Opening the Black Box of Self-Employment: Identifying Alternative Work Arrangements in the United States[1]

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Abstract: While 18.4% of workers report engaging in self-employment, there exists a dearth of data identifying heterogeneity in the nature of these work arrangements. To address this gap, this paper uses novel data using machine learning leveraging internal data collected in the 2003-2019 waves of the Panel Study of Income Dynamics on respondents' narrative descriptions of their industry and type of work along with their employer names. The paper uses these data to examine trends in the prevalence and nature of self-employment work arrangements, transitions across these arrangements, and who works in these arrangements. Findings show disparate trends in the share of workers engaging in different types of self-employment work arrangements that would otherwise be masked. Further results suggest that the informally self-employed tend to be less educated, are less likely to be male and non-Hispanic White, have less labor income, and have worse measures of wellbeing.

Keywords: Self-employment, non-traditional work arrangements, independent contractors, work, wellbeing, employment trends

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Self-employment consists of a wide array of different work arrangements, but is often reported in administrative and survey data as a singular, homogenous category. For example, an individual pursuing self-employment in the transportation sector could 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. The characteristics of these jobs - the barriers to entry, risks, work stresses, and compensation - are likely to vary considerably. However, in most existing data sources, we would be unable to meaningfully differentiate these jobs.

A substantial share of self-employment consists of alternative work arrangements – work that falls outside of traditional employer-employee relationships. However, as discussed in the National Academies of Sciences, Engineering, and Medicine (2020) report on measuring alternative work arrangements, existing data sources on alternative work arrangements offer limited insight into the changing nature of work to inform appropriate policy. Administrative data do not capture work associated with income not reported to tax authorities, and survey data do not capture activity that survey respondents do not consider to be work. Due to these data limitations, it has been difficult to estimate the size of the workforce engaged in alternative work arrangements, examine how such arrangements are changing over time, and to understand how these jobs affect workers' wellbeing.

Understanding such heterogeneity in self-employment has become all the more important as new technologies such as electronic platforms have introduced new means of engaging in self-employment with potentially more far-reaching effects on the economy. The introduction and growth of the platform gig economy, one type of alternative work arrangement, have raised the question about how big this sector is, as well as the extent to which such jobs crowd out employment in other sectors, and the extent to which such jobs are good for workers' wellbeing. Answering these questions requires identifying such work separately from other types of self-employment.

This paper fills existing gaps by using novel data constructed using machine learning and internal respondent narratives on industry, type of work, and employer names collected in the 2003-2019 Panel Study of Income Dynamics (PSID). These data separately identify wage and salaried employment, business ownership, platform gig work, informal self-employment, and formal self-employment. The paper uses these data to examine: (1) how the prevalence and nature of different self-employment work arrangements has changed over time, (2) how individuals transition across different types of self-employment, and (3) the work and worker characteristics associated with different types of self-employment. While many surveys use narratives on industry and type of work to produce codes classifying industry and occupation, to our knowledge, this is the first effort to use them to identify different types of self-employment. By identifying who works in different self-employment arrangements over time, this paper aims to inform future policy making related to regulating and providing benefits to self-employed workers.

Measuring Self-Employment

Self-employment is notoriously hard to measure. While both administrative data and surveys are able to provide some insight about self-employment, they also each face challenges. As a result of these challenges, discrepancies appear across administrative and survey data sources in identifying trends in self-employment broadly and in specific arrangements such as contingent work and gig employment (Abraham et al., 2018, 2021a; Allard and Polivka, 2018; Jackson et al., 2017; Katz and Krueger, 2019a, 2019b).

Measuring Self-Employment in Administrative Data

Administrative data are derived from tax reporting and can be used to identify wage and salaried employment separately from self-employment based on the types of income reported in tax filings. However, unlike administrative records of wage and salary income which come from third-party reporting by employers on Form W-2s, administrative records of self-employment income rely on both third-party reporting by firms on 1099-K and 1099-NEC forms[2] as well as taxpayer reporting of other self-employment income.

While 1099 forms do provide valuable information on some self-employment income, these forms suffer from incomplete coverage. Self-employed workers are only issued a 1099-NEC form by firms from which they received compensation of $600 or more. While the income threshold is relatively low, self-employed workers primarily receiving payment from non-firms or through payment processors, such as sellers on eBay or drivers on ride-share apps like Uber or Lyft,[3] are not captured. Additional coverage is provided through the 1099-K form, which requires payment processors to report a payment recipient's transactions if they exceed $20,000 and the number of transactions exceeds 200.

In the absence of third-party reporting, taxpayers report self-employment income through their tax filings on Schedules C and SE. Absent noncompliance, taxpayer-reported self-employment income should provide comprehensive and accurate estimates of self-employment. However, taxpayers face incentives to strategically report taxable income, and lacking third-party information reporting, are more likely to strategically report (Slemrod et al., 2017). This leads to concerns regarding the accuracy of administrative data (Mortenson and Whitten 2020;

[2] The Form 1099-NEC replaced the Form 1099-MISC in the 2020 tax year.
[3] These workers may receive a 1099-NEC if, for example, they participated in a bonus or referral program. However, the bulk of their earnings would not be covered by the 1099-NEC.

Saez 2002) as the IRS estimates only a 44% tax reporting compliance rate among self-employed workers (Slemrod, 2016), consistent with the results of Abramowitz (2025) finding self-employment income underreported in administrative data as compared to the Health and Retirement Study. Furthermore, administrative data can be sensitive to reporting incentives as Garin et al. (2022) found that recent increases in taxpayer-reported self-employment in tax data are largely explained by changes in reporting behavior in response to reporting incentives rather than actual changes in self-employment activity.

Measuring Self-Employment in Surveys

Since individuals do not face the same economic incentives to misreport on surveys as on their tax filings, surveys can be valuable complements to administrative data, especially in the context of measuring self-employment. Surveys can also capture greater breadth and detail of a variety of measures often absent in administrative data such as physical and mental health, education, and time use.

However, surveys were designed to capture traditional wage and salaried employment, and accordingly, an ample literature documents myriad issues as survey questions may not capture the way individuals perceive their work, especially in less traditional work arrangements (Allard and Polivka, 2018; Bureau of Labor Statistics, 2018; Abraham and Amaya, 2019; Bracha and Burke, 2021; Abraham et al., 2023), and can produce divergent estimates based on sampling modes, methods, and timing (Katz and Krueger, 2019b).

To overcome these issues, some recent work has conducted independent surveys to ask respondents questions specific to the topic of interest. As one such example, Abraham et al. conducted a Gallup telephone survey module to identify independent contracting (Abraham et al., 2021b; 2023). Conducting such surveys in combination with focus groups allows refining of questions to address common misalignments between the question intent and the respondent's response. However, response rates may be low and new surveys cannot provide historical data to understand changes in outcomes of interest over time.

An alternative approach is to use collected measures in existing surveys as proxies for identifying heterogeneity in self-employment. For example, Levine and Rubinstein (2017) examined differences in the characteristics of individuals engaged in incorporated self-employment and unincorporated self-employment, aiming to distinguish between entrepreneurs and other business owners, consistent with earlier work (Carr, 1996; Budig, 2006; Ozcan, 2011). Similarly, Boeri et al. (2020) considered differences between the self-employed with employees and the solo self-employed to distinguish between more and less formal self-employment. Likewise, Moulton and Scott (2016) used broad occupation codes, number of employees, and the presence of household business assets to identify more and less desirable categories of self-employment.

A drawback to these approaches is the extent to which such proxies reflect their intended measures. For example, Light and Munk (2018) use data from the 1979 NLSY to show that the majority of reported self-employment does not reflect business ownership: they find that 68 percent of self-employment is not identified as business ownership and 30 percent of incorporated self-employment is associated with neither business ownership nor reported business income.

Novel Data on Self-Employment

While the aforementioned 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 and long-running surveys. The present study adds to the literature by exploring heterogeneity in self-employment work arrangements based on respondents' descriptions of their work. While many surveys use such narratives to produce codes classifying industry and occupation, to our knowledge, this is the first effort to use them to identify different types of self-employment. By leveraging narrative survey information to capture the breadth of self-employment work arrangements, we can identify their prevalence and trends and understand their links with individual wellbeing. This work contributes to a more thorough understanding of the determinants and outcomes associated with different work arrangements. By using PSID data, this work benefits from the breadth of information collected in the PSID both contemporaneously and longitudinally as well as high survey response rates: over 2003-2019, wave-specific response rates on the main PSID ranged from 88.3% to 94.3% (University of Michigan Institute for Social Research, 2023).

Data and Methods

Panel Study of Income Dynamics

This analysis uses the 2003-2019 PSID. The PSID is a longitudinal dataset that began in 1968 with a sample of approximately 5,000 U.S. households; it was updated annually through 1997 and bi-annually thereafter. As of 2017, it had grown to include over 10,000 families and 24,000 individuals. The PSID asks questions on a breadth of topics including employment, income, and physical and mental health. While the PSID collects some information on all household members, most measures are collected only for the reference person ("Head") and their spouse/long-term cohabitor. Relevant to our analyses, the PSID asks respondents to describe all of the work for money that the reference person and spouse have done since January 1 of the prior wave year. Respondents are subsequently asked whether the reference person and spouse are self-employed or employed by someone else on up to four jobs that they reported holding since the prior survey wave.[4]

Classification of Work Arrangements in the PSID

In addition to publicly-available PSID data, the analysis leverages internal data collected in the PSID on narrative descriptions of industry and occupation and employer names to classify work arrangements into a useful framework (Abramowitz et al., 2023). The narratives include answers to the following open-ended questions: "What kind of business or industry is that [job] in?" and "In your work for [your employer] what is your occupation?" and tend to be 3-4 sentences long. Interviewers are instructed to record occupation and industry answers verbatim and are provided guidelines to ascertain complete information on the respondent's job and job duties/activities. They are directed to probe for clear, complete answers and specifics of what the respondent does on the job and the business or industry type in order to be able to distinguish among unskilled workers, semi-skilled workers, and skilled workers, as well as among white-collar occupations. Interviewer instructions for the 2015 wave are included in Appendix 1 (PSID, 2017). The PSID collects this information for all of the respondent's and the spouse's jobs held since January 1 of the prior survey year through the time of the survey.[5] Among employed respondents and spouses, 99.9% provided current job narratives to the open-ended industry and type of work questions. Some respondents who self-report as not employed also reported current job narratives.[6] These narratives were collected to assign industry and occupation codes to PSID

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[4] Respondents are generally the reference person or the spouse. In a small number of cases, when the reference person or the spouse is unavailable, another family unit member will complete the interview.

[5] For example, in survey year 2019, respondents are asked about their jobs in the 2017 and 2018 calendar years as well in the survey year through the time of the interview.

[6] The PSID asks multiple times for employment status. If the respondent ever mentions being employed in the first three instances, the PSID codes these individuals as employed. If the respondent never answers that they are employed, the PSID asks a more general question of whether the respondent is "doing any work for money now?"

respondents' jobs, consistent with practices across many major surveys. We use them for a different purpose: to identify different types of self-employment work arrangements.

The classification uses the employer names and narrative responses to the open-ended industry and type of work questions to code each job as one of five work arrangements (platform-mediated gig work, informal self-employment, formal self-employment, business owners, wage and salaried employees), with a small number assigned no label due to insufficient information. All narratives, including those that respondents described as wage and salary, were classified by the machine learning process. This was by design to allow respondents identifying as wage and salaried employees to potentially be classified as self-employed and vice versa. The classification schema is presented in Table 1. "Platform-mediated gig work" includes work for app- or Internet-based platforms where workers are assigned their work and paid through the platform (e.g., Doordash, Uber, Lyft).[7] "Informal self-employment" includes work done independently for non-business entities (e.g., cleaning, handyman) as well as itinerant forms of work (e.g., freelancer, babysitting, day laborer). "Formal self-employment" includes self-employment worked for another business entity or dictated by a formal contract with clients, such as self-employment under an "umbrella" company (e.g., real estate agents, financial planners at an advisory company), consultants, independent contractors, or subcontractors. "Business ownership" includes explicit reports of (1) owning or running a business or family farm, (2) being a partner in a firm or business, (3) being self-employed and managing their own or a family member's business or supervising employees, or (4) having business assets and

An affirmative answer to this question leads to the creation of a current job narrative, despite the respondent being classified as not employed in the public PSID data. Of non-employed respondents, 4.4% reported they had done some work for money.

[7] We do not classify marketplace platforms (e.g., Etsy) where workers simply list products or services that are then found by customers on the platform as platform-mediated gig work.

listing a formal name for the business. Finally, "wage and salaried employment" includes employees and employed supervisors including short-term employment and work at a temp agency.

The classification first distinguishes between wage and salaried work arrangements and self-employment work arrangements. While the approach incorporates information from self-reports of employment status and self-employment status on a given job, in cases where the narrative information and self-reported employment status or employment status conflict, the approach reclassifies work arrangements to align with the narrative information.[8] Overall, among those with a current main job narrative, we find that our classification-based measure and the PSID's self-reports of primary self-employment match in 96.5% of cases. In particular, 1.0% of wage and salaried self-reports were re-classified as self-employment, and 6.0% of self-employment self-reports were re-classified as wage and salaried employment.

Among the self-employed, the classification further distinguishes business ownership (requiring investment and managerial responsibilities), working independently but typically for a business entity (providing greater structure to the employment relationship), and working independently but typically for an individual or on an electronic platform, or having itinerant work (offering less structure to the employment relationship). The distinction between informal self-employment arrangements like freelancing and formal self-employment arrangements like independent contracting reflects a freelancer's relationship with a client being briefer and less formalized than an independent contractor. Whereas independent contractors are likely to have a contract with a client as part of an on-going relationship, a freelancer either interacted with their

[8] For example, an Uber driver might mistakenly classify herself as an employee. Alternatively, an employee at a temp agency might mistakenly classify herself as self-employed.

client only once or their successive interactions are independent and the interaction was not dictated by a contract. While the classification was not defined by occupation, reports of job activities (e.g., “cleaning” and “handyman”) were used to the extent that they suggest the likely nature of the relationship (in terms of brevity and formality) between worker and client. For example, a journalist would be considered a freelancer and classified in informal self-employment if it seemed that they submitted articles to papers at-will, but would be considered an independent contractor and classified in formal self-employment if they provided information to suggest that they had some agreement with the paper to submit articles regularly.

We used a machine learning model to automate our classification approach. To produce the “truth” data for training the model, two reviewers classified the same subset of 30% of the data according to the described schema. For each job, reviewers were presented with the respondent’s narrative descriptions of industry, occupation, and job title, the provided employer name/description, and information on the year, whether the job was the respondent’s main job, and if the respondent considered it to be self-employment. Reviewers were trained to consider all of this information to classify each job. For example, if the respondent classified themselves as self-employed but described what would otherwise be a standard wage and salaried employment role along with an employer’s name, reviewers were advised to overrule the self-classification and classify the job as wage and salaried employment. Reviewers were trained to apply the schema to have categories higher in the schema take precedence over categories lower in the schema. For example, narratives identifying work on a platform are classified as platform-mediated gig work, as platform-mediated gig work is the first category in the schema. Reviewers classified each job report for a respondent independently of any other jobs reported by that respondent during the same wave or in other waves. We took this approach to consider crosswave job reports independently so as to not impose consistency in work activities across survey waves in the presence of potentially meaningful distinctions.

The two reviewers had an agreement rate of 82.9%. Records for which the two reviewers disagreed were adjudicated by a third reviewer. We do not see significant differences in narrative length across categories, consistent with the interviewer instructions (PSID, 2017) to probe for clear complete answers and specifics of what the respondent does on the job and the business or industry type.

We then used machine learning to automate the classification. The manually-classified data were used to train a BERT-based machine learning model to classify the remainder of the data. This model is known for its robustness in handling imbalanced data due to its deep contextual understanding of language. Compared to traditional machine learning methods, this choice helped mitigate some of the issues arising from class imbalance, whereby some categories are overrepresented in the data. After training the model on the subset of classified data, we ran the model to compute the probability that each record belonged to each category and identify the predicted category based on the highest probability. To ensure a high level of accuracy, we flagged any prediction with a probability below a confidence threshold of 95%. Two reviewers then classified these low-probability cases following the same procedure as for producing the training data, with an agreement rate of 67.9%, lower than in the first round, reflecting that these records represent harder-to-classify cases. As in the first round, records for which the two reviewers disagreed were adjudicated by a third reviewer. This approach ensured that uncertain predictions, which are more likely to involve under-represented categories, received extra scrutiny to improve overall classification accuracy (Abramowitz et al., 2023).

For most analyses, we aggregate platform-mediated gig work into the informal self-employment category to make inferences based on sufficient sample size. While platform-mediated gig workers are considered independent contractors for tax purposes, we aggregate platform-mediated gig work into the informal self-employment category because we observe that the characteristics of platform-mediated gig workers are most similar to workers engaged in informal self-employment.

Sample Inclusion Criteria

While the PSID collects narratives for all jobs held over the two years prior to the interview, we limit our primary analysis to main jobs held at the time of the interview, with some supplemental analysis of secondary jobs held at the time of interview. We focus on jobs held at the time of interview to frame our analysis at a given point in time. To identify currently-held main jobs, we rely on internal PSID coding of jobs as "current main jobs." To identify currently-held secondary jobs, we rely on both internal PSID coding of jobs as "other" as well as publicly-available information on the timing of job spells. By construction, individuals can hold multiple secondary jobs. For 0.5% of job narratives, we cannot distinguish whether the job is currently or previously held, and we exclude these from our main analysis.

In Figure 1, we report our sample criteria and the effect on overall sample size. We restrict our base sample to respondent-waves linked to any job narrative between 2003-2019, [9] among respondents age 16 or older who are classified at least once as a reference person or spouse. This leaves us with 116,634 respondent-waves linked to 89,923 current job narratives. We drop any

[9] While narratives are available beginning in 1997 and the classification approach has been applied to the 1997-2019 data, we do not include data from the 1997–2001 survey waves in this paper's analyses due to changes in how the PSID coded main jobs that prevent us from consistently identifying main jobs separately from secondary jobs.

observations for which we cannot assign employment status, reducing our sample to 108,466 respondent-waves linked to 89,923 current job narratives. Of this sample, 27,263 respondent-waves are categorized as non-employed, 70,796 respondent-waves are categorized as wage and salaried, and the remaining 10,407 respondent-waves are categorized in some form of self-employment.

Analysis

Using this classification, we examine (1) how the prevalence and nature of different self-employment work arrangements has changed over time, (2) how individuals transition across different types of self-employment, and (3) the characteristics of individuals working in different types of self-employment. We residualize estimates of transitions controlling for state-level unemployment rates, age, and educational attainment, as well as dummy variables for gender, white/non-white status, marital status and home ownership, and year fixed-effects.[10] We deflate all measures of dollar amounts to 2019 dollars using the CPI-U. Finally, we weight all analyses using the PSID's cross-sectional individual weights.[11]

Results

Trends in Work Arrangements

We first examine how the shares of workers in different self-employment work arrangements have changed over time. Figure 2 presents trends by work arrangement for main jobs in Panel A and for secondary jobs in Panel B. Figure 2 shows that informal self-employment

[10] Controls for age are binned indicators for age < 25, age 25-34, age 35-44, age 45-54, age 55-64, and age 65+. Controls for educational attainment are binned indicators for completing less than a high school degree, a high school degree or equivalent, some college education, and a bachelor's degree or greater.
[11] For a detailed description of PSID cross-sectional individual weights, see Chang et al. (2019).

increasingly has become the most common form of self-employment over our time period for both primary and secondary employment. For main jobs, in Panel A, we see a rise in informal self-employment, from 4.9% in 2003 to 5.9% in 2019, with much of this rise occurring after 2009. This is partly driven by trends in platform gig work—excluding platform gig workers, we find the share of informal self-employment to be 5.4% in 2019. However, roughly half of this rise remains unexplained by rising platform gig work. In contrast, we see a decline in formal self-employment from 5.0% in 2003 to 3.4% in 2019, with much of this decline occurring after 2009. For business ownership, we see an increase following the Great Recession that has subsequently returned to pre-recession levels. For secondary jobs, in Panel B, over 2003-2019 we see that while the share of workers in formal self-employment or business ownership has been relatively constant, the share in informal self-employment has risen.

While these estimates are not directly comparable to those in the literature given our development of novel measures of self-employment work arrangements, we find that they point to similar patterns. Estimating the shares of workers in incorporated and unincorporated self-employment using the 1995-2012 Current Population Survey Annual Social and Economic Supplement (CPS ASEC) and the 1982-2012 National Longitudinal Survey of Youth (NLSY), Levine and Rubinstein (2017) found that 90.4-91.8% of workers are salaried, 6.2-6.8% are unincorporated self-employed, and 1.5-3.4% are incorporated self-employed, corresponding to 18.1-54.8% of self-employed workers being incorporated. Using the Princeton Self-Employment Survey conducted in April 2017, Boeri et al. (2020) found that 7.7% of workers are solo self-employed, while 2.3% of workers are self-employed with employees, corresponding to 23.0% of self-employed workers having employees.

We think of our combined informal and formal categories as comparable to Levine and Rubinstein's (2017) unincorporated self-employed and Boeri's solo self-employed and our business owners as comparable to their incorporated self-employed and self-employed with employees, respectively. In our data, over 2003-2019, we see 5.2% or workers in informal self-employment and 4.2% in formal self-employment, combining to 9.4%. Over 2003-2019, we see approximately 5.2% of workers classified in business ownership, corresponding to 35.6% of self-employed workers being business owners. Overall, we see more self-employment in all categories, consistent with prior literature showing that the CPS ASEC undercounts the self-employed (Abraham et al., 2018, 2021a; Abramowitz, 2025). We are not surprised to see a greater share of the self-employed classified in business ownership as compared to the share self-employed with employees, as not all business owners in our data have employees, and not all are incorporated. Taken together, we find our estimates to be plausible given the conceptual differences in categories and differences across datasets.

How Workers Transitions across Work Arrangements

To understand the job transitions driving these trends, we next examine how workers transition across work arrangements from one survey wave to the next. Table 2 presents residualized transition matrices across our four work arrangements and non-employment.[12] The work arrangement in the prior survey wave is represented in rows while the current survey wave work arrangement is represented in columns.

In Panel A of Table 2, each cell shows the weighted percentage of respondents having that combination of prior and current work arrangements, and in Panel B of Table 2, each cell shows

[12] Non-residualized estimates show qualitatively similar patterns.

the corresponding number of observations. Panel A of Table 2 shows that across all work arrangements, respondents are most likely to persist in the work status that they had in the prior survey wave. However, relative to non-employment and wage and salaried employment, self-employment is associated with greater diversity in transitions both across self-employment work arrangements and out of self-employment. We see that 67.0% of the nonemployed and 84.5% of wage and salaried workers in the previous wave stay in their respective roles. On the other hand, we see that self-employed workers are not nearly as likely to remain in their roles across survey waves with only 43.9% of informally self-employed workers and 41.1% of formally self-employed workers staying in their roles across waves. Business owners are also less likely to persist in their roles than wage and salaried employees, but more likely to remain in their roles than any other type of self-employment, with 64.6% of business owners remaining in their roles across survey waves. In addition, we see that relative to all other work arrangements, the informally self-employed are more likely to enter non-employment: 17.4% of those informally self-employed in the previous wave became nonemployed in the current survey wave, nearly double the probability of any other self-employment work arrangement.

To understand the extent to which transitions reflect meaningful changes in job characteristics, in Panel C of Table 2, each cell shows the weighted percentage of respondents that report having positive business assets in the current wave for each combination of prior and current work arrangements. We see clear patterns with increased business asset ownership among those staying as business owners, followed by the formally self-employed, informally self-employed, and then wage and salaried employees. For example, 85.9% of business owners staying in business ownership report positive business assets, compared to 66.6% who transition into informal self-employment and 57.9% transitioning from informal self-employment.

Likewise, we see that 41.1% of formally self-employed stayers report positive business assets, compared to 24.0% of informally self-employed stayers and 8.3% of both wage and salaried employees and nonemployed stayers. These patterns suggest the classification transitions reflect meaningful underlying differences in business asset ownership.

We acknowledge several limitations for interpreting the estimates from these transition analyses, mainly: 1) our classification approach may inflate the appearance of transitions, particularly between self-employment work arrangements, as respondents may describe the same job differently in different survey waves even though they have not changed their job activities and 2) our transition analyses do not include transitions associated with waves when respondents did not respond to the survey. With regard to (1), despite this limitation, we believe our estimates are instructive about patterns of transitions with our point estimates representing upper bounds. With regard to (2), we find that self-employment transitions for respondents in the waves before and after they are missing show similar patterns to those for respondents that were not missing, suggesting that such respondents do not bias our estimates.

Characteristics of Work and Workers by Work Arrangement

We first examine differences in occupational tasks and industry composition across work arrangements in Figure 3. In Panel A, we show three common measures of occupational task content for each of our work arrangements. Our measures of abstract, manual, and routine tasks replicate those of Autor and Dorn (2013). Following Hurst, Rubinstein, and Shimizu (2024), we convert these into z-score measures, such that our measures reflect unweighted standard deviation differences in task content for a given occupation relative to all other occupations.[13] In

[13] For example, a value of 1 would imply a given occupation has a task requirement one standard deviation above the average occupation.

Panel B, we aggregate 2-digit NAICS codes into nine industry categories, and report the share of workers in each category engaged in one of our three self-employment categories.[14]

These figures demonstrate that our classification captures substantial differences in the composition of tasks and industries of across self-employment work arrangements. In Panel A, we see that informally self-employed workers engage in occupations with the lowest levels of abstract task intensity and the highest levels of manual task intensity. On the other hand, business owners engage in occupations with the highest levels of abstract task intensity and the lowest levels of routine task intensity. In Panel B, we see that different self-employment arrangements are concentrated in different industries.

To better understand the characteristics of workers in different work arrangements, Table 3 presents demographic, work, and labor market characteristics and measures of wellbeing across work arrangements on main jobs. We break out platform gig workers to assess their comparability to informally self-employed workers. Examining demographic characteristics in Table 3, we can see that the informally self-employed are less educated than workers in all other work arrangements, though these differences are slight relative to wage and salaried employees and platform gig workers. The informally self-employed tend to be older than wage and salaried employees and slightly younger than or similar in age to other self-employed workers. We also see that the informally self-employed are more racially diverse than all other work arrangements, with the exception of platform gig workers. Table 3 further shows informal self-employment is associated with having lower labor earnings, fewer weekly hours worked, and lower wages relative to all other types of work other than platform gig work. In fact, platform gig workers and

[14] Educational Services (NAICS 61); Goods-Producing (NAICS 11, 21-23, 31-33); Health Care (NAICS 62); Information and Finance (NAICS 51-53); Leisure and Hospitality (NAICS 71-72); Other Services (NAICS 81); Prof. Services (NAICS 54-56); Public Admin. (NAICS 92); Trade and Transport (NAICS 42, 44-45, 48-49).

informally self-employed workers report similar labor market outcomes. Despite similar labor market outcomes, platform gig workers are more likely to report not owning a business and are less likely to report having positive business assets relative to informally self-employed workers, instead reporting levels similar to wage and salaried employees. On the other hand, formally self-employed workers and business owners are more likely to report owning a business and are more likely to report having positive business assets than the informally self-employed.

Finally in Table 3, we examine the extent to which different roles are associated with differential wellbeing. The informally self-employed are the least likely to report: (1) being in good health, (2) the absence of psychological distress, and (3) being very satisfied with their lives relative to all other work arrangements other than platform gig workers. As with labor market outcomes, we find that differences in self-reported well-being between platform gig workers and informally self-employed workers are statistically insignificant.

In Table 4, we examine how the characteristics of workers vary by secondary work arrangements.[15] The patterns we find in Table 3 largely hold. However, we find that the large gaps in economic outcomes—total labor earnings, weekly hours, and hourly wages—that we observed in Table 3 between informally self-employed workers and wage and salaried employees shrinks. In fact, those that hold secondary informal self-employment work largely similar hours to those who hold secondary wage and salaried employment.[16]

These results suggest salient differences in the composition of self-employment across the income distribution. To directly examine this, in Figure 4, among the employed, we report self-employment shares for those that hold primary informal self-employment, primary non-informal

[15] Whereas workers can only retain a single main job category by definition, workers can hold multiple secondary jobs. Thus, the same worker can be classified as a secondary job holder in multiple work arrangements.
[16] We note that this is also largely true for those who hold secondary platform gig work.

self-employment, and only secondary self-employment by income quintiles. We find a U-shaped distribution with the largest share of workers engaged in self-employment at the bottom (23.4%) and top (16.4%) income quintiles. As we move along the income distribution, the composition of self-employment changes. In the bottom quintile, 13.1% of workers are engaged in informal self-employment as their main job, in contrast with 1.3% at the top income quintile. On the other hand, workers in the top income quintile are slightly more likely to be engaged in formal self-employment or business ownership (10.9%) than workers in the bottom quintile (7.6%).

Our classification also suggests important heterogeneity in the composition of self-employment by gender and age. In Panel B of Figure 4, we report the composition of self-employment across the age distribution separately for men and women. We see that the share of workers engaged in self-employment increases with age for both men and women. While men persistently have higher rates of overall self-employment across the age distribution than women, this is largely driven by the much larger rates of non-informal self-employment among men. Relative to men of comparable ages, women are consistently more likely to be informally self-employed than men. On average, 5.7% of women aged 31 – 64, and 12.4% of women aged 65 and older report being informally self-employed; in contrast, 4.3% and 11.0% of men of corresponding age groups report being informally self-employed. Overall, these findings show that the composition of self-employment is not constant across important subgroups. Accordingly, it is important to account for such heterogeneity when conducting causal analyses of the effects of self-employment.

Discussion

This paper used novel data to examine the breadth of self-employment work arrangements to understand: (1) how the prevalence and nature of different self-employment work arrangements has changed over 2003-2019, (2) how individuals transition across different types of self-employment, and (3) the work and worker characteristics associated with different types of self-employment.

We demonstrate that our approach captures divergent trends within self-employment: formal self-employment shares have fallen, whereas informal self-employment shares have risen. Business ownership experienced large fluctuations, rising following the Great Recession and subsequently returning to pre-Great Recession levels.

We also document that our classification captures meaningfully different types of work and workers. Relative to other self-employed workers, business owners are far more likely to report having positive business assets, followed by the formal self-employed, and then the informally self-employed, with consistent patterns related to transitions. We also find very different compositions of self-employment work arrangements by industry. We further find that on a wide set of demographic, work characteristics, labor market, and wellbeing measures the informally self-employed are relatively similar to platform gig workers, but diverge sharply from the formally self-employed and business owners. Additionally, we see that women and low-income workers are far more likely to engage in informal self-employment than men or higher-income workers. Taken together, our results support the notion that the informally self-employed face less rewarding work prospects and decreased wellbeing than workers engaged in other types of self-employment.

While our estimates are not directly comparable to those in the literature, we believe the magnitudes of our estimates are reasonable compared to those of Levine and Rubinstein (2017) and Boeri et al. (2020) and show consistent patterns. Levine and Rubinstein (2017) find that the incorporated self-employed earn more than comparable salaried workers, while the unincorporated self-employed earn much less. Boeri et al. (2020) find strong evidence that solo self-employment and self-employment with workers are two distinguishable labor market statuses, characterized by different transitions from and into unemployment. They find that compared to the self-employed with employees, the solo self-employed are more likely to be female, slightly older, and have lower earnings. We find similar patterns for our category of informal self-employment.

Overall, our findings suggest salient differences in trends, transitions, and characteristics of the self-employed that would otherwise be masked in administrative data and other survey sources. Prior work has shown that administrative data miss substantial amounts of self-employment activity at both the intensive and extensive margins and surveys generally do not probe to the necessary extent to identify work arrangements of interest. Using novel data, we are able to identify these self-employment work arrangements and find that they do reflect substantially different work characteristics and are engaged in by individuals with different characteristics. It is important to identify these differences to understand how the nature of work is changing over time and to inform future policymaking to improve the wellbeing of workers.

It is important to note that 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 the respondents provided sufficiently detailed narratives. In particular, one substantial limitation is the ability to distinguish between employees and independent contractors, especially independent contractors who work for one employer. For example, Abraham et al. (2024) found that roughly 10 percent of people who said they worked for an employer later said they were an independent contractor when they were explicitly asked. Conversely, since someone working as a long-term independent contractor can look a lot like an employee, our classification could have erroneously reclassified some independent contractors as employees. To address this concern, we re-estimated our estimates of characteristics by work arrangements in Table 3 and Table 4 for the self-employed overall and wage and salaried employees without any recoding of self-identified self-employed jobs. Our results showed no statistically significant differences in our estimates.

In addition to this substantive concern, our analysis has several other limitations. We acknowledge that there is some degree of subjectivity and error in reviewer coding of work arrangements. We have mitigated this concern by having every job record reviewed by at least two reviewers according to a standardized classification schema. Another limitation of this analysis is that we only examine current jobs and focus on current main jobs. Future work could examine all jobs held to develop a more nuanced understanding of how individuals hold and transition across multiple jobs over time. In addition, while our analysis focused on job reports independently from wave to wave, future machine learning approaches could examine the same job across waves to identify changes in reporting by respondents. A limitation of using the PSID for this analysis is that because respondents report all jobs held since the prior wave two years earlier, mapping jobs across waves is not straightforward. However, such an approach is ripe for future exploration.

Our findings suggest that future policy should consider differences across self-employment arrangements. Our analysis identified significant differences in physical and economic wellbeing outcomes across work arrangements, with particularly worse outcomes for those in informal self-employment. To the extent that workers engage in informal self-employment because they cannot find more lucrative work arrangements, either as a way to generate income between job spells or for longer-term durations, one approach to improving outcomes for the informally self-employed is to help them find more formal work either as wage and salaried employees or in more formal self-employment arrangements. This could take the form of work training programs, job search assistance, or support for starting a business. However, the informally self-employed may choose this work over other work arrangements in order to pursue increased flexibility. This mechanism points to the potential value of incorporating more location and hours flexibility into wage and salaried work arrangements. Future work could further explore the circumstances leading to engaging in informal self-employment to better identify the extent to which each of these mechanisms leads workers to engage in informal self-employment and thus which policy responses would most improve worker wellbeing.

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

References

Abraham, Katharine G., and Ashley Amaya. 2019. 'Probing for Informal Work Activity.' Journal of Official Statistics 35(3):487–508.

Abraham, Katharine G., John Haltiwanger, Claire Hou, Kristin Sandusky, and James R. Spletzer. 2021a. 'Reconciling Survey and Administrative Measures of Self-Employment.' Journal of Labor Economics 39(4):825-860.

Abraham, Katharine, John Haltiwanger, Kristin Sandusky, and James Spletzer. 2018. 'Measuring the Gig Economy: Current Knowledge and Open Issues.' Working Paper No. 24950. Cambridge, MA: National Bureau of Economic Research.

Abraham, Katharine G., Brad Hershbein, and Susan N. Houseman. 2021b. 'Contract Work at Older Ages.' Journal of Pension Economics and Finance, 20(3):426–447.

Abraham, Katharine G., Brad Hershbein, Susan N. Houseman, and Beth Truesdale. 2024. 'The Independent Contractor Workforce: New Evidence on its Size and Composition and Ways to Improve its Measurement in Household Surveys.' ILR Review, 77(3):336-365..

Abramowitz, Joelle. 2025. 'Comparing Survey and Administrative Measures of Self-Employment Income: New Implications from the Health and Retirement Study.' National Tax Journal, 78(1).

Abramowitz, Joelle, Jenna Kim, and Jinseok Kim. 2023. 'C-NARS/P: An Open-Source Tool for Classification of Narratives in Survey Data Using Pre-Trained Language Models.' Technical Report.

Allard, Mary D., and Anne E. Polivka. 2018. 'Measuring Labor Market Activity Today: Are the Words Work and Job Too Limiting for Surveys?' Monthly Labor Review. U.S. Bureau of Labor Statistics.

Autor, David H., and David Dorn. 2013. 'The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market.' American Economic Review 103(5): 1553-1597.

Boeri, Tito, Giulia Giupponi, Alan B. Krueger, and Stephen Machin. 2020. 'Solo Self-Employment and Alternative Work Arrangements: A Cross-Country Perspective on the Changing Composition of Jobs.' Journal of Economic Perspectives 34(1):170–195.

Budig, Michelle J. 2006. 'Intersections on the Road to Self-Employment: Gender, Family and Occupational Class.' Social Forces 84(4):2223–2239.

Carr, Deborah. 1996. 'Two Paths to Self-Employment?: Women's and Men's Self-Employment in the United States, 1980.' Work and Occupations 23(1):26–53.

Chang, Wen, Raphael Nishimura, Steven G. Heeringa, Kate McGonagle, and David Johnson. 2019. 'PSID Cross-Sectional Individual Weights, 1997–2017.' Ann Arbor, MI: University of Michigan Institute for Social Research.

Garin, Andrew, Emilie Jackson, and Dmitri Koustas. 2022. 'New Gig Work or Changes in Reporting? Understanding Self-Employment Trends in Tax Data.' Working Paper No. 2022-67. University of Chicago Becker Friedman Institute for Economics.

Garin, Andrew, Emilie Jackson, and Dmitri Koustas, and Alicia Miller. 2023. 'The Evolution of Platform Gig Work, 2012-2021.' Working paper No. 31273. Cambridge, MA: National Bureau of Economic Research.

Harris, Seth D., and Alan B. Krueger. 2015. 'A Proposal for Modernizing Labor Laws for Twenty-First-Century Work: The "Independent Worker".' Discussion Paper 2015-10. Brookings, The Hamilton Project.

Hurst, Erik, Yona Rubinstein, and Kazuatsu Shimizu. 2024. 'Task-Based Discrimination.' American Economic Review 114(6): 1723-1768.

Jackson, Emilie, Adam Looney, and Shanthi P. Ramnath. 2017. ‘The Rise of Alternative Work Arrangements: Evidence and Implications for Tax Filing and Benefit Coverage.’ Working Paper No. 114. Internal Revenue Service Office of Tax Analysis.

Katz, Lawrence F., and Alan B. Krueger. 2019a. ‘The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015.’ ILR Review 72(2):382–416.

Katz, Lawrence F., and Alan B. Krueger. 2019b. ‘Understanding Trends in Alternative Work Arrangements in the United States.’ RSF: The Russell Sage Foundation Journal of the Social Sciences 5(5):132-146.

Mortenson, Jacob A., and Andrew Whitten. 2020. ‘Bunching to Maximize Tax Credits: Evidence from Kinks in the US Tax Schedule.’ American Economic Journal: Economic Policy 12(3):402-32.

Levine, Ross, and Yona Rubinstein. 2017. ‘Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More?’ The Quarterly Journal of Economics 132(2):963–1018.

Light, Audrey, and Robert Munk. 2018. ‘Business Ownership versus Self-Employment.’ Industrial Relations 57(3):435-468.

Moulton, Jeremy G., and John C. Scott. 2016. ‘Opportunity or Necessity? Disaggregating Self-Employment and Entry at Older Ages.’ Social Forces 94(4):1539–1566.

National Academies of Sciences, Engineering, and Medicine. 2020. ‘Measuring Alternative Work Arrangements for Research and Policy.’ Washington, DC: The National Academies Press.

Özcan, Berkay. 2011. ‘Only the Lonely? The Influence of the Spouse on the Transition to Self-Employment.’ Small Business Economics 37:465–492.

Panel Study of Income Dynamics (PSID). 2017. 'PSID 2015 Question By Question Objectives (QxQs).' Available at: https://psidonline.isr.umich.edu/data/Documentation/Fam/2015/QxQs.pdf.

Saez, Emmanuel. 2002. Optimal Income Transfer Programs: Intensive versus Extensive Labor Supply Responses. The Quarterly Journal of Economics 117(3):1039-1073.

Slemrod, Joel, Brett Collins, Jeffrey L. Hoopes, Daniel Reck, and Michael Sebastiani 2017. 'Does Credit-Card Information Reporting Improve Small-Business Tax Compliance?' Journal of Public Economics 149:1-19.

Slemrod, Joel. 2016. 'Caveats to the Research Use of Tax-Return Administrative Data.' National Tax Journal 69(4):1003-1020.

University of Michigan Institute for Social Research. 2023. 'PSID-2021 Main Interview User Manual: Release 2023.' Available at: https://psidonline.isr.umich.edu/data/Documentation/UserGuide2021.pdf.

Tables

Table 1: Classification Schema

Work Arrangement	**Job Characteristics**
Platform gig work	Identifies platform name (including platforms identified by Harris and Krueger (2015) or on Wikipedia at the time of the classification) or gives other indication of working on a platform
Business owner or president, or owner of family farm	Says they own or run a business OR mentions business assets AND lists business name
Self-employed, informal (non-contract) basis	Working in roles such as a babysitter, caregiver, cleaner, handyman, doing odd/spare jobs, day laborer, maker, performer, seasonal work, multi-level marketing, sales, freelancer
Self-employed, formal (independent contractor) basis	Working in roles such as an independent contractor, subcontractor, consultant, working for an "umbrella" company (e.g., real estate agent at real estate company, financial planner at advisor company)
Employee	Does not report any of the above roles and reports working for someone else for pay

Table 2: Wave-to-Wave Transitions in Work Status

Panel A: Wave-to-Wave Transitions in Employment Status (%)

		Current Wave				
		W&S Employment	*Informal SE*	*Formal SE*	*Business Ownership*	*Not Working*
Prior Wave	*W&S Employment*	84.5%	1.3%	0.9%	1.9%	11.3%
	Informal SE	21.9%	43.9%	8.3%	8.5%	17.4%
	Formal SE	25.2%	10.5%	41.1%	14.7%	8.5%
	Business Ownership	13.6%	6.5%	8.2%	64.6%	7.1%
	Not Working	25.7%	3.5%	1.2%	2.6%	67.0%

Panel B: Wave-to-Wave Transitions in Employment Status (Observations)

		Current Wave				
		W&S Employment	*Informal SE*	*Formal SE*	*Business Ownership*	*Not Working*
Prior Wave	*W&S Employment*	39,785	662	490	368	4,864
	Informal SE	625	1,144	202	175	616
	Formal SE	479	190	733	236	164
	Business Ownership	288	129	181	1,274	171
	Not Working	4,060	715	177	139	11,234

Panel C: Share with Positive Business Assets in Current Wave by Wave-to-Wave Transitions in Employment Status

		Current Wave				
		W&S Employment	*Informal SE*	*Formal SE*	*Business Ownership*	*Not Working*
Prior Wave	*W&S Employment*	8.3%	22.2%	29.1%	63.8%	7.8%
	Informal SE	12.2%	24.0%	30.6%	57.9%	12.6%
	Formal SE	25.8%	39.6%	41.1%	58.8%	15.4%
	Business Ownership	52.9%	66.6%	68.1%	85.9%	42.4%
	Not Working	8.7%	14.2%	25.3%	56.2%	8.3%

[a] *Source*: Internal PSID narrative data on industry and occupation and employer names (2003-2019) classified into work arrangement types. Additional information on work status comes from the public PSID (2003-2019) merged to the narrative data classified into work arrangement types.
[b] Panel A reports the share of respondents transitioning to a given current main job type conditional on their main job type in the prior survey wave, Panel B reports the corresponding number of observations, and Panel C reports the corresponding share with positive business assets in the current wave for each cell. Panels A and C report estimates controlling for state-level unemployment rates, age bins (age < 25, age 25-34, age 35-44, age 45-54, age 55-64, age 65+), gender, white/nonwhite status, education (less than high school, high school, some college, BA+), marital status, home ownership, and year fixed-effects. Estimates use cross-sectional PSID weights.
[c] Abbreviations: W&S, wage and salaried; SE, self-employment.

Table 3: Characteristics by Type of Work Arrangement on Main Job

	Platform Gig Work		Informal Self-Employment		Formal Self-Employment		Business Ownership		Wage and Salaried Employment	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Age	52.9*	2.47	48.6	0.57	50.0	0.66	50.8***	0.57	44.4***	0.12
Years of Education	13.8**	0.27	13.1	0.14	14.4***	0.10	14.3***	0.13	13.9***	0.06
% Male	65.6***	6.02	46.8	1.81	65.3***	2.16	74.8***	1.55	50.5**	0.46
% White, Non-Hispanic	38.6***	6.09	67.3	2.54	82.3***	2.43	87.6***	1.89	74.3**	1.74
% Black, Non-Hispanic	21.5**	4.72	10.5	1.22	5.9***	0.98	3.2***	0.66	10.5	1.21
% Hispanic	-	-	18.3	1.91	7.4***	1.56	5.5***	1.15	10.9***	0.94
Labor Income (000's) - Prior Year	25.2	3.93	27.8	1.21	69.8***	3.18	80.9***	3.85	57.7***	0.74
Weekly Hours - Prior Year	31.5***	0.91	28.0	0.63	35.8***	0.64	43.5***	0.95	39***	0.10
Hourly Wages - Prior Year	16.4	3.51	19.5	0.66	37.7***	1.49	36.9***	1.59	28.7***	0.38
% Don't Own a Business - Prior Year	90.9***	1.38	63.4	1.67	43.6***	1.79	17.1***	1.48	90.4***	0.43
% With Positive Business Assets	-	-	21.9	1.18	37.3***	1.86	71.2***	1.99	6.8***	0.40
% Reporting Good Health	83.6	2.44	82.8	1.16	91.3***	0.84	91.8***	1.01	90.5***	0.32
% Not in Psychological Distress	96.6	0.54	95.9	0.53	98.5***	0.31	98.2***	0.46	98.1***	0.15
% Very Satisfied with Life	47.2**	8.72	65.7	1.98	71.1*	2.01	79***	1.93	73.1***	0.57
Observations	68		4,106		2,923		3,310		70,796	

[a] *Source*: Internal PSID narrative data on industry and occupation and employer names (2003-2019) classified into work arrangement types. Demographics come from the public PSID (2003-2019) merged to the narrative data classified into work arrangement types.
[b] *** p<0.01, ** p< 0.05, * p < 0.10 for t-test of difference in means compared to workers classified as having informal self-employment for their current main job.
[c] We report demographics by current main job type. Reported observations represent true counts of observations in our data. % Hispanic and % With Positive Business Assets in Platform Gig Work are censored due to sample size falling below disclosure requirements. Estimates use cross-sectional PSID weights.

Table 4: Characteristics by Type of Secondary Work Arrangement

	Platform Gig Work		Informal Self-Employment		Formal Self-Employment		Business Ownership		Wage and Salaried Employment	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Age	41.4**	1.48	45.3	0.49	47.6**	0.88	47.7*	1.13	44**	0.41
Years of Education	14.4	0.26	14.3	0.12	15.1***	0.12	14.6	0.19	14.4	0.09
% Male	72.9*	7.38	59.3	2.42	66.4**	2.67	76.4***	2.74	48.8***	1.81
% White, Non-Hispanic	61.9**	8.30	82.4	1.75	85.5	2.36	86.7	2.57	75.8**	2.27
% Black, Non-Hispanic	23.8	9.97	7.9	1.21	7.7	1.78	4.7*	1.15	12.2**	1.79
% Hispanic	-	-	7.0	1.02	4.5*	1.03	3.6**	1.09	8.0	1.08
Labor Income (000's) - Prior Year	53.5	5.73	50.5	1.44	78.3***	3.33	80.2***	4.25	56***	1.36
Weekly Hours - Prior Year	36.9	2.16	35.7	0.76	38.7*	1.44	40.8***	1.41	35.0	0.51
Hourly Wages - Prior Year	23.9	2.47	23.4	0.53	35.4***	1.62	34***	2.02	25.9***	0.64
% Don't Own a Business - Prior Year	88.1***	6.60	59.1	2.19	45.9***	2.80	16.4***	2.19	78.9***	1.81
% With Positive Business Assets	-	-	23.8	1.62	32.1***	2.37	72.7***	2.65	14.6***	1.52
% Reporting Good Health	95.1***	0.95	91.1	1.02	95***	0.98	94.4	2.07	92.3	0.64
% Not in Psychological Distress	99.5***	0.22	97.2	0.59	98.6	0.64	99.1**	0.48	98.2	0.27
% Very Satisfied with Life	37***	8.19	69.2	2.05	74.3	3.55	77.8*	4.02	73.2	1.47
Observations	79		1,998		886		437		4,737	

[a] *Source*: Internal PSID narrative data on industry and occupation and employer names (2003-2019) classified into work arrangement types. Demographics come from the public PSID (2003-2019) merged to the narrative data classified into work arrangement types.
[b] *** p<0.01, ** p< 0.05, * p < 0.10 for t-test of difference in means compared to workers classified as having informal self-employment for their secondary job.
[c] We report demographics by current secondary job type. Since an individual can hold multiple secondary jobs, there is some overlap across columns. Reported observations represent true counts of observations in our data. % Hispanic and % With Positive Business Assets in Platform Gig Work are censored due to sample size falling below disclosure requirements. Estimates use cross-sectional PSID weights.

Figures

Figure 1. Sample Construction

Base Sample

Ages 16 or older, 2003-2019 survey waves, classified as Reference Person or Spouse at least once

(Sample = 128,445 respondent-waves for 21,786 respondents)

Merged Narratives

Linked to any job narrative (current or prior)

(Sample = 116,634 respondent-waves for 19,428 respondents, Narratives = 122,921, Current Main Job Narratives = 81,208, Current Secondary Job Narratives = 8,715)

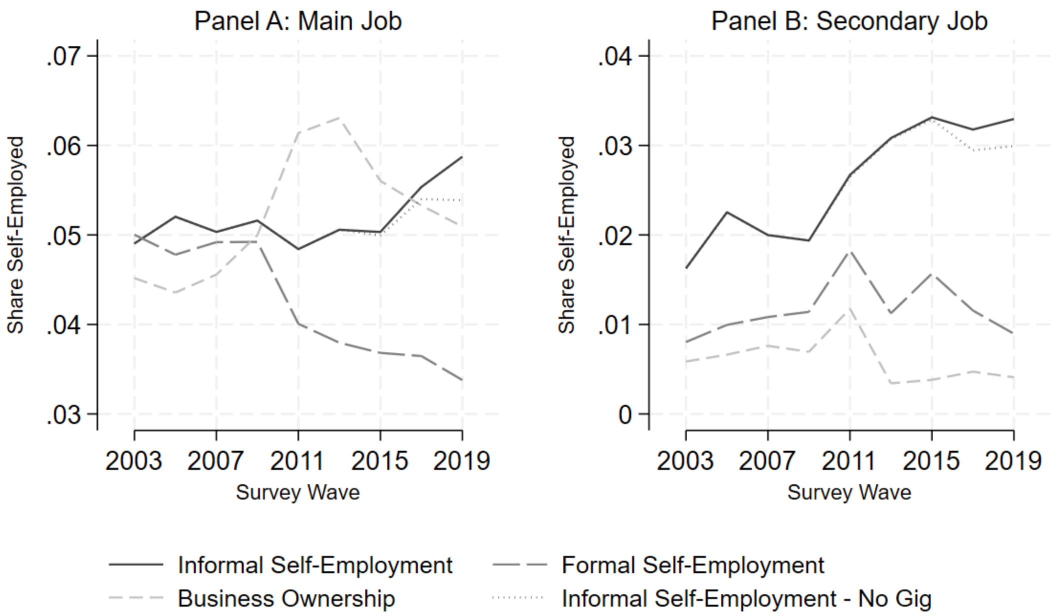
(Informal = 4,174, Formal = 2,923, Owner = 3,310, Wage = 70,796, Non-Employed = 27,263, Missing = 8,168)

Drop if missing work arrangement

(Sample = 108,466 respondent-waves for 19,428 respondents, Narratives = 122,914, Current Main Job Narratives = 81,208, Current Secondary Job Narratives = 8,715)

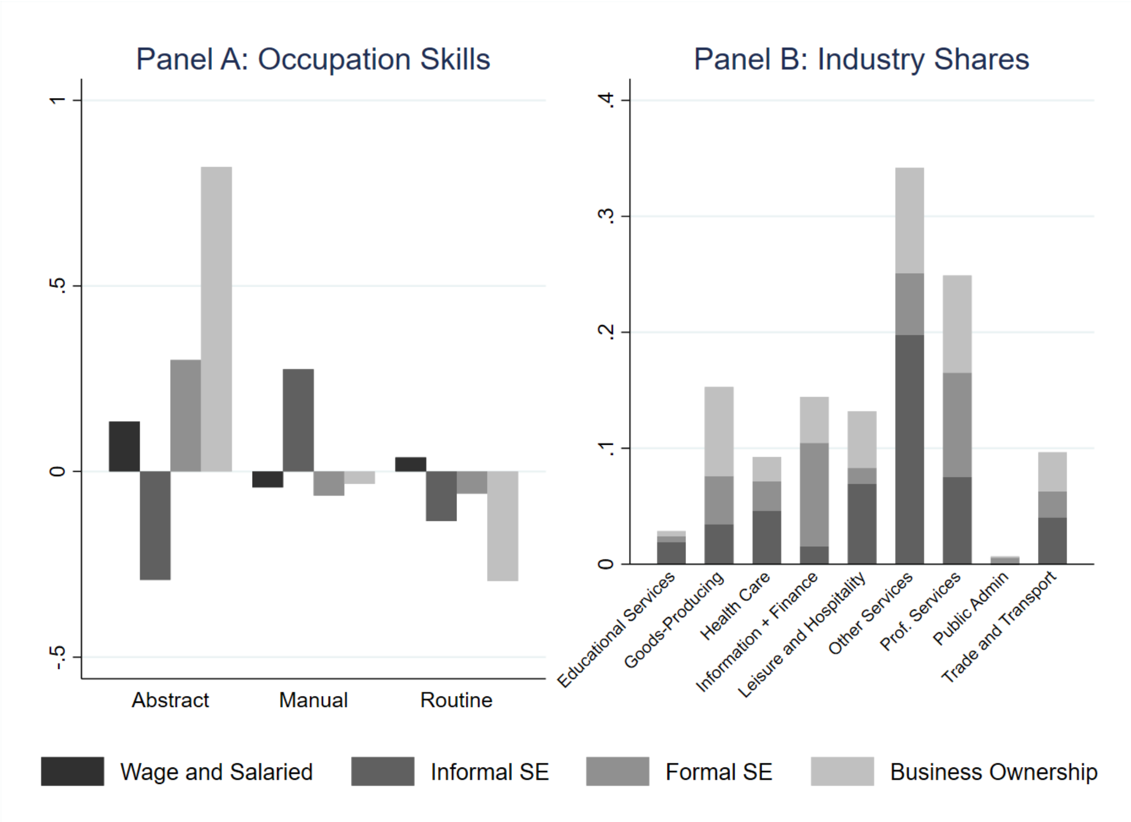
(Informal = 4,174, Formal = 2,923, Owner = 3,310, Wage = 70,796, Non-Employed = 27,263)

Figure 2: Share of Workers who are Self-Employed by Work Arrangement and Survey Wave



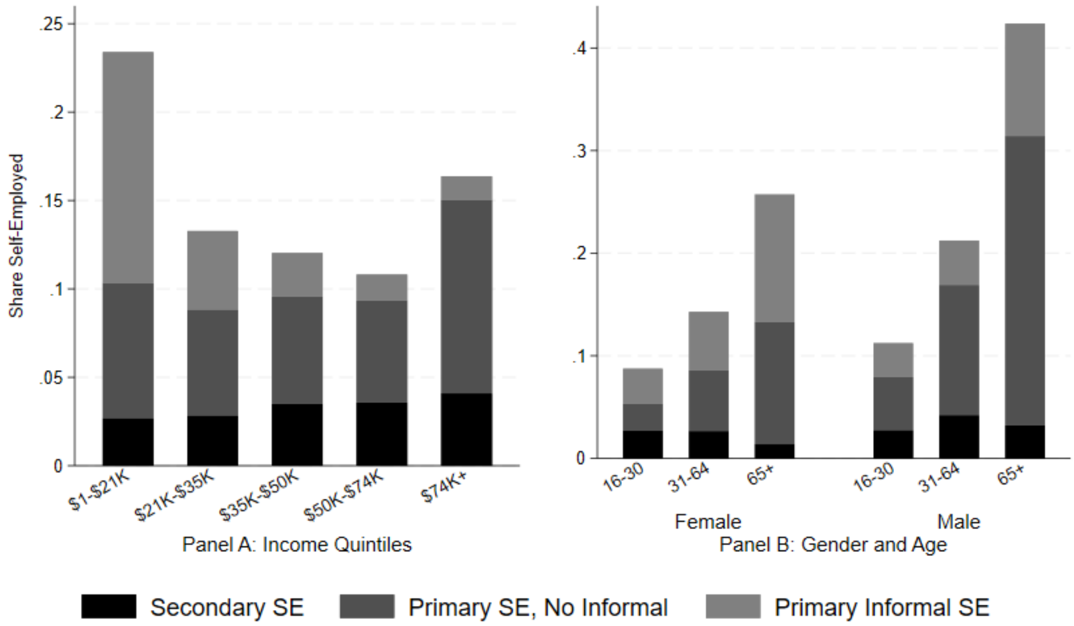
[a] *Source*: Internal PSID narrative data on industry and occupation and employer names (2003-2019) classified into work arrangement types and public PSID data (2003-2019).
[b] We report employment shares by current main job and secondary job type. We derive main and secondary job designations from the restricted PSID narrative data and public PSID data. Since workers can hold multiple secondary jobs, overlap across secondary job categories occurs. Our sample is restricted to respondent-waves in which a job narrative was given for a current main job. Estimates use cross-sectional PSID weights.

Figure 3: Self-Employment Shares by Occupational Skills and Industry Groups



[a] *Source*: Internal PSID narrative data on industry and occupation and employer names (2003-2019) classified into work arrangement types. Demographics come from the public PSID (2003-2019) merged to the narrative data classified into work arrangement types. Task data come from Autor and Dorn (2013).
[b] We plot the share of self-employed workers among the employed by aggregated industry groups: Educational Services (NAICS 61); Goods-Producing (NAICS 11, 21-23, 31-33); Health Care (NAICS 62); Information and Finance (NAICS 51-53); Leisure and Hospitality (NAICS 71-72); Other Services (NAICS 81); Prof. Services (NAICS 54-56); Public Admin. (NAICS 92); Trade and Transport (NAICS 42, 44-45, 48-49. Estimates use cross-sectional PSID weights.
[c] Abbreviations: SE, self-employment.

Figure 4: Self-Employment Shares by Subgroups



[a] *Source*: Internal PSID narrative data on industry and occupation and employer names (2003-2019) classified into work arrangement types. Demographics come from the public PSID (2003-2019) merged to the narrative data classified into work arrangement types.
[b] We plot the share of self-employed workers among the employed by income quintiles and by gender and age. For this figure, workers classified as having secondary self-employment must report no primary self-employment. Earnings are rounded to the nearest $100 to maintain confidentiality. Estimates use cross-sectional PSID weights.
[c] Abbreviations: SE, self-employment.