The Ups and Downs of the Gig Economy, 2015–2017

Anat Bracha and Mary A. Burke

Abstract:

A variety of researchers and public entities have estimated the prevalence of nontraditional work arrangements—using diverse definitions—in recent decades, and the topic has received increasing attention in the past five years. Despite numerous media reports that the prevalence of nonstandard work has increased since the Great Recession, not all sources agree on this point, and very little evidence exists relating to hours or earnings from such arrangements and their changes over time. Using unique data from the Survey of Informal Work Participation (SIWP), we describe changes in informal work activity across 2015, 2016, and 2017 along multiple dimensions and for a variety of specific jobs. Considering the net changes observed between 2015 and 2017, we find that participation rates and earnings were mostly flat across the period, while average hours for gig workers declined by economically and statistically significant margins. The aggregate number of full-time equivalent jobs embodied in informal work—a measure combining participation rates and hours—also declined by an economically significant margin between 2015 and 2017. A major exception to these trends is that average ridesharing hours more than quadrupled between 2015 and 2017. We find some evidence that the recent declines in informal work hours represented a response to declining unemployment rates, but during this time period there also appears to have been upward structural pressure on gig work that provided a particular boost to platform-based work.

Keywords: gig economy, informal work, survey, business cycle fluctuations

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1. Introduction

The term "gig economy" is by now a common phrase that refers to many forms of nonpayroll-based or independently contracted work, including internet platform-based work such as driving for Uber or Lyft as well as offline work such as babysitting or house sitting. Some journalistic accounts have painted a picture of rapid growth in recent years in the gig economy workforce—also referred to as the "on-demand" or "independent" workforce, among other terms. These popular media depictions notwithstanding, the size and the growth rate of the gig economy, as well as its implications for worker well-being, remains the subject of considerable debate. On the one hand, several economic studies using survey and/or administrative data have found that alternative work arrangements—defined variously—have increased in prevalence in recent decades or at least since the onset of the Great Recession (see Section 2 below for discussion of the relevant literature). On the other hand, recent Bureau of Labor Statistics (BLS 2018) survey results find no significant increase in the prevalence of alternative work arrangements between 2005 and 2017, a finding which has led some observers to conclude that the growth of the gig economy has been vastly overstated (Casselman 2018).[1]

Resolving or clarifying this debate has potentially important welfare implications for US workers. For example, while jobs in the gig economy offer flexible hours and independence, such employment typically lacks the benefits that accompany payroll work, such as subsidized health insurance or 401(k) matching. Fluctuations in the prevalence of informal work also hold potential implications for monetary policy and for the measurement of employment. For instance, Bracha and Burke (2018) find that measures of informal work may help explain the seemingly flat Phillips curve that has been observed since 2008, a result which suggests that central bankers may wish to track changes in informal work activity over time. In a different vein Abraham et al. (2013) suggest that nonstandard work arrangements may explain discrepancies between employment statistics based on surveys of households as opposed to those based on surveys of employers

This paper assesses changes in informal work activity across 2015, 2016, and 2017 to investigate whether participation in the gig economy increased or decreased as conditions in the US labor market improved during that time period. Although the period we observe is relatively short, the US labor market improved significantly between 2015 and 2017: the unemployment rate declined by nearly 1 full percentage point, enough to potentially elicit a cyclical response in informal work activity. We focus on this time frame given the availability of the Survey of Informal Work Participation within the Survey of Consumer Expectations (SCE-SIWP or SIWP for short), from which we draw our informal work measures.[2] Specifically, there are three comparable annual iterations of SIWP from December 2015, December 2016, and December 2017 based on three independent and nationally representative samples of US household heads. We use the survey responses to measure informal work activity in terms of the participation rate, hours, and earnings across a broad set of job categories as well as separately by the type of work.

Considering the extensive margin—that is, the participation rate—we find that the share of household heads who engaged in any type of paid informal work (not including survey-taking) appears somewhat

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[1] Casselman, Ben. June 7, 2018. "Maybe the Gig Economy Isn't Reshaping Work After All." *New York Times*. Retrieved from https://www.nytimes.com/2018/06/07/business/economy/work-gig-economy.html.
[2] Survey of Consumer Expectations, © 2013-2018 Federal Reserve Bank of New York (FRBNY).

lower in 2017 compared with 2015, but the difference is not statistically significant. However, considering measures along the intensive margin, meaning the number of hours, we observe clear declines in average hours per month spent on informal work, conditional on participation in the gig economy, as well as sizable declines in our estimate of the aggregate amount of informal work performed in the US economy, expressed in terms of full-time equivalent jobs (FTEs). That is, examining the extensive margin alone—as has been done in most previous studies—would yield little support for a countercyclical response. However, the decline in average hours among informal workers suggests that informal work activity does behave countercyclically, at least along the intensive margin.

Examining hours of work by the task performed, we observe a net decline between 2015 and 2017 for almost all the tasks we surveyed. The exception is that ridesharing activity increased markedly over this three-year period, whether measured in terms of hours per worker or total FTEs. That finding motivated us to assess trends in informal work by conditioning the result on whether a worker reported using an online platform or mobile application in finding and/or doing the work. We find that the share of household heads who engaged in any type of informal work involving use of the internet or mobile platforms increased by 30 percent between 2015 and 2017. That increase may explain recent reports of rapid growth in the online or platform economy (Hall and Krueger 2018, Farrell and Greig 2016), even though the extent of informal work overall did not increase between 2015 and 2017.

We investigate more directly whether informal work responds to the phase of the business cycle by exploiting variation in labor market conditions and informal work outcomes across US census divisions and over time. We find that average informal hours, as well as the participation rate and FTEs, are all positively related to the unemployment rate by census division (controlling for aggregate time effects and census division fixed effects), although the relationship appears more robust in the case of hours than for the other two outcomes. The results are consistent with the hypothesis that informal work activity—along the intensive margin of hours in particular—was subject to downward (meaning countercyclical) pressure at a time when the US unemployment rate was declining. However, the analysis also reveals evidence of positive trend movements in informal work outcomes between 2016 and 2017—especially in average hours worked conditional on someone participating in the gig economy.

Finally, we examine two additional measures that may shed light on the response of independent work (along the participation or extensive margin) to improving economic conditions: the self-employment rate and the freelancing rate. The SIWP survey included questions to estimate the rate of primary self-employment—that is, the share of employed individuals who are self-employed in their main job. (Our measure of informal work participation may include secondary or side jobs)—and freelancing activity (a category not explicitly mentioned in our list of informal work activities). We find that the self-employment share was quite stable, holding at just under a 12 percent rate across 2015, 2016, and 2017 and that the estimated freelancing share declined modestly between 2015 and 2017. These findings offer further evidence against the presence of an increasing trend in independent work along the extensive margin since 2015.

In sum, our results tell a somewhat nuanced story: informal work activity may have been subject to downward cyclical pressure in response to improvements in the labor market, and such a response appears to have been stronger along the intensive margin of hours of work, conditional on participation in the gig economy. At the same time we find evidence of structural upward pressure on informal work that accords with the increasing participation in the gig economy enabled by the use of mobile apps and

online platforms. Perhaps the most vivid example of technology-driven trends is that ridesharing activity increased between 2015 and 2017 despite improvements in the US labor market. However, we cannot rule out the possibility that ridesharing hours increased because of rising consumer demand for such services in recent years, suggesting that a procyclical response may be the correct explanation in that particular case.

The paper proceeds as follows: Section 2 discusses related literature, Section 3 describes the SIWP survey, and Section 4 presents sample characteristics. The results are discussed in Section 5, robustness checks are presented in Section 6, and Section 7 concludes.

2. Related Literature

While different surveys use somewhat varying definitions of informal and/or independent work, we have the unique opportunity to validate our estimates of informal work participation and hours with results of two recent surveys that each employed a definition of informal work that was very similar to our own. We are referring to the Enterprising and Informal Work Survey (EIWA) of 2015 and the Survey of Household Economics and Decisionmaking (SHED) of 2016 and 2017, both of which were conducted by the Federal Reserve Board and both of which included modified versions of the main questions about informal work activity that we developed for the SIWP.[3] Reassuringly, the estimates of informal work participation and average hours among informal workers from these two surveys are quite close to our own.[4] However, we cannot use these data to infer changes in informal work participation across years due to differences between the EIWA and the SHED, and due to a small change in the SHED between 2016 and 2017.[5]

Only a few studies thus far have examined the change in informal work over time, and the results are not conclusive. For instance, according to the US Bureau of Labor Statistics there was no increase between 1995 and 2017 in the share of "alternative workers"—independent contractors, on-call workers, temporary-help agency workers, or workers provided by contract firms—or the share of "contingent workers," meaning those people in jobs that do not offer an explicit or an implicit contract for long-term employment.[6] This result is based on the BLS's Contingent Worker Supplement (CWS) to

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[3] The list of informal work activities used to elicit participation closely mirrors our own, but with somewhat greater attention to separating activities conducted online from work conducted offline. However, there are some differences in how participation in the informal labor market is defined, particularly with regard to the reference period. See Robles and McGee (2016), Federal Reserve Board (2018), and our Appendix for details on the wording of questions in these respective surveys.

[4] Informal participation rates were estimated at 36 percent from the 2015 EIWA, 28 percent from the 2016 SHED, and 31 percent from the 2017 SHED. Our estimates from the same years referring to virtually the same list of activities (but pertaining to household heads and conducted in December rather than October or November) are, respectively, 32 percent, 25 percent, and 28 percent. See Figure 3 for more details.

[5] The EIWA elicits information on informal participation based on activities in the previous six months and the SHED asks about activities in the previous month. The 2017 SHED included ridesharing as a separate line item, but the 2016 SHED did not. See "Report on the Economic Well-Being of U.S. Households in 2017" and "Report on the Economic Well-Being of U.S. Households in 2016," both published by the Board of Governors of the Federal Reserve System, and available here: https://www.federalreserve.gov/consumerscommunities/shed.htm.

[6] The defining job attributes for either group must apply to the individual's main job and not merely to a second or third job. Either concept may also admit some wage and salary workers, so neither share would be equivalent to a

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the Current Population Survey (CPS) that estimates the alternative worker share (among employed adults) at 10 percent in 1995 (BLS 1995), 10.7 percent in 2005 (BLS 2005), and 10.1 percent in 2017 (BLS 2018). (The generally smaller contingent worker share declined over that same time period.[7]) Somewhat similarly, Katz and Krueger (2016) and Abraham et al. (2018) observe flat or even declining self-employment rates between 1996 and 2015 based on household surveys (primarily the CPS).[8] In contrast, Katz and Krueger (2016) claim to reveal a significant increase in the share of *alternative workers* between 2005 and 2015. Using a facsimile of the Contingent Worker Supplement as part of the RAND-American Life Panel, they placed the alternative worker share at 15.8 percent as of 2015 and noted the large increase over the BLS's 2005 estimate of 10.7 percent. Similarly, a study by the US Government Accountability Office (2015) finds an increase in the share of *contingent workers* (rather than alternative workers) in the United States between 2005 and 2010, using either a very narrow or very broad measure of such work, based on data from the 2005 CWS (as fielded by the BLS) and the 2010 General Social Survey (GSS).[9] Further support for positive trends in nonstandard work can be found in studies that use tax-filing data to measure self-employment. According to a few different studies, the filing of tax forms indicating self-employment, such as the Schedule C, increased significantly in recent decades (Jackson, Looney, and Ramnath 2017, Katz and Krueger 2016, and Abraham et al. 2018), and one study found that the trends were driven by an increase in independent labor rather than business ownership (Jackson, Looney, and Ramnath 2017). Likewise, an analysis by Dourado and Koopman (2015) of 1099-MISC forms, which are used to report income received outside of traditional employment relationships, indicates an escalation in such filings from 2000 to 2015.

To help make sense of these various estimates, the table on the following page lists and briefly describes the different concepts of nonstandard work mentioned in the paragraph above, as well as additional concepts mentioned in the rest of this section.

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self-employment rate. Although these two work concepts differ somewhat from informal work as we measure it, there is likely to be some overlap and therefore the trends in alternative and contingent work are relevant here.

[7] The BLS produces three different estimates of the contingent worker share. According to the intermediate estimate, the contingent worker share was estimated at 2.8 percent in 1995, 2.5 percent in 2005, and 1.6 percent in 2017. See BLS 1995, BLS 2005, and BLS 2018 for details. One caveat to comparing the 2017 estimates to earlier estimates is that the 2017 CWS was fielded during May whereas earlier iterations were fielded in February, and as such may have been subject to different seasonal influences (see, for example, BLS 2018 and Burke and Bracha 2016).

[8] On average between 1996 and 2012, almost two-thirds of those individuals who reported self-employment income on their taxes did not report self-employment income in the CPS-ASEC, but roughly half of those who reported self-employment income in the CPS-ASEC did not report any self-employment income to the Internal Revenue Service.

[9] The GAO estimates that the "core contingent worker share"—those in inherently unstable employment situations—increased from 5.6 percent of employed workers in 2005 to 8 percent in 2010, while a very broadly-defined contingent worker share (that even includes part-time payroll work) increased from 30.6 percent to 40 percent over the same period.

Work Concept/Label	Types of Work Included	Primary vs. Secondary Job	Population Frame
Informal Work (Bracha and Burke)	Any Paid Informal Work; Current Engagement	Either	US Household Heads
Enterprising and Informal Work (Robles and McGee)	Any Paid informal Work in the Past Six Months	Either	US Adults
Informal or Gig Work (Federal Reserve Board)	Any Paid Informal Work in the Past Month	Either	US Adults
Alternative Work (BLS, Katz and Krueger)	Independent Contractors, On-Call, Temporary Help, or Contract Firm Workers	Primary	Employed US Adults
Contingent Work (BLS)	No Long-Term Contract	Primary	Employed US Adults
Contingent Work (GAO)	Unstable employment; jobs with no benefits	Primary	Employed US Adults
Self-Employment (CPS)	Works for Self as Business Owner or Independent Worker	Primary	Employed US Adults
Self-Employment (Jackson et al.)	Work Requires Filing Schedule C Tax Form	Either	US Labor Force
Freelance Work (Freelancers Union and Upwork	Supplemental, Temporary, or Contract-Based Work in Past Year	Either	US Adults with earnings in Past 12 Months
Independent Work (McKinsey Global Institute)	Paid by Task, Short-Term Relationship; Current Engagement	Either	Working Age Population in US and EU
Off-the-Books Workers (Abraham et al.)	Employed in CPS but Have No UI Record (Independent Work)	Either	US Adults
Marginal Workers (Abraham et al.)	Have UI record but not employed in CPS (temp and low-wage work)	Either	US Adults
Platform-Based Workers (Farrell and Greig)	Earned Money using Platform in Current Month	Either	US Adults

One explanation for the discrepancy between Katz and Krueger's (2016) estimate of the alternative worker share of 15.8 percent and the BLS's 2017 estimate of 10.1 percent (BLS 2018) is that the alternative worker share decreased sharply between 2015 and 2017. However, these two estimates may not be fully comparable to each other owing to differences in sampling and other methods, as suggested by Abraham et al. 2018. In addition, separate estimates of freelancing activity, although defined somewhat differently from alternative work, indicate that such activity may have increased between

2015 and 2017 (Freelancers Union and Upwork, 2015-2017).[10] Earlier trends in self-employment rates also offer no clear guidance on recent trends in alternative or informal work, given that estimates of self-employment based on tax filings indicated a rising prevalence of self-employment, while those estimates based on the CPS indicated flat self-employment.[11] In sum, we lack conclusive evidence as to whether nonstandard work arrangements—whether contingent, alternative, or informal work—have been increasing or decreasing recently with the improvement in economic conditions.

Previous research suggests that some forms of nontraditional work move procyclically while others behave countercyclically. For example, Abraham et al. (2013) found suggestive evidence that, between 1996 and 2003, the share of workers labelled as "marginal" moved procyclically while "off-the-books" employment responded countercyclically. Marginal workers are those who have an employer wage report but who appear as unemployed or not in the labor force in the CPS, such as those in short-duration or low-earnings payroll jobs, and off-the-books workers are those who classify as employed in the CPS but have no UI wage record, as is typical of independent contractors and employees who are paid under the table. Based on their findings, Abraham et al. (2013) argue that more research into the cyclical properties of different types of nonstandard work is essential to understanding time-varying discrepancies between payroll versus household employment data. Similarly, Katz and Krueger (2017) observe a modest countercyclical response of the share of Schedule C income filers to the aggregate unemployment rate between 1979 and 2014, and a small procyclical response of temporary help employment between 1990 and 2015.[12] The concept of informal work captured by our survey conforms more closely to notions of independent or off-the-books employment rather than to temporary or marginal payroll employment, and so based on these prior findings our measures might be expected *a priori* to behave countercyclically.

Examining changes over time in different types of nonstandard work may be especially important given the recent proliferation of mobile platforms and other technologies that enable gig employment. Some studies that focus exclusively on platform-based work report that the participation rate in such work has increased rapidly since 2012, albeit from very low initial levels. For instance, Hall and Krueger (2018) find that the number of active driver-partners for Uber (defined as a driver providing at least four passenger-trips in the reference month) increased from effectively zero in mid-2012 (when UberX service was launched) to over 460,000 by December 2015,[13] while Farrell and Greig (2016) find that

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[10] The Freelancers Union and Upwork surveys both define a freelancer as anyone who engaged in supplemental, temporary, project-based or contract-based work in the preceding 12 months, whether full-time or part-time, and their estimated freelancer share is calculated out of all US adults earning any money in the preceding 12 months. For results details for 2017 view the slide deck at https://www.slideshare.net/upwork/freelancing-in-america-2017/1.

[11] Abraham et al. 2018 find that for the same individual, self-employment status often differs when comparing administrative data and survey data. They determine that the discrepancies may arise in part because the CPS definition requires self-employment in the main job whereas tax-based estimates do not—for example a payroll worker with an informal second job may file a Schedule C tax form but would most likely not be classified as self-employed in the CPS—and also possibly for more subtle reasons related to what individuals perceive as work when answering household surveys.

[12] However, Katz and Krueger (2017) also show that most of the increase between 2005 and 2014 in the combined share of Schedule C and temporary employment can be explained by an increasing structural trend rather than by the increase in unemployment during that period.

[13] Categorical information on hours per driver per month are reported in the survey data for 2014 and 2015, but with insufficient precision to infer trends in average hours with confidence.

between October 2012 and June 2016, the current-month participation rate in online platform-based work increased from 0.1 percent to 0.9 percent of US adults. However, the combined participation rate in platform-based work (the share of employed people who do such work as their main job) was estimated at just 0.5 percent as of 2015 (Katz and Krueger 2016), or 0.7 percent of the workforce as of 2014 based on reported earnings from online platforms (Jackson, Looney, and Ramnath 2017).

This current study makes several new contributions to the literature regarding recent trends in nontraditional and independent work. First, we draw on three consecutive years of data collected by using an identical survey instrument and conducted during the same month within each year, an approach which ensures that our estimates are fully comparable across the different years. That comparability enables us to make rigorous inferences about the direction and magnitude of recent changes in informal work activity. Second, we estimate these changes along several dimensions—the participation rate, average hours and earnings among informal workers, and aggregate FTEs—whereas most previous studies focused exclusively on participation rates. Third, our survey allows us to test for changes in activity for each of several types or categories of informal work, an analysis which elucidates some important contrasts between task-specific trends and trends in our composite measures of informal work. Finally, ours is the first study to test whether informal work activity exhibited a cyclical response during the recent economic recovery—albeit over a short three-year time period—and is one of only a handful of recent studies examining the cyclical properties of informal work in the United States.

3. Survey Description

The findings in this paper are based on three consecutive annual waves of the Survey of Informal Work Participation (SIWP for short): the SIWP 3, conducted in December 2015, the SIWP 4, conducted in December 2016, and the SIWP 5, conducted in December 2017. Data from SIWP 1 (conducted in December 2013) are not used because the questions about informal work activities were different at the time, and data from SIWP 2 are not used because that survey was fielded in January 2015, and may have been subject to different seasonal influences relative to the subsequent annual surveys conducted in the month of December. (Consistent with monthly seasonal patterns in payroll employment, informal work participation rates are lower in SIWP 2, fielded in the month of January, than in SIWP 3, fielded eleven months later in December.)

Each survey was administered as a special module within the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). The regular SCE is a monthly, internet-based survey that is completed by a rotating panel of about 1,300 heads of household. Each monthly sample is designed to be nationally representative of US household heads along a number of demographic dimensions—age, income, education, and region. There is no overlap in the set of respondents to SIWP 3, 4, and 5, and the samples can be considered independent of each other.[14] The method of constructing the sample weights is described below in Section 4.

[14] Respondents can stay on the SCE panel only for a maximum of twelve consecutive months, which rules out participating in consecutive December surveys.

The SIWP consists of three blocks of questions: (1) general questions such as household size, home ownership status, employment status (self-reported by selecting from a list), number of jobs held, characteristics of the main job (including whether it involves self-employment), and other items; (2) questions about informal work or gig economy activity and (separately) questions about freelancing activity, which are described in detail below; and (3) selected questions borrowed from the Current Population Survey (CPS) that are used to determine each individual's employment status as it would be assigned by the BLS. We obtain basic demographic information on respondents—such as age, sex, and race—from the monthly SCE, which was completed by all of our respondents either during the same month that the SIWP was taken or at an earlier date.[15] The full text of the survey can be found in the Appendix.

Conceptually, we think of gig economy work as any paid work with the following characteristics:[16] (1) it monetizes the value of workers' possessions and/or monetizes their time and skills, (2) it is paid for on a per-task basis (3) it allows the worker to choose when and how much to work, and (4) it does not involve a long-term contract and does not provide benefits such as health insurance, unemployment insurance, or pension contributions. Our survey was designed to assess gig economy activity in the United States by eliciting information about participation in specific paid work activities that are likely to satisfy the above criteria.[17]

Figure 1 (Panel a) shows the complete text of the main question (as it appeared in the online survey) that asked about current engagement in "paid informal work or side jobs."[18] In the question, respondents were presented with a list of specific activities and were required to indicate "yes" or "no" concerning their current involvement in each activity. As seen in the same Figure, the last item on the list offers the option for respondents to write in any other paid informal work activities they engaged in that were not already included in the list of activities specifically named elsewhere in the question. The interface did not change across the three annual surveys that we examine in the paper. A respondent who indicated that he or she was currently engaged in at least one type of informal work was asked— separately for each item selected from the list—to quantify his/her typical hours and earnings per month in the given activity. For each selected activity, we asked if websites and/or mobile platforms

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[15] In SIWP 3, the questions about gig economy activity were asked before the CPS questions. In later surveys the order was randomized—half of the survey respondents answered the CPS questions first and the other half answered them last. In Section 6 we show that our main results are robust to controlling for the order in which these questions appeared.

[16] Note that this concept of gig work does not require that the work be mediated by a website or a mobile application.

[17] Many of the qualifying activities listed in our survey questions satisfy these criteria, such as driving for Uber, working for Amazon MTurk, responding to surveys, selling goods on eBay, renting out one's own property, and posting videos to YouTube. However, some jobs on the list may not always meet all the criteria of gig work. For example, a weekly house cleaning job may last for an extended period and the employer may provide some benefits such as paying into the unemployment insurance fund. Similar conditions might apply to services such as lawn care, babysitting, eldercare, and work as a personal assistant. But we do not observe these details in our survey—our question refers specifically to "informal paid activities or side jobs," and is therefore unlikely to pick up work performed under formal contracts and/or involving benefits.

[18] A side job is "a job undertaken in addition to one's main occupation, as a supplementary source of income." That is, the term refers to a paid activity. However, even if a survey respondent did not think of side job as a paid activity, the follow-up questions in Figure 1, panel b asks about hours of work doing the specific activity for pay and our definition of gig worker takes that into account, as explained below.

were used in finding and/or performing such work. Figure 1b shows an example of this group of follow-up questions for the case of babysitting.

We classify someone as a gig economy worker if and only if the individual (1) indicated that he or she was currently engaged in at least one of the work activities listed or wrote in an unlisted activity in the space provided, and (2) reported a strictly positive total number of hours spent working for pay in the relevant activity or activities. We apply both criteria in order to remove any doubt that an individual actually engaged in paid gig work. For example, a few individuals marked "yes" concerning their engagement in one or more informal activities, and yet reported zero hours of work expended in all such activities.[19] As discussed below we first consider a broad definition of gig work and then a narrower definition that focuses on labor-intensive activities.

Because we do not explicitly include "professional freelance work" on the list of informal paid activities in the survey question shown in Figure 1a, our definition of a gig worker is not likely to capture freelance architects, freelance lawyers, and similar types, although in a few cases respondents used the "other" option to write in that they engaged in freelance work. Beginning with SIWP 3 our survey included a separate question that asked whether individuals performed professional services on a freelance basis; if so, they were asked for the typical monthly hours and earnings associated with such work—see the Appendix for details. Someone qualifies as a freelance worker if they report being currently engaged in freelance activity and report strictly positive hours of such activity in a typical month. Therefore we report on freelancing activity separately from gig economy activity.

We also ask whether an individual's main job involves being self-employed, or instead working for someone else. These responses are used to calculate a primary self-employment rate, as described below, which is useful as a point of comparison with recent BLS estimates of the self-employment rate and is also comparable to some other concepts of alternative work, as discussed below. Finally, the survey included a subset of the questions routinely used in the monthly CPS to determine employment status. The responses to these questions reveal the employment status that would most likely be assigned to an individual by the BLS.[20] In particular, we are able to classify individuals as being either (1) employed, (2) unemployed, or (3) not in the labor force, using the same criteria used by the BLS.[21]

4. Sample Characteristics

The weighted summary statistics for the baseline sample in each survey wave are shown in Table 1. Each baseline sample includes all respondents to the given survey, with the exception of some individuals who reported outlying values for certain items and those who failed to provide answers to key

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[19] The EIWA and SHED surveys, which used similar descriptions of paid work activities, elicits for each activity whether the individual earned any money from engaging in such activities during the previous six months (EIWA) or during the previous month (SHED). Someone qualifies as an informal participant if they answer yes to earning money in any of the listed activities during the relevant time period, or wrote in an unlisted activity. See Robles and McGee (2016) and Federal Reserve Board (2017 and 2018).

[20] We did not include all the questions related to employment status that are included in the CPS household survey. See the Appendix for the set of questions used to determine BLS employment status.

[21] Also using BLS definitions, we can distinguish between full-time employment and part-time employment, and can identify those who classify as being employed "part-time for economic reasons."

questions.[22] The weights for each survey wave are designed so that the baseline sample is approximately representative of all US household heads in terms of educational attainment, household income, age, and geographic region, based on matching the corresponding characteristics among household heads in the American Community Survey (ACS) for the preceding year.[23] In terms of employment status, our baseline samples exhibit somewhat higher rates of employment and labor force participation compared with household heads in the CPS for the same year (based on non-seasonally adjusted CPS data for December of the given year)—as shown in Figure 2. The confidence intervals for our estimates include the CPS values in all but one case—pertaining to our employment rate estimate for December 2016—and therefore our sample is approximately representative of US household heads in terms of employment status. In light of the differences, however, the analysis below takes some steps to account for employment status when assessing changes in informal participation over time.

There are, however, two dimensions along which our baseline samples may not be nationally representative of household heads—internet access and self-employment. Internet access was required for participating in our online survey; therefore all respondents had internet access, whereas roughly 84 percent of US household heads had such access in 2015.[24] To correct for the potential bias in estimates of informal work introduced by this discrepancy, we conduct a robustness check in which we reweight the sample to make it representative in terms of having internet access (in addition to the other demographic factors). As discussed in Section 6, this exercise indicates that our main findings are robust. Separately, we may oversample self-employed individuals, who might also be more likely to engage in informal work. The self-employment shares in our three survey waves (out of all respondents in the baseline survey) range from 10 percent to 11 percent, whereas the corresponding shares among household heads in the ACS for the same time periods are lower, ranging from 8 to 9 percent. However, self-employed individuals may be one of two types, incorporated or unincorporated, depending on whether they run an incorporated business (regardless of size) or instead work for themselves in a noncorporate entity. The self-employment rate based on the ACS refers only to unincorporated self-employment, whereas our own measure of self-employment includes both incorporated and unincorporated types.[25] Further below we show that, as a share of employed individuals, our self-employment rates line up quite closely with those based on the CPS, which include both incorporated and unincorporated types of self-employed individuals. Nonetheless, to allay any concern that an oversampling of self-employed individuals may introduce an upward bias in informal work activity, we conduct a second robustness check in which we exclude the self-employed from all calculations. Again, we find that our main results are robust.

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[22] We exclude a small number of respondents who reported individual earnings (from a formal job) of $600,000 per year or more.

[23] For example, weights for December 2015 are designed to target the average demographic characteristics of US household heads in the 2014 ACS (along the dimensions stated above). The lag occurs because the weights are constructed immediately after the survey is fielded, when the same year's ACS data are not yet available. Revising the weights ex-post in order to match the contemporaneous ACS demographics is unlikely to result in any meaningful differences in our results, as our target characteristics do not change significantly from year to year.

[24] This estimate is based on the Consumer Confidence Survey (CCS) from 2015, which draws on a nationally representative sample of household heads. Participants in the SIWP were recruited from the sample of CCS participants.

[25] The ACS definition of self-employment is restricted to unincorporated self-employment. Our own survey doesn't ask about incorporation status; it merely asks whether an individual is self-employed.

The baseline sample supplies us with our best estimate of informal work patterns across 2015, 2016, and 2017 among the US population of household heads. To ensure that our results are not driven primarily by the behavior of the retired population, we analyze a nonretiree sample from each wave that simply omits self-reported retirees from the baseline sample for the given wave. The weighted summary statistics for the nonretiree sample are shown in Table 2. As expected, employment rates are higher in the nonretiree samples than in the baseline samples.

5. Descriptive Analysis

This section proceeds by describing the changes across our three survey years for several measures of informal work activity, for the baseline and nonretiree samples in each year and for two different criteria for defining informal work. We begin by describing changes based on the raw (weighted) data for the participation rate, hours worked, earnings, and the FTEs of informal work, both for a broad measure of informal work and a narrower measure focusing on labor-intensive jobs. Next we analyze changes in the participation rate by sex, adjusting for changes in sample demographics across the survey periods. We also calculate participation rates and average hours separately for each specific type of informal work and describe task-specific changes over time. We then show survey-based estimates of the self-employment rate and the freelancing rate for each of our survey periods, each considered as a share of all employed individuals (using the BLS definition of employment).

5.1 Raw Trends in Informal Participation, Hours, Earnings, and FTEs (Baseline and Nonretirees)

To reiterate, gig economy participants are defined as those who indicated that they were "currently engaged" in at least some type of qualifying work and reported a nonzero total number of typical hours per month spent doing such work. However, in all our measures of informal work participation we disqualify those whose only type of gig work consists of responding to surveys, since otherwise all of our respondents would be considered gig workers.[26] We also omit survey-taking hours and earnings from all calculations. For example, if someone reports positive hours and earnings from both babysitting and survey-taking, we exclude their survey-taking hours and earnings from the calculation of their total informal hours and earnings. We refer to estimates using these criteria for informal work as "excluding survey-only."

We also construct a narrower measure of participation that further omits those who engaged exclusively in renting out their own property and/or selling goods, whether through consignment shops or websites like Craigslist or eBay. While such activities draw significant numbers of participants, based on our observations these activities on average are less labor-intensive than other types of gig work such as personal services (see Bracha and Burke 2016). Furthermore, the money earned in such rental or selling activities may derive largely from the value of an individual's assets, such as an apartment in a

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[26] To the extent that gig workers who respond to surveys also perform other informal work, our estimate of the gig economy participation rate will not be biased downward based on this restriction, and it would be biased upward if we included survey-only workers. However, we do not include time spent responding to surveys in our estimate of the total hours of gig work per worker, and therefore the average total hours estimate (barring other sources of bias) is most likely too low.

prime location in Manhattan or a collection of rare vinyl records. Therefore, in order to focus on labor-intensive gig work that does not rely primarily on asset ownership, we derive separate estimates of gig economy activity that omit renting and selling activities. In this case, when adding up hours (or earnings) for a given informal worker, we omit any hours (or earnings) derived from renting and selling activities (as well as hours spent taking surveys). We refer to estimates using these restrictions as "excluding renting/selling" or "labor-intensive gig work."

Figure 3 shows the estimates of four different outcomes related to informal work, for each annual survey wave and for each baseline sample and non-retiree sample in each wave. Throughout this figure we apply the "excluding survey-only" criteria for informal work activity. For the baseline sample, the participation rate estimates (Panel A) are lower in December 2016 (25 percent) and December 2017 (28 percent) compared with December 2015 (32 percent), but the difference is statistically significant only when considering the 2016 rate versus the 2015 rate. (The modest increase in participation between 2016 and 2017 also is not statistically significant.) For the nonretiree sample the pattern in the participation rates across the surveys is qualitatively similar—the 2015 to 2016 rate decline is significant; in 2017 it rebounds modestly by a statistically insignificant margin, and the net change from 2015 to 2017 is not statistically significant. Within each survey, the participation rate appears to be higher for the nonretiree sample relative to the baseline sample, but in general the confidence intervals on the rates for these two groups overlap.

Panel B of Figure 3 shows our estimates of average hours per month of informal work for each survey period and each sample—among informal workers only and not including paid hours from survey work. For either sample definition, we observe a statistically unambiguous drop in average hours between 2015 and 2016, followed by a statistically insignificant uptick in 2017 over 2016. The differences remain highly statistically significant when comparing 2015 hours with 2017 hours. Within any survey period, the average hours among informal workers are nearly equal between the baseline sample and the nonretiree sample.

Panel C of Figure 3 shows estimates of average full-time equivalent jobs (FTEs) of informal work per household head, expressed as a percentage of one FTE position. This calculation represents the average hours spent engaging in informal work per month, not conditioning on participation (nonparticipants are observed to have zero hours), divided by 160 hours. [27] Unlike our estimates of average hours per month, these estimates do not condition on participation in informal work but rather combine information on both participation and hours into a single measure. For 2015 the estimates of the average FTE percentage performed by a household head are small but nontrivial, at 4.3 percent for the baseline sample and 5.2 percent among nonretirees. In 2016 the estimates decline by more than half from their respective 2015 levels to 2.1 percent (baseline) and 2.4 percent (nonretirees), although it is not straightforward to determine the statistical significance of the changes. In 2017, either for the baseline sample or the sample that excludes retirees, the average FTEs (at 2.9 percent and 3.2 percent respectively) are slightly higher than in 2016, but remain below their 2015 levels by economically nontrivial margins.

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[27] The 160 hours represents the number of work hours per month in a full-time job, assuming 40 hours per week and four weeks per month. To estimate aggregate FTEs in the household head population (in millions) we can take our estimate of FTEs per household head and multiply by the size of the household head population in the United States for the relevant date.

Panel D of Figure 3 shows the average earnings per month that an individual receives from engaging in informal work, conditional on participation. (Again, earnings from survey-taking are not included.) For both samples and all three survey periods, the point estimates of the average earnings per month are economically nontrivial (ranging from $361 to $476) and are statistically different from zero. The estimates are somewhat lower for either 2016 or 2017 than for 2015, and are roughly the same between 2016 and 2017, but the relatively large confidence intervals imply that the apparent declines in earnings from 2015 when compared to the later years are not statistically significant.

Figure 4 is analogous to Figure 3 within each panel, except that all the outcomes depicted in Figure 4 pertain to our narrower concept of labor-intensive gig work. That is, the participation rates shown in Figure 4 exclude those people who only engaged in renting, selling, and/or survey work, and the estimates of hours and earnings exclude any hours and earnings from these three types of tasks. Comparing these estimates in Figure 4 to the corresponding outcomes including all nonsurvey gig work shown in Figure 3, the participation rates are substantially lower for labor-intensive gig work (Panel A) and the average hours are generally higher (Panel B), while the average earnings (Panel C) and average FTEs (Panel D) are uniformly lower for labor-intensive work, based on point estimates only. Again we observe that the outcomes are quite similar between the baseline sample and the nonretiree sample.

In terms of changes over time, the patterns in labor-intensive gig work are qualitatively similar to those described above for all gig work. In particular, the participation rate (for either the baseline or nonretiree sample) is basically flat across the three annual surveys when considering the confidence intervals, although for both samples our point estimates of participation decline somewhat between 2015 and 2016 and then increase slightly between 2016 and 2017. While the participation rate is not statistically different across the three years, we again observe large and statistically significant declines in average hours among informal participants when comparing either 2015 to 2016 or 2015 to 2017. (The moderate increase in average hours between 2015 and 2016 is not statistically significant.) We also continue to see large declines in average FTEs, especially when comparing 2015 and 2016—where our estimates decline by more than half—but also find a significant decline when comparing 2015 and 2017. Average earnings again appear to decline from 2015 to 2016 and then hold steady in 2017, although our confidence intervals are too large to rule out the possibility that there was no change in earnings across all three surveys.

Taken together, Figures 3 and 4 tell a consistent story in which participation rates in informal work (and earnings among informal workers) either held steady or possibly declined between 2015 and 2016, whereas the average hours participants spent engaging in informal work declined unambiguously over the same period, and by margins that are economically significant in all cases (regardless of how we define the sample or how we define informal work). Average FTEs also declined substantially between 2015 and 2016. Some measures of informal work appear to increase by small to moderate margins between 2016 and 2017, while others are flat, but the increases are never statistically significant. Considering the net changes in outcomes between 2015 and 2017, participation rates and earnings are effectively unchanged under all conditions, and the decline in average hours is significant when focusing the analysis on labor-intensive gig work, and this result holds separately for both men and women. The average FTEs remain much lower in 2017 compared with 2015, at least based on the findings for point estimates. Based on these results from analyzing the raw trends, it seems safe to say that informal work activity did not increase on net between 2015 and 2017, along either the extensive or the intensive margin.

Looking back at the descriptive statistics presented in Tables 1 and 2, we observe some changes in the weighted demographic characteristics across the three survey periods, although along most dimensions the sample appears quite stable over time. For example the share of respondents to our survey with only a high school education or less in the baseline sample (Table 1) declines from 36 percent in 2015 to 33 percent in 2017, and the nonwhite share declines from 24 percent to 21 percent between the same dates. Along most dimensions (but not for race) the changes in the weighted sample characteristics reflect changes in the broader population, based on the design of our sample weights. Even so, it is important to determine whether these recent changes in informal work outcomes simply reflect changing demographics. To this end, we conduct simple tests showing that demographics in fact play no important role in driving the trends that we document. We omit these results for sake of brevity and because exploring the implications takes us beyond the goal of this current paper.[28]

5.2 Trends in Participation and Hours by Task: The Rise of Ridesharing

So far we have considered estimates of informal work outcomes that combine behaviors across multiple activities. However, the recent time patterns in these composite measures might obscure differences in trends across diverse types of informal work. As noted above, some recent studies suggest that participation in online-based or platform-based gig work has increased in recent years (Farrell and Greig 2016, Hall and Krueger 2018), while others suggest that offline-based informal work increased more than online-based work between 2016 and 2017 (Federal Reserve Board 2018). Our survey elicits participation, as well as hours and earnings, separately for several specific kinds of gig work, enabling us to track changes over time in average outcomes for each type of work.

Table 3 shows the participation rates by task or job type for each survey period, expressed in absolute terms as well as in terms of relative rank. The tasks are ordered according to their ranked participation rate as of December 2015. The participation rate for a given task or task category represents the (weighted) percentage of the baseline sample respondents who (1) indicated being currently engaged in the task and (2) reported positive hours per month engaged in the task. Here we comment primarily on the direction of the changes in specific participation rates between 2015, 2016, and 2017, based on point estimates only. This analysis is for the most part merely suggestive, because the confidence intervals on the task-specific participation rates (not shown) are generally quite large.

In all three survey periods, renting and selling activities had by far the highest participation rate, possibly because this category combines multiple tasks, whereas others consist of a single job or task (such as dog walking). Comparing participation rates between 2015 and 2016, the estimates declined for nine out of the 12 tasks, including renting/selling. However, participation in both ridesharing and online tasks increased between 2015 and 2016—in the case of ridesharing the estimated participation rate doubled, albeit from the very low initial level of 0.5 percent. Between 2015 and 2017 on net, the participation

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[28] To test for whether changing demographics influenced our results, we pool the microdata from our three annual surveys and employ probit models of individual participation in informal work arrangements against time dummies and demographic characteristics. We find that the signs and significance of the time effects line up closely with the time patterns shown in the raw data. We also run ordinary least square (OLS) models of average hours conditional on participation in the gig economy (estimated over the participant sample only) against demographics, and once again the time effects agree with those found in the raw data. These results available from the authors upon request.

rates declined for six of the tasks and increased by at least a slim margin for the remaining seven tasks. Online tasks experienced the largest net increase, rising from 1.3 percent to 2.7 percent of the baseline sample.

It is useful to contrast the results for jobs that can be considered "new" technology-enabled jobs—meaning jobs recently made possible by the availability of new technologies—and jobs that have existed for decades. While the distinction can be hard to discern in some cases, we clearly identify three tasks that are obviously relatively new (online tasks, posting content online, and driving for ridesharing services enabled by mobile applications) and six that are obviously traditional (babysitting, eldercare, house cleaning, house painting, house sitting and lawn care). We find that each of the new technology-related jobs saw participation rates increase between 2015 and 2017, while there is no clear growth pattern among the more traditional side jobs—some of the latter experience net declines in participation and others declined from 2015 to 2016 but then ended 2017 with higher participation rates than in 2015.

Apart from distinguishing between new and old types of informal work, we can classify informal workers according to whether or not they used the internet or a mobile application ("app") in the course of doing any of their gig work. In particular, our survey asks, for each gig worker and each task in which they engaged, whether the individual used the internet or an app in the course of finding that work and/or completing that work. We use these responses to measure the share of survey respondents who both engaged in gig work and used the internet or an app in relation to that work—a measure we term the "participation rate with internet/app use." As seen in Table 5, the participation rate with internet/app use (excluding survey-only work) held steady between 2015 and 2016 and then increased by 4 percentage points (or roughly 40 percent) between 2016 and 2017. (The latter increase is statistically significant.) For comparison, Table 5 also shows the participation rates *without* internet/app use for each of the three survey periods—that is, the share who engaged in gig work but indicated that they did not use the internet or an app in doing so.[29] Excluding survey-only work, the participation rate not involving internet/app use declines by more than 6 percentage points in 2016 and then declines further (by just 0.5 percentage point) in 2017. That is, the two different classes of participation rates moved in opposite directions. However, when focusing only on labor-intensive gig work, the trend in internet-using participation no longer differs starkly from the trend in non-internet using participation. Both rates decline on net between 2015 and 2017, but taking their respective confidence intervals into account both series should be considered flat across the three years. Therefore, the increase in internet-using participation rates between 2016 and 2017 reflects an increase in renting and/or selling activities enabled by the internet or mobile apps.

Table 4 shows, for each survey year and each task, the average hours per month spent doing the task among those who engaged in it, as well as the rank order of each task in terms of average hours. We find that on net between 2015 and 2017, the average hours only increased for three activities: renting and selling, online tasks, and ridesharing. Moreover, only the average ridesharing hours grew sharply and steadily across our surveys, going from 7.3 hours per month in 2015 to 11.4 in 2016 and then to 34.6 hours in 2017. As each of the tasks that displayed increasing average hours tend to involve use of

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[29] By construction, the set of qualifying participants do not overlap between the two types of participation, so the two rates add up to the unconditional rates shown in Figure 3 and Figure 4.

the internet or apps, these patterns agree with the suggestive results above indicating increased participation rates in new jobs and increased participation rates involving internet/app use.

Tables A1 and A2, shown in the Appendix, are analogous to Tables 3 and 4, but for the nonretiree sample instead of the baseline sample. The qualitative patterns noted for the baseline sample are mostly robust when excluding retirees. In particular, participation rates in ridesharing and online tasks both appear to increase across 2015, 2016, and 2017, with average ridesharing hours experiencing large and unambiguous gains across all three survey, going from eighth place in 2015 to first place in 2017.

5.3 Trends in the Self-Employment Rate and the Freelance Rate

We also examine two other indicators of independent work: the self-employment rate and the freelance rate. Self-employment status is based on a direct survey question—those individuals who report having a job are asked to indicate whether they are self-employed or instead work for an employer or firm. Those who report having multiple jobs are asked whether they are self-employed in their main job, which is the one that involves the most hours. Among those reporting that they are self-employed we do not ask whether they work for themselves in an incorporated business as opposed to an unincorporated business. The self-employment rate is calculated as a share of all employed individuals, where being employed is determined by applying the same criteria used by the BLS to a series of CPS-style questions. As a point of comparison, we also calculate self-employment rates among household heads in the CPS for the same three years, including all self-employed individuals, whether their business is incorporated or unincorporated. The latter rates are similar in concept to ours because we do not condition on incorporation status, the CPS requires self-employment to apply to the main job, and the CPS defines employment the same way that we do.

Table 6 shows the results—note that none of the estimates are seasonally adjusted. The self-employment rates from our survey— ranging from 11.6 to 11.8 percent —are quite close to (but slightly higher than) the corresponding rates from the CPS for the same three-year time period.[30] More importantly, however, both the SIWP data and the CPS data indicate that the rate of primary self-employment has not changed significantly since 2015. While this result may seem to contrast with previous studies which found, based on tax filings, an increase in self-employment rates (for example, between 2005 and 2014, as in Jackson, Looney, and Ramnath 2017), we stress that the self-employment rates based on our survey and based on the CPS are not comparable to estimates based on tax filings because the latter do not require defining self-employment based on an individual's main job.

We now turn to examining freelance rates. While our estimates of informal work participation and hours do not explicitly include freelance work, we ask separate questions that elicit specific information about freelancing activity. We use the responses to estimate a freelancing participation rate. First, we ask a yes/no question as to whether an individual performed "professional services on a freelance basis." Those who respond yes are then asked about their typical monthly hours devoted to and monthly earnings derived from freelance work. Individuals qualify as freelancers if they answer yes to the first question and report positive hours in the follow-up question, and the freelance rates are calculated as a share of all employed individuals (based on the CPS questions) in the baseline sample. The results are

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[30] Therefore, our survey does not appear to oversample the self-employed as a share of all employed individuals.

shown in row 3 of Table 6. The point estimates for each year between 2015 and 2017—roughly 9 percent, 6 percent, and 5 percent, respectively—suggest that professional freelancing participation among employed individuals declined during that time period (on the extensive margin), although the confidence intervals are too large to allow us to distinguish the estimates from each other. We note that these rates are much lower than those calculated by Freelancers Union and Upwork, which estimated an increase from 34 to 36 percent between 2015 and 2017.[31] However, the latter survey defines freelance work more broadly to include any form of supplemental, temporary, or contract-based work, rather than specifically asking about "professional services" work, as we do.

5.4 Does Informal Work Have a Cyclical Component?

As mentioned above, only a handful of recent studies have investigated the cyclical properties of nonstandard work arrangements, and the findings so far suggest that particular types of nonstandard work may move differently over the business cycle. For example, two previous studies have suggested that participation rates for independent work arrangements (such as independent contracting) and unreported or "off-the-books" work increase during downturns and/or recede during expansions (Katz and Krueger 2017, Abraham et al. 2013).[32] However, the same studies have found that temporary-help jobs and other forms of marginal payroll work—such as low-hours and low-earnings jobs—appear to behave procyclically. Our concept of informal work appears to fit more in the category of independent work, and so *a priori* we expect that it might move countercyclically, for example by declining with the employment rate and increasing with the unemployment rate.

As preliminary evidence, Figure 5 plots the published national unemployment rates (nonseasonally adjusted) from the BLS for each December between 2014 and 2017 (left panel), alongside our estimates of FTEs of informal work (for labor-intensive work) per US household head for each of our survey periods (right panel). (We show unemployment rates beginning in 2014 to provide additional context and because these earlier labor market conditions may be relevant for subsequent informal work activity.) We find that the headline U-3 unemployment rate, the broader U-6 rate, and our FTE measure declines over this four-year period.[33] While the U-3 and U-6 unemployment rates decline monotonically between 2014 and 2017, our FTE measure drops sharply between 2015 and 2016 and then rebounds somewhat, but on net falls from 3.6 percent to 2.1 percent (the figures refer to aggregate FTEs as a percentage of the household head population). That is, qualitatively our finding regarding the decline in FTEs between 2015 and 2017 fits the hypothesis that informal work activity should move in the same direction as the unemployment rate.

To undertake a more rigorous test of the cyclical response of informal work, we exploit variation across the US census divisions and over time in labor market conditions. Specifically, we construct the three

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[31]See Freelancers Union and Upwork 2015, 2016, and 2017 (three separate studies).

[32] Katz and Krueger (2017) test for cyclical behavior of alternative work, controlling for trend movements, while Abraham et al. (2013) base their tentative conclusions on changes in the raw participation rates over time.

[33] The U-3 unemployment rate refers to the share of individuals in the labor force who in the CPS reported not having a job in the previous week and who had actively looked for work within the previous four weeks. The U-6 unemployment rate consists of the sum of unemployed individuals, those deemed marginally attached to the labor force, and those employed part-time for economic reasons, as a share of the labor force plus the marginally attached. For the definitions of these two categories, see https://www.bls.gov/bls/glossary.htm#D.

measures of informal work—the labor-intensive participation rate, average hours among participants, and FTEs per household head—at the census-division level within each survey period and for each of our baseline and nonretiree samples. For each informal work outcome, we regress the outcome alternately against each of three different business cycle indicators, also measured at the census- division level: the U-3 unemployment rate, the U-6 unemployment rate, and the part-time for economic reasons (PTER) share of employed individuals.[34] We include only one labor-market indicator at a time in each model because the measures are highly collinear. We adopt an OLS model of first differences in order to flush out fixed differences across the census divisions and to control for serial correlation in shocks to informal work activity across the time periods. The aggregate time trends are captured by the constant term and a dummy term for the later time interval.[35]

In the main specifications we use the contemporaneous changes in labor market indicators, on the assumption that these may exert the most influence over the labor supply decisions pertaining to informal work. However, unemployment rates may be endogenous in the informal work measures for a variety of reasons, such as the fact that engaging in informal work may reduce the chances that someone gets classified as unemployed under the CPS.[36] To minimize potential endogeneity bias, we can substitute one-year lagged unemployment-rate changes on the right-hand side. In doing so we find that results are robust and in some cases even stronger than in our main estimates.

It is appropriate to focus on the results for the nonretiree sample because the labor supply of retirees may be less sensitive to business cycle conditions, although we also provide the results for the baseline sample. For the nonretiree sample, shown in Table 7, we observe a positive association between the U-3 unemployment rate and each of the informal work outcomes. Although the estimates come with large standard errors—which is not surprising in light of the small number of observations—the associations are economically significant and, for both hours and FTEs, at least marginally statistically significant. The broader U-6 unemployment rate also displays positive associations with each of our informal work outcomes, and in the case of average hours among participants in the gig economy, the estimated coefficient is highly statistically significant as well as economically substantial: a 1 percentage-point decline in the U-6 rate is associated with a decline in average hours on the order of 11.6 hours per month. The latter effect means that the actual decline in the national U-6 rate between 2015 and 2016 can explain about 65 percent of the observed decline (between those same dates) in the average hours that nonretired gig workers dedicated to (labor-intensive) informal work. The association between U-6

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[34] The U-3 and U-6 unemployment rates and the PTER share are calculated for the entire adult population in the given census division rather than only among household heads, based on the assumption that the behavior of household heads with respect to informal work activity might respond to the employment situation(s) of all household members.

[35] The estimation employs Huber-White standard errors to account for potential heteroscedasticity in the dependent variables, as these may be estimated with differing precision across census divisions. However, given the small number of observations in the regressions, the Huber-White standard errors may be too small. Despite the suspected heteroscedasticity we prefer to use OLS instead of weighted least squares, for reasons discussed in Solon, Haider, and Wooldridge (2015) and Lewis and Linzer (2005). Nonetheless, we can show that running weighted-least squares regressions that use sample sizes by census division for the weights makes no meaningful difference in results.

[36] The relationship between informal work participation status and BLS employment status is complex, as shown in Bracha and Burke (2016). Not all individuals who engage in informal work get classified as employed based on their responses to CPS questions.

and FTEs of informal work achieves marginal statistical significance (as did the association between U-3 and FTEs). The PTER share displays much weaker associations with our informal work measures—the point estimates are much smaller than for both U-3 and U-6, none are statistically significant, and the association with the participation rate carries a negative sign.[37]

In sum, the analysis suggests that informal work hours among participants in the gig economy, as well as FTEs of informal work per household head, exhibit at least weak countercyclical associations with the BLS measures of unemployment. Among these associations, the one between informal hours and the U-6 rate appears statistically most convincing. Perhaps the U-6 unemployment rate predicts informal hours better than the U-3 rate does because only the former unemployment measure captures labor market slack along the intensive margin. For example, the results suggest that informal workers dial back their informal hours as they transition from part-time to full-time employment. Based on this same reasoning, however, we would expect informal hours to respond positively to the PTER share, but our results do not strongly support that hypothesis.

The estimated constant terms reflect the average change across the US census divisions for a given outcome between 2015 and 2016, net of the influence of the given labor market indicator by census division. These terms should capture aggregate structural trends, but may also embed aggregate cyclical influences insofar as these affect informal work outcomes over and above the labor market conditions present within a given census division. For example, the supply of labor for performing online tasks most likely depends on the aggregate (i.e., the national or even international) demand for such labor, as these tasks can be performed anywhere in the world and delivered anywhere else at a negligible cost. The constant coefficients carry negative signs in all the nine models shown in Table 7, but most of these coefficients are statistically insignificant. However, the models that include just the PTER share obtain relatively large (negative) constant terms that are highly statistically significant in two cases, which could result if the PTER share does a poor job of capturing cyclical factors. In stark contrast, the coefficients on the 2017 dummy are uniformly positive, as well as both economically and statistically significant. Taken together, these estimates imply that the aggregate trends in informal work outcomes between 2016 and 2017 were at least more positive in comparison to the trends observed in the earlier period or, in some cases (pertaining to hours and FTEs), were strictly positive in absolute terms. The same broad time effects hold even if we omit ridesharing activity from our measures of informal work, which means that the large increase in ridesharing hours does not explain the apparent structural increase in average hours of informal work that occurred between 2016 and 2017.

The results of similar regressions conducted on the baseline sample for labor-intensive gig work are shown in Table 8. These results are qualitatively very similar to those just reported in Table 7. However, as expected, presumably because the outcome measures shown in Table 8 include retirees, the

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[37] Examining scatter plots of the U-3 and U-6 unemployment shares against each of our measures of informal work, we find that for one case, the informal participation rate in New England seems to be an outlier. We therefore ran each regression excluding both observations from New England. The revised results are mostly robust: we observe only negligible changes in the U-6 rate coefficients, respectively, in the model of average hours and the model of FTEs, and both estimates retain at least marginal statistical significance. However, the coefficients on the U-3 unemployment rate in both the hours and FTE equations are somewhat smaller when excluding New England, and neither result is statistically significant.

coefficient estimates on the U-3 and U-6 unemployment rates are uniformly smaller than before and never achieve more than marginal statistical significance. Nevertheless, the aggregate time effects accord quite closely with those estimated using the nonretiree sample in terms of both magnitudes and statistical significance.

6. Robustness Checks

As noted above, we face concerns that, among household heads, our survey oversamples the self-employed and those with internet access. Intuitively we might expect that self-employed individuals and those with internet access are more likely to engage in informal work and to engage in more hours, conditional on their participation in the gig economy. Indeed, we find that the informal participation rate among self-employed individuals is higher than for the rest of the sample. To control for any influence that these sample characteristics may have on our main results, we undertake two robustness checks. In the first check we omit self-employed individuals from the sample and reproduce the estimates of participation rates and average hours among participants for each survey period, as well as replicating the regression analysis. In the second check we reproduce the results after reweighting the sample (as described in the third paragraph below) to align our sample's estimate of internet access propensity with the actual internet access rate observed in a nationally representative sample of household heads as of 2015. In both sets of robustness checks, the time patterns in the raw participation rates and other outcomes are highly robust, and the regression results do not differ markedly from those described above. However, for some regression coefficients we obtain smaller point estimates and/or lower levels of statistical significance.

Figure A1 shows the results that are obtained after omitting self-employed individuals from each of the baseline and nonretiree samples, and using the "excluding survey-only" criteria for informal work. Figure A2 is similar to Figure A1 but adopts the labor-intensive criteria for informal work. Comparing Figures A1 and A2 to Figures 3 and 4, respectively, the participation rates (Panel A) are about the same or lower (by 0 to 3 percentage points) after excluding the self-employed, and average hours among informal workers (Panel B) are also lower in most cases (by 0 to 3 hours per month). However, the qualitative patterns over time closely resemble what we observed previously. Participation rate estimates decline between 2015 and 2016 and then are either flat or recover partly in 2017, resulting in small-to-moderate net declines over time that are not statistically significant. As before, the average hours decline by economically significant margins between 2015 and 2017, but when excluding the self-employed, the net declines are generally not statistically significant given the smaller sample sizes.[38]

Table A3 reproduces the first-difference regression results on the nonretiree sample, omitting the self-employed. Again we observe positive and economically significant associations between each of our informal work outcomes and either the U-3 or U-6 unemployment rate, but the coefficient estimates lose both magnitude and significance compared with the earlier results. These regression results might imply that the association between the unemployment rate and engaging in informal work holds more

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[38] Dropping the self-employed reduces the baseline sample size by 10 to 11 percent depending on the year, and cuts the participant-only sample size by roughly 17 percent per year.

strongly among the self-employed, or the weaker effects could reflect the fact that, for some outcomes and time periods we lose some of the variation in outcomes across census divisions when dropping the self-employed from the regression. With only minor exceptions, the aggregate time effects mirror the previous results quite closely.

To assess how robust our results are to the fact that all of our survey respondents had internet access, we design a set of alternative sample weights in order to correct for this issue. Respondents to the SIWP are recruited from the universe of participants in the Conference Board's Consumer Confidence Survey (CCS), a representative sample of household heads in the United States. Using microdata from the complete December 2015 CCS that contain basic demographic information and an indicator of whether the respondent had internet access, we fit a probit regression for having internet access on a list of demographic factors, and use the estimated coefficients to produce a propensity score for internet access for each respondent to the SIWP.[39] These scores yield an imputed probability of having internet access, which we employ as if we did not know whether they actually had internet access. (We use the same probit model, based on the 2015 CCS, to estimate the internet propensity scores for the respondents in each of our surveys, because we could only obtain the CCS microdata for 2015.) We employ the propensity score to construct a discrete (imputed) indicator of internet access, which equals 1 if the score exceeds 50 percent and 0 if the score is 50 percent or less, and take the (weighted) average of these to get an imputed internet access rate for each of our survey waves.[40] (We must discretize the score to accommodate the weighting method.) We then construct a set of sample weights (separately for each survey) such that the (weighted) imputed internet access rate in our sample closely matches the actual internet access rate in the 2015 CCS sample, while still targeting the ACS sample along the demographic dimensions used to design the original weights. Using these internet-adjusted weights, we recalculate the main results of interest.

Figures A3 (excluding survey-only activity) and A4 (excluding renting/selling only activity) show the estimated participation rates and average hours among participants for each survey (and each sample) using the internet-adjusted weights. Compared with the original results (shown in Figures 3 and 4), the estimated participation rates using the internet-adjusted weights are either virtually the same or only slightly lower (none of the differences are statistically significant), and the changes in participation over time echo the previous results both quantitatively and qualitatively. The average hours conditional on participation (see Figures A3 and A4, panel B) are again not significantly changed when using the adjusted weights—in most cases, hours are a bit lower but in two cases they are higher—and the direction of the change in hours across the three surveys is preserved in each case. Again, we observe

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[39] The demographic factors are age, household income, geographic region, and educational attainment. We do not observe which participants in the CCS subsequently participated in our survey. Nonetheless, since our participants were drawn from the CCS sample, the estimated relationship between demographic characteristics and internet access draws in part on the information provided by those who wound up taking our survey, as well as other CCS respondents.

[40] Based on the CCS from December 2015, the share with internet access in the United States among household heads was 84.1 percent as of that date. In line with our expectations, the imputed internet access share in the SIWP (also for December 2015) is higher, at 90.7 percent. We obtain similar imputed internet access shares in the 2016 and 2017 SIWP waves—at 92.4 percent and 90.2 percent, respectively. However, we lack the CCS microdata for 2016 and 2017 and therefore we cannot compare internet access rates between the SIWP and the CCS for either of those two years.

somewhat larger confidence intervals than before, such that the net declines between 2015 and 2017 in either participation rates or hours are never statistically significant.

Table A4 shows the results for first-difference regressions estimated on the nonretiree sample using the internet-adjusted weights. None of the associations between the two BLS unemployment rates (U-3 or U-6) and the informal work outcomes can be distinguished from zero—although the coefficients on U-3 and U-6 remain positive in the models of average hours and FTEs. Nonetheless, in the models of participation and FTEs there is evidence of an aggregate countercyclical effect (between 2015 and 2016 at least) that shows up in the constant terms, which become unambiguously negative in the participation models and marginally significant (and negative) in the models of FTEs. These results indicate—and we can verify—that using the internet-adjusted weights reduces the between-census division variation in the outcome variables (especially participation and FTEs), but that across all census divisions the common change in participation (or FTEs) between 2015 and 2016 fits a countercyclical story. In addition, the positive aggregate trends between 2016 and 2017 are mostly robust compared with results obtained using the original weights.

Another concern related to robustness is that the method of ordering the survey questions changed between 2015 and the two later surveys. In 2015 all respondents completed the block of questions about informal work first and then responded to the block of CPS-style questions. In the 2016 and 2017 surveys we randomized the ordering of the two main blocks of questions, such that half of the respondents (selected at random) completed the informal work questions first, while the other half completed the CPS-style questions before answering the informal work questions. To ensure that the changes in outcomes across our surveys do not reflect any influence from the ordering of the questions, we restrict the samples from the 2016 and 2017 surveys to those respondents who viewed the informal work questions first, so that the order of questions is the same across all three time periods for all subjects. Using those restricted samples for 2016 and 2017 (and the full sample for 2015), Figure A5 shows the estimates of all four informal work outcomes for the broader definition of informal work and for either the baseline or the nonretiree sample. Figure A6 shows the same four outcomes but for labor-intensive work only. In both figures and across all measures, the half-sample estimates from 2016 and 2017 lie well within the confidence intervals of the previous (full-sample) estimates for the same year, indicating that the ordering of the questions did not significantly influence the subjects' responses. In addition, the qualitative patterns in the changes over time for each outcome remain intact, for both definitions of informal work (all work except surveys and labor-intensive work only) and for either sample (baseline and nonretirees).

7. Conclusion

Using the data from three consecutive annual surveys eliciting rich information on engagement in informal work, we provide new evidence on recent US trends in such activity. Considering either our broader or narrower concept of informal work, we find that participation rates did not change significantly on net between 2015 and 2017, while our point estimates suggest that if anything, the participation rates declined during that period. These estimates are close to the participation rates based on the Federal Reserve Board's EIWA and SHED surveys—estimated at 36 percent of US adults in 2015 (EIWA), 28 percent in 2016 and 31 percent in 2017 (SHED)—validating our headline estimates of

informal work participation.[41] Furthermore, conditional on participation in the gig economy, between 2015 and 2017 the average hours among informal workers showed unambiguous declines, and the aggregate amount of informal work as measured in FTEs also fell substantially, while average earnings among informal workers were effectively flat.

Our composite measures of informal work would appear to contradict recent popular narratives depicting rapid growth in the independent workforce in response to structural changes in the organization of work. However, we also find some supporting evidence for the story of a rising gig economy based on several separate lines of investigation. First, participation rates increased across our surveys for selected technology-enabled jobs such as ridesharing and online tasks, and the average ridesharing hours increased dramatically among drivers, although in absolute terms these technology-enabled jobs still account for only a very small segment of the US population of household heads. Second, an estimate of participation conditional on using the internet or an app in any task increased between 2015 and 2017, although this increase appears to have been driven by renting and selling activities (such as AirBnB or eBay) rather than by an increase in labor-intensive activities involving new technologies. Third, regression analysis suggests that labor-intensive informal work activity (whether participation, hours, or FTEs) experienced upward structural pressure between 2016 and 2017, after controlling for labor market conditions at the census-division level. Still, taken together our results caution against making broad conclusions about trends in the informal or gig economy, but rather serve to emphasize the importance of measuring such activity along both the extensive and intensive margins of participation as well as by the type of task being performed.

The regression analysis further suggests that declines in either U-3 or U-6 unemployment rates may help to explain the declines in average hours among informal workers observed during our time period, as well as the declines in FTEs. Stated differently, our measures of informal work appear to behave countercyclically, in keeping with some evidence from earlier studies on similar concepts of informal work. However, the regression results do not necessarily indicate a causal relationship between labor market slack and informal work activity, and the confidence in our estimates is limited by the small number of observations we employ.

Complementing the regression analysis, our analysis of additional survey responses offer direct (if qualitative) evidence that points to a causal relationship between cyclical labor market conditions and decisions about whether (and how much) to engage in informal work arrangements. Within each of our survey periods, among those engaged in labor-intensive gig work, roughly 39 percent or more of the respondents reported that their decision to undertake such work was spurred in part by experiencing adverse circumstances such as job loss or stagnant wages, and at least 40 percent reported that such work had helped them offset economic hardships either "somewhat" or "very much." Moreover, at least 60 percent of informal workers in each of our surveys identified "earning extra money" as a motivation for their participation in the gig economy.

Our combined results also suggest that informal work hours may exhibit greater sensitivity to the business cycle than the discrete participation decision. The inherent flexibility of informal work

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[41] The consistently lower estimates from our surveys may suggest that household heads (as opposed to adults in general) are less likely to engage in informal work, but other differences between the surveys might also contribute to the gaps—for example the EIWA elicits participation based on earnings in the previous six months whereas we elicit participation based on current engagement and positive hours.

arrangements supports such an interpretation, whereby individuals might adjust their informal work hours in an attempt to smooth income fluctuations, without necessarily forgoing engagement in such work altogether during favorable economic times. Somewhat along these lines, our survey results yield direct evidence that many informal participants in the gig economy view such work as an inferior substitute for having a formal job. A hypothetical survey question (fielded in 2016 and 2017 only) asked informal workers how likely they would be to substitute informal work hours for formal hours under various pay conditions. In both 2016 and 2017, a combined 25 percent or more said they would either be somewhat likely or very likely to make such a switch provided that the hourly pay in the formal job were at least half as much (but not greater than) their hourly informal pay. Assuming that their formal pay might be greater than or equal to their informal pay, the share indicating that they were either somewhat likely or very likely to switch to a formal job exceeds two-thirds of the informal workers in both years. These responses are to hypothetical questions only, and lacking longitudinal data we cannot directly show that informal work hours serve as an income-smoothing device.

To the extent that informal work does play an income-smoothing role, the welfare and policy implications may not be straightforward. On the one hand, the opportunity to work informally serves as a form of insurance against economic shocks; on the other hand, informal work may constitute an unreliable source of income insurance, as the demand for informal labor may also fluctuate with the business cycle. In future research we plan to dig more deeply into the individual-level data to learn what drives individual labor market decisions along both the extensive and intensive margins of informal work, in order to make more robust policy conclusions. Within such investigations, an analysis of trends of participation in the gig economy by gender, income, and educational attainment represent high priorities.

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Figure 1: Selected Questions from Survey of Informal Work Participation Within the Survey of Consumer Expectations (SCE-SIWP)

Panel (a): Engagement

For each of the informal paid activities or side jobs listed in the table below, please respond to the following question:

Please provide a response for each row listed below.

	Are you **currently** engaged in this activity?	
	Yes	No
Babysitting	○	○
House sitting	○	○
Dog walking	○	○
Yard or lawn care (i.e., mowing, weeding, etc.)	○	○
Housecleaning	○	○
House painting	○	○
Eldercare services	○	○
Providing services to other people (for example picking up their dry cleaning, helping people move houses, running errands, booking travel, or other personal assistance)	○	○
Selling goods at consignment shops	○	○
Selling goods on eBay, craigslist, or similar websites	○	○
Renting out property such as your car, your place of residence, or other items you own	○	○
Driving for a ride sharing service like Uber, Lyft, or Sidecar	○	○
Responding to surveys, including phone surveys, online surveys, and in-person surveys	○	○
Getting paid to complete tasks online through websites such as Amazon Mechanical Turk, Fiverr, or similar sites (examples of such tasks include, but are not limited to, editing documents, reviewing resumes, writing songs, creating graphic designs, rating pictures, etc.)	○	○
Posting videos, blog posts, or other content online, such as on YouTube, and receiving pay (including ad revenues or commissions) as a result	○	○
Other informal paid activity or side jobs (please specify)	○	○

Panel (b): Follow up Questions for a Specific Informal Work Activity

You reported that you have engaged in the following informal paid activity:

Babysitting

Considering the past two years or 24 months, in how many months did you engage in this activity **for pay**?

Please enter numbers in the box(es) below.

[____] months out of 24

The following questions refer to a typical month (within the past two years) in which you engaged in this activity.
In a typical month in which you engaged in this activity **for pay**, how much time do/did you spend on this activity? If less than one hour, report only in minutes.

Please enter numbers in the box(es) below.

[____] hours and

[____] minutes per month

In a typical month in which you do/did this activity, how much money do/did you typically earn doing this activity?

Please enter a number in the box below.

[____] dollars per month

Do/did you use websites and/or mobile platforms in the course of doing this work, and/or finding such work?

Please select only one.

○ Yes

○ No

Figure 2: Comparison of Employment Statistics Between the CPS Sample of US Household Heads and the Baseline Sample of the SCE-SIWP
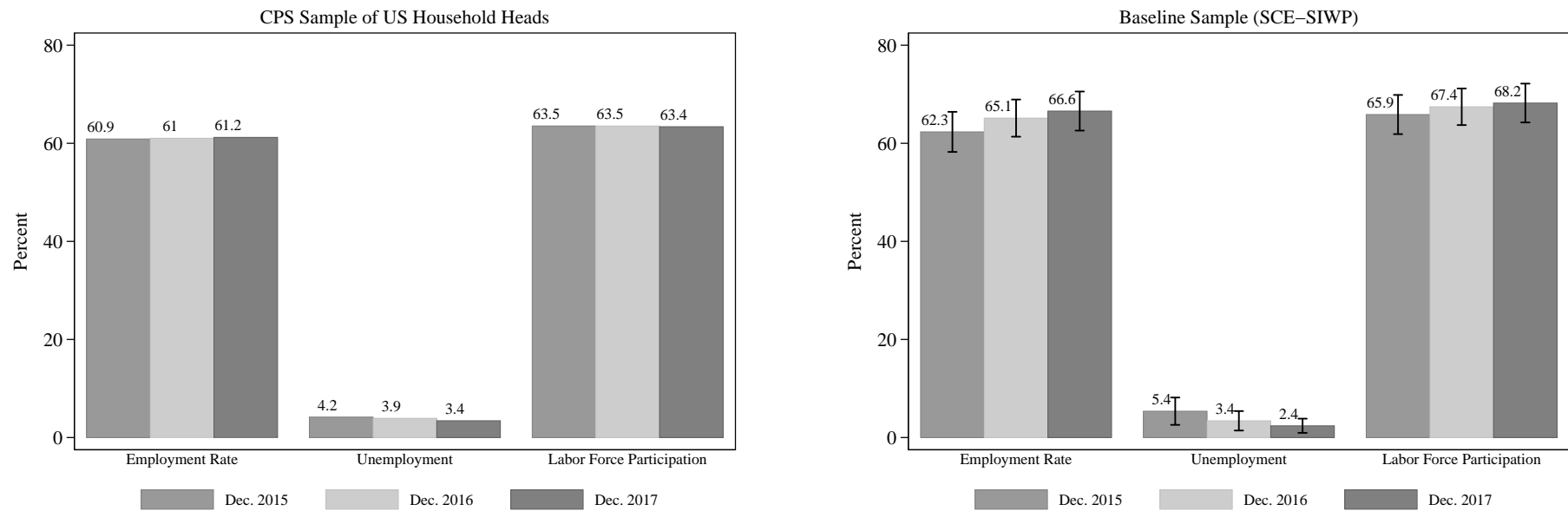
CPS Sample of US Household Heads

Baseline Sample (SCE–SIWP)

Source: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).

Notes: The black lines through each bar show the 95 percent confidence interval around each estimated mean.

Figure 3: Informal Work Measures, Excluding Survey–Only Activity
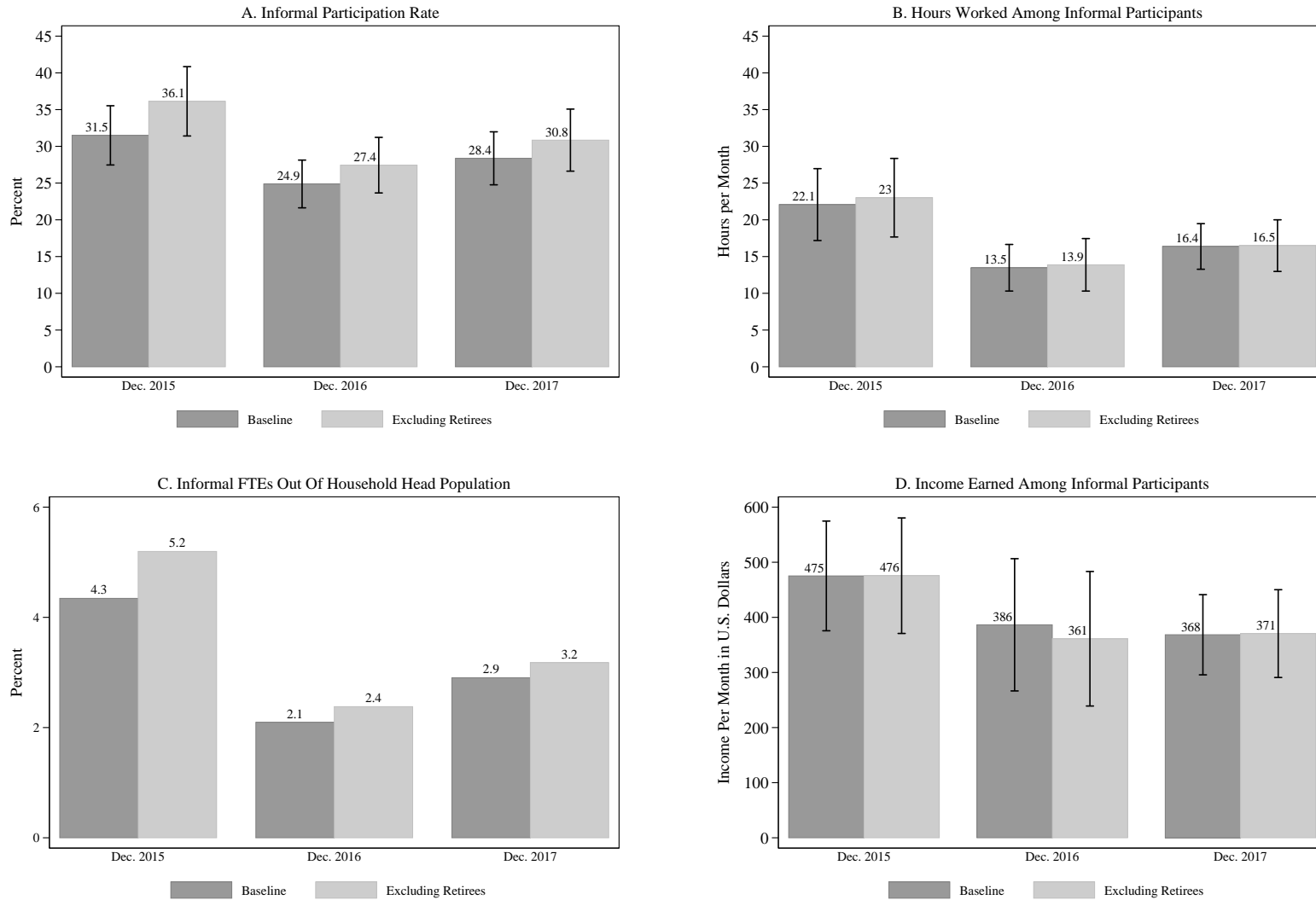
A. Informal Participation Rate

B. Hours Worked Among Informal Participants

C. Informal FTEs Out Of Household Head Population

D. Income Earned Among Informal Participants

Source: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).

Notes: The black lines through each bar show the 95 percent confidence interval around each estimated mean. Informal FTEs are out of household head population.

Figure 4: Informal Work Measures, Labor–Intensive Activities
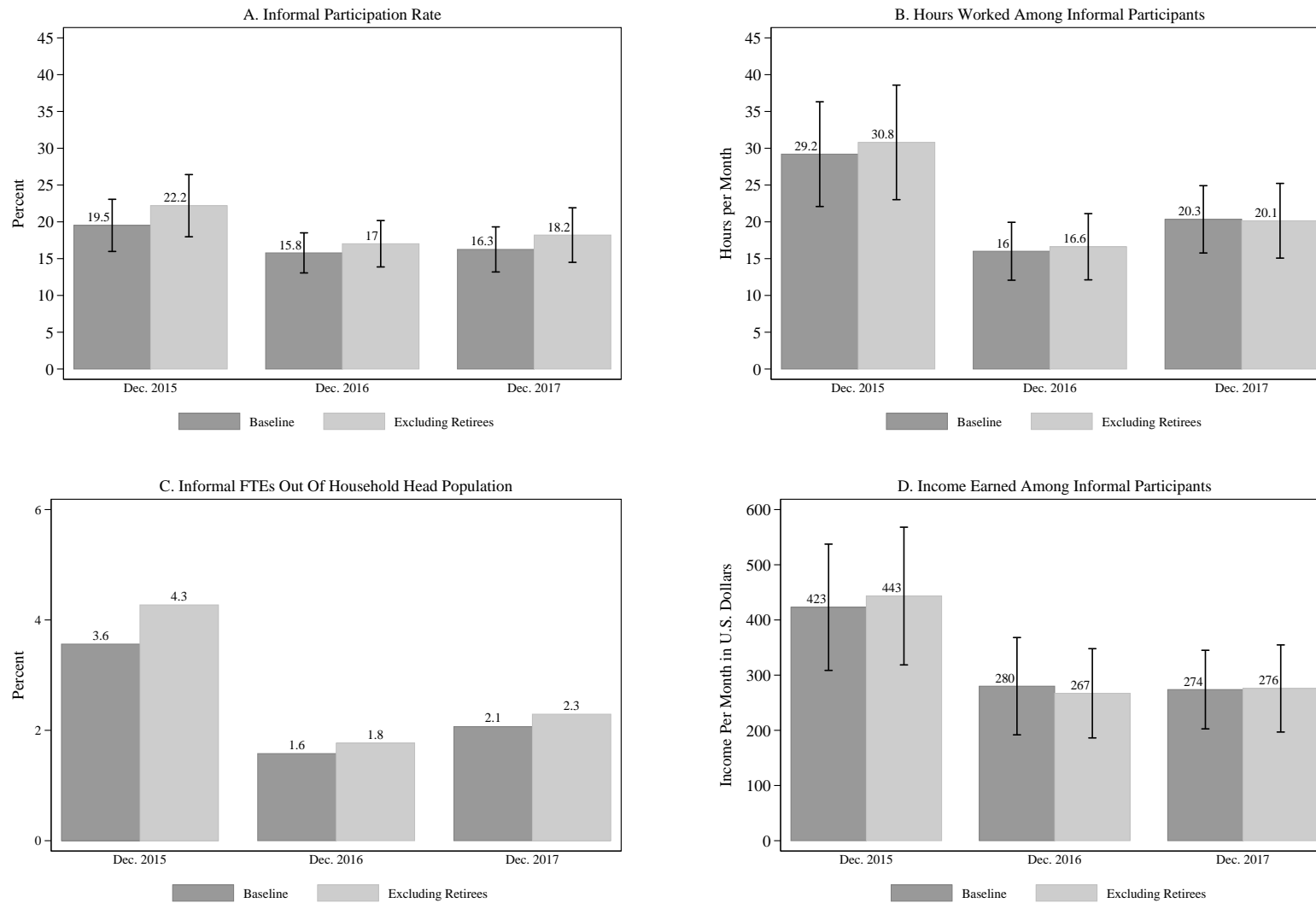
A. Informal Participation Rate

B. Hours Worked Among Informal Participants

C. Informal FTEs Out Of Household Head Population

D. Income Earned Among Informal Participants

Source: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).

Notes: The black lines through each bar show the 95 percent confidence interval around each estimated mean. Informal FTEs are out of household head population.

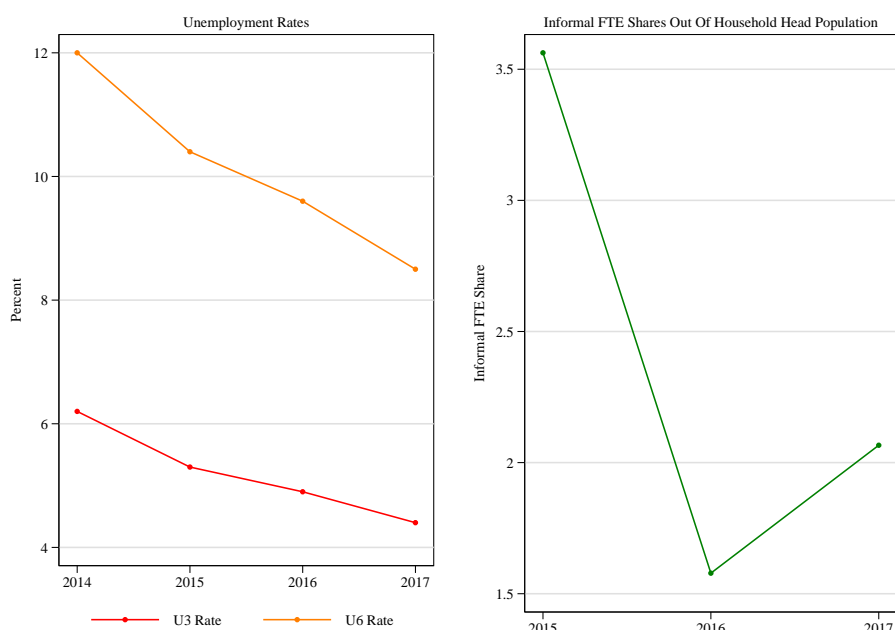Figure 5: US Unemployment Rates for Adult Population and Informal FTE Shares for Household Heads

Notes: The U-3 and U-6 rates are based on the US population, while the informal FTEs are derived from the baseline sample, excluding renting/selling activities.

| | Dec. 2015 | | | | | Dec. 2016 | | | | | Dec. 2017 | | | | |
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Age	963	51	15	22	87	1,057	51	15	21	91	1,065	51	15	21	88
Female	963	.49	.5	0	1	1,057	.5	.5	0	1	1,065	.5	.5	0	1
Non-White	963	.24	.43	0	1	1,057	.25	.44	0	1	1,065	.21	.41	0	1
High School or Less	963	.36	.48	0	1	1,057	.34	.47	0	1	1,065	.33	.47	0	1
Some College	963	.31	.46	0	1	1,057	.32	.46	0	1	1,065	.32	.47	0	1
Bachelors or More	963	.33	.47	0	1	1,057	.34	.48	0	1	1,065	.35	.48	0	1
Married or Cohabiting	963	.65	.48	0	1	1,057	.62	.49	0	1	1,065	.64	.48	0	1
Owns Home	963	.7	.46	0	1	1,057	.71	.46	0	1	1,065	.7	.46	0	1
Employed	963	.65	.48	0	1	1,057	.65	.48	0	1	1,065	.67	.47	0	1
Full Time**	952	.51	.5	0	1	1,049	.49	.5	0	1	1,052	.51	.5	0	1
Part Time**	952	.14	.34	0	1	1,049	.16	.36	0	1	1,052	.15	.36	0	1
Unemployed	963	.03	.18	0	1	1,057	.02	.15	0	1	1,065	.02	.13	0	1
Not in Labor Force	963	.32	.47	0	1	1,057	.32	.47	0	1	1,065	.32	.47	0	1
Retired	963	.21	.41	0	1	1,057	.21	.41	0	1	1,065	.23	.42	0	1
Self-Employed	963	.1	.3	0	1	1,057	.11	.31	0	1	1,065	.1	.3	0	1
Formal Income (Annual) in USD	963	46,537	45,818	0	550,000	1,057	47,782	51,890	0	577,000	1,065	49,134	52,396	0	500,000
Formal Hours (Weekly)	963	35	16	0	84	1,057	34	16	0	80	1,065	35	17	0	168
Formal Wage (Hourly) in USD	963	22	22	0	383	1,057	24	26	0	287	1,065	24	24	0	287
Inf. Participation (Excl. Surveys)	963	.31	.46	0	1	1,057	.25	.43	0	1	1,065	.28	.45	0	1
Inf. Participation (Excl. Surveys/Rent/Sell)	963	.2	.4	0	1	1,057	.16	.36	0	1	1,065	.16	.37	0	1
Informal Income (Monthly) in USD***	166	423	589	1	4,000	172	280	600	1	6,000	167	274	454	1	3,000
Informal Hours (Monthly)***	166	29	33	.083	134	172	16	21	.25	140	167	20	24	.17	140
Informal Wage (Hourly) in USD***	166	26	44	.67	245	172	26	56	.25	613	167	23	52	.25	713

Sources: Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).

Notes: Weights based on US household head targets of education, income, age, and region. **Among those classified as employed, due to missing data we cannot determine part-time versus full-time employment status for all individuals, as indicated by the smaller sample sizes in these rows. ***Statistics regarding informal earnings and informal hours are based only on the sample of (nonrenting/selling) informal work participants with nonmissing values for these outcomes.

Table 2: Weighted Summary Statistics, Excluding Retiree Sample

	Dec. 2015					Dec. 2016					Dec. 2017				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Age	758	46	13	22	80	831	46	13	21	83	806	45	13	21	84
Female	758	.5	.5	0	1	831	.52	.5	0	1	806	.52	.5	0	1
Non-White	758	.27	.45	0	1	831	.28	.45	0	1	806	.25	.43	0	1
High School or Less	758	.35	.48	0	1	831	.33	.47	0	1	806	.31	.46	0	1
Some College	758	.3	.46	0	1	831	.32	.47	0	1	806	.32	.47	0	1
Bachelors or More	758	.34	.48	0	1	831	.35	.48	0	1	806	.37	.48	0	1
Married or Cohabiting	758	.64	.48	0	1	831	.6	.49	0	1	806	.66	.47	0	1
Owns Home	758	.64	.48	0	1	831	.66	.47	0	1	806	.68	.47	0	1
Employed	758	.78	.42	0	1	831	.79	.41	0	1	806	.81	.39	0	1
Full Time**	756	.64	.48	0	1	827	.62	.48	0	1	804	.65	.48	0	1
Part Time**	756	.14	.34	0	1	827	.17	.37	0	1	804	.16	.37	0	1
Unemployed	758	.03	.18	0	1	831	.03	.16	0	1	806	.02	.13	0	1
Not in Labor Force	758	.19	.39	0	1	831	.18	.39	0	1	806	.17	.38	0	1
Retired	758	0	0	0	0	831	0	0	0	0	806	0	0	0	0
Self-Employed	758	.09	.29	0	1	831	.1	.3	0	1	806	.11	.31	0	1
Formal Income (Annual) in USD	758	48,078	47,881	0	550,000	831	49,759	52,659	0	577,000	806	50,427	52,640	0	500,000
Formal Hours (Weekly)	758	36	16	0	80	831	34	16	0	70	806	36	16	0	168
Formal Wage (Hourly) in USD	758	23	24	0	383	831	25	27	0	287	806	25	25	0	287
Inf. Participation (Excl. Surveys)	758	.36	.48	0	1	831	.27	.45	0	1	806	.31	.46	0	1
Inf. Participation (Excl. Surveys/Rent/Sell)	758	.22	.42	0	1	831	.17	.38	0	1	806	.18	.39	0	1
Informal Income (Monthly) in USD***	143	443	603	1	4,000	146	267	530	1	6,000	138	276	452	3	3,000
Informal Hours (Monthly)***	143	31	34	.083	134	146	17	23	.25	140	138	20	24	.17	140
Informal Wage (Hourly) in USD***	143	27	46	.67	245	146	23	34	.52	375	138	24	54	.25	713

Sources: Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).

Notes: Weights based on US household head targets of education, income, age, and region. **Among those classified as employed, due to missing data we cannot determine part-time versus full-time employment status for all individuals, as indicated by the smaller sample sizes in these rows. ***Statistics regarding informal earnings and informal hours are based only on the sample of (nonrenting/selling) informal work participants with nonmissing values for these outcomes.

Table 3: Rankings by Task Participation, Baseline Sample

	Dec. 2015		Dec. 2016		Dec. 2017	
	Rank	Rate (%)	Rank	Rate (%)	Rank	Rate (%)
Rent/Sell Activities	1	16.3	1	13.0	1	16.7
House Cleaning	2	6.2	4	1.9	2	4.6
Other Informal Work	3	5.8	2	6.0	3	4.4
Personal Service	4	4.6	3	2.5	4	2.8
Lawn Care	5	4.4	7	1.6	8	2.0
Eldercare	6	2.4	8	1.3	9	1.7
Babysitting	7	2.2	6	1.7	5	2.7
House Painting	8	1.4	10	0.9	13	0.4
Online Tasks	9	1.3	5	1.7	6	2.7
House Sitting	10	1.2	12	0.7	7	2.0
Dog Walking	11	1.1	13	0.7	11	1.2
Posting Online	12	0.8	11	0.8	10	1.2
Driver / Ride Sharing	13	0.5	9	1.0	12	1.0

Table 4: Rankings by Task Average Hours Among Participants, Baseline Sample

	Dec. 2015		Dec. 2016		Dec. 2017	
	Rank	Ave Hours	Rank	Ave Hours	Rank	Ave Hours
Eldercare	1	37.1	2	24.9	2	23.7
House Sitting	2	30.1	3	24.1	3	21.2
Babysitting	3	24.6	1	25.1	4	16.4
Other Informal Work	4	24.5	4	14.2	5	13.6
House Cleaning	5	16.8	6	10.1	9	7.9
Personal Service	6	12.5	12	4.5	13	6.3
Lawn Care	7	10.6	8	6.4	10	7.5
House Painting	8	9.6	9	6.4	7	8.1
Dog Walking	9	8.2	7	9.1	11	6.7
Rent/Sell Activities	10	7.7	10	6.4	8	8
Driver / Ride Sharing	11	7.3	5	11.4	1	34.6
Posting Online	12	7	11	5.8	12	6.9
Online Tasks	13	5.5	13	3.1	6	8.5

Table 5: Participation by Internet/App-Use over SCE-SIWP Waves in Baseline Sample

	Dec. 2015	Dec. 2016	Dec. 2017
All (Excl. Survey) Participation			
With Internet/App-Use	10.9%	10.4%	14.4%
Without Internet/App-Use	20.6%	14.5%	14.0%
Labor-Intensive Participation			
With Internet/App-Use	8.9%	8.5%	8.3%
Without Internet/App-Use	10.6%	7.3%	8.0%

Sources: Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).

Table 6: Self-Employment and Freelancing over SCE-SIWP Waves Among Baseline Sample

	Dec. 2015	Dec. 2016	Dec. 2017
Self-Employment Share (SIWP)*	11.8%	11.7%	11.6%
Self-Employment Share (CPS)**	11.2%	11.3%	11.3%
Freelancing Share*	8.7%	6.1%	5.1%

Sources: Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).
Notes: *Self-employment (SIWP) and freelancing shares are out of employed. **Self-employment (CPS) includes both incorporated and unincorporated self-employment for consistency of the comparisons.

Table 7: Census Division Regressions (First Difference): Labor-Intensive Gig Work, Excluding Retirees

	Participation			Ave Hours			FTEs		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
U3 Rate	6.065			18.330*			4.269*		
	(7.627)			(10.083)			(2.292)		
U6 Rate		2.186			11.609**			2.153*	
		(3.098)			(5.275)			(1.020)	
PTER Share			−1.777			2.385			0.460
			(6.893)			(14.305)			(3.045)
Year=2017	8.690***	9.000***	9.400**	15.867***	15.204***	19.317**	3.307***	3.328***	4.094***
	(2.625)	(3.044)	(3.945)	(4.155)	(4.040)	(6.556)	(0.951)	(1.057)	(1.370)
Constant	−4.361	−5.326	−8.392**	−5.019	−2.183	−14.789**	−1.024	−0.997	−3.330*
	(3.026)	(3.616)	(3.231)	(5.586)	(6.019)	(6.124)	(1.010)	(1.200)	(1.586)
R–Squared	0.37	0.36	0.35	0.52	0.54	0.45	0.48	0.46	0.40
Observations	18	18	18	18	18	18	18	18	18

Sources: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), Bureau of Labor Statistics / Haver Analytics, and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).
Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Census Division Regressions (First Difference): Labor-Intensive Gig Work, Baseline Sample

	Participation			Ave Hours			FTEs		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
U3 Rate	5.864			13.608			2.942		
	(6.171)			(10.816)			(1.832)		
U6 Rate		1.990			9.644*			1.592*	
		(2.811)			(5.478)			(0.852)	
PTER Share			2.073			−0.584			0.330
			(5.776)			(14.062)			(2.483)
Year=2017	6.114**	6.453**	7.438**	16.519***	15.698***	18.683**	2.846***	2.826***	3.391***
	(2.326)	(2.692)	(3.022)	(4.478)	(4.193)	(6.846)	(0.820)	(0.868)	(1.092)
Constant	−2.447	−3.522	−5.166	−6.734	−3.449	−14.720**	−1.061	−0.917	−2.646*
	(2.985)	(3.638)	(3.048)	(6.432)	(6.461)	(5.456)	(0.901)	(1.015)	(1.330)
R–Squared	0.34	0.31	0.31	0.49	0.51	0.45	0.47	0.46	0.41
Observations	18	18	18	18	18	18	18	18	18

Sources: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), Bureau of Labor Statistics / Haver Analytics, and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).
Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table A1: Rankings by Task Participation, Excluding Retiree Sample

| | Dec. 2015 | | Dec. 2016 | | Dec. 2017 | |
	Rank	Rate (%)	Rank	Rate (%)	Rank	Rate (%)
Rent/Sell Activities	1	18.8	1	14.6	1	18.0
House Cleaning	2	7.0	3	2.3	2	5.4
Other Informal Work	3	6.4	2	6.1	3	4.5
Personal Service	4	5.5	4	2.1	5	3.1
Lawn Care	5	5.0	7	1.7	8	2.0
Eldercare	6	2.9	8	1.5	9	1.8
Babysitting	7	2.8	5	2.1	6	2.9
House Painting	8	1.6	9	1.2	13	0.3
Online Tasks	9	1.5	6	1.9	4	3.2
House Sitting	10	1.4	13	0.7	7	2.4
Dog Walking	11	1.3	12	0.8	11	1.3
Posting Online	12	1.0	10	0.9	10	1.6
Driver / Ride Sharing	13	0.5	11	0.9	12	1.0

Table A2: Rankings by Task Average Hours Among Participants, Excluding Retiree Sample

| | Dec. 2015 | | Dec. 2016 | | Dec. 2017 | |
	Rank	Ave Hours	Rank	Ave Hours	Rank	Ave Hours
Eldercare	1	36.9	2	26.1	2	27
House Sitting	2	32.9	1	27.7	3	23.1
Other Informal Work	3	25.8	5	13.7	4	14.9
Babysitting	4	24.6	3	25.8	5	14.7
House Cleaning	5	18	6	9.4	7	8.1
Personal Service	6	12.9	12	6	12	6.2
Lawn Care	7	11.2	10	6.4	11	6.3
Driver / Ride Sharing	8	9.1	4	15.6	1	34
Dog Walking	9	8.9	7	8.2	13	2.8
Rent/Sell Activities	10	7.9	8	6.7	8	7.9
Posting Online	11	7.4	9	6.5	10	6.9
House Painting	12	6.7	11	6.4	9	7.7
Online Tasks	13	6.1	13	3	6	8.7

Table A3: Census Division Regressions (First Difference): Labor-Intensive Gig Work, Excluding the Self-Employed and Retirees

	Participation			Ave Hours			FTEs		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
U3 Rate	6.582			11.124			2.967		
	(9.019)			(10.682)			(2.713)		
U6 Rate		0.969			7.861			1.109	
		(3.095)			(6.424)			(1.049)	
PTER Share			−1.942			3.912			0.658
			(6.541)			(11.607)			(2.249)
Year=2017	5.248*	6.032*	6.015	13.094***	12.431***	15.603**	2.326***	2.464**	2.930**
	(2.570)	(3.284)	(4.342)	(3.771)	(3.570)	(5.983)	(0.737)	(0.955)	(1.334)
Constant	−2.321	−4.982	−6.700**	−6.351	−3.691	−11.514***	−0.884	−1.310	−2.380**
	(2.942)	(3.609)	(2.992)	(5.993)	(7.002)	(3.869)	(0.955)	(1.201)	(0.990)
R–Squared	0.19	0.16	0.17	0.45	0.47	0.42	0.36	0.32	0.30
Observations	18	18	18	18	18	18	18	18	18

Sources: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), Bureau of Labor Statistics / Haver Analytics, and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).
Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Census Division Regressions (First Difference): Labor-Intensive Gig Work, with Internet-Adjusted Weights, Excluding Retirees

	Participation			Ave Hours			FTEs		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
U3 Rate	0.018			12.131			1.922		
	(7.775)			(8.796)			(1.917)		
U6 Rate		−0.208			5.965			0.962	
		(2.837)			(5.791)			(0.815)	
PTER Share			−2.241			1.234			0.263
			(5.494)			(11.330)			(2.064)
Year=2017	5.773**	5.843*	5.399	22.694***	22.804***	24.919***	3.233***	3.245***	3.597***
	(2.293)	(2.750)	(3.681)	(5.588)	(6.341)	(5.936)	(0.754)	(0.829)	(1.045)
Constant	−6.637**	−6.886**	−7.344***	−7.157	−7.255	−13.731***	−1.718*	−1.714*	−2.739***
	(2.777)	(3.059)	(2.300)	(6.122)	(7.205)	(4.307)	(0.951)	(0.975)	(0.897)
R–Squared	0.19	0.19	0.19	0.59	0.59	0.57	0.54	0.53	0.51
Observations	18	18	18	18	18	18	18	18	18

Sources: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), Bureau of Labor Statistics / Haver Analytics, and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).
Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Informal Work Participation Rates and Hours Without the Self-Employed, Excluding Survey-Only Activity
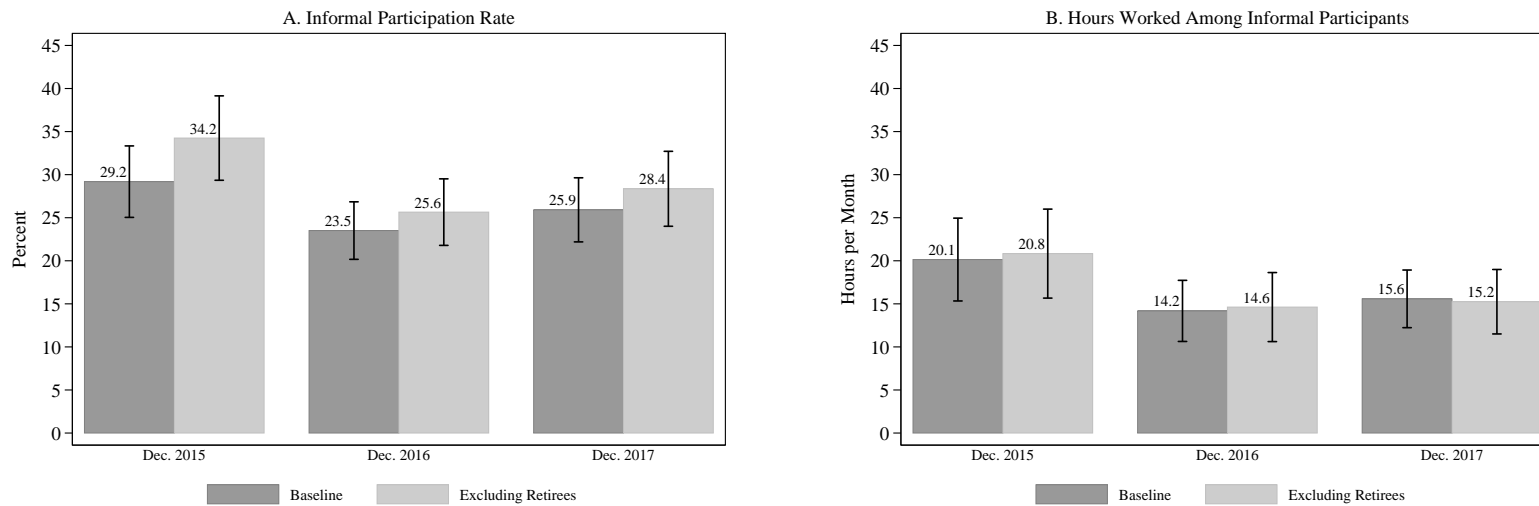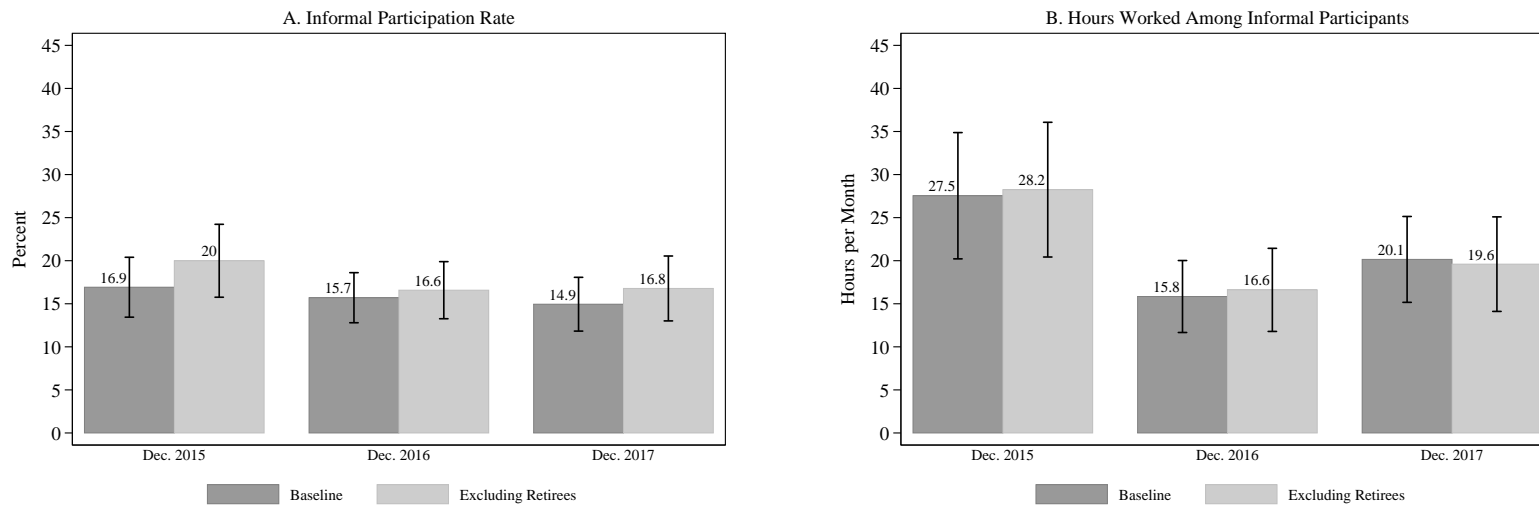
A. Informal Participation Rate

B. Hours Worked Among Informal Participants

Figure A2: Informal Work Participation Rates and Hours Without the Self-Employed, for Labor-Intensive Activities

A. Informal Participation Rate

B. Hours Worked Among Informal Participants

Notes: The black lines through each bar show the 95 percent confidence interval around each estimated mean.

Figure A3: Informal Work Participation Rates and Hours Using Internet-Adjusted Weights, Excluding Survey-Only Activity

A. Informal Participation Rate

B. Hours Worked Among Informal Participants
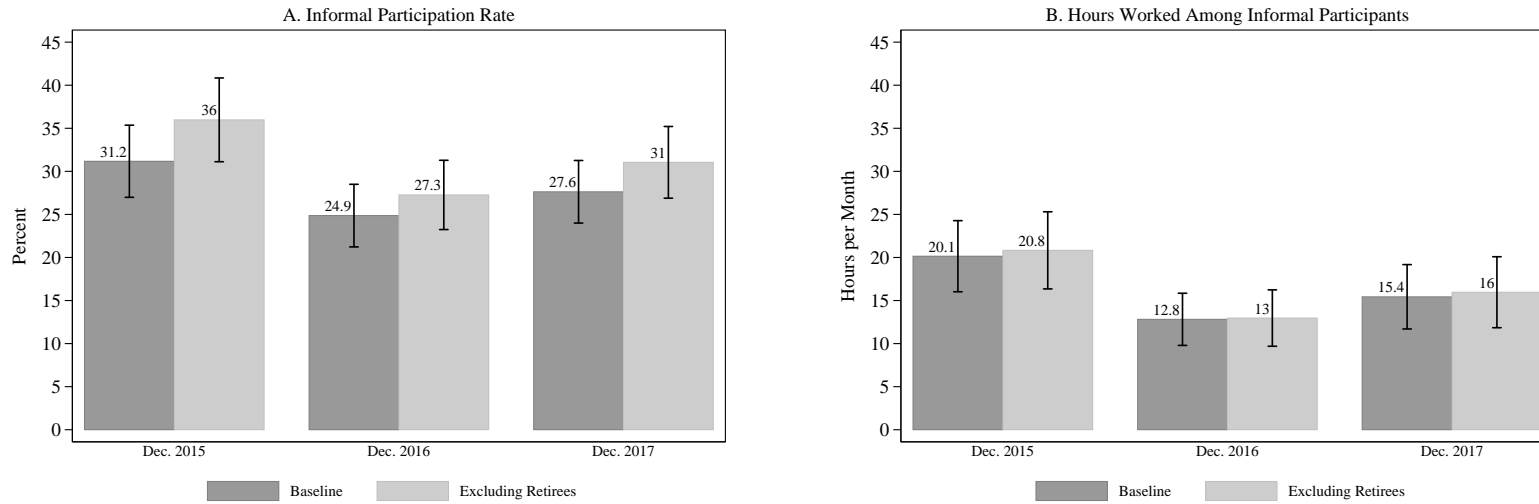
Figure A4: Informal Work Participation Rates and Hours Using Internet-Adjusted Weights, for Labor-Intensive Activities
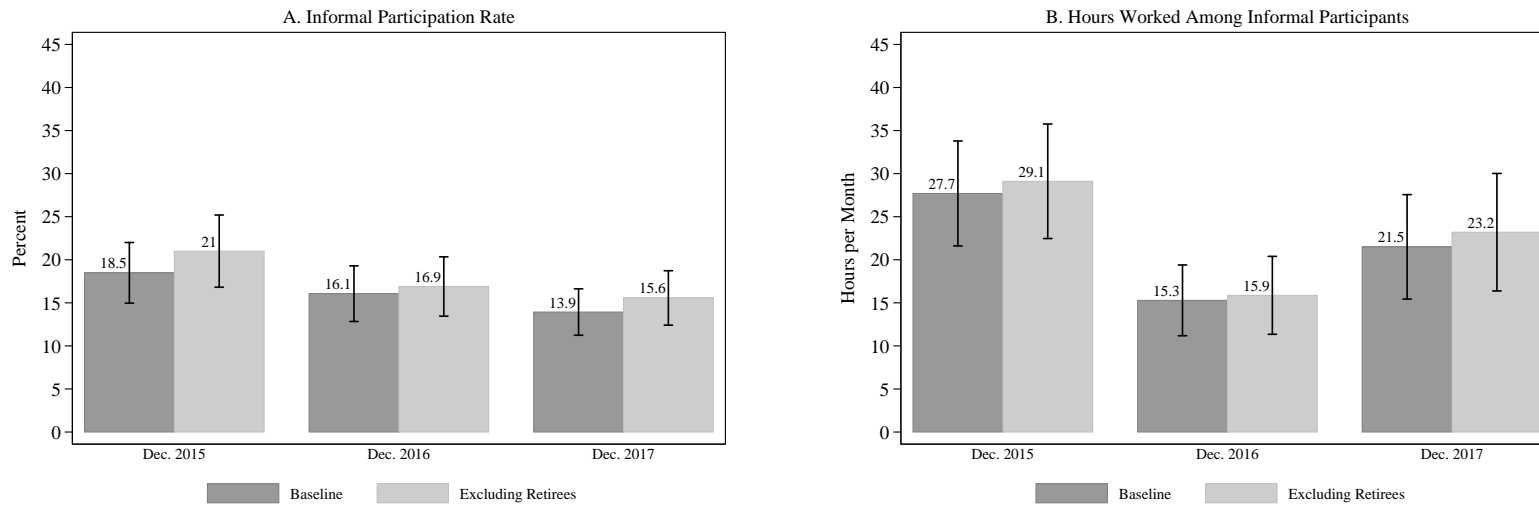
A. Informal Participation Rate

B. Hours Worked Among Informal Participants

Source: Authors' calculations based on IPUMS-CPS (Flood et al. 2018), and Survey of Informal Work Participation within the Survey Consumer Expectations (SCE-SIWP), ©2015-2017 Federal Reserve Bank of New York (FRBNY).

Notes: The black lines through each bar show the 95 percent confidence interval around each estimated mean. Weights are based on household heads with targets of education, age region, and access to internet in December 2015.
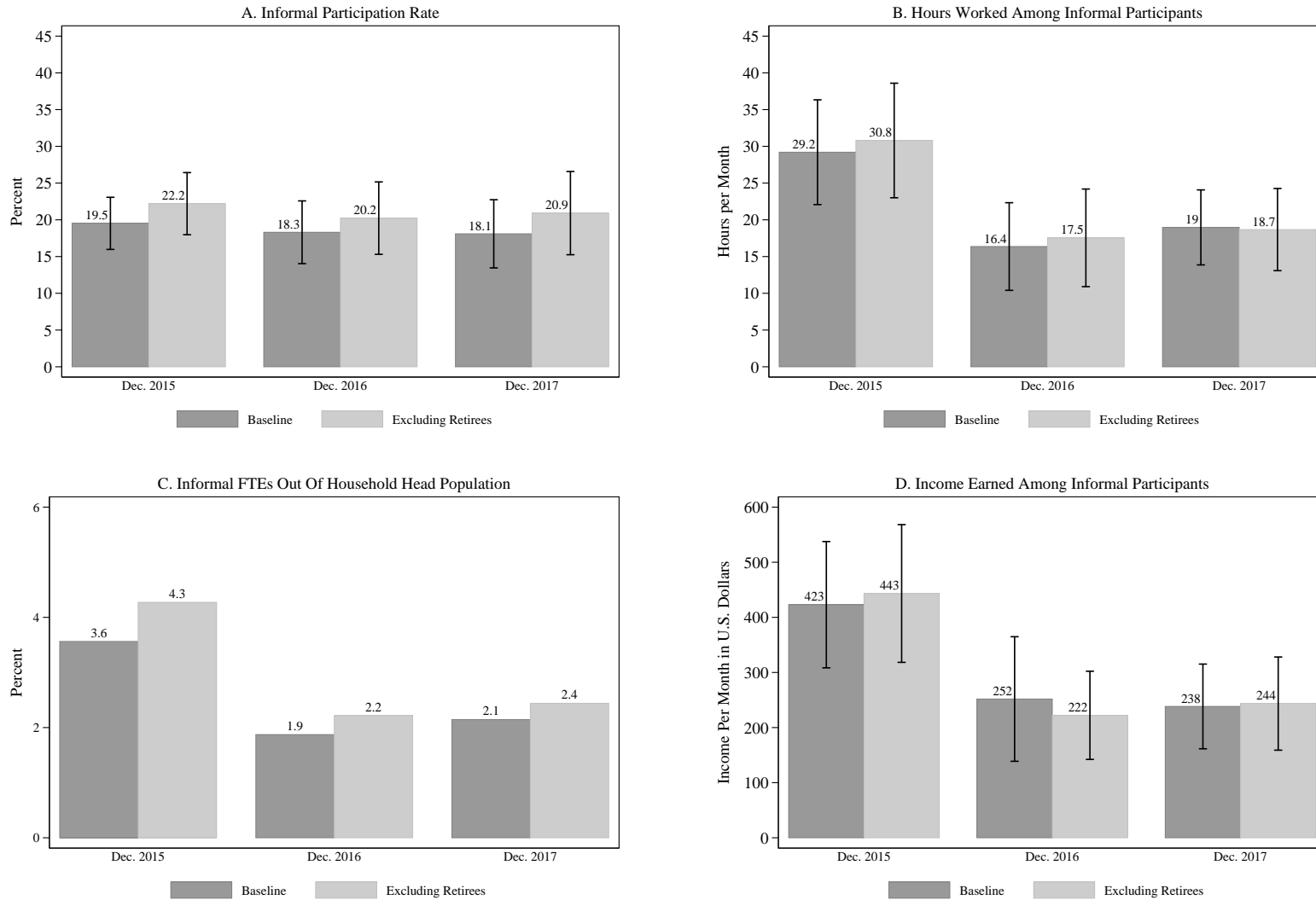
40

Figure A5: Informal Work Measures for Those Who Saw Informal Work Survey Questions First, Excluding Survey-Only Activity
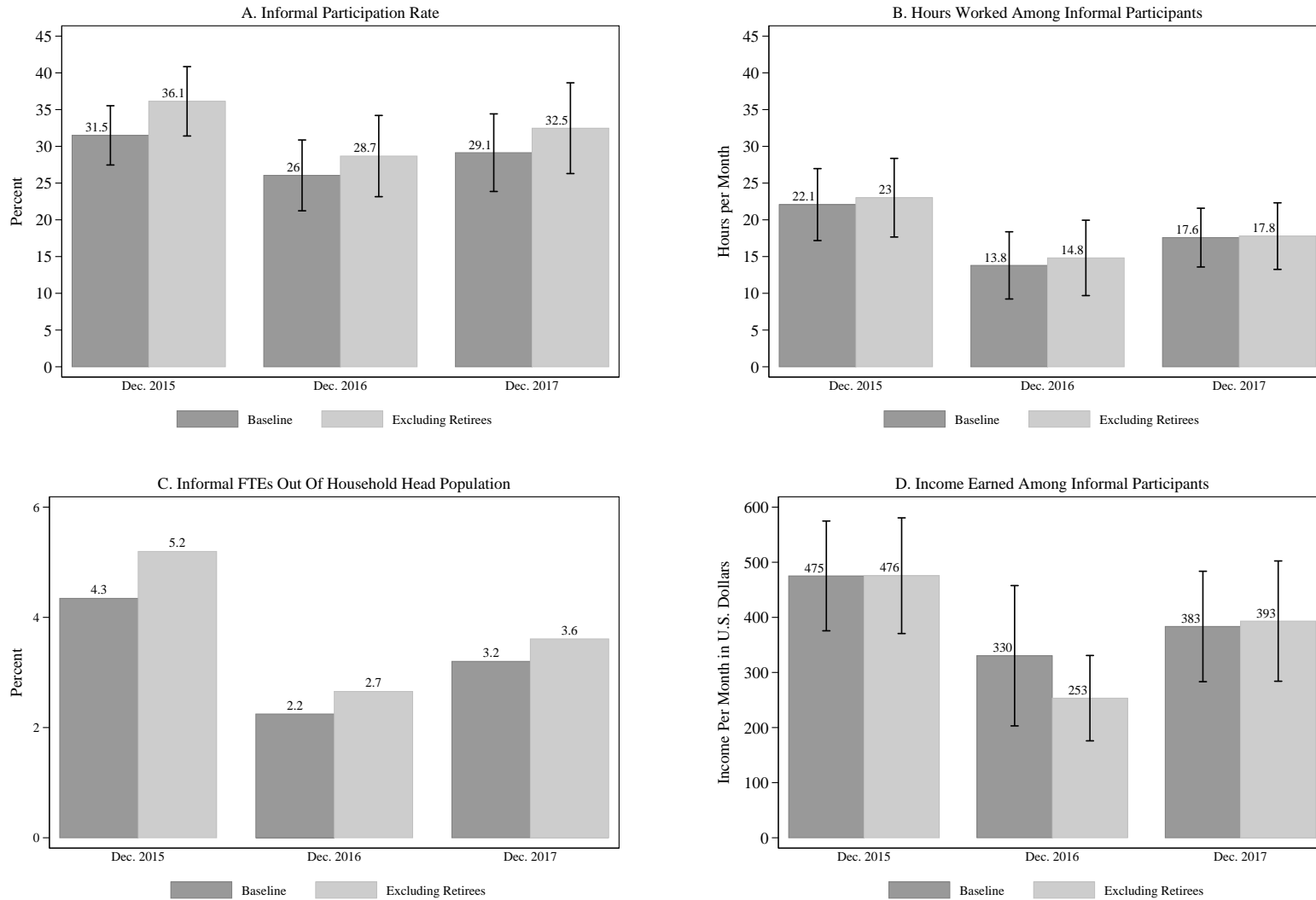
Notes: The black lines through each bar show the 95 percent confidence interval around each estimated mean. Informal FTEs are out of household head population.

Figure A6: Informal Work Measures for Those Who Saw Informal Work Survey Questions First, Labor-Intensive Activities

Notes: The black lines through each bar show the 95 percent confidence interval around each estimated mean. Informal FTEs are out of household head population.