of nontraditional and straddler types

	Nontraditional Type	**Straddler Type**
Positive	*All workers* Older than 55 Less than high school degree Social Security Recipient *Younger workers* Hispanic + younger Other race, non-Hispanic + younger *Older workers*	*All workers* *Younger workers* Higher minimum wage + younger *Older workers* Higher education + older
Negative	*All workers* Younger than 35 Higher income Marital experience *Younger workers* Higher education + younger Higher unemployment rate + younger *Older workers* Black + older	*All workers* Unemployment rate *Younger workers* Other race, non-Hispanic + younger *Older workers*

Source: Summary of coefficients in Tables 5 and 6.

Although there are numerous interesting aspects of these results, we think that three in particular warrant dedicated discussion about research implications and motivations for future work.

Nontraditional type as a function of barriers

Our definition of nontraditional type is that the worker does not have any earnings from traditional sources in a calendar year. That could either be because a worker prefers nontraditional earnings sources or they are unsuccessful in attaining traditional earnings. Our results suggest that the latter is true. Nontraditional types are predicted by factors associated with barriers to the traditional labor market, including lack of success (workers with less than a high school degree; workers with lower household income) and lack of access (Hispanic workers with a higher share of immigrants). Our analysis, however, was surface level: educational attainment, race, household income. Future research could focus on specific low-wage populations in the labor market, such as individuals without work documentation, formerly incarcerated individuals, individuals with a disability, among numerous others, and examine their tendency toward nontraditional type versus traditional or straddler.

These and related topics can be thought of as investigating the “supply” of nontraditional types. If it is the result of barriers, which barriers, to what degree, how do they vary in regulatory or economic conditions, etc.? A companion topic is investigating the “demand” for nontraditional workers through a study of nontraditional earnings sources, such as misclassification of contractors, off-the-book hiring, and others. And of course, the “price” of nontraditional work in terms of wage and nonwage compensation, working conditions, and secondary outcomes that result from worse wage and working conditions.

For example, in terms of supply, there has been a renaissance of research in the last 10 to 20 years studying monopsony in the labor market and the concentration of employer power (see Ashenfelter et al. [2022] for a discussion). This research primarily focuses on employee wages and has said less about the effect of monopsony on earnings from, and employment in, nonemployee employment. This paper shows through the study of nontraditional type arrangements that those are not necessarily sporadic or temporary, but that a share of the workforce works only in such arrangements. Given that they are representative of workers with traditional labor market barriers, their presence in a market could be related to that market's concentration of employer power.

Or, in terms of price: A worker's Social Security benefits are a function of their lifetime earnings. However, independent contractors underreport their income in filing taxes (Bruckner and Hungerford 2021; Schreur and Veghte 2018), suppressing their future benefit. If the nontraditional type is a function of labor market barriers, then they by extension present a potential barrier to accessing Social Security or fully benefitting from it. This could pose a risk to Social Security's finances and benefit adequacy in the future.

Straddler type to proxy for nontraditional motivation

Straddler types, a convention we introduce in the paper, have less intuition from prior research as they sit somewhere between multiple job holders and having a side income, side hustle, side gig, etc. As we noted in the introduction, nonemployee employment could be a function of preferences or constraints: A worker could want a flexible or independent work arrangement or be unsuccessful at finding traditional employment. The only consistent predictor of straddler types is that it is less likely when the unemployment rate is higher and is more common among higher-educated, older workers. Hence if, as we discussed in the previous section, our nontraditional type predictors provide support for the constraints, then to a degree, our straddler type provides support for preference.

By extension, a key benefit of our analysis is that is provides a clear, easy to identify, and frequently observed indicator that could proxy for whether nonemployee employment is likely the result of preference, or possibly, not the result of constraint: having recently had a traditional job. The only difference between nontraditional type and straddler type is that straddler type individuals received traditional earned income in the same calendar year they received nontraditional income. Yet, they have almost no overlapping predictors. These results call for further research in the SIPP as well as different surveys, but if it is supported by additional evidence, it could prove to be a useful identifier in the study of nonemployee employment. Indeed, we propose that this may be the most useful value added of our typology to future research because it could be handy to researchers.

Social Security recipients' motivations and limitations

The most novel and compelling finding we have is the relationship between Social Security recipiency and nontraditional type. As noted previously, our attempts to interact Social Security recipiency with other demographic and financial variables did not yield any significant results.

Social Security is a lifetime, inflation-adjusted cash benefit. A beneficiary pursuing exclusively nontraditional work could suggest a combination of motivations.

First, we observe that beneficiaries supplement their benefits with earned income. Perhaps this means that benefits are insufficient. Our analysis examined household income relative to poverty, but the official poverty threshold has many weaknesses when used as a proxy for economic security, especially among a population that has high-cost expenditures (e.g., health spending) that grow in price faster than inflation. Or, older beneficiaries in a period of dissaving may experience an income shock that they have insufficient savings to meet, or they may experience an acute need for additional spending. Prior work, for example, has found that mothers increase their labor supply when their adult children lose their job (Edwards and Wenger 2019) and that parents send transfers to children when they are going through a divorce (McGarry 2016), just two examples from a large literature on intergenerational transfers. Future research could investigate how Social Security recipients' nontraditional earnings vary with savings, shocks, or costs to their household or family.

Second, nontraditional earnings can overlap with off-the-book earnings or underreported earnings. Nontraditional work among recipients may mean that the program is structured in a way that discourages work among those who still want to work but do not want to hit tax penalties. We did not delineate between the type of Social Security benefit — Old Age, Survivors, or Disability — but did see its predictive power for those older and younger than 65. Old Age and Survivors beneficiaries with high enough earnings face a potential tax penalty.[6] Disability recipients also face a

[6] The relationship between Social Security benefits and non-Social Security income depends on whether the beneficiary is younger or older than their full retirement age (FRA). Social Security beneficiaries who claimed benefits early, before reaching FRA, and who earn above a certain amount can see a benefit reduction. Social Security beneficiaries after FRA may see a portion of their benefits subject to federal income tax, if their non-benefit income is high enough. See Social Security Administration (n.d.-c, n.d.-a) for additional explanation.

benefit loss if they earn a substantial amount.[7] The potential loss of benefits has been shown to disincentivize work (Weathers II and Hemmeter 2011). This is a tractable area of future research from our findings, given that many of the tax cutoffs and earnings penalties are stark, and researchers could look for earnings bunching, similar to the kink point bunching of the Earned Income Tax Credit (Saez 2010).

Third, if nontraditional earning reflects the previously discussed constraints — that they are easier jobs to get for low-employment populations — then nontraditional earnings among Social Security beneficiaries could reflect labor market barriers that exist for older workers who wish to earn income. The Age Discrimination in Employment Act of 1967 prohibits discrimination against workers over age 40 in terms of hiring, discharge, compensation, and terms of employment. However, older workers still report discrimination on account of age as a barrier to work (Adams 2004; Chou and Choi 2011). In addition to discrimination, older workers may lack accommodation in the workplace that allows them to remain working. A study of working conditions in the U.S. found that many older workers have difficulty maintaining employment as they age for this reason (Maestas et al. 2017).

Fourth, if nontraditional earnings reflect previously discussed preferences — that they are preferable jobs for workers who desire flexibility — then nontraditional earnings among Social Security beneficiaries could reflect the desire to continue working as part of retirement. Retirement as a one-time, permanent transition from full-time work to no

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[7] Disability Insurance beneficiaries may also be eligible for, and subsequently lose with earnings, Medicare. However, Medicare and benefits are not coincidental on either end. Beneficiaries are only eligible for Medicare after 24 months of benefits, and beneficiaries do not lose Medicare until 93 months after benefits cease (technically the end of the Trial Work Period). See Social Security Administration n.d.-b) for additional explanation.

work is now the exception, rather than the rule (for a discussion see Carman, Edwards, and Brown [2022]). Indeed, in the same survey that found older workers need accommodation to stay in the workforce, older workers also reported a strong desire for flexible work and incorporating part-time work as part of their move to retirement (Maestas et al. 2019).

Each of these motivations for nontraditional earnings has separate policy implications for Social Security, whether to in terms of tax collection, tax and benefit incentive structure, or how its benefit design reflects (or does not reflect) modern retirement transitions. For example, if it is the case that half of workers go back to work after initially retiring (Maestas 2010), or “unretire,” then there may be a value added to Social Security for allowing partial benefit claiming at a certain age or for a certain amount of years. This could enable longer work lives and possibly ameliorate the incentive to underreport earnings or seek nontraditional work.

Caveats

There are two primary reasons why our findings presented here may not be representative of nontraditional earnings experiences in the U.S., but instead capture a part of it. First, our data spans the years 2013 to 2019; the entirety of our analytic observation occurs during an economic expansion in which the U.S. was steadily adding payroll employment jobs, the unemployment rate was falling, and labor force participation was increasing. Given the suggestive relationship between the unemployment rate and straddler type, we would not expect nontraditional earnings rates to be constant during an economy-wide contraction, but our data do not currently allow for us to examine this directly. The data are not currently available through the pandemic period of 2020 to 2021, which included spiked unemployment rates and then rapid job gain, both of which would provide insight into nonemployee employment.

Second, it is unclear to what extent the SIPP accurately captures nontraditional earnings. It does have some advantages over existing surveys; for example, it asks about seven sources of earned income with the same battery of classification questions for each. But it is not perfectly clear what "other work arrangements" signifies, either in aim of the survey instrument or in respondents who answer affirmatively that that describes their earnings situation. Nontraditional earnings are difficult to capture in any survey. However, there is reason to think that the prior iteration of the SIPP, before the most recent redesign, might have performed better at capturing nontraditional work. Rather than asking about seven sources of earned income with identical questions, the prior SIPP (covering the 1996-2008 panels), instead asked about two jobs and two sources of business income. Beyond that, it asked if an individual ever "moonlighted" and earned money on the side. In a separate part of the survey on income sources, individuals are asked if they had any casual earnings.

Hence, in the prior SIPP, the classification of nontraditional earnings includes any income from an unincorporated business, which is also captured in the post-2014 SIPP, as well as moonlighting income and casual earnings, which is not. In Table 8, we show the annual rates of earner types in both surveys: Those with at least one job and, conditional on having at least one job, the share that are traditional, nontraditional, or a straddler. Again, straddler type is income from both sources within a calendar year. Comparing the two survey estimates has the similar challenge of covering over 20 years of labor market activity, during which labor force participation was not constant, two recessions occurred, and the opportunity for nontraditional earnings changed with the advent of platform-based gig work and the trend toward independent contracting.

The SIPP's prior design generated much higher estimates of nontraditional work, though this varies by sole or straddler. The share of workers who are nontraditional type falls over the span of four panels, from over 7% in 1996 to around 3.5% in the last five years of the prior design, 2007 to 2012. The new SIPP picks up the next year and has similar rates of nontraditional type, ranging from 2.9% to 3.5%. Hence, nontraditional type may be consistently measured across the 25 years of survey data. (As far as further research and motivations, this allows more comprehensive work on barriers as a role in nontraditional earnings and Social Security recipient earning patterns.)

Estimates of straddler type, on the other hand, vary considerably in the survey's two eras. In the prior SIPP, straddlers fall from over 10% of workers to around 5.5%. But the new SIPP starts with a straddler rate below 1%, and does not see rates higher than 1.3%. This is not surprising given the differences in the survey instrument: Asking directly about side income makes it more likely for an individual to report it. As it is, we have no way of discerning if the differences between the panels are due to misclassification, underreporting, or a combination of both. Our straddler type was much more likely to be older, more highly educated, and have a higher income. It could be that the new SIPP is missing the younger, less educated, and lower-income straddler types because the nature of their nontraditional earnings were not equally likely to be reported.

Table 8: Traditional and nontraditional earnings in two SIPP design eras

1996-2008 SIPPs	Survey sample size (#)	Workers with at least one job (%)	Traditional worker (%)	Nontraditional worker (%)	Straddler (%)
1996	27,905	71.0%	78.8%	7.7%	13.5%
1997	50,048	70.6%	82.1%	6.9%	11.1%
1998	47,119	70.1%	83.3%	6.6%	10.0%
1999	35,326	70.4%	84.3%	6.5%	9.1%
2001	44,282	72.0%	81.9%	6.5%	11.6%
2002	41,762	70.2%	84.4%	6.5%	9.0%
2003	10,599	68.7%	86.1%	6.6%	7.3%
2004	62,273	68.4%	87.3%	3.6%	9.2%
2005	56,379	67.2%	89.6%	3.2%	7.2%
2006	25,447	65.8%	90.7%	3.2%	6.0%
2007	6,274	64.2%	91.9%	3.4%	4.7%
2009	55,410	64.7%	89.8%	3.5%	6.7%
2010	51,559	62.7%	90.6%	3.5%	5.9%
2011	48,621	61.7%	90.8%	3.6%	5.6%
2012	45,975	61.1%	90.9%	3.6%	5.5%

2014-2018 SIPPs	Survey sample size (#)	Workers with at least one job (%)	Traditional worker (%)	Nontraditional worker (%)	Straddler (%)
2013	54,322	59.7%	96.4%	2.9%	0.8%
2014	42,071	60.2%	95.8%	3.1%	1.1%
2015	34,818	58.9%	95.9%	2.9%	1.2%
2016	30,924	59.0%	95.8%	3.0%	1.2%
2017	48,823	60.3%	96.2%	2.8%	1.0%
2018	38,659	56.9%	95.5%	3.3%	1.2%
2019	40,929	57.2%	95.3%	3.4%	1.3%

Source: U.S. Census Bureau, Survey of Income and Program Participation. The table shows the share of adult respondents in a calendar year who had at least one source of earned income and, conditional on reporting income, the distribution of mutually exclusive and exhaustive earner types: traditional, nontraditional, and straddler.

A final caveat is that the SIPP is not necessarily the preferred data set for earnings and employment analysis, as we noted and discussed in the data section. Moreover, the newly redesigned SIPP is a more recent release and there is less familiarity among all researchers with the survey instrument and population. The prior era of the SIPP had nearly two decades of accumulated research experience in how to optimize use of the data and its drawbacks, which researchers are still uncovering with the redesign. A panel of the National Academies of Sciences, Engineering, and Medicine (NASEM) performed an assessment of the redesign, and noted that while it outperformed the prior SIPP in employment and earnings data, the data was slow to be released and still needs more research into its weaknesses (National Academies of Sciences, Engineering, and Medicine 2018). We have included in our Technical Appendix the variable names and coding schema in defining worker typology and have made our code publicly available. A hoped-for contribution of this paper is to enable more research into the redesigned SIPP by lowering barriers to entry.

Conclusion

Income earned from the selling of labor in the U.S. falls into two broad types: employee and nonemployee employment. This paper aims to understand more about who works in the latter. The challenges to this include that nonemployee employment spans numerous earnings arrangements, those arrangements vary in how similar or different they are from employee employment, and those arrangements are not always well captured, or equally captured, in survey data. Moreover, the frequency of nonemployee employment and its coincidence with employee employment also both vary. As a means of parsing these numerous arrangements, we created a typology of workers: one traditional job; multiple traditional jobs; nontraditional; straddler. Our definition of traditional grouped employee employment with self-incorporated business, and left nontraditional as the remainder of all other arrangements. A contribution of our paper is to identify these workers in the newly redesigned SIPP and compare our identification with the prior SIPP.

In our analysis, we performed basic regressions to understand what factors predict whether a worker belongs in the nontraditional type and straddler type. We found support that nontraditional types skew to those with less success in the traditional labor market, and that despite both having nontraditional earnings, the straddler type skewed to those with more success in the traditional labor market. This is a subtle but helpful finding in directing future research into nonemployee work arrangements. Our primary contribution was to identify the strong predictive power Social Security recipiency has on belonging to the nontraditional type. We discussed the four key motivations Social Security recipients can have in seeking nontraditional earnings and potential research to further investigate them.

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Technical Appendix

This appendix provides supplemental technical documentation for issues that arose in the execution of our analysis, and is organized by their presentation in the paper.

Balancing of 2014 and 2018 SIPPs

The 2014 SIPP was a stand-alone panel; at its completion, the 2018 SIPP began with the intention that each subsequent panel would begin one year following the previous. For our analysis, the 2014 panel is much larger than the 2018 panel, since it was not intended to “share” yearly sample size with other panels. We do not use the subsequent panels (2019, 2020, etc.) because they do not have three years of data yet.

To understand how the analytic sample varies across the two panels, we run the following regression:

$$Demographic = \alpha + \beta * SIPP_{2014} + \varepsilon$$

The dependent variable (*Demographic)* is a binary flag for the demographic variable in question and the independent variable ($SIPP_{2014}$) is a binary flag indicating that the record belongs to the 2014 SIPP panel (the base group is the 2018 SIPP). We run a regression for each of the demographics presented in Table 3 and present the coefficient and significance level for the coefficient on the 2014 SIPP flag.

Table A1: Balancing test between 2014 and 2018 sample along demographic characteristics

Demographic	Coefficient	Significance level: * = 10%; ** = 5%; *** = 1%
Race-ethnicity: White, non-Hispanic	-0.009	***
Race-ethnicity: Black, non-Hispanic	0.031	***
Race-ethnicity: Hispanic	-0.008	***
Race-ethnicity: All other, non-Hispanic	-0.013	***
Education: Less than high school	0.039	***
Education: High school equivalent	0.012	***
Education: Some college or Associate's	-0.003	***
Education: Bachelor's	-0.027	***
Education: Graduate or professional	-0.021	***
Sex: Female	0.003	***
Age: 0 to 17 years	0.022	***
Age: 18 to 19 years	0.000	***
Age: 20 to 29 years	0.008	***
Age: 30 to 39 years	0.003	***
Age: 40 to 49 years	0.004	***
Age: 50 to 59 years	0.003	***
Age: 60 to 64 years	-0.005	***
Age: 65+ years	-0.036	***

There are statistically significant differences in the demographic composition of the 2014 and 2018 SIPP panels. The high degree of statistical significance is likely driven by the large sample sizes (see Table 1), and the differences could either reflect population changes over the years of study, changes to the SIPP's panel accuracy, or a combination of both. The biggest differences are that the 2014 SIPP has more Black individuals, more individuals with a high school degree or less, and fewer elderly individuals. In contrast, the working age population, gender share, and share white or Hispanic is very similar.

Defining work arrangements in the redesigned SIPP

The 2014 SIPP was the first panel to reflect a major redesign in SIPP survey and methodology. The prior 20 years of SIPP data (from the 1996, 2001, 2004, 2008 panels) had followed a separate but harmonious design. To ease in replication of our analysis and to encourage further research in this area, we provide the variable names and definition schema of our earning types with the new SIPP variables that researchers are, at the time of writing, relatively unfamiliar with.

Table A2: Variables required for defining work arrangements and type of earnings

Variable in SIPP	Definition	Use in Traditional Definition
ejb1_jborse- ejb7_jborse	Description: The variable describes the type of work arrangement, whether work for employer, self-employed, or other Response code: Employer Self-employed (owns a business) Other work arrangement Universe: Respondents who held a job during the reference month	Worked for an employer: ejb`j'_jborse== 1  Self-employed, incorporated: ejb`j'_jborse== 2 & ejb`j'_incpb == 1  Self-employed, not incorporated: ejb`j'_jborse == 2 & ejb`j'_incpb == 2  Other arrangement ejb`j'_jborse == 3
ejb1_incpb-ejb7_incpb	Description: Variable showing if business `j’ was incorporated  Response code: Yes No  Universe: ejb`j’_jborse = 2 where `j’ refers to the job number	Self-employed, incorporated: ejb`j'_jborse== 2 & ejb`j'_incpb == 1 Self-employed, not incorporated: ejb`j'_jborse == 2 & ejb`j'_incpb == 2
tjb1_msum-tjb7_msum	Monthly earnings from job `j’, varying with the number of days in the month  Response code: 0:$99,999,999  Universe: Job `j’ was held in the reference month	

Person-month, person-year, versus person-panel categorization

The SIPP provides monthly observations of employment variables, allowing us to assign individuals into worker types based on their work arrangements in a single month, in a calendar year, or over the three years of the panel. For the regression analysis, we chose to examine person-year patterns of work arrangements, which adhered with policy and economic variables, such as the unemployment rate or the minimum wage, and allowed for a reasonable amount of time to observe straddling. In Tables A3 and A4, we replicate the person-year means presented in Table 3 of the paper on the person-month and person-panel levels.

Table A3: Distribution of earner types within demographic by person-month

Demographic	Sample Shares	Nonearner	Traditional earner (one job)	Traditional earner (multiple jobs)	Non-traditional earner	Straddler
Race-ethnicity						
White, non-Hispanic	67.7% (1097748)	47.6% (522875)	46.3% (508533)	4.2% (45591)	1.5% (16399)	0.4% (4350)
Black, non-Hispanic	11.5% (186624)	50.4% (93979)	44.4% (82872)	3.7% (6819)	1.3% (2507)	0.2% (447)
Hispanic	13.9% (224928)	41.5% (93457)	52.5% (118164)	3.2% (7101)	2.5% (5550)	0.3% (656)
All Other, non-Hispanic	6.9% (112572)	45.3% (50970)	49.3% (55534)	3.4% (3796)	1.7% (1945)	0.3% (327)
Education						
Less than high school	12.9% (208800)	66.1% (137968)	30.3% (63234)	1.4% (2883)	2.1% (4324)	0.2% (391)
High school & equivalent	29.1% (471816)	53.0% (250108)	42.7% (201437)	2.5% (11877)	1.5% (7190)	0.3% (1204)
Some college	27.9% (451728)	45.0% (203492)	49.0% (221491)	4.1% (18444)	1.5% (6997)	0.3% (1304)
Bachelor's	18.2% (294804)	34.8% (102708)	57.4% (169085)	5.7% (16697)	1.6% (4688)	0.6% (1626)
Graduate/ professional	12.0% (194724)	34.4% (67005)	56.4% (109856)	6.9% (13406)	1.6% (3202)	0.6% (1255)
Sex						
Male	46.7% (757584)	41.1% (311656)	52.5% (397850)	4.1% (30727)	1.9% (14250)	0.4% (3101)
Female	53.3% (864288)	52.0% (449625)	42.5% (367253)	3.8% (32580)	1.4% (12151)	0.3% (2679)
Age Group						
Age: [18, 20)	1.3%	54.2%	41.5%	3.5%	0.6%	0.2%

	(20448)	(11082)	(8495)	(711)	(119)	(41)
Age: [20, 29)	12.6% (204408)	30.5% (62431)	62.4% (127463)	5.6% (11414)	1.2% (2517)	0.3% (583)
Age: [30, 39)	14.8% (240840)	24.9% (59858)	67.2% (161872)	5.4% (12946)	2.0% (4915)	0.5% (1249)
Age: [40, 49)	15.5% (251208)	26.4% (66340)	65.7% (165008)	5.5% (13770)	1.9% (4890)	0.5% (1200)
Age: [50, 59)	19.3% (313416)	36.1% (113012)	56.7% (177697)	4.8% (15196)	2.0% (6125)	0.4% (1386)
Age: [60, 65)	10.2% (165456)	53.1% (87848)	41.6% (68889)	3.0% (4933)	1.9% (3105)	0.4% (681)
Age: [65, inf)	26.3% (426096)	84.7% (360710)	13.1% (55679)	1.0% (4337)	1.1% (4730)	0.2% (640)

Source: U.S. Census Bureau, Survey of Income and Program Participation. The first column expresses distribution across demographic groups within demographic category (e.g., distribution among age groups), the subsequent columns express distribution of a distinct demographic group across earner types (e.g., distribution of women among earner types). Distribution is presented as percentage with number of observations in parentheses.

Table A4: Distribution of earner types within demographic over first three years of survey

Demographic	**Sample Shares**	**Nonearner**	**Traditional earner (one job)**	**Traditional earner (multiple jobs)**	**Non-traditional earner**	**Straddler**
Race-ethnicity						
White, non-Hispanic	67.7% (30493)	37.5% (11432)	48.2% (14705)	9.7% (2967)	1.9% (581)	2.6% (808)
Black, non-Hispanic	11.5% (5184)	38.0% (1972)	48.2% (2501)	9.8% (506)	1.9% (99)	2.0% (106)
Hispanic	13.9% (6248)	28.8% (1797)	56.2% (3514)	8.8% (550)	3.0% (189)	3.2% (198)
All Other, non-Hispanic	6.9% (3127)	32.6% (1019)	53.2% (1665)	9.4% (293)	2.0% (61)	2.8% (89)
Education						
Less than high school	12.9% (5800)	55.3% (3205)	35.6% (2063)	4.2% (243)	3.1% (182)	1.8% (107)
High school & equivalent	29.1% (13106)	42.2% (5525)	46.6% (6105)	7.1% (924)	2.0% (266)	2.2% (286)
Some college	27.9% (12548)	32.4% (4067)	52.1% (6543)	11.0% (1381)	2.0% (253)	2.4% (304)
Bachelors	18.2% (8189)	25.4% (2078)	56.7% (4645)	12.6% (1034)	1.7% (139)	3.6% (293)
Graduate/professional	12.0% (5409)	24.9% (1345)	56.0% (3029)	13.6% (734)	1.7% (90)	3.9% (211)
Sex						
Male	46.7% (21044)	30.7% (6455)	54.0% (11364)	9.8% (2064)	2.2% (465)	3.3% (696)
Female	53.3%	40.7%	45.9%	9.4%	1.9%	2.1%

	(24008)	(9765)	(11021)	(2252)	(465)	(505)
Age Group						
Age: [18, 20)	1.3%	17.1%	64.1%	16.4%	0.5%	1.9%
	(568)	(97)	(364)	(93)	(3)	(11)
Age: [20, 29)	12.6%	11.9%	65.2%	18.7%	1.2%	3.1%
	(5678)	(673)	(3700)	(1060)	(68)	(177)
Age: [30, 39)	14.8%	14.2%	65.7%	14.1%	2.0%	3.9%
	(6690)	(953)	(4397)	(946)	(134)	(260)
Age: [40, 49)	15.5%	16.6%	65.2%	12.4%	2.2%	3.6%
	(6978)	(1161)	(4550)	(867)	(151)	(249)
Age: [50, 59)	19.3%	26.3%	58.2%	9.8%	2.5%	3.2%
	(8706)	(2288)	(5069)	(851)	(217)	(281)
Age: [60, 65)	10.2%	40.8%	48.2%	5.9%	2.7%	2.4%
	(4596)	(1877)	(2216)	(270)	(123)	(110)
Age: [65, inf)	26.3%	77.5%	17.6%	1.9%	2.0%	1.0%
	(11836)	(9171)	(2089)	(229)	(234)	(113)

Source: U.S. Census Bureau, Survey of Income and Program Participation. The first column expresses distribution across demographic groups within demographic category (e.g., distribution among age groups), the subsequent columns express distribution of a distinct demographic group across earner types (e.g., distribution of women among earner types). Distribution is presented as percentage with number of observations in parentheses.

Determining concurrent traditional job holding

The SIPP tracks up to seven unique jobs (see variables EJB1_JBORSE to EJB7_JBORSE) in any given month and includes a generated count of the total number of jobs an individual worked in that month (see variable RMNUMJOBS). However, the variable RMNUMJOBS does not distinguish cases when an individual has a job and changes employers (flagged as two jobs in the month) versus working two (or more) jobs in the same month simultaneously (also flagged as two, or more, jobs).

The SIPP does include additional detail that allows us to account for this distinction, specifically, for each job in each month the SIPP provides the start month (e.g., EJB1_BMONTH) and end month (e.g., EJB1_EMONTH) that the individual worked that job. Given this additional detail, we can adjust the total count of jobs worked in a month accounting for job switching. For example, suppose an individual is flagged as working two jobs in a particular month (let's call these Jobs 1 and 2). If the end month for Job 1 overlaps with the start month for Job 2 and the duration of Job 2 is greater than one month worked, this is flagged as a change in primary job. On the other hand, if Job 2 overlaps with Job 1, but Job 1 persists beyond the duration of Job 2 or Job 2 only lasts for one month, this is not considered a job change but rather a truly separate job from Job 1. The if-else statement below formalizes this example:

Suppose an individual works two jobs in a single month, Jsobs 1 and 2. Then:

- If End $Month_1$ == Start $Month_2$ & End $Month_2$ – Start $Month_2$ > 1
- Then flag as a job switch, else treat as distinct jobs.

If a job switch is indicated, we subtract one for the provided total count of jobs worked in a given month. The full algorithm, looping over jobs 2 through 7 is as follows:

For j = 2:7:

IF End $Month_{j-1}$ == Start $Month_j$ & End $Month_j$ – Start $Month_j$ > 1:

Replace RMNUMJOBS = RMNUMJOBS - 1

ELSE

RMNUMJOBS = RMNUMJOBS

We proceed with our analyses using this adjusted count of jobs worked.