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The "Gig Economy" and Independent Contracting: Evidence from California Tax Data

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Abstract

We use de-identified data from California personal income tax returns to measure the frequency and nature of independent contracting work in California. We identify independent contractors by the presence of a Schedule C on the tax return and/or the receipt of a Form 1099 information return. We estimate that 14.4% of California workers aged 18-64 in tax year 2016 had some independent contracting income; over half of these do not have traditional jobs generating W-2s and get all of their earnings from independent contracting. Workers with low earnings are significantly more likely to earn independent contracting income and to rely primarily or exclusively on that income. We explore the characteristics of independent contractors and their distribution across family type, geography, and industry.

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I. Introduction

Most labor market policy in the United States is designed for long-term employment relationships. Self-employed workers, including independent contractors and on-demand platform ("gig") workers, are excluded from labor market protections such as wage and hour laws, occupational safety and health regulations, unemployment insurance, and employer-provided health insurance and retirement programs. They are also poorly covered by our tax collection system, which relies heavily on employer reporting of worker earnings for enforcement. Growth in independent contracting thus threatens to undermine our labor market arrangements, with implications for regulation, tax collection, and worker wellbeing.

Unfortunately, to date we have little consistent, rigorous evidence about the prevalence and nature of independent contracting, let alone changes over time (National Academics of Sciences, Engineering, and Medicine 2020; Casselman 2018; Bernhardt and Thomason 2017; Government Accountability Office 2015). Anecdotes and non-representative samples sometimes indicate large increases in freelance work (Freelancers Union, Upwork, and Edelman Intelligence 2016), but these are not always mirrored in more representative data (Abraham et al. 2020). Moreover, even official surveys rely on worker self-reports, which do not always align with workers' status under employment and labor laws (Abraham et al. 2020); indeed, the misclassification of workers who would qualify as employees under employment law tests but are treated as independent contractors by employers is thought to be an important phenomenon (de Silva et al. 2000). The primary worker survey on this topic, the Bureau of Labor Statistics' Contingent Worker Supplement (CWS), shows no growth in alternative work arrangements from 2005 to 2017, but as we discuss below it may miss a substantial fraction of independent contractor work. Employer surveys and many administrative data sources are of little help, as they are oriented toward traditional jobs.

This paper uses California tax data to provide an alternative lens on many of the outstanding empirical questions about independent contracting. Tax data provide important advantages over other sources (Bernhardt and Thomason 2017). In particular, they distinguish clearly between earnings from traditional jobs, reported on W-2 forms, and those from sole proprietorships, reported on Schedule Cs and Form 1099s. The tax distinction aligns closely with the core distinction in US employment and labor laws between employees, who are covered by a wide range of employment protections, regulations, and safety net programs, and independent contractors, who are not.[2] Tax data also include information about earnings from both traditional and non-traditional employment for a given tax filer, both within a year and over time. This makes it possible to measure how workers combine traditional and independent contracting work, a topic that cannot be fully explored in worker surveys that ask only about the main job at a point in time. The implications of a side gig as an Uber driver, supplementing a main job with an employer, are different from the implications of workers relying on independent contracting for their main source of income. Similarly, the implications of a short six-month spell as an Uber driver are different from multi-year reliance on independent contracting income.

For these reasons, tax data are crucial to advancing our understanding of the new world of work. We follow several previous studies (e.g., Collins et al., 2019; Lim et al., 2019, Jackson et al., 2017) in using these types of data to understand the dimensions of independent contracting.

We use de-identified, individual-level data from California personal income tax returns for tax years 2012 through 2017 to measure the prevalence and nature of self-employment and independent contracting. We use three types of tax forms to identify non-traditional jobs: Schedule C filings, used to report profits and losses from sole proprietor businesses; 1099-MISCs, issued by employers of independent contractors who earn more than $600 per year; and 1099-Ks, used by some online platform economy employers such as Uber and Lyft. We explore the prevalence of independent contracting (hereafter, IC) earnings, how individuals combine this work with

[2] The alignment is close, but not perfect; the definition of an employee varies slightly across domains and jurisdictions.

traditional jobs, and how participation in independent contracting varies with worker demographics and geography.

We build on previous work with tax data (most notably Collins et al., 2019) in several ways. We explore more thoroughly the extent to which workers combine traditional and IC work both within and across years. We also investigate which segments of the labor market (defined by industry, earnings level, and geography) are most reliant on IC work. Last, although there are measurement challenges inherent in the use of tax data, we are able to explore two potentially important sources of mismeasurement: Individuals who receive IC earnings from on-demand labor platforms but do not report them on tax returns, and overstatement of IC earnings among those who face negative marginal tax rates due to the Earned Income Tax Credit.

California is a particularly interesting location to study IC work. It is the birthplace of on-demand platforms and adoption in the state occurred earlier and at higher rates than in other parts of the country, yielding richer information on this emerging form of work (Farrell and Greig 2016b). California is also the world's fifth largest economy (if viewed as a nation) and is home to roughly 40 million people, more than the smallest 21 states combined. Nevertheless, we must caution that, while of independent interest, patterns in California may not exactly match those elsewhere.

A second caution is that we can only measure IC income that leads to individual or third-party tax reporting. The IRS estimates that only 1% of traditional wage and salary earnings are not reported, but that nearly two-thirds of income without third-party reporting is not (Internal Revenue Service 2016). This is in part because third-party reporting is more systematic and clearer for traditional jobs, which generate W-2s, than for independent contracting jobs. Collins et al. (2019) find that 29 percent of individuals who received 1099-MISCs (typically indicative of self employment work) do not file Schedule C.[3] We use both individual tax returns and 1099 third-party reports. The third-party reports enable us to capture much of the earnings that are not

[3] In our data, the share is slightly lower, 24%.

reported on individual returns. However, when there is no third-party reporting we capture only the earnings that individuals report. In a supplementary analysis, we show that third-party reporting has a causal effect on individual reporting, implying that our coverage of non-1099 IC earnings is limited by underreporting. Fortunately, in the 2016 tax year that was the focus of our analysis (though not more recently) many of the major platform employers, including Uber and Lyft, generated 1099-Ks for all of their workers above a low earnings threshold, even when this was not legally required. This leads us to believe that the under-coverage is not terribly severe outside of the cash-based economy.

A related issue is that we rely upon employers' classification of relationships into traditional employment (generating W-2s) or independent contracting (leading, variously, to 1099s and/or Schedule Cs). Insofar as workers who should be counted as traditional employees are misclassified by their employers as ICs, we will overstate the prevalence of actual independent contracting.

There is yet another sense in which we depend on tax reporting. An apples-to-apples comparison of W-2 and IC earnings requires reducing the latter to account for business expenses that would be borne by the employer in a traditional employment relationship. We rely on Schedule Cs to identify these business expenses and thus to calculate the earnings net of expenses on IC work that are most closely analogous to the earnings reported for traditional workers. This means that we may understate IC profits for those who file Schedule Cs and over-report their expenses in order to reduce their tax burdens, but overstate IC profits for those who receive IC income but do not file Schedule Cs (for whom we impute zero expenses).

Despite these limitations, our results add important new texture to our understanding of IC work in the California labor market. We find that IC work constitutes a small segment of the labor market. In 2016, we estimate that 12.1% of working-age adult tax filers in California had any IC income. About half of these were exclusively IC workers, with no W-2 earnings. The professional services, personal services, and transportation industries account for significant shares of IC workers; IC workers are also overrepresented in arts and entertainment, repair and maintenance, real estate, and construction.

Few workers appear to mix W-2 and IC work in substantial amounts. In 2016, only 2.8% of workers (19% of those with any IC earnings) received significant income from both sectors, where each provided at least 15% of the annual total. By comparison, 4.2% of workers (29% of those with IC income) used IC work as a supplement while obtaining over 85% of their total earnings from W-2 relationships, while 7.0% of workers (49% of those with IC income) were exclusively IC workers. Moreover, many of the workers who combine both types of earnings in substantial amounts are, on closer inspection, merely transitioning from one sector to the other – mixing the two types of income for multiple years in a row is relatively rare.

We also measure the share of IC workers with earnings from on-demand labor platforms, the so-called "gig" economy. We identify only 1.4% of workers (9.8% of IC workers) as receiving income from online platform employers (OPE) in 2016. This group is bimodally distributed -- over half receive less than 15% of their earnings from IC work, while another quarter have no W-2 work at all.

IC workers, on average, have lower earnings than do traditional employees, with fairly substantial over-representation in the lower deciles of the earnings distribution, but there are important differences in the types of IC work. Some high-income workers receive small shares of their earnings from IC work, but there are few primarily-IC workers in the top deciles of the distribution. By contrast, more than half of workers whose earnings come primarily from IC work are in the bottom three deciles of the earned income distribution, with total annual earnings under $20,542. Workers with OPE income have somewhat higher earnings, while still being below average relative to the overall workforce. The median worker with OPE income falls just above the 30th percentile of the overall earnings distribution; only about one-quarter of OPE workers fall in the upper half of the overall distribution.

II. Defining terms

Public concern over the “future of work” is rising and many predict that the jobs of the future will involve short-term relationships with little loyalty between worker and firm (Katz and Krueger 2019; Government Accountability Office 2015; Vinik 2018). It has been surprisingly difficult, however, to verify the prevailing perception that “gig” work is a large or rapidly growing component of the labor market. Part of the problem is widely varying different definitions of gig work; some use the term specifically for on-demand platforms such as Uber and TaskRabbit, while others use the term broadly to denote any type of work that is precarious or contingent – with many definitions (such as independent worker) in between.

Confounding the definitional problem is the use of surveys or datasets where samples are not representative, and conflicting estimates when researchers compare worker self-reports to other data sources. The result is very different estimates of the number of gig workers in the US, ranging from 600,000 to 55 million.[4] The Bureau of Labor Statistics’ 2017 Contingent Worker Survey release highlights the issue, finding 10.6 million independent contractors in total – a smaller share of the workforce than in the same survey in 2005 and many fewer than in other analyses (Bureau of Labor Statistics 2018). However, an important limitation of the Contingent Worker Survey is that it focused on workers’ main jobs; independent contracting work done to supplement another job, as with many Uber drivers, is explicitly excluded (Bernhardt 2018).

Drawing on previous research on the changing organization of work (e.g., Bernhardt and Thomason 2017), we focus on independent contracting as our primary analytic and empirical

[4] For a sample of key studies, see Farrell and Greig 2018; Katz and Krueger 2016; Freelancers Union, Upwork, and Edelman Intelligence 2016; Burson-Marsteller and The Aspen Institute 2016; Manyika et al. 2016; Smith 2016; Robles and McGee 2016; Intuit and Emergent Research 2016; Mishel 2015, 2018; MBO Partners 2016; Hathaway and Muro 2016; US Government Accountability Office 2015; Bureau of Labor Statistics 2005, 2018; Board of Governors of the Federal Reserve Board 2018; Collins et al., 2019.

object.[5] This aligns with the fundamental distinction between employees and independent contractors in US employment and labor laws, determining access to a wide range of rights, benefits and social insurance programs for workers. The category of independent contractors includes both online platform work (such as driving for Uber or finding jobs through TaskRabbit) as well as traditional independent contractor work (such as construction workers, real estate brokers, and hair stylists).[6]

Even with this clarifying definition, however, research still generates significant differences in estimates of both prevalence and trends over time. One part of this difference is the underlying data source. Abraham et al. (2020) analyze differences between worker survey data (the Current Population Survey) and federal tax data, documenting significant error in workers' self-reports of independent contractor income, especially when they also hold a W-2 job.[7] Abraham, Hershbein and Houseman (2019) further document the important role of question wording in contributing to workers' misidentification of their employment status.

Researchers have therefore turned to tax data as a better, though by no means perfect, source for measuring independent contracting. In using tax data for this project, we build on the work of US Treasury researchers Jackson, Looney, and Ramnath (2017), who measure W-2 and sole proprietor earnings as a percentage of total earnings for individual tax filers. However, these authors focus mainly on implications for tax collections. Our work complements and extends theirs by analyzing independent contracting work for its industry composition, its distribution over the

[5] For other useful ways of classifying new forms of work, see Cappelli and Keller (2013) and Kalleberg (2011).

[6] There is ongoing legal and political debate about the boundaries between independent contracting and traditional work, and many argue that, for example, Uber is violating the law by not treating its drivers as employees. California voters in 2020 passed Proposition 22, which classified app-based drivers as independent contractors. As noted above, we rely on employers' classifications of workers, and so likely overstate the prevalence of independent contracting.

[7] See also Dey, Houseman, and Polivka (2009) who document similar reporting error in worker survey estimates of the prevalence of temp work, when compared to payroll data.

earnings distribution, and its role in workers' short-term employment trajectories, and by presenting estimates specific to California.

We also relate closely to a contemporaneous analysis of IRS data by Collins et al. (2019). Collins et al. focus on understanding "online platform" work, for companies such as Uber and Lyft, though they also present estimates for independent contracting more broadly. Following Collins et al. (2019), we define online platform work fairly narrowly: An online platform worker is one who receives a 1099 from one of a set of identified Employer Identification Numbers (EINs) in the online platform economy (OPE). We developed a list of such firms, including the well-known rideshare companies Uber and Lyft as well as others such as TaskRabbit, Fiverr, Varsity Tutors, and Postmates, and can identify 1099s issued by these firms in our data.[8] Where Collins et al. (2019) emphasize measuring trends in the size of the online platform and independent contracting sectors, we focus more on understanding the role that this work plays in the labor market – how workers mix independent contracting with traditional jobs, and the distribution of independent contracting work across workers of different ages, family structures, incomes, industries, and geographies within California.[9]

A second source of differences in estimates of the prevalence and trends in independent contracting is the distinction between independent contracting conducted as a main source of income or as a supplement to a traditional job. The 2017 BLS Contingent Worker Survey counts only those for whom independent contracting is the main job. By contrast, surveys such as the "Freelancing in America" survey conducted by the Freelancers Union and Upwork (2016) count

[8] We do not include other firms that might arguably be counted as part of the online platform economy where payments are not primarily for labor delivered, such as Airbnb or Paypal.

[9] Lim et al. (2019) undertake a similar exercise using IRS data. Unlike us and Collins et al. (2019), they include 1099-Ks from all payers, but not Schedule Cs without associated 1099s. They also impose several additional restrictions aimed at excluding small businesses from their IC definition. For example, they exclude any Schedule C with more than $10,000 in deducted expenses other than for car and travel expenses.

anyone who had any amount of independent contracting income, no matter how small, as a “gig” worker.

The distinction between workers for whom independent contracting is the main occupation and workers who do some independent contracting on the side may help to explain the conflicting findings on trends in independent contracting over time. National studies using the Current Population Survey (CPS) find that the rate of unincorporated self-employment as a main job has declined slightly over the past several decades (Bureau of Labor Statistics 2017). But studies using tax data to examine the number of 1099 forms or Schedule C filings show clear increases since the early 2000s (Katz and Krueger 2016, 2019; Abraham et al. 2020; Collins et al. 2019). One potential explanation is that independent contracting for supplemental income has increased, while the rate of independent contracting as a main job has remained steady. Collins et al. (2019) present evidence consistent with this hypothesis, showing that independent contracting has grown as a share of all employment but that the growth is less impressive if only relationships paying above some minimal level are counted. Lim et al. (2019), however, find that the growth of workers with only IC earnings has been faster than that of workers with IC income overall.

We divide workers with IC income into four groups, based on the share of their total earnings that comes from IC work: Those who are exclusively IC workers, with no W2 earnings at all; those who have W2 earnings but derive 85% or more of their earnings from IC work; those who have both W2 and IC earnings and derive at least 15% of their total annual earnings from each; and those for whom IC work is a small supplement to W2 work, accounting for less than 15% of the total. As we show, the final group is large, and the characteristics of primarily and exclusively IC workers are quite different from those of the broader population of workers with any IC income.

Our emphasis on the ways that workers combine W-2 and IC work also sheds light on the extent to which workers use independent contractor income to smooth income fluctuations in their primary, W-2 jobs. Several recent studies emphasize this insurance role (Manyika et al. 2016;

Farrell and Greig 2018; Koustas 2018). We find a smaller role for IC work as a form of insurance: by our estimates, people displaced from W-2 jobs via mass layoff events make up only one quarter or less of the lost income through increased IC earnings.

Finally, because academic researchers are largely focused on questions of measurement, deeper substantive analyses of the characteristics and work patterns of independent contractors have been less common. For example, little research exists on the industry and income distribution of independent contracting, largely due to data limitations. Individual tax data allows us to identify the industries in which independent contractors and sole proprietors operate. Tax data also enables us to construct a profile of how the use and patterning of independent contracting varies across the age, family structure, and income distributions.

III. Data

We use the population of individual tax returns in California over several years, as maintained by the Franchise Tax Board (FTB), the state's tax authority.[10] Because the data sets cover the state of California and are sizeable, sampling error is not a concern – any difference among groups large enough to be substantively meaningful is sure to be statistically significant.

We link together information from several different tax forms. The "backbone" of our database is the California tax return, the 540 form (or variants, such as the 540-2EZ). This is our source for information on family structure, age, and total family income. We link this return, at the individual level, to Schedule C forms filed as part of federal tax returns and to three forms filed by employers to report payment of labor earnings. The Schedule C contains detailed information about self-employment and sole proprietor income, expenses, and profits. We have access to the

[10] We access these data through a collaboration with the FTB. All of the data we work with are de-identified, but linkable across sources and over time via new IDs created to replace Social Security Numbers (SSNs), Employer Identification Numbers (EINs), and other identifiers. We exclude non-resident and part-year resident filers. In some cases we rely on FTB's internal analysis of files that it was not able to share with us directly.

federal tax return, including the Schedule C, only for those who e-file their taxes. Accordingly, most of our analysis is restricted to e-filers. We discuss implications of this below. We also use Forms W-2, 1099-MISC, and 1099-K for e-filers.[11] Form W-2 provides earnings from traditional jobs; Form 1099-MISC is used for most IC work, and is required whenever a firm or individual pays a self-employed IC worker more than $600; and Form 1099-K is used by many online platform employers (e.g., Uber, Lyft, TaskRabbit) to report payments to those who work through their platforms. [12,13]

Both the 1099-MISC and the 1099-K are also used for forms of payments that would not be considered IC work. We consider only 1099-MISCs reporting non-zero amounts of "non-employee compensation." To distinguish OPE workers receiving 1099-Ks from business transaction recipients – the 1099-K was created for use by payment processors such as MasterCard and Paypal – we focus on 1099-Ks issued by a group of 55 Employer Identification Numbers (EINs) associated with OPE firms.[14] These forms are required only when cumulative payments in a year exceed $20,000, though some OPE firms have at times adopted the practice of issuing 1099-Ks to all workers.[15] This appears to have been the case for the largest of the OPE firms in tax year 2016, the primary focus of our analysis; after 2016, following guidance from the

[11] The 1099 files that we use are from the Information Return Master File (IRMF) database provided by IRS to FTB. The FTB has access to returns that are determined to be California returns by the IRS.

[12] We see many information returns, particularly 1099s, that do not correspond to any 540 variant. It is not clear whether these represent real California workers, are issued in error, or are sent to people outside of California. We exclude these information returns from our analyses.

[13] A rideshare firm will typically report base earnings from driving on a 1099-K and other payments (bonuses, toll reimbursements) on a 1099-MISC. The same worker will often receive both.

[14] We follow Collins et al. (2019), who use a similar strategy. We compiled a list of 84 OPE platforms through a variety of methods including web searches and searches of online app stores. This list is available upon request. Due to confidentiality reasons, we provided this list to FTB, and FTB identified a list of 55 Employer Identification Numbers (EINs) corresponding to platforms on this list. It then identified for us which records in our data (in which employers' and individuals' identifying information is masked) correspond to this group of EINs. This enables us to identify the OPE sector but not individual firms.

[15] The law requires issuance of 1099-K when a payment processor pays more than $20,000 or when there are more than 200 transactions. The latter criterion does not appear to be relevant to the OPE firms in our sample.

IRS, OPE firms began to adhere to the $20,000 threshold (National Academics of Sciences, Engineering, and Medicine, 2020, p. 115).[16]

Similarly, Schedule Cs may be used to report earnings from small businesses, the proprietors of which we do not consider independent contractors. We exclude from our IC definition anyone whose Schedule C includes deductions for wages paid or for contract labor expenses.

In principle, all IC earnings should be reported on Schedule C, whether or not there is third-party reporting, but many workers may not report fully. We combine reported IC income on the Schedule C with third-party-reported 1099 income in the following way. We define gross IC receipts as the maximum of gross receipts as reported on the Schedule C, if present, and total 1099 earnings, summed across both forms and all employers. These gross earnings are not comparable to W-2 wages, as employment expenses are typically paid by the employer for W-2 workers but by the IC worker him- or herself (Parrott and Reich 2018). Thus, to measure IC earnings comparable to W-2 earnings we must net out expenses associated with IC work. We measure expenses as the total reported expenses on the Schedule C. This leads to two potential errors. Many IC workers may over-report their expenses to reduce their tax burdens.[17] On the other hand, we expect that Schedule Cs will reflect only expenses associated with earnings that are also reported on the Schedule C; insofar as workers are not reporting 1099 gross earnings on their Schedule Cs, the associated expenses are likely not reported as well.[18] This would lead us to overstate net IC earnings.

[16] This suggests that similar analyses conducted for tax years after 2016 will miss a large share of OPE work, particularly given evidence that we present below (in Appendix E) suggesting that OPE workers are less likely to report IC earnings when they are not reported on 1099-K forms.

[17] There is an important category of workers – potential recipients of the Earned Income Tax Credit – who have an incentive to *underreport* expenses in order to inflate their taxable earnings. See Appendix D.

[18] We effectively assume that 1099 income in excess of what is reported as gross earnings on Schedule C is not offset by any expenses. Collins et al. (2019) make the opposite assumption, that any 1099 earnings not reported on the Schedule C are largely if not fully offset by unreported expenses.

We construct net IC earnings as adjusted gross earnings, as defined above, less expenses listed on the Schedule C. Most of our analyses do not count those with zero or negative net IC earnings as IC workers, though we present some statistics on the prevalence of this group.

To measure workers' total earnings, we add together net IC income with W-2 earnings. We then measure the share of total earnings coming from IC work. As noted earlier, we consider someone who gets 85% or more of their earnings from one type of work (W-2 or IC) to be primarily of the dominant type, and those who get between 15% and 85% from each to be "mixers." In some analyses, we combine primarily (85-99%) W-2 workers with exclusively (100%) W-2 workers, and similarly for primarily and exclusively IC workers, to form three categories: Primarily or exclusively W-2 workers, mixed earners, and primarily or exclusively IC workers.

To assign workers to industries, we use the industry of the issuing firm for W-2 workers. Schedule Cs include a field for taxpayers to report the industry in which the business operates. We assign IC work to this industry, when it is available. When it is not, we use the industry of the 1099 issuing firm. When a worker receives multiple W-2s or multiple 1099s, we use the one of each with the largest gross earnings.

Although 2016 is our focus, we also construct analogous estimates for tax years 2014 and 2015. These allow us both to measure short-term time trends in IC work and to understand how workers are mixing independent contracting with traditional jobs. A worker might have both IC and W-2 income in 2016 because she held both roles simultaneously, or because she switched from one to the other mid-year. We can distinguish these by linking data to prior and subsequent years. We do not have access to complete 1099 files either before 2014 or after 2016, but we can get a sense of time trends by measuring the share with Schedule Cs from 2012 through 2017.

As noted above, we have Schedule Cs only for those who e-file taxes, and we thus limit our analyses to this subpopulation. **Table 1** shows mean characteristics of California tax units in 2016, first overall and then for the e-filer and paper-filer subpopulations separately. Only 13% of tax units file paper returns. Paper filers are a bit older and have lower incomes than e-filers, and are more likely to be single. The lower panel of the table shows return-level (i.e., for each filing unit) summaries of the types of earnings reported.[19] We report these using two definitions of the various terms, one using our preferred definitions and available only for e-filers and another using alternative definitions that we can compute for both paper filers and e-filers. For the latter summary, we count all Schedule Cs, including those with negative or zero net income and those with reported labor expenses, and we use the wage earnings line of the 540, rather than W-2s, to identify wage earnings.

Using the common definitions, earnings patterns differ non-trivially between the two populations. Paper-filed 540s are 5.4 percentage points less likely to include wage earnings than are e-filed returns, and 3.4 percentage points less likely to include Schedule Cs (though they are slightly more likely to link to 1099s). However, because paper filers are such a small share of the total, the e-filer distributions are quite similar to the total population distribution.

Columns 4 and 5 of Table 1 present estimates that use the e-filer sample but weight it to resemble either the paper filer population (column 4) or the full population (column 5) on observable characteristics. We construct weights based on a propensity score model for paper filing, using as predictors only variables observed for both paper and e-filers.[20] The reweighted e-filer population closely resembles the paper filer and all filer populations on demographics. However, even after reweighting, the e-filers have notably higher rates of Schedule C filing than paper filers. This suggests that e-filers are not selected so much on observable as on

[19] For paper filers, we observe an indicator for the presence of a Schedule C, but not its contents. In Table 1, we count any tax unit with a Schedule C as having IC income, regardless of whether net income is positive or there are labor expenses reported.

[20] We use a logistic regression, where the outcome is an indicator for a paper filer. Explanatory variables are number of dependents, filing status indicators, metropolitan area indicators (for Los Angeles, San Diego, and San Francisco), fraction of filers in the zip code who paper file, and flexible functions of age and AGI, all interacted with marital status. Importantly, we do not use information about either W-2 or Schedule C earnings as predictors. We generate a predicted probability, p, for each observation in the e-filer subsample, representing the share of individuals with similar characteristics who paper filed. When reweighted by p/(1-p), the e-filer subpopulation matches the observed characteristics of the paper filers; when reweighted by 1/(1-p), it matches the all-filer characteristics.

unobservable determinants of IC work, implying that our analysis based on e-filers may overstate the prevalence of IC work. However, given the large share of e-filers in the population, this is unlikely to introduce major error. We measure the sensitivity of our main results to selection into e-filing by presenting some analyses based on this reweighting below.

Table 2 provides detail about our construction of our independent contracting measure, exploring the contrast between the common and preferred measures in Table 1. Here, we conduct the analysis at the individual rather than tax unit level and limit the analysis to e-filers. 15.5% of California e-filers file Schedule C forms, while a partially overlapping 5.0% receive 1099-MISC or 1099-Ks. Of the Schedule C filers, about one in ten report having labor expenses, so are counted in our taxonomy as small businesses. Another one in five report expenses that equal or exceed their gross reported earnings. Some of these may be people who in fact have positive net IC earnings but overstate their expenses to eliminate them, but because we cannot verify the reported expenses we exclude these workers from our tabulations of IC workers. The remainder, 10.8% of filers, have Schedule Cs that we count as indicating IC work. Only about one-third of those with Schedule Cs receive 1099-MISC or 1099-K forms (many Schedule C filers are reporting income received directly from customers). An additional 1.3 percent of filers receive 1099s but do not file Schedule Cs. About one-third of these filers receive 1099-Ks, a notably larger share than among Schedule C filers with 1099s, suggesting that 1099-K recipients are less likely to file Schedule Cs than are 1099-MISC recipients.

Table 3 further explores definitional issues by comparing estimates that we obtain from FTB data with those that Collins et al. (2019) report for California from IRS data. There are several differences between our measures and those used by Collins et al. First, Collins et al. use the Schedule SE to measure self-reported self-employment income, where we focus on the Schedule C. For comparability with Collins et al., in this table we include Schedule Cs with zero or negative net earnings. Second, we are not able to tie either Schedule Cs or W-2s to individuals when the return was filed on paper. In these cases, we assume that when a married couple files a paper return with one of these, both members of the couple have that type of earnings. Third, we rely on a different 1099 file than the one that Collins et al. (2019) use at the IRS. Taxpayers provide 1099 data to the IRS, and by agreement the IRS shares data for payees with California addresses with FTB. We rely on tabulations performed by the FTB of these data. .

Table 3 includes four columns. Column 1 reports estimates for California from Collins et al. In column 2, we report estimates for all California tax filers from the FTB data, using definitions that can be applied equally to paper- and e-filers. We count somewhat more individuals with Schedule Cs but many fewer with 1099s than do Collins et al. We have not been able to explain this difference, which must reflect differences in the 1099 data files that we and Collins et al. use. In any event, Collins et al. find a high degree of overlap between Schedule C filers and 1099 recipients, and we come close to their overall prevalence estimate of independent contracting (20.5% of those with positive earnings vs. 18.9%). Columns 3 and 4 report estimates for the subpopulation of e-filers, for whom we have more information: Column 3 uses the definition from column 2, which can be applied equally to paper and e-filers, while column 4 uses our preferred definitions, excluding negative-net-earnings Schedule Cs.

Overall, our data give similar but not identical estimates of the overall prevalence of independent contracting to those reported by Collins et al. (2019). Our estimate of the number of workers receiving 1099s, however, is much lower. This discrepancy seems to reflect differences between the 1099 data that FTB holds and 1099 data maintained by the IRS. Insofar as the FTB file is missing 1099s that should be included, we are nevertheless able to capture much of this independent contracting income via Schedule C forms. As a result, our estimate of the overall prevalence of independent contracting roughly matches that of Collins et al. (2019).

IV. Prevalence of independent contracting

Table 4 aggregates the relevant cells from Table 2 to present our estimates of the overall prevalence of independent contracting in the California labor market in 2016. 12.1% of 18-64 year old e-filing tax filers have independent contracting income, about evenly divided between those who also have W-2 income and those who do not. We find that 5.9% of the population, and 7.0% of those with positive earnings, have exclusively IC earnings. For comparison, 77.9% have W-2 earnings, including the 6.2% with both W-2 and IC earnings. It is important to remember that these workers may not hold multiple jobs at the same time; some may have transitioned from a W-2 job early in the year to an IC job later, or vice versa. We return to this below.

Table 4 also breaks out OPE workers. We find that OPE workers, defined as those with any OPE 1099s during the tax year regardless of the amount or of any other earnings, are a small share of the IC sector – only 1.4% of all workers with positive earnings, or about one-tenth of all workers with IC earnings, have OPE earnings. Among those whose earnings come exclusively from IC work, only 5% have OPE earnings.

Table 5 explores several alternative measures of IC prevalence. The first column repeats estimates from Table 4. The second column adds back into the IC group those who were excluded from our initial classification due to zero or negative profits on their Schedule Cs, or to expenses that led us to classify them as business proprietors rather than independent contractors. This increases the prevalence of IC work somewhat, from 12.1 to 13.6% of the workforce, with a larger impact on the IC only category than on mixed IC and W2 workers. Columns 3 and 4 expand the scope to include those aged 65-80. The number of W-2 workers declines by more than the number of IC workers after age 65, so including older individuals raises the IC share of those with earnings slightly, driven by the IC-only category.

Figure 1 shows the share of taxpayers with independent contracting income over time. We have complete 1099 data for only three years, from 2014-2016, but can look over six years at the prevalence of Schedule Cs. We therefore show series using our preferred definitions for the shorter period, and show a series for all Schedule Cs for 2012-2017. We also show series, in dashed lines, for IC-only workers, and in a dotted line for OPE workers.[21]

The picture is remarkably stable. The share of IC workers rose slightly, from 14.0% to 14.4%, between 2014 and 2016, while the share whose earnings came exclusively from IC work declined from 7.3% to 7.0%. The share receiving OPE income more than quadrupled between 2014 and 2016 but from a very low base, from just 0.3% to 1.4%. Over the longer window, the share of workers with Schedule Cs rose slightly, from 12.4% in 2012 to 12.9% in 2017, while the share with Schedule Cs but no W-2 earnings declined slightly from 7.0% to 6.9%.

A. Mixing of W-2 and IC earnings

We now examine the share of earnings coming from IC work for those who have IC earnings, using our preferred IC definition and the 18-64 age range. As seen in Table 4, nearly half of those with IC earnings have no W-2 income. **Figure 2** shows the distribution of the share of earnings coming from independent contracting among the other half of IC workers, those who mix W-2 and IC income. A large majority of workers with both sources of earnings obtain the bulk of their earnings from their W-2 jobs; for the median worker with both sources of earnings, IC work accounts for only 10.6% of total earnings. There is substantial heterogeneity here, however; a long tail of workers obtains much larger shares from IC work.

We adopt a simple classification of workers with both IC and W-2 income, who we refer to as “mixers,” into three subgroups: Those who are primarily W-2 workers with some independent contracting work (accounting for 15% or less of total earnings) on the side; those who are primarily IC workers with a small amount of W-2 income (again, 15% or less of total earnings); and those who have significant shares of both W-2 and IC work. **Table 6** shows the distribution of workers

[21] Prior to 2016, we are not confident that all OPE firms were filing 1099-K forms for all workers (as opposed to only for workers earning over the $20,000 threshold). Therefore, we may be somewhat underestimating the share of workers with OPE income in 2014 and 2015.

across categories, expanding the mixed group into these three subgroups. Over half of mixers fall into the first subgroup, with more than 85% of their earnings from their W-2 jobs. Most of the rest, accounting for 2.8% of the total workforce, derive substantial portions from each sector. Only 7% of mixers, accounting for 0.5% of the workforce, are primarily IC workers with a bit of W-2 earnings on the side. We also examine the presence of OPE earnings within each category of workers. Over half of those with OPE income are primarily W-2 workers. These are the classic moonlighters, with regular jobs but some platform work on the side. Only 0.7% of those in the workforce, or less than half of OPE workers, have OPE income and receive more than 15% of their earnings from IC work.[22] About half of these have only IC earnings.

Appendix Table A-1 repeats Table 6, reweighting the e-filer sample to resemble the full filing population, as in Table 1. This has little impact on the results.

As noted above, blending of W-2 and IC income in a single tax return could reflect transitions between sectors for workers who never blend the two at any point in time. Because we observe earnings only at an annual frequency, a worker who switches sectors entirely on any day other than New Year's Day will appear as a mixer in that year. To assess this, we examine year-to-year stability of workers' earnings shares. In **Table 7**, we tabulate workers' status in tax year 2016 against their status in tax year 2015, using the same five categories as in Table 5 plus non-employment. The first row shows workers with just W-2 income in 2015: 93% of these workers remain in the same status in 2016, while a plurality of the remainder have no earnings at all in 2016. Just over four percent have any independent contracting income in 2016; of these, most obtain less than 15% of their 2016 earnings from independent contracting. The story is similar, but in reverse, for those who had only IC earnings in 2015. Fully 75% of these workers

[22] Note that this tabulation counts *workers*, not *earnings*. Reich and Parrott (2020) emphasize that full-time Uber drivers – who likely fall in the "IC only" category here – account for a much larger share of Uber earnings or miles driven than they do of Uber drivers.

remain in the same status in 2016. Only about 12% had any W-2 earnings in 2016, and a third of those had transitioned fully out of independent contracting to the “W-2 only” category.

The middle categories are the most interesting, and speak to the interpretation of mixed incomes in the cross section. Of the individuals who earned between 15% and 85% of their income from independent contracting in 2015, only about one-third were still in this category the following year. Nearly as many shifted to exclusively W-2 work, while another sizable share shifted to exclusively IC. Similarly, among those who were primarily W-2 or primarily IC workers in 2015, large shares shifted to work exclusively in that sector in the following year.

This pattern suggests that many workers who appear to be mixing IC and W-2 work are not really mixing the two types of work on an ongoing basis but rather appear that way because they transitioned from one sector to the other mid-year. To shed further light on this, **Appendix Table A-2** shows three-year transitions, from 2014 to 2015 to 2016. Only 1.6% of individuals had both W-2 and IC earnings (at any ratio) in each of these three years, much less than the 3.5% who were exclusively IC workers in all three years or the 8.2% who had both W-2 and IC income at some point during the three-year period.

V. Who are the independent contractors?

A. Demographics

Table 8 shows statistics on the prevalence of IC work by individual demographics. For parsimony, we combine exclusively W-2 with primarily W-2 workers (all those receiving 85% or more of their earnings from W-2 work) and exclusively IC with primarily IC workers (using the same threshold). All statistics are limited to the population with earned income.

The first panel shows age breakdowns. Somewhat surprisingly, IC income is much more prevalent among older than among younger workers. There is no indication that traditional jobs are disappearing for young people, 94% of whom earn all or nearly all of their money from W-2 jobs and only 9.4% of whom have any IC earnings at all. There is little difference across age groups in the rate of mixing work in the two sectors; the entire age difference comes from those with little or no W-2 earnings. Workers aged 26-40, however, are more likely than older or younger workers to have OPE earnings.

The second panel shows results by filing status. There are few big differences here. Married workers are slightly more likely to work as independent contractors. The third panel shows results by metropolitan area. Independent contracting is more prevalent in the Los Angeles area than elsewhere in the state, but the differences are not enormous.

The fourth panel shows results by filing unit Adjusted Gross Income, adjusted for family size,[23] while the fifth panel shows results by individual earnings. In each case, we divide the sample into quartiles. Independent contractors are vastly overrepresented among low-earnings workers and low-income households. This is especially true for workers who are primarily or exclusively IC earners, and who earn some or all of their independent contractor income from on-demand platforms. That said, even among the lowest quartiles of individual earnings and family income, the percent with OPE income is still quite small, at 2.4 and 2.6 percent, respectively.

Finally, we also divide filers by the average income of the zip code in which they live. This shows a different pattern: IC work is somewhat more common in high-income zip codes, driven largely by IC moonlighting and mixing. Primary reliance on IC work and OPE work are fairly evenly distributed.

B. Earnings distribution

Figures 3 and 4 further investigate the earnings distribution of IC workers. **Figure 3** shows the distribution of total earnings among each of the five groups of workers shown in Table 6, as well as for a composite group that combines all workers with positive shares of both W-2 and IC earnings. The earnings distribution is substantially higher for W-2-only (median=$38,400) than for

[23] Following common practice, we equivalize incomes across families of different sizes by dividing by the square root of the number of people in the filing unit.

IC-only (median=$12,500) workers. Mixers who derive the vast majority of their earnings from W-2 work have higher earnings (median=$46,700) than the W-2 only workers, while those who derive most of their earnings from IC work resemble the IC-only workers (median=$17,600). The true mixers, with more than 15% of their earnings from each sector, are intermediate between the W-2-only and IC-only workers (median=$20,700).

In **Figure 4**, we divide workers into ten deciles based on their total (IC plus W-2) earnings, and measure the prevalence of different types of IC work in each. (Exact numbers corresponding to this figure are in **Appendix Table A-3**.) Workers with low earnings are significantly more likely to earn IC income and to rely primarily or exclusively on that income. In the bottom three deciles, 12-24% of workers rely primarily or exclusively on IC income, as compared with less than 4% in all deciles above the median. OPE earnings are also more prevalent among those with low earnings, though less dramatically so.

C. Geography

Figures 5-8 dive deeper into geographic patterns. **Figure 5** shows IC prevalence by zip code across the state, without regard to the degree to which IC work is mixed with W-2 earnings. IC workers are overrepresented, with IC prevalence rates above the state average of 14.4 percent, in the coastal population centers, and in the sparsely populated Sierras and northwest coast. The state's agricultural areas have proportionally fewer IC workers. Closer inspection of the Los Angeles and San Francisco Bay Areas (**Figures 6A and 6B**) indicate that IC work is especially prevalent in higher-income suburban and edge cities such as Marin County and Berkeley near San Francisco and in Malibu and the San Fernando Valley near Los Angeles.

The geographic distribution of IC work in Figures 5 and 6 appears to correlate positively with area income. **Figure 7** illustrates this more systematically. Here, we divide zip codes into twenty groups based on the average AGI of filers in the zip code and plot the share of tax payers with IC income in each group. IC shares are modestly higher in the high-income zip codes than in lower-income areas (though the IC share is also high in the lowest-income zip code group).

The highest income zip codes have IC rates about one-fifth higher, on average, than do zip codes in the second through sixth deciles. This is entirely a phenomenon of those who use IC work to mix with or supplement W-2 work; there is a zero or negative trend across zip code income in the share of workers who rely exclusively or primarily on IC work.

Figure 8 shows smoothed versions of the IC-zip code mean AGI relationship separately for three major metropolitan areas and for the rest of the state. Los Angeles has higher independent contracting rates throughout the zip code income distribution, but IC work is rising with zip code mean income in every area. As before, the zip code income gradient is driven by mixers; there is a weak relationship of zip code income with primary IC workers in Los Angeles, but not (except at the lowest income levels) in the other areas of the state.

Taken together, Figures 4-8 illustrate a kind of Simpson's paradox: IC work is more common in higher-income zip codes, but less common among higher-income families and workers. Evidently, across zip codes the higher income areas have higher prevalence of IC work as a supplement to main work, but within zip codes we see lower income people more likely to have IC income, and to use it as their primary source of earnings.

D. Industries

In **Table 9**, we explore the distribution of independent contractors across industries. To do so, we compare the industry distribution of W-2 employment, both from the Quarterly Census of Employment and Wages and from W-2 workers in our sample[24], to that of IC workers. It is important to note that the industry definitions may differ across sectors: W-2 workers are assigned to the industry of the employing firm, while IC workers are, when possible, assigned based on the industry that they list on their Schedule C. To illustrate, this means that a person working as a

[24] The QCEW counts all jobs, where our W-2-based count counts workers. These would differ for multiple job-holders.

handyman for a large retailer would be assigned to the retail trade sector if classified as a W-2 worker but to the repair and maintenance sector if an independent contractor.[25]

Independent contractors are concentrated in a few industries, with the top five (professional services; personal and laundry services, which includes both personal care services and hairdressers; administrative services; transportation; and health care and social assistance) accounting for over half of all independent contractors but only one-quarter to one-third of W-2 workers. Industries vary in whether independent contractors are generally doing this as their sole job (e.g., in construction, where three-quarters of independent contractors rely on this work for more than 85% of their total earnings) or are mixing with traditional jobs (e.g., professional services and the arts, where the shares are under one-half). One can see the influence of platform ridesharing here as well: Ground transportation accounts for 5.3 percent of independent contractors, with only 39% of them – among the lowest across all sectors – relying on independent contracting for nearly all of their earnings. Finally, OPE work is even more concentrated than independent contracting overall, with fully 36% employed in ground transportation.

VI. Potential overreporting of IC income

Many taxpayers with low earnings face negative effective tax rates: Due to refundable tax credits like the EITC, their total income tax burden may be negative, leading to refunds rather than tax bills. At sufficiently low incomes, these taxpayers even face negative *marginal* tax rates: Each additional dollar that they earn qualifies them for a larger tax credit and thus a larger refund. This creates an incentive to over-report income. Previous national evidence suggests that many taxpayers seem to report just enough independent contracting income to qualify for the maximum available Earned Income Tax Credit (Chetty et al. (2013; see also Saez 2010). While it is possible

[25] A similar issue besets industry classifications for W-2 workers: Consider a janitor working for a bank versus one employed by a building services firm with which the bank contracts for janitorial services. Note also that when an IC worker does not file a Schedule C or does not report a valid industry code we use the industry associated with the 1099-issuing firm, just as with W-2 workers.

that this reflects people managing their work effort to just reach the maximum EITC, it could also be more about reporting than actual work effort.

There is little in the current tax administration system that would stop a tax filer from inflating independent contracting income to obtain a larger EITC. Earnings reported on the Schedule C include both third-party-reported income from 1099s as well as earnings without third-party reporting. These latter earnings, which often come in cash, are very poorly reported (Internal Revenue Service 2019, p. 14), and without intensive audits the IRS cannot identify this mis-reporting. Moreover, where an audit might identify unreported income such as cash or under-the-table payments by examining bank records, it would be much harder to identify over-reported income even with an audit. Further yet, an IC worker could also inflate earnings for the purpose of the EITC not by over-stating gross earnings but by under-stating IC expenses, which would be even harder to police.

All of this suggests that over-reporting may be common, particularly among those eligible for the EITC, and that such over-reporting may be concentrated in IC earnings. Appendix D presents several analyses aimed at understanding the scope of this, and the degree to which it influences our earlier estimates. We indeed find that people with IC income are disproportionately likely to have reported income close to the EITC kink, consistent with earlier work (e.g., Chetty et al., 2013; Saez 2010). However, we see the same disproportionate "bunching" near the EITC kink for those whose Schedule C gross revenues align with their 1099 information reports. This suggests that the bunching is not driven by people manufacturing fictional income. It may reflect real work behavior, or simply under-reporting of IC expenses. We show in Appendix Table D-1 that, whatever the explanation for bunching, it does not importantly affect our main conclusions about either the prevalence of IC work or the income distribution of IC workers.

VII. Conclusion

This paper uses tax data to overcome measurement issues associated with understanding the prevalence of independent contracting. By categorizing jobs by the presence of self-employment income, the share of the worker's total earnings, the type of work, and the industry in which it is performed, we provide important context on the extent to which workers rely on independent contracting in addition to other sources of income. Tabulations of these measures by region and examination of their variation over time shed light on the growth and distribution of independent contracting in California.

This work has important policy implications for both tax administration and labor regulation. Identifying trends in which firms use particular tax forms can help tax authorities devise policies to enforce better reporting of compensation for independent workers. By providing new evidence on the number of workers excluded from traditional labor market protections due to their participation in non-standard work arrangements, our work can also inform efforts to change labor regulations to better serve such workers. Of course, the results only apply to California's labor market, but the lessons may point the way toward similar investigations in other states.

The primarily limitation in our work is that we rely on individual self-reports to measure independent contracting expenses, and on self-reports and third-party reporting to identify independent contractors. This means that we do not observe independent contracting income that is not reported to tax authorities; that we may over- or under-state the share of IC gross earnings that go to offset business expenses; and that we are not able to identify misclassification of workers as independent contractors (or vice versa). A high priority objective for future work should be to obtain better estimates of the impact of over- and under-reporting on tax-based measures of the prevalence and nature of independent contracting, and to adjust reporting structures to enable better tax enforcement for this sector.

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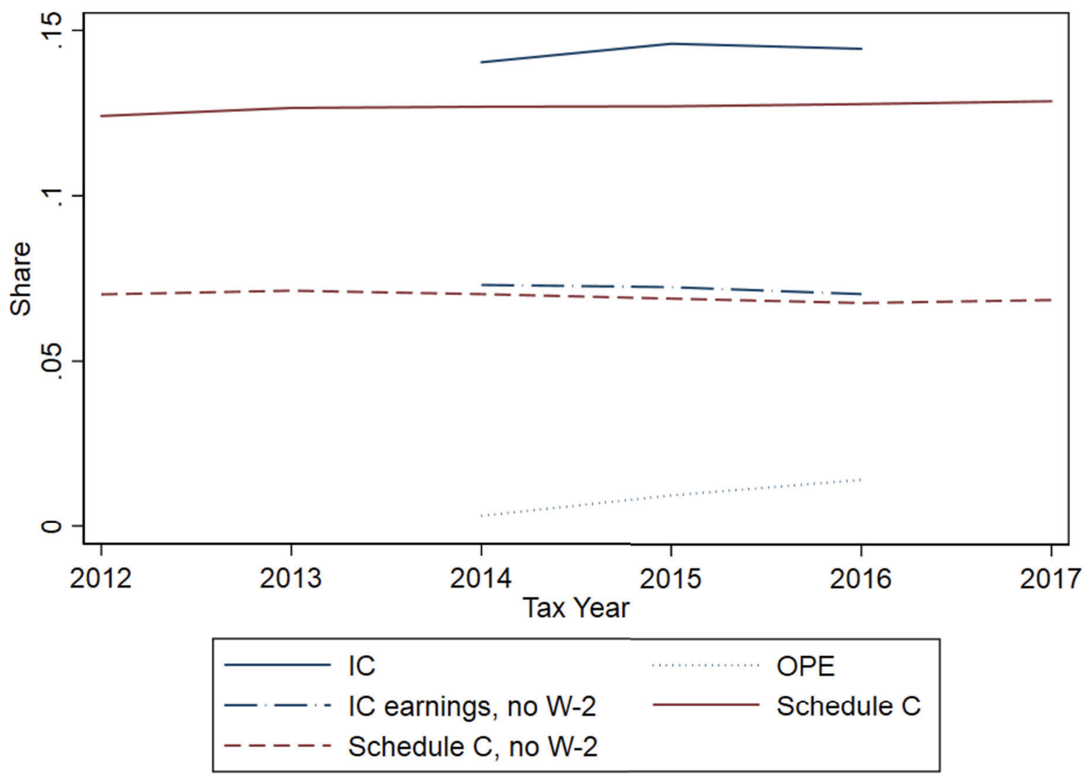
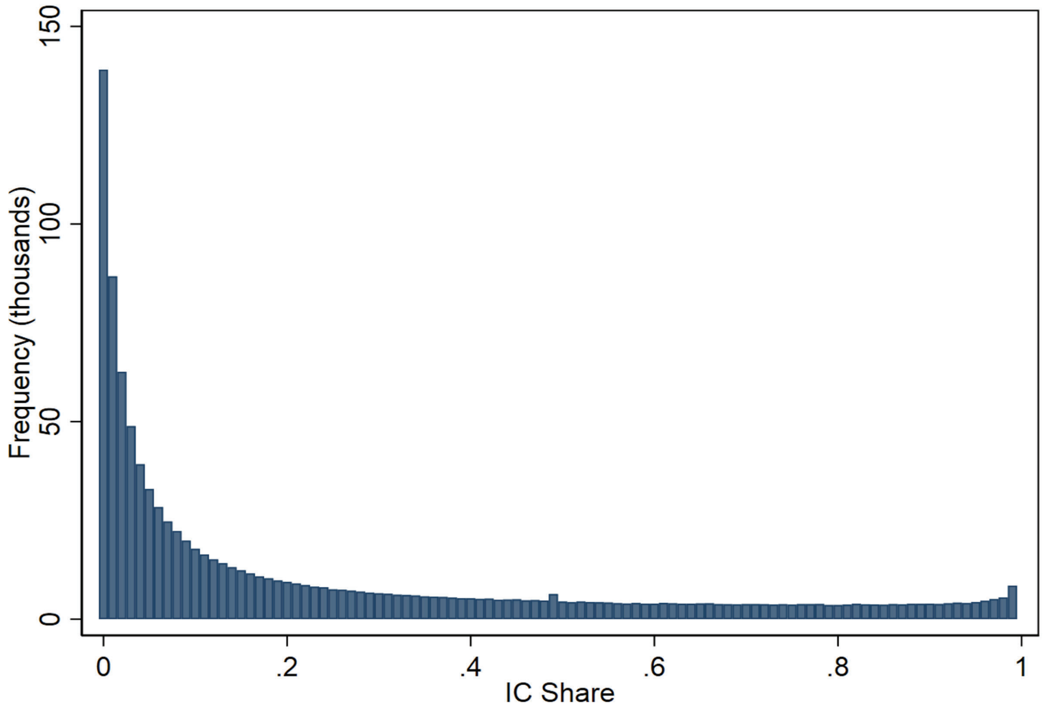
Figures

Figure 1. Share with IC Income, 2012-2017



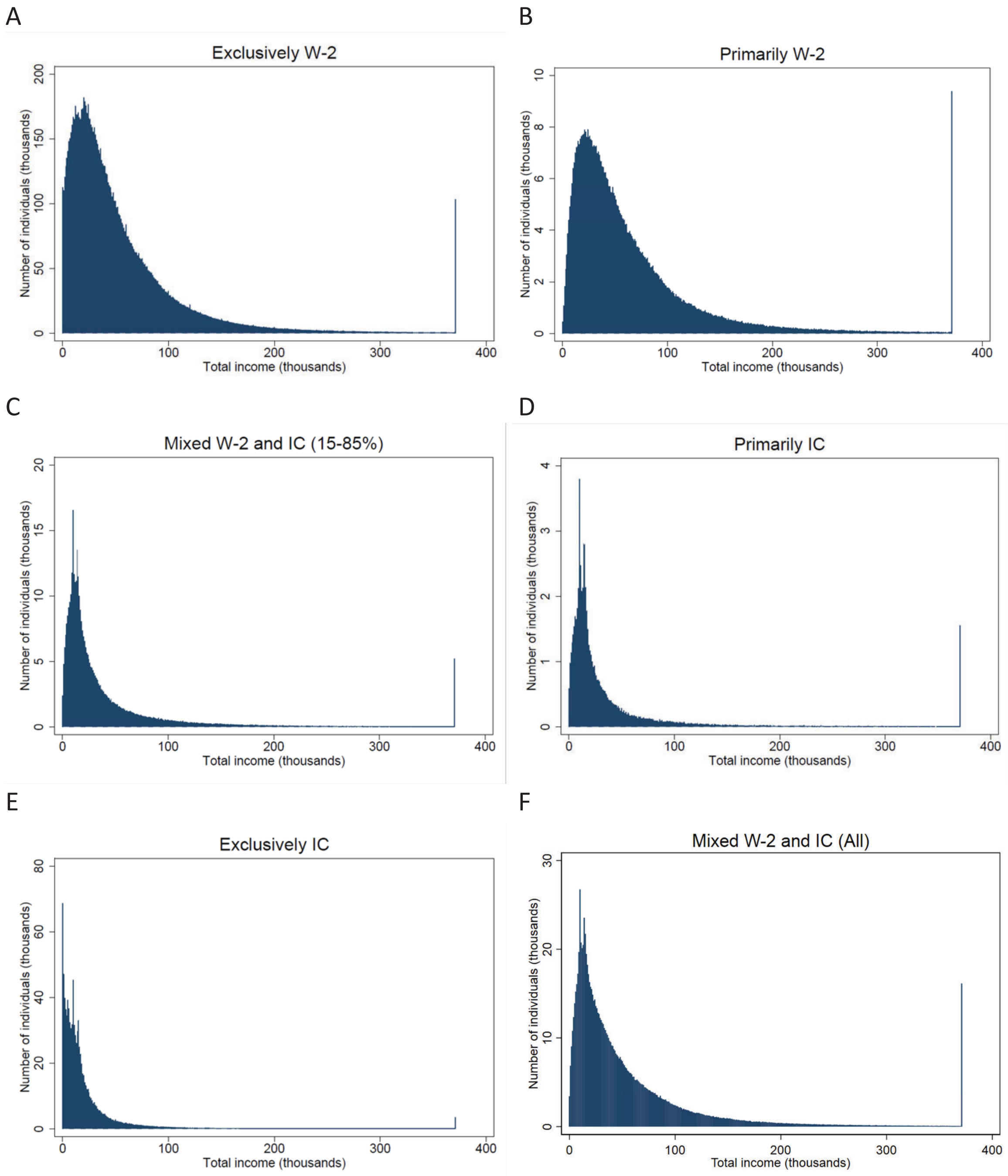
Notes: Denominator for all series is e-filers aged 18-64 with earned income from W-2 and/or IC work. IC series use our preferred definition (excluding Schedule Cs with labor expenses, including recipients of 1099s without Schedule Cs). OPE series includes only recipients of 1099s from identified OPE firms. Schedule C series exclude forms with negative or zero net profits. "No W-2" series exclude anyone with any W-2 earnings.

Figure 2. Mixer IC share distribution



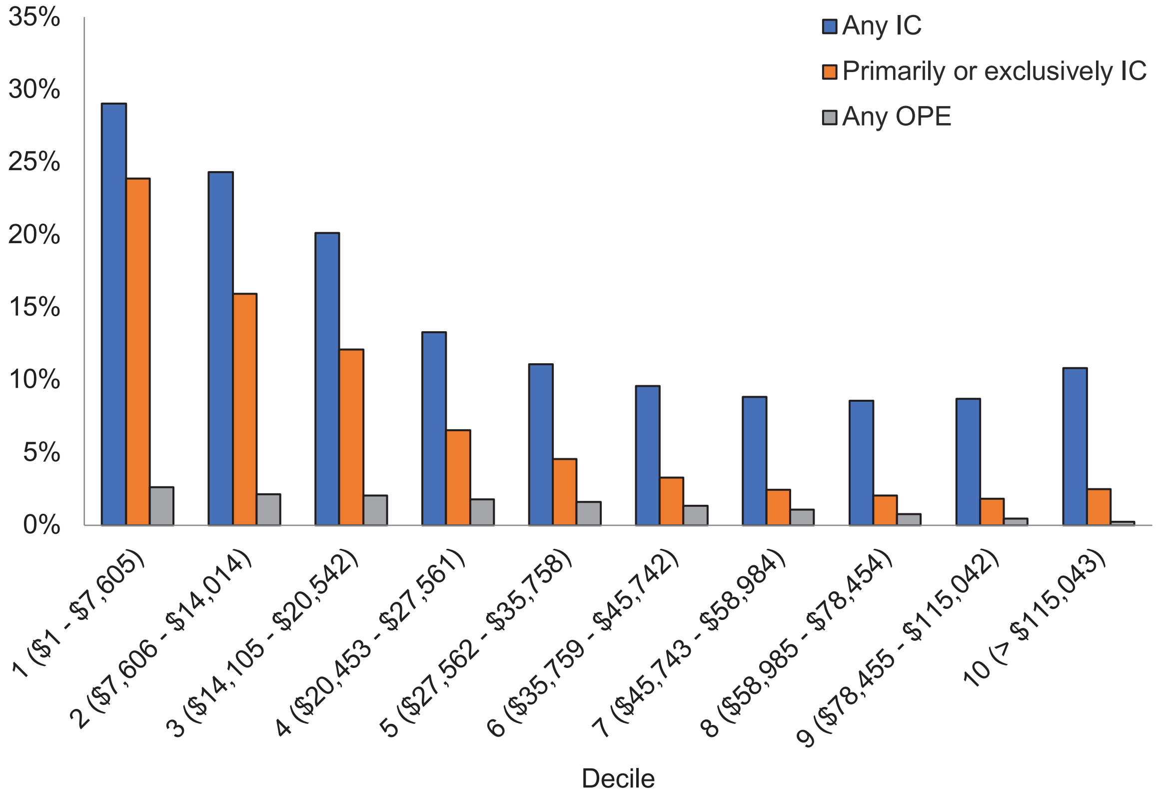
Notes: Figure shows the distribution of the share of earnings coming from IC, among e-filers aged 18-64 with positive IC earnings and positive W-2 earnings.

Figure 3. Earnings distribution by earnings type



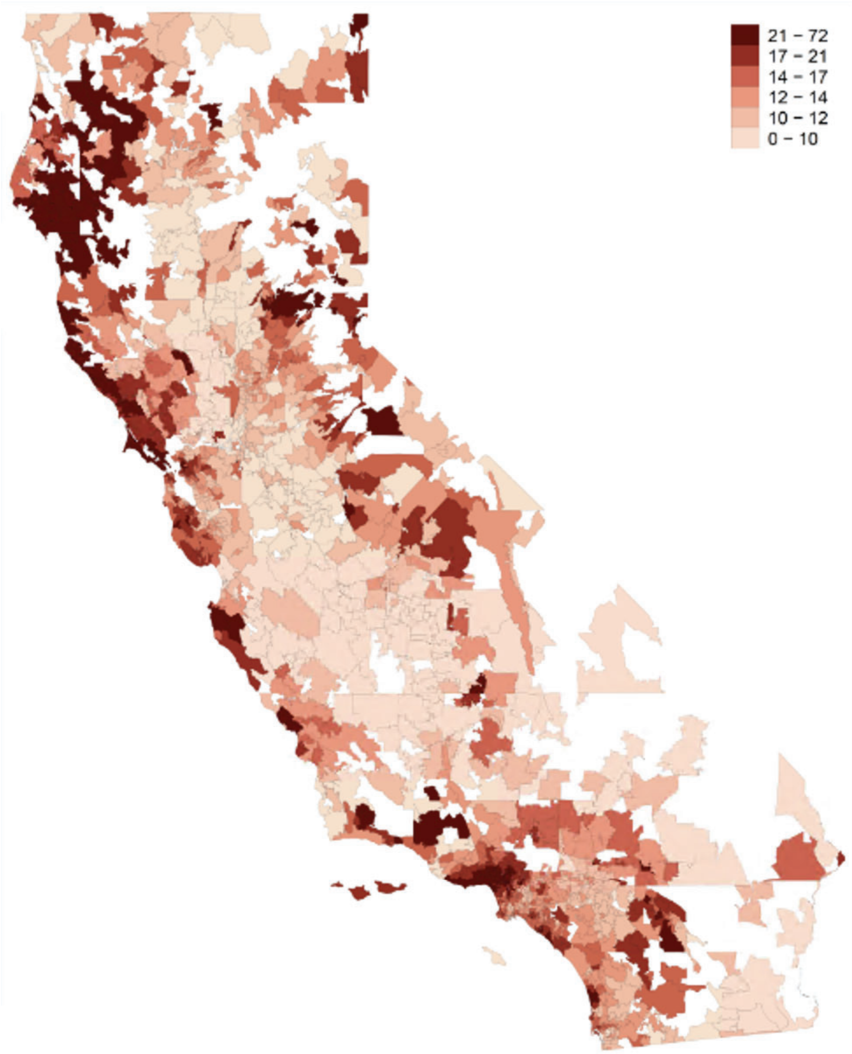
Notes: Each panel describes the distribution of earnings in the indicated subgroup of workers. Subgroups displayed in panels A-E are mutually exclusive; panel F corresponds to the combination of the subgroups shown in panels B, C, and D. Earnings are censored at $371,211.

Figure 4. Prevalence of IC earnings by decile of total earnings



Notes: Workers are divided into deciles by total earned income. Figure shows the share of workers in each decile with the indicated form of income.

Figure 5. IC prevalence by zip code

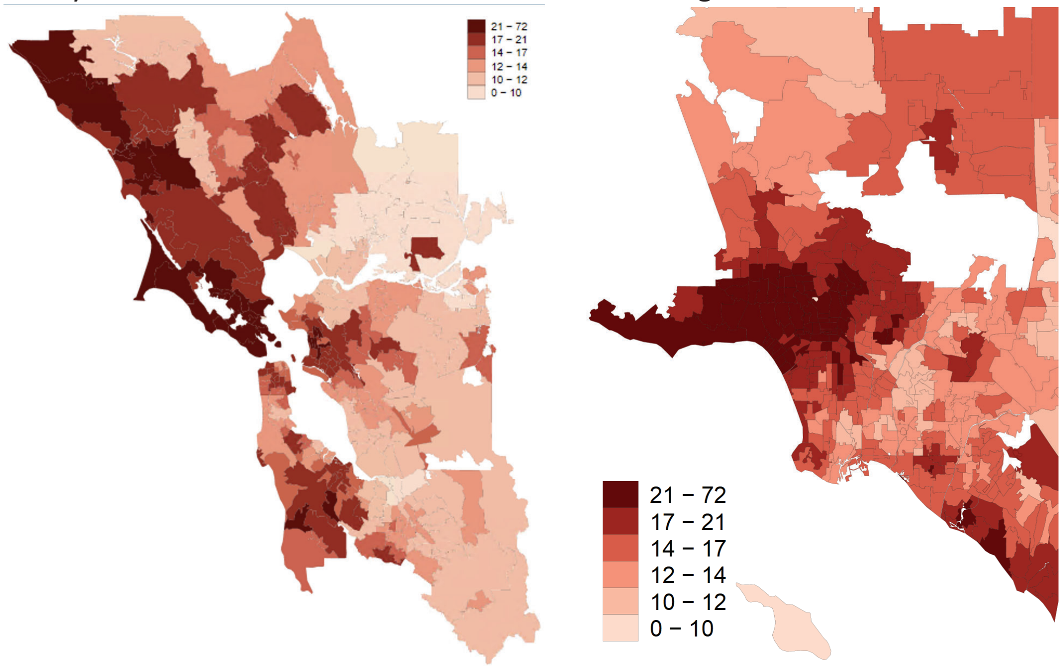


Notes: Map shows the fraction of individuals with positive earnings in each zip code with positive IC earnings. Zip codes with fewer than 20 returns are excluded.

Figure 6. IC prevalence by zip code, major metropolitan areas

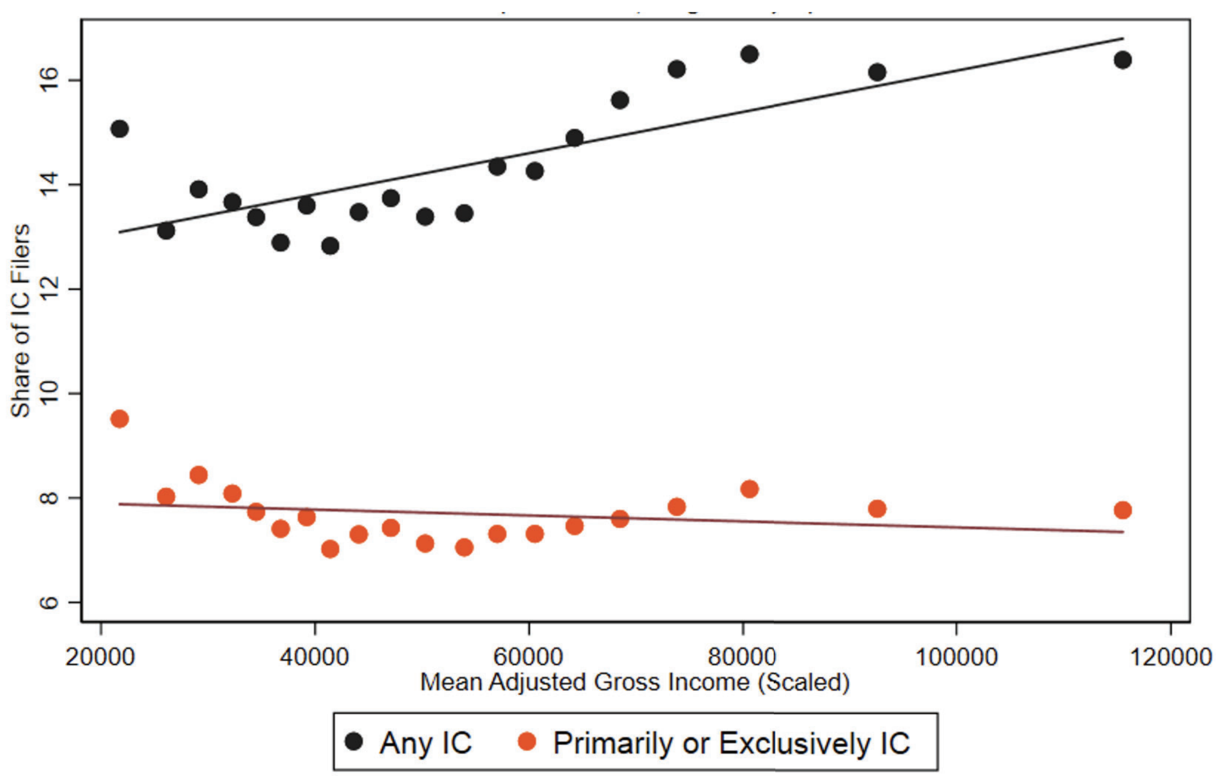
A. Bay Area

B. Los Angeles



Notes: Maps show the fraction of individuals with positive earnings in each zip code with positive IC earnings. Zip codes with fewer than 20 returns are excluded.

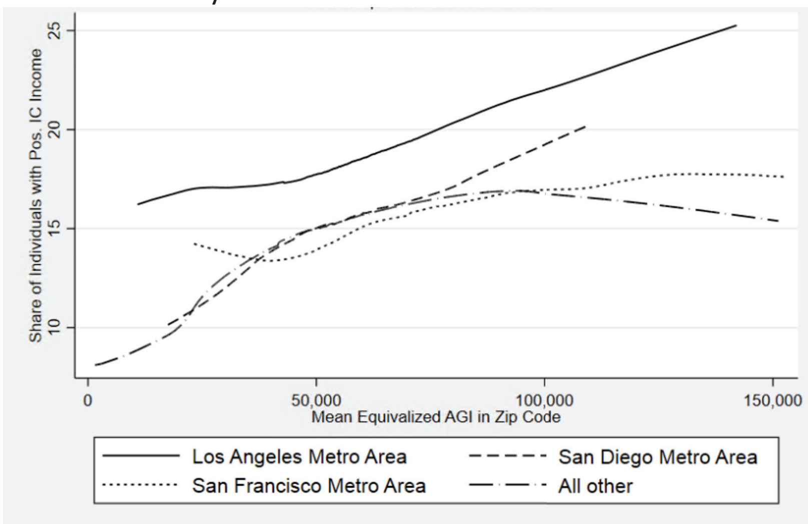
Figure 7. Fraction with IC earnings by zip code mean AGI



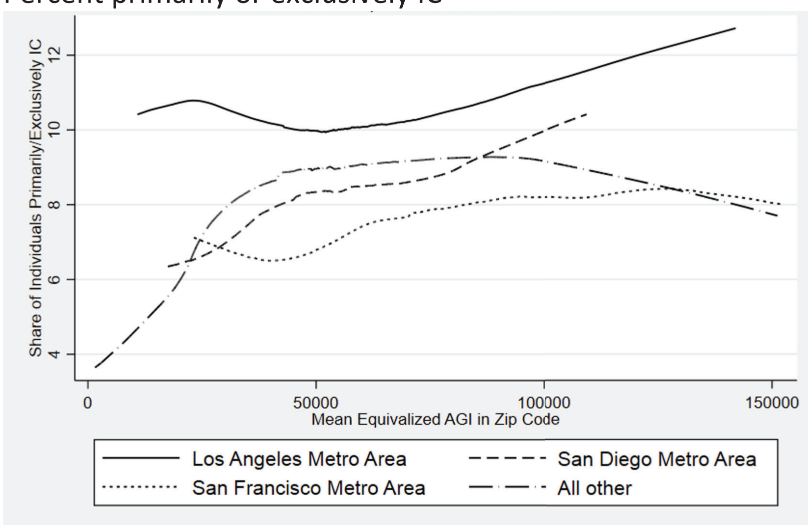
Notes: Zip codes are weighted by the number of individuals in the sample, then divided into twenty bins based on mean AGI. AGI is equivalized across families of different sizes by dividing by the square root of the number of people in the filing unit (taxpayer, spouse, and dependents).

Figure 8. Fraction with IC income by metropolitan area and zip code mean AGI

A. Percent with any IC income



B. Percent primarily or exclusively IC



Notes: Figures present lowess regressions of the fraction of workers with positive IC earnings (panel A) or with more than 85% of earnings from IC work (panel B), in each case out of everyone with positive total earnings, in a zip code against the mean equivalenced AGI in the zip code, separately for four regions of California.

Table 1. Summary statistics for e-filers and paper filers in working-age households, tax year 2016

	All filers	E-Filers (87%)	Paper filers (13%)	E-Filers reweighted to match paper filers	E-filers reweighted to match all filers
Number of filing units (1,000s)	14,111	12,335	1,776		
Age					
Mean	39.8	39.6	41.5	41.4	39.8
SD	13.5	13.4	14.0	5.3	14.4
Federal AGI					
Mean	70,048	70,976	63,335	63,670	70,095
SD	180,857	178,885	194,389	66,035	190,730
Family Status					
Single	47.3	46.8	51.2	51.1	47.3
Married	36.4	36.7	34.3	34.4	36.4
Head of Household	16.3	16.5	14.5	14.5	16.3
MSA					
Los Angeles	42.8	43.0	41.7	41.6	42.8
San Francisco	14.7	14.4	16.1	16.0	14.7
San Diego	8.3	8.4	7.8	7.7	8.3
Rest of state	34.2	34.2	34.4	34.4	34.2
Types of earnings (filing unit level)					
Traditional employment					
Any wage earnings on 540	89.6	90.2	84.8	87.7	89.9
Any W-2 forms*	--	87.6	--	85.4	87.3
Independent contracting					
Schedule C	19.5	19.9	16.5	20.2	20.0
Schedule C with positive net profits*	--	15.5	--	15.8	15.5
1099	7.7	7.7	7.8	7.6	7.7
Any OPE 1099	1.8	1.9	1.6	1.8	1.9

Notes: W-2 forms and the content of Schedule Cs are observed only for e-filers, so these rows are set to missing for populations including paper filers. Universe is filers in tax year 2016 with at least one working age (18-64) member. All statistics are at the filing unit level; age is that of the head if between 18 and 64, and otherwise that of the spouse.

Table 2. Presence of different indicators of IC income, TY 2016

	Total	Schedule C			No Schedule C
		With labor or contractor expenses	No labor expenses		
			Negative/zero net earnings	Positive net earnings	
Total	100.0%	1.5%	3.2%	**10.8%**	84.5%
1099s					
None	95.0	1.5	3.2	**7.1**	83.2
1099-MISC	**4.3**	0.4	0.7	**3.3**	**1.0**
1099-K	**1.1**	0.0	0.2	**0.7**	**0.4**
Both	**0.4**	0.0	0.1	**0.4**	**0.0**
Either	**5.0**	0.4	0.8	**3.7**	**1.3**

Notes: Sample is 18-64-year-old e-filers. All entries are percentages of the full sample; cells are not mutually exclusive. Those with Schedule Cs are separated by whether they report labor or contractor expenses and, for those that don't, by whether reported Schedule C expenses exceed adjusted gross earnings (defined as the maximum of Schedule C gross receipts and total 1099 earnings). Bold cells are counted in our independent contractor definition.

Table 3. Comparison with Collins et al. (2019)

	Collins et al. (2019) estimates for California	Our estimates		
		Full population	E-filers	
			Using full-population definitions	Using preferred definitions
Panel A: Individuals				
N	--	22,500,000	19,547,000	19,547,000
N with positive earnings	18,743,952	19,693,000	17,249,000	17,171,000
Among those with positive earnings, share with:				
Linked W2s or Reported Wages	89.9%	*93.5%*	93.8%	94.4%
Schedule SE / Schedule C	15.1%	*17.4%*	16.9%	12.9%
1099	14.2%	6.2%	6.2%	6.2%
Any IC	20.5%	*18.9%*	18.3%	15.2%
IC Only	10.1%	*6.5%*	6.2%	5.6%
OPE 1099	1.8%	1.4%	1.4%	1.4%
Panel B: Filing units				
N		16,535,000	14,330,000	14,330,000
N with positive earnings		14,693,000	12,864,000	12,797,000
Among those with positive earnings, share with:				
Linked W2s or Reported Wages		92.1%	92.2%	92.9%
Schedule SE / Schedule C		21.1%	21.4%	16.5%
1099		8.1%	8.0%	8.1%
Any IC		22.9%	23.0%	19.4%
IC Only		7.9%	7.8%	7.1%
OPE 1099		1.8%	1.8%	1.8%

Notes: Column 1 is drawn from Collins et al. (2019), Table A1. Full population definitions (columns 2 and 3) use reported wages from the Form 540 to measure wage and salary earnings, and include all Schedule Cs, including those with negative or zero net profits. IC income in these columns corresponds to the presence of a Schedule C or any linked 1099. Both members of a married couple are assumed to have any form of earnings that appears on the return. Preferred definitions (column 4), use our preferred definitions, as discussed in the text, and tie all income to the specific individual receiving it.

Table 4: Prevalence of traditional and independent contracting in 2016, working-age e-filers

Earned income source	All filers		Filers with earned income		
			Total	No OPE	With OPE
	N *	%	%	%	%
No earned income	2,698,000	16.2%	--		
W2 only	11,912,000	71.7	85.6	85.6	
W2 and IC	1,032,000	6.2	7.4	6.3	1.1
IC only	979,000	5.9	7.0	6.7	0.3
Total (age 18-64)	***16,621,000***	100.0	100.0	98.6	1.4

Notes: Sample consists of all California resident e-filers in tax year 2016 aged 18-64. Observation counts are rounded to the nearest 1,000 for privacy.

Table 5. Sensitivity analysis on IC prevalence

IC definition	Ages 18-64 Baseline	Ages 18-64 Include zero/negative profits & small businesses	Ages 18-80 Baseline	Ages 18-80 Include zero profits & small businesses
Panel A: All e-filers				
No earned income	16.2%	15.2%	22.1%	21.0%
W2 only	71.7	71.2	66.2	65.7
W2 and IC	6.2	6.7	5.7	6.2
IC only	5.9	6.9	6.0	7.0
Panel B: E-filers with earned income				
W2 only	85.6	83.9	84.9	83.2
W2 and IC	7.4	7.9	7.4	7.9
IC only	7.0	8.1	7.7	8.9

Notes: Column percentages sum to 100% within each panel and column.

Table 6. Proportion of earned income from traditional jobs and independent contracting, working-age e-filers, 2016

Earned income source	N	%	IC workers, by presence of OPE income	
			No OPE	With OPE
W2 only	11,912,000	85.6%	--	--
Primarily (>=85%) W2	581,000	4.2	3.4%	0.76%
Mixed earners (15-85% W2)	383,000	2.8	2.5	0.28
Primarily (>=85%) IC	67,000	0.5	0.4	0.04
IC only	979,000	7.0	6.7	0.34
Total (age 18-64)	***13,923,000***	**100%**	**13.0%**	**1.42%**

Note: Observation counts are rounded to the nearest 1,000. Sample excludes individuals with zero earnings. All percentages are of the total population of 18-64-year-old e-filers with positive earned income.

Table 7. Transitions between 2015 and 2016

2015 status (row %)	2016 status: W2 only	Primarily W2 (>85%)	Mixed W2 & IC	Primarily IC (>85%)	IC only	No earnings	Total (1,000s)
W2 only	93%	3%	1%	0%	0%	3%	8,628
Primarily W2	51	37	7	1	2	1	417
Mixed	34	13	34	4	13	3	265
Primarily IC	18	4	19	22	32	5	47
IC only	5	1	5	2	75	13	704
No earnings	10	0	0	0	4	85	1,957

Notes: Sample is individuals who e-filed in 2015 and 2016. Entries show row percentages, with row counts in the final column. "IC only" workers have positive IC earnings but no W2 income. Primarily IC, mixed earner, and primarily W2 earners have both IC and W2 earnings, with the proportion from W2 <15%, 15-85%, or >85%, respectively. "No earnings" includes individuals with neither a W2 nor IC income. All categorizations use our preferred definitions.

Table 8. Who are the independent contractors?

	Share with IC earnings				
	Any IC	Any OPE	Primarily or exclusively W-2 (<15% IC)	Mixed (15-85% IC)	Primarily or exclusively IC (>85%)
Age					
18-25	9.4%	1.8%	94.1%	2.9%	3.1%
26-40	14.4	4.0	90.4	3.0	6.6
41-55	16.5	2.2	87.8	2.7	9.5
56-64	17.7	0.6	86.0	2.5	11.5
Filing status					
Head of household	14.0	1.7	89.6	3.2	7.2
Married	15.5	1.5	88.8	2.5	8.7
Single	14.0	1.1	90.4	3.0	6.6
Region (MSA)					
Los Angeles	16.9	1.7	87.7	3.2	9.1
San Francisco	15.1	2.1	89.9	2.1	8.0
San Diego	15.1	1.6	91.4	2.3	6.4
Rest of state	15.1	0.8	90.4	2.6	7.0
Family income (AGI, equivalized)					
1st quartile	24.8	2.6	78.0	5.0	17.0
2nd quartile	12.4	1.7	91.8	2.4	5.8
3rd quartile	10.7	1.0	94.1	1.8	4.1
4th quartile	11.0	0.4	94.2	2.0	3.8
Individual earnings					
1st quartile	26.5	2.4	76.0	4.8	19.2
2nd quartile	13.6	1.8	90.5	2.9	6.6
3rd quartile	9.3	1.2	95.5	1.7	2.8
4th quartile	9.6	0.4	96.0	1.8	2.1
Zip code mean AGI (equivalized)					
1st quartile	13.9	1.4	89.2	2.7	8.1
2nd quartile	13.8	1.5	90.1	2.6	7.4
3rd quartile	14.3	1.4	90.2	2.7	7.2
4th quartile	16.8	1.4	88.6	3.3	8.0

Note: Entries show row percentages, among 18-64 e-filers with non-zero earned income (W-2 plus IC). Columns 3-5 are mutually exclusive and add to 100%, but columns 1-2 overlap with them and with each other. Adjusted gross incomes (AGIs) are equivalized across families of different sizes by dividing by the square root of the number of people in the filing unit (taxpayer, spouse, and dependents).

Table 9. Industry composition of independent contractors

Industry (NAICS code)	QCEW Jobs	FTB data: W2 workers	Independent contractors, by IC earnings share: Any IC income	IC share < 15%	IC share > 85%	OPE workers
11: Agriculture, Forestry, Fishing and Hunting	2.5%	1.4%	0.4%	0.3%	0.5%	0.0%
21: Mining Quarrying, and Oil and Gas Extraction	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%
22: Utilities	0.6%	0.5%	0.1%	0.1%	0.0%	0.0%
23: Construction	4.7%	2.9%	6.1%	2.4%	8.7%	0.5%
31-33: Manufacturing	7.7%	7.6%	1.0%	1.1%	1.0%	0.1%
42: Wholesale Trade	4.3%	4.3%	1.8%	2.1%	1.8%	0.3%
44-45: Retail Trade	10.0%	9.2%	4.9%	4.7%	5.4%	0.9%
48-49: Transportation and Warehousing	3.7%	3.0%	9.9%	10.3%	9.7%	41.7%
485: Transit and Ground Passenger Transport.	0.5%	0.4%	5.3%	7.7%	3.9%	36.2%
51: Information	3.2%	2.6%	2.8%	4.4%	1.6%	7.1%
52: Finance and Insurance	3.3%	3.4%	2.4%	2.3%	2.2%	0.8%
53: Real Estate and Rental and Leasing	1.7%	1.5%	4.9%	2.9%	6.2%	0.7%
54: Professional, Scientific, and Technical Services	7.3%	7.4%	14.2%	15.5%	12.8%	2.1%
55: Management of Companies and Enterprises	1.3%	0.3%	0.0%	0.0%	0.0%	0.0%
56: Administrative and Support and Waste Mgmt. and Remediation Svcs.	6.5%	6.0%	7.6%	4.2%	9.7%	1.2%
61: Educational Services	8.4%	6.3%	3.2%	6.2%	1.6%	0.5%
62: Health Care and Social Assistance	14.2%	9.3%	8.0%	6.4%	8.0%	0.8%
71: Arts, Entertainment, and Recreation	2.1%	1.4%	5.0%	6.6%	3.7%	1.0%
72: Accomodation and Food Services	9.6%	6.0%	1.3%	1.2%	1.4%	0.6%
81: Other Services (except Public Administration)	3.1%	3.4%	15.8%	8.4%	20.7%	4.5%
811: Repair and Maintenance	0.9%	0.8%	2.9%	1.1%	4.2%	0.4%
812: Personal and Laundry Services	1.0%	0.9%	12.0%	5.7%	15.9%	4.0%
92: Public Administration	4.9%	5.6%	0.3%	0.5%	0.2%	0.0%
99: Unclassified	0.6%	0.0%	0.1%	0.1%	0.1%	0.1%
Unmatched EINs		17.7%	10.1%	20.1%	4.6%	37.0%

Notes: Entries are column percentages, and entries for 2-digit NAICS codes sum to 100. Where 3-digit NAICS codes are listed, these are included in the relevant 2-digit total as well. We assign workers to the NAICS industry associated with their highest-earnings W2 in Column 2; workers with missing EINs are excluded. In columns 3-6, we assign them to (a) the industry indicated on their Schedule C, if valid, and (b) to the industry associated with the employer issuing their largest 1099, if not. Column 6 limits to workers with positive OPE income, but the industry may not be the one associated with their OPE 1099.

Appendix A. Additional results

We present several additional results in this appendix.

Appendix Table A-1 explores the role of paper filers in the overall independent contractor share. As discussed in the main text, we reweight the e-filer sample for which we have full data to match the observable characteristics of the entire population, inclusive of paper filers, and compute the IC share in the reweighted sample. This has little impact on our estimates of IC prevalence.

Appendix Table A-2 presents the distribution of individuals across different employment types through three tax years, 2014, 2015, and 2016. Of interest here is the degree to which people observed mixing W-2 and IC income in a particular year are actually just in the process of transitioning from one sector to the other. We see some evidence for this: Of those who have only IC earnings in 2014 and have both IC and W-2 earnings in 2015, fully 40% have only W-2 earnings in 2016. This is a small group, however. The group that has only W-2 earnings in 2014 and both types of earnings in 2015 is more than five times as large, and we see very few people in this group transitioning to IC only in 2016.

Appendix Table A-3 presents the distribution of workers across earnings deciles, corresponding to Figure 4.

Appendix B. Job loss and independent contracting

Policymakers have expressed interest in understanding how employees recover from job loss, and in the role independent contracting may play in that. How common is it for workers to begin independent contracting (IC) roles after losing W-2 jobs? To what extent do employees who have lost W-2 jobs rely on IC work to make up the lost earnings, and how much do they make up? Do workers eventually transition back to a W-2 job, and how long does it take to recover the lost earnings? Understanding whether and how W-2 work interacts with independent contracting in the context of job loss has implications for personal income tax revenues collected by the FTB, given differences in tax collection from the two types of earnings. We find that job loss from mass layoffs does lead to increases in IC participation and earnings, but that the response is small. Out of every 100 displaced workers, only about 6 begin to participate in the IC sector, and overall their average IC earnings make up only less than 3% of their lost pre-displacement wages.

A large literature in labor economics has documented significant and large negative consequences of job displacement on short and long-run earnings profiles, mortality, and education (Jacobson et al., 1993; Jacobson et al., 2005; Sullivan and von Wachter, 2009). These papers have principally leveraged earnings data from unemployment insurance records, analogous to W-2 data. However, these data only cover traditional employment relationships. An emerging literature (e.g., Koustas, 2018; Garin et al. 2020) has emphasized the potential for workers to leverage independent contracting (IC) arrangements to partially mitigate earnings losses in unemployment. Indeed, recent work finds that some displaced workers never subsequently reenter the W-2 covered labor force (Jackson, 2020). This suggests that prior research on the consequences of job loss may overstate the magnitude of earnings losses, and that independent contracting may be playing an insurance role in workers' careers.

We leverage detailed earnings reporting in tax data to understand the effect of job loss on 1) independent contracting (IC) activity and 2) *total* earnings trajectories, inclusive of IC earnings.[1] We identify workers who leave their employers in firm downsizing events, as these are unlikely to represent voluntary departures. For these workers, we follow their earnings in both traditional (W-2) work and IC work in subsequent years, measuring each as a share of their pre-displacement W-2 earnings.

To implement this design, we begin with the population of California W-2 filings between tax years 2012 and 2017. We identify a sample of firms that underwent "mass layoffs" in 2014: firms with employment of 50 or more where employment and payroll dropped substantially relative to the firm's prior average. We call workers who left the firms in such events -- receiving W-2s from the downsizing firms in 2014 but not in 2015 -- "mass layoff (ML) separators," and we measure the effect of job loss by tracking their earnings in 2015 and subsequent years. This method of analyzing displaced workers is fairly standard in the labor economics literature: by analyzing earnings trajectories for workers displaced as part of a larger firm mass layoff event, we more credibly isolate the effect of layoff separately from worker characteristics (Jacobson et al., 1993). We examine the full group of ML separators and two subgroups who appear more affected: i) those with no W-2 earnings from any firm in 2015 ("ML non-employed"), and ii) those who receive UI income in 2015 ("ML UI recipients").

[1] That is, summing together earnings from both traditional W-2 and IC employment. In this appendix, we use the Magmedia data to measure 1099 receipt, and thus likely understate the role of IC responses somewhat relative to what we would obtain with IRMF data.

Changes in earnings for ML separators may be affected by broader trends in earnings. We also examine two additional groups for further context. First, we consider workers at the same downsizing firms who did not leave in 2015 (“ML stayers”). Second, we identify workers who separated from jobs at a comparison group of firms, meeting the same size criteria but not undergoing mass layoff events in 2014 (“non-ML separators”).

Table B-1 shows summary statistics for our five samples. As a useful check on our research design, characteristics of ML separated workers and retained workers are remarkably similar across a number of demographics (such as age, family size, marital status, pre-displacement earnings, and previous IC experience).

We begin by documenting the effect of job displacement on W-2 earnings. **Figure B-1** plots, in Panel A, average W-2 earnings by year for our five groups. On average, ML separated workers suffer earnings losses of about 10% in the year after job loss, with this gap disappearing after two years.The gap is larger for ML UI recipients and ML non-employed, each group selected on the basis of labor market outcomes in 2015; moreover, earnings declines are also more persistent for these workers, remaining well below their pre-displacement levels even in 2017. This largely reflects declines in the probability of working at all. Panel B of the figure shows the share of workers in each group with *any* W-2 income in each year. We see that 21% of ML separated workers leave W-2 employment entirely, with little recovery in 2016 and 2017.[2]

[2] One caveat is that we only observe California W-2 filings: if workers in our sample leave the state, we will erroneously interpret these workers as having zero W-2 income. Using earnings data instead covering the entirety of the US, von Wachter, Song, and Manchester (2009) demonstrate that this “mobility bias” is likely to be small on average; it is almost certainly smaller in California than in the country as a whole.

To what extent are these earnings losses mitigated by IC employment? We next consider changes in IC participation after job loss. **Figure B-2** plots the percentage of ML separators who have any IC income, as measured using different sets of tax forms. When measuring IC participation as above (positive adjusted Schedule C profits or 1099 income without a Schedule C), IC employment increases by only about 6 percentage points. This is unlikely to be enough to mitigate earnings losses for most workers. The increase is similar if we include in our IC measure those who file Schedule Cs with negative net earnings or if we count only 1099 recipients as IC workers. Panel B of the figure considers the preferred IC measure across our different subgroups. It shows that pre-displacement participation is relatively similar across groups. Moreover, ML Stayers' IC participation rises only modestly following the ML event. Thus, most of the increase in IC participation seen for the separators is credibly tied to the job loss event. As expected, ML non-employed separators have the largest transitions into IC employment, with an increase of about 15 percentage points -- though this does not nearly offset the more than 80 percentage point decline in this group's W-2 employment in 2015 or the 40 percentage point decline that remains in 2017. All of the other groups of separators see similar changes over time, with increases of about six percentage points between 2013 and 2015, stability in 2016, and small declines in 2017.

Next, we consider how the amount of IC income changes after job loss. **Figure B-3** plots average IC income for ML separators, as a share of the individual's W-2 earnings in 2012 and 2013. In the ML separator sample and using our preferred IC definition, IC earnings increase from about 2% of baseline W-2 earnings in 2012 and 2013 to about 5 percent in 2015 and 7 percent in 2016. The roughly 2.5 percentage point increase from 2014 to 2015 makes up about 25% of the W-2 earnings loss over this year. Note that this increase is a composite of both extensive and intensive margin responses: As seen in Figure B-2, there are increases in IC participation, and in addition there may be changes in average IC amounts of those who would have participated in any case.[3] The second panel of Figure B-3 graphs IC income across our different subgroups, showing relatively similar pre-displacement earnings and further establishing the causal relationship between job loss and post-displacement IC income trends. For most of our groups, IC income increases by about 2 percent of pre-displacement earnings, much less than the declines in W-2 earnings seen in Figure B-1. For the ML non-employed, whose W-2 earnings fell by 80 or 100 percent (depending on the base year considered) and remained 60 percent below the pre-displacement level in 2017, IC earnings make up less than ten percentage points of the loss.

We now put these results together by analyzing total earnings trends. **Figure B-4** plots W-2 and total earnings losses (that is, W-2 and IC earnings together) before and after displacement. As before, Panel A shows all ML separators. As in figure B-1, W-2 earnings fall by about 10 percent in 2015. When we add IC earnings to this, the decline is reduced only slightly. Panel B shows other groups of separators, for which IC earnings make up even smaller shares of the lost W-2 earnings.

In a supplementary analysis not detailed here, we leverage non-earnings tax information to further investigate this finding. This earnings loss does not appear to be substantially mediated by the unemployment insurance (UI) system, as UI takeup rates are fairly similar both before and after job displacement. We also find significant heterogeneity in these earnings

[3] In a supplementary analysis not shown here, we split the estimation sample by workers' pre-2015 history of IC employment. This exercise reveals significant heterogeneity: very little of the income response is due to new entrants. Indeed, workers with no prior IC history replace only about 8% of their W-2 earnings, while those with prior history replace around 50%.

losses by age (older workers are more likely to suffer larger losses, with some dropping out of the labor force entirely) and prior earnings (higher income workers suffer larger losses).

Appendix C. Firm differences in the use of independent contracting

Why and how do firms use independent contractors? We explore whether firms vary systematically in their use of IC work. This analysis helps identify sectors of the economy where IC work is likely to be most prevalent, potentially valuable for tax enforcement and enforcing the proper classification of workers, and also for understanding the degree to which IC work is displacing traditional jobs.

Firms vary in systematic ways in their use of independent contractors. In this appendix, we explore a particular dimension of this variation: Whether it relates to firm pay policies more generally. An extensive literature in recent years has documented that firms vary substantially in the policies they adopt toward compensation of their (W-2) workers. Some firms systematically pay higher wages than others, and the same worker, with the same skills, can earn substantially more if he or she works at a high-wage than a low-wage firm (Card, Heining, and Kline 2013; Bloom et al. 2019). We show that the methods used in this literature can be used to identify high- and low-wage firms in the tax data, and we explore whether these firms vary systematically in their use of IC work.

Whether high-wage firms are more or less reliant on IC workers than low-wage firms is ex ante ambiguous. On the one hand, insofar as the high-wage firms are pursuing so-called “high-road” strategies, they may be less likely to misclassify workers as ICs, and may prefer the stability of a traditional employment relationship over more casual independent contracting relationships. This would suggest a negative relationship between a firm's wage policy and its use of IC workers. On the other hand, if union contracts or other constraints compel the high-wage firms to pay above-market wages, they may attempt to evade those constraints by misclassifying workers or by outsourcing work to lower-cost independent contractors, creating a positive association between firm pay practices and the use of IC workers. Drenik et al. (2020) find that in Argentina, temp workers placed at high-wage firms also earn higher wages than do temp workers placed at lower-wage firms, but we are not aware of similar estimates from the U.S.

To measure firm wage policies, we adopt now-common methods from labor economics (Abowd, Kramarz, Margolis 1999 [hereafter, *AKM*]; Card, Hening, Kline 2013 [hereafter, *CHK*]). We begin with the universe of W-2 workers aged 20-60 in California in tax years 2012-2017. We use the (coded) EINs on W-2s to identify a set of worker-employer matches, along with the associated earnings. Where workers have multiple W-2s in a single year, we aggregate their earnings across all of them, but assign the worker to the employer that accounted for the largest share. We exclude the smallest employers -- those with fewer than 15 worker-years in our sample. We further exclude workers observed at only one firm and worker-year observations with annual earnings under $4,000.

We then estimate a decomposition of earnings into a component that is associated with the worker, a component associated with the employer, and a residual component. Following AKM, the model is:

$$y_{ijt} = \alpha_i + X_{it}\beta + \psi_j + \epsilon_{ijt}$$

Here, y_{ijt} represents the earnings of worker i in year t, when that worker is employed at firm j. We interpret α_i, the "person effect," as a measure of worker skills that are invariant to the firm that i is employed at. Similarly, $X_{it}\beta$ reflects time-varying worker skills, primarily age, that are also invariant to the employer. ψ_j is a pay premium that firm j pays to all of its employees, normalized relative to the average firm -- a high-ψ_j firm is one that pays workers more, on average, than those workers would obtain at the average firm, while a low-ψ_j firm pays less. ϵ_{ijt} reflects all other components of earnings, including match effects (if a particular worker i receives more of a premium at firm j than do other workers) and idiosyncratic factors that cause earnings to vary within a job match. While this is a very simple decomposition, it has been found to have remarkable success for explaining patterns of wages in a range of settings (see, e.g., CHK).

In the AKM model, worker and firm effects are measured relative to the average worker and the average firm. That means we can measure whether a firm pays more or less than the average firm, but not the absolute pay premium that the firm offers. Even relative effects can be measured only for workers and firms who are "connected," meaning that there exists a chain of workers who overlap at the same firms and connect the firms. To illustrate, firms 1 and 2 are connected if worker A is observed both at firm 1 and firm 3, worker B is observed at firm 3 and firm 4, and worker C is observed at firm 4 and firm 2. This chain of connections allows us to disentangle whether observed pay differences between firms 1 and 2 are due to differences in firm wage policies (ψ_j) or in the types of workers that the two firms employ (α_i). Following the literature, our analysis focuses on the largest connected set within our sample. After imposing our worker-level sample exclusions and then limiting to the largest connected set, we are left with 68 million worker-year observations.

Table C-1 reports a variance decomposition of earnings, following the above equation. Consistent with past work, the ϵ_{ijt} error term (labeled "AKM residual SD" in the table) accounts for a substantial share of earnings, roughly 20 percent of the variance in log earnings $(0.513/1.14)^2=0.2$). The worker effects account for 51 percent, while the firm effects account for 5 percent -- not an overwhelming share, but a sizable component. This implies that working for a 90th percentile firm rather than a 10th percentile firm is associated with an approximately 66 percent increase in earnings.

The second through fifth columns of Table C-1 show how the distribution of the different components varies across regions of California, assigning workers based on their residential locations. We consider four regions: The Los Angeles area, including Los Angeles, Orange, Riverside, and Ventura counties; the Bay Area, including the nine Bay area counties; San Diego; and the rest of the state. Much of the cross-region differences in earnings are attributable to differences in mean worker effects, but we also see that San Diego and the Bay Area have higher-wage firms than Los Angeles or the rest of the state. Not surprisingly, the dispersion within each region in both worker and firm effects is much larger than the between-region variation.

Figure C-1 illustrates this graphically. We divide individuals and firms into ten groups by α_i and ψ_{ij}, and show the proportion of individuals in each person- and firm-effect decile, separately for the Los Angeles and Bay Areas, the two largest metropolitan regions in the state. In Figure C-1 we see that about 18 percent of the workers in the Bay Area are in the top decile of the person effect distribution, as compared with only 9 percent of workers in Los Angeles.

The pattern is similar for firms: 20 percent of firms in the Bay Area are in the top decile of the firm effect distribution, as compared with around 7 percent in LA. **Figure C-2** shows the joint distribution for LA, the Bay Area, and for the rest of the state, divided into coastal and non-coastal counties. High-wage workers tend to work at high-wage firms, corresponding to elevated density in the right and left corners of the plots, but not uniformly. Moreover, high-wage workers at high-wage firms are dramatically overrepresented in the Bay Area and in the “other coastal” region, while low-wage workers at low-wage firms are overrepresented in LA and the “other non-coastal” region.

Figures C-3, C-4, and C-5 provide another look at this geographic distribution. Here, we show the average worker effect for workers in each zip code (C-3) and the average firm effect of the firms at which the workers work (C-4). Figure C-5 shows more detail for the Los Angeles and Bay Areas, which are hard to see in the state-wide maps. Both high-wage workers and high-wage firms are concentrated in the state’s largest metropolises. Within those cities, those who live in wealthier areas (see the coastal zip codes in Los Angeles, or Marin or southeastern Contra Costa counties in the Bay Area) have higher average person effects and also, to a somewhat lesser extent, work at firms with higher average firm effects. In Figure C-5, we can also see large concentrations of low-wage workers and low-wage firms in South Los Angeles and the adjacent suburbs.

Table C-2 shows how firm and worker earnings effects vary with industry. It shows mining and oil and gas extraction-related firms pay the largest firm premiums, but also represent a small share of all firms. Firms in industries requiring high levels of skill and training, such as Information and Professional, Scientific, and Technical Services, also pay large premiums and represent a sizable share of workers and firms. Workers in these industries also tend to be high earners. In contrast, firms in Food Services, covering roughly 10 percent of all workers, have low pay premiums and also tend to attract low earners. Industries explain only a small share of the dispersion in firm effects, however; firm pay premia vary nearly as much within industries as they do overall. **Figure C-6** provides a graphical view of the differences across industries, showing that mean firm effects are very strongly positively correlated with mean worker effects across industries: High-wage industries employ high-wage workers. The largest outlier is educational services, which has low-wage firms but not low-wage workers.

Figure C-7 shows that these firm policies really matter. We show the fraction of workers eligible for the federal EITC by individual and firm effect deciles.[4] Not surprisingly, low-wage workers and those at low-wage firms are more likely than others to be eligible for the EITC; among the lowest-wage workers at the lowest-wage firms, over 60% are eligible for the EITC. Somewhat more surprising is that individual and firm effects seem to matter to similar degrees -- although firm effects are less variable than person effects, we see that moderate person-effect workers at low-wage firms are quite likely to be eligible for the EITC. The second panel shows the share of workers who claim the EITC, conditional on estimated eligibility. Take-up rates are highest among the low-person-effect, low-firm-effect cells that also have the highest eligibility rates. Take-up drops off for the highest person effect workers, who are likely eligible for relatively small credits.

Having developed our measure of firm wage policies, we now turn to examine how different types of firms vary in their reliance on independent contracting. To do this, we construct two measures of firm-level reliance. The first is the share of all workers who are IC workers -- the number of 1099-MISCs and 1099-Ks issued divided by the total of the number of 1099-MISCs, 1099-Ks, and W-2s. The second is the share of compensation paid to IC workers,

[4] To approximate EITC eligibility, we use the number of children reported on the 1040 (or, for paper filers, the number of dependents listed on the 540) as the number of qualifying children.

the total dollar value of non-employee compensation on all 1099-MISCs and 1099-Ks issued, divided by the sum of this and total W-2 employee compensation. We then explore how this IC intensity varies with firm pay policies. This is shown in **Figure C-8**. High-firm-effect firms use two to three times as much IC labor as do low-firm-effect firms. This is suggestive that firms that offer high wages may use IC work to evade the union contracts or fairness norms that support those high wages, and cuts against the hypothesis that firms that are generally exploitative of workers are the largest users of independent contractors.

Appendix D. Exploring whether bunching near the EITC kink reflects reporting or work responses

As discussed in the main text: “bunching” at the EITC kink point is not necessarily driven by people manufacturing fictional income. Instead, it may reflect real work behavior or a potential underreporting of IC expenses. Regardless, this bunching does not impact our main findings in the paper, as we outline below.

Many taxpayers who qualify for the EITC face incentives to report higher earnings, as these qualify them for more generous EITCs. This incentive only lasts until the point that the taxpayer reaches the maximum EITC eligibility, however, and Chetty et al. (2013) and Saez (2010) find that this leads to “bunching” of tax returns at the lowest reported income level that qualifies for this maximum EITC. This could reflect true labor supply responses, as workers work more up to the point that their EITCs are maximized and then stop. It could also reflect tax reporting behavior -- for example, workers might report more independent contracting income than they truly obtained in order to receive a higher EITC (which is large enough to more than offset the higher self employment taxes they would owe). Chetty et al. (2013) and Saez (2010) find that bunching is concentrated among filers with independent contracting income, supporting the hypothesis that it may reflect reporting rather than real responses. We investigate this bunching in our data, both to understand it in its own right and to shed light on the extent to which our primary estimates of IC participation may be biased by EITC-driven misreporting.

Figure D-1 shows the distribution of total reported income, separately for returns with Schedule Cs (Panel A) and without (Panel B). We scale income as a multiple of the smallest amount that would lead to a maximum federal EITC benefit for that household size. Thus, a value of 1 corresponds to a household with income exactly corresponding to the first EITC kink point. Panel A shows clear bunching around this point: There are about 50% more filers with incomes right at the kink than at levels just above or just below it. By contrast, Panel B shows no sign of bunching among those without Schedule Cs -- although the kink is close to the peak of the density, there are no more households right at the kink than one would expect from patterns nearby.

The EITC is more generous for families with more children. **Figure D-2** further divides the Schedule C filers into those without (panel A) and with (panel B) dependents. There is a small amount of bunching among those without dependents, but vastly more among those who would qualify for larger EITC credits.

Chetty et al. (2013) document substantial geographic variation in the rate of this type of overreporting. They report estimates of the bunching frequency at the 3-digit zip code group level. **Figure D-3** shows a scatterplot of the share of returns with IC income against Chetty et al.'s (2013) measure of bunching frequency. We see more IC work in high-bunching zip codes, consistent with the idea that a fraction of the IC work that we observe reflects misreporting, but the gradient is fairly shallow.

Although Chetty et al. (2013) find that this bunching sometimes reflects real work responses, the dramatic differences between Schedule C and non-Schedule C returns strongly suggest that much of the bunching in the former reflects income reporting. There are several potential types of misreporting that could contribute to this: Some taxpayers may report earnings from non-existent sources, may over-report earnings from sources from which they have true earnings, or may under-report (or reduce over-reporting of) expenses associated with IC work. Any of these may distort our estimates of the prevalence of independent contracting.

We take two approaches to assessing the impact of EITC-related misreporting on our estimates. First, we investigate whether it likely derives from over-reporting of IC earnings. Filers that over-report independent contracting income are unlikely to have third-party-reported 1099s to correspond to the full amount of their claimed income. In **Figure D-4**, we limit attention to Schedule C filers with dependents, and further separate them into those whose Schedule C gross revenues approximately match (to within 10%) the income that is reported on their 1099s and those for whom it does not match. Bunching is common in both groups, though more so in the latter group. We can be confident that the first group is not overreporting gross revenues, so the presence of bunching here indicates that this is not the entire explanation. Evidently, at least a portion of bunching derives either from actual work behavior or from underreporting of business expenses.

Our second approach is to assess the impact of EITC-related misreporting on our estimates, by down-weighting returns showing Schedule C income right near the EITC kink. We identify the excess density of Schedule C filers right near the EITC-maximizing threshold, and weight returns with Schedule Cs near this threshold by the ratio of the expected density (based on a polynomial fit to points away from the threshold) to the observed density. Downweighting to eliminate bunching is an extreme approach, as it in effect assumes that the overreported returns would have had zero earnings without the overreporting. **Table D-1** reproduces the analysis from Table 6 with this adjustment. It has little effect on our overall conclusions – while overreporting is prevalent, it is not a large enough share of Schedule C returns to make much difference overall. **Table D-2** repeats the distributional analysis from Table A-3 with this reweighting.

Appendix E. Underreporting of IC earnings

We use a combination of 1099s and Schedule Cs to identify independent contracting income. This means that we should in principle count all IC earnings that are subject to third-party reporting via 1099-MISCs and 1099-Ks, whether or not the taxpayer reports the earnings on his/her tax return, but we miss IC earnings that neither the taxpayer nor the employer reports. The IRS estimates that nearly two-thirds of income without third-party reporting is not reported on individual returns (Internal Revenue Service 2016, 2019), though we are not aware of an estimate specific to IC earnings. This underreporting has fueled efforts to expand third-party reporting as a means of improving tax compliance.[5]

In this Appendix, we develop and implement a strategy for estimating the effect of third-party reporting of IC earnings on the degree of underreporting.[6] Our strategy takes advantage of changes in the rules and in employer practices regarding issuance of 1099-Ks for OPE work over time. Per IRS guidance, 1099-Ks must be furnished to payees receiving total

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[5] https://www.rhsmith.umd.edu/faculty-research/smithbraintrust/insights/tax-loophole-you-could-drive-uber-through

[6] The analysis in this appendix relies on the Magmedia version of the 1099 data, where the analysis in the main paper relies on IRMF. While Magmedia's overall 1099 coverage appears to be incomplete, it appears complete for the OPE firms that are relevant to this analysis.

payments above $20,000 or more than 200 transactions in a year.[7] Before this guidance, however, these thresholds were ambiguous. Moreover, many OPE firms have adopted practices of issuing 1099-Ks to workers who do not meet the thresholds for mandatory reporting. For example, Uber and several other companies have issued 1099-Ks for all of their workers, even those with earnings well below $20,000, in at least some years.[8]

We focus on OPE firms that scaled back their 1099-K issuing practices, following the IRS guidance, in 2017. Specifically, we identify from among our list of OPE firms the subset that appear to have issued 1099-Ks to all workers in tax year 2016 but that only issued forms above the $20,000 threshold in tax year 2017.[9] **Appendix Figure E-1** shows the distribution of the amounts of 1099-Ks issued by these firms in 2016 and 2017, separately for forms above and below $20,000. The distributions appear similar above $20,000, in the right-hand panels. Below $20,000, however, they are quite different. In 2016 roughly 91% of all 1099-Ks issued by these firms were for less than $20,000, accounting for 40% of the total dollar value of 1099-K-covered earnings. In 2017 both shares fell to 0%. Assuming the distribution of actual earnings at these firms was the same in both years, this implies that 91% of the workers who in 2016 would have received a 1099-K did not receive a form in 2017, and that 40% of earnings obtained from these firms was not covered by third-party reporting.

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[7] The American Rescue Act, signed in March 2021, will lower the threshold to $600, with no minimum transaction threshold. See https://www.forbes.com/sites/lizfarmer/2021/03/12/federal-stimulus-bill-has-huge-tax-change-for-gig-workers/?sh=71b7b44e3805. The distinction between which OPE workers are covered by 1099-MISCs vs. 1099-Ks is a complex one that we do not explore; for our purposes, we focus on OPE firms that in practice use 1099-Ks for covered workers.

[8] https://www.sfgate.com/business/networth/article/Here-s-why-Uber-and-Lyft-send-drivers-such-6092403.php

[9] We identify these by counting the number of 1099-Ks issued for amounts under $20,000 in each year. We include in our analysis firms where this number fell by at least 90% from 2016 to 2017.

Our strategy is based on the idea that a worker who received a 1099-K for, say, $10,000 in earnings from an OPE firm in 2016 is quite likely to have continued working for the firm in 2017, but quite unlikely to have earned enough to have received a 1099-K in that year. If this worker's tax reporting depends on the presence of third-party reporting, we should expect his or her reported IC earnings to decline in 2017. Of course, not all such workers will have remained with the same firm in 2017, and the amount of their earnings may have gone up or down. But we can measure this tendency by examining 2015 to 2016 transitions, as we have 1099-Ks for all workers at the firms in these years. So if the real transition patterns are the same between 2015 and 2016 as they are between 2016 and 2017, we can infer the effect of third-party reporting from changes between the average 2016 reporting of workers who were with the firms in 2015 and the average 2017 reporting of similar workers who were with the firms in 2016.

Appendix Figure E-2 illustrates the strategy. On the left side, we array workers by the amount of earnings reported on 1099-Ks from these firms in tax year 2015. We show in the upper left panel mean 1099-K-reported earnings from the same firms for these workers in 2016, and in the lower left panel the change from 2015 to 2016. Not surprisingly, there is some mean reversion between years, and 2016 earnings are generally lower than 2015 earnings for those with high 2015 earnings. But at lower earnings levels the changes are minimal: A typical worker with earnings between $10,000 and $11,000 in 2015 had $11,429 in earnings in 2016. We can be confident that this pattern accurately reflects changes in actual earnings, as the firms in our sample issued 1099-Ks for all earnings in these two tax years.

The right panels of Figure E-2 show the same analysis, rolled forward one year. We array workers by their 2016 1099-K earnings, and show 2017 1099-K earnings in the upper panel, and the difference between the 2016 and 2017 amount in the lower panel. In 2017, third-party reporting was incomplete. Thus, a typical worker who earned between $10,000 and

$11,000 from one of our firms in 2016 received 1099-Ks for only $6,888 in 2017, meaning that the typical third-party-reported earnings fell by 40% between 2016 and 2017 for workers who had received around $10,000 in the prior year.

Appendix Figure E-3 further explores the strategy. This repeats the comparisons in the lower panels of Figure E-2, but separates out third-party reported earnings from the firms in our OPE sample into three components: 1099-Ks for amounts below $20,000, 1099-Ks for amounts above $20,000, and 1099-MISCs of any amount. We see very small changes in the second and third categories, which were reported consistently across years; all of the change seen in Appendix Figure E-2 comes from the first category, which ceased in 2017. This is consistent with our assumption that our comparison between individuals in 2015 and 2016 with similar 1099-K earnings identifies people with similar real behavior, and that the only change between them is in whether their earnings are subject to third-party reporting.

Appendix Figure E-4 shows how this change in third-party reporting translates into changes in self-reported earnings. We show here the change in Schedule C gross earnings from 2015 to 2016 (blue) or 2016 to 2017 (red), as before averaging each as functions of the first year's 1099-K payment. Those who did not file a Schedule C are assigned zero for that year. Continuing with our example of workers with 1099-Ks in the base year with $10,000 to $11,000 in earnings, average reported gross IC earnings increased by $2,135 between 2015 and 2016, but by only $1,295 between 2016 and 2017. This difference, and its pattern across different base-year earnings levels, is consistent with the decline in third-party reporting translating into a (much smaller) decline in self-reporting on the Schedule C.

We can use the comparison between Appendix Figure E-2 and Appendix Figure E-4 to identify the effect of third-party reporting on the share of earnings that are reported on Schedule

Cs. Formally, this is an instrumental variables regression, where we combine observations from 2015-6 and 2016-7 and instrument for the amount of third-party-reported earnings in the second year of each pair with the interaction of the amount in the first year of each pair and an indicator for whether this year was 2016. Specifically, let X_{it} represent an indicator for receiving a 1099-K in year t, and let Y_{it} represent gross earnings reported on that individual's Schedule C. We are interested in estimating the effect of X_{it} on Y_{it}:

$$Y_{it} = \alpha + X_{it}\beta + \epsilon_{it}.$$

If we estimate this via Ordinary Least Squares, there is an omitted variables bias: People with different X_{it} likely differ in the amount that they actually earned in year t from independent contracting, and the β coefficient does not isolate the effect of third-party reporting from differences among people who simply have different earnings. To instrument for this, we use a series of dummies D_{it-1} for different ranges of the amount of 1099-K received for tax year t-1 from one of the OPE firms that changed policies in 2017, interacted with P_t, an indicator for t being a year when 1099-K reporting is universal. We control for main effects for each of these, so only changes in the relationship between D_{it-1} and X_{it} from t=2016 to t=2017 are used to identify β. Thus, we estimate a system of equations:

$$Y_{it} = \alpha_1 + X_{it}\beta + D_{it-1}\gamma_1 + P_t\theta_1 + Z_{it}\pi_1 + \epsilon_{it}$$

$$X_{it} = \alpha_2 + D_{it-1}P_t\phi + D_{it-1}\gamma_2 + P_t\theta_2 + Z_{it}\pi_2 + u_{it} .$$

Here, our instruments are the dummies $D_{it-1}P_t$, while D_{it-1}, P_t, and Z_{it} represent controls. Our assumption is that the relationship between D_{it-1} and ϵ_{it} did not change over time, so that $D_{it-1}P_t$ is excludable from the first equation.

Appendix Figure E-5 shows the first-stage coefficients γ_2. The coefficients here show the difference between the probability of receiving a 1099-K in 2016 and the probability of receiving one in 2015, for workers at each level of 1099-K earnings in the prior year. Estimates are relative to the excluded category of more than $61,000 in 1099-K earnings in the prior year. The U-shape pattern is exactly what we expect from the change in reporting: Those with very low levels of base-year earnings are unlikely to receive 1099-Ks in the subsequent year regardless of the reporting regime, and those with very high levels of base-year earnings likely continued to earn above the reporting threshold the next year even when it was raised, but those with intermediate base-year earnings were likely to continue to have earnings but to remain below the threshold, so saw large declines in their chances of receiving a 1099-K.

Appendix Table E-1 presents 2SLS estimates of the effect of receiving a 1099-K on a range of outcomes. We find that receiving a 1099-K raises the likelihood of filing a Schedule C by 15 percentage points. It also increases reported gross Schedule C income by $5,500, though this is not precisely estimated. Interestingly, this is largely offset by increased reported expenses; the increase in net reported income is only $284. We find a statistically significant increase in the amount of reported car and truck expenses of $1,994, consistent with the idea that the third-party reporting brings the worker’s gig job onto the books. We can also explore other measures. Total federal and state taxes paid (including self-employment taxes) increase by $818 and $216, respectively. There are some unexpected results, however: Receipt of a 1099-K appears to reduce the amount of W-2 earnings by a statistically significant amount, even using our strategy that exploits just variation coming from reporting differences and not differences in the amount of IC work.

Appendix Table E-2 presents estimates from a somewhat richer model in which we treat both an indicator for receipt of a 1099-K and the amount of the K (if any) received as separate endogenous variables, with the same instruments. (The first stage for the amount of the 1099-K is shown in **Appendix Figure E-6**.) The pattern of results can be hard to interpret, and it is helpful to realize that the estimated effect of receipt of a 1099-K corresponds to what is forecast for receipt of a 1099-K with zero earnings; for higher earnings levels, the implied effect is a weighted sum of the effects in the two columns. We see that higher 1099-K payments are associated with increases in Schedule C net profits and in self-employment tax paid, with net positive effects when reported payments exceed about $5,000. Interestingly, while receipt of a 1099-K appears to increase the share of workers who file Schedule Cs, this does not vary meaningfully with the amount of the 1099-K. Third-party reporting also raises the likelihood of being identified in our data as an OPE worker; although this effect diminishes slightly as the amount of the 1099-K rises, it remains positive for any 1099-K amount under $30,000. As before, we see a puzzling effect on W-2 earnings, with receipt of a form reducing W-2 earnings but by a diminishing amount as the amount of 1099-K earnings rises.

Overall, this analysis indicates that third-party reporting does impact individuals' propensity to report the income on tax returns. The effects are not enormous, perhaps in part because even with third-party reporting many do not report their OPE earnings on Schedule Cs. They appear to operate largely through inducing people to file Schedule Cs, and much less so through the amounts reported on the Schedule Cs. Further investigation into the potential to follow up third party reports with taxpayer education to ensure that 1099-K income is correctly translated onto the tax return would be valuable.

Appendix Table A-1. Proportion of earned income from W2 and/or IC, working-age e-filers, 2016

	E-filers			E-filers reweighted to match full population		
Earned income source	**%**	**IC workers, by presence of OPE income**		**%**	**IC workers, by presence of OPE income**	
		No OPE	**With OPE**		**No OPE**	**With OPE**
W2 only	85.6%	--	--	85.5%	--	--
Primarily (>=85%) W2	4.2	3.4%	0.76%	4.1	3.4%	0.75%
Mixed earners (15-85% W2)	2.8	2.5	0.28	2.8	2.5	0.28
Primarily (>=85%) IC	0.5	0.4	0.04	0.5	0.4	0.04
IC only	7.0	6.7	0.34	7.1	6.8	0.35
Total (age 18-64)	**100%**	**13.0%**	**1.42%**	**100%**	**13.1%**	**1.42%**

Note: Sample excludes individuals with zero earnings.

Appendix Table A-2. Three-year transitions

2014 status	2015 status	N (1,000s)	% of total	2016 status (row percentages)			
				No earnings	W2 only	Mixed	IC only
No earnings	No earnings	1,636	13.6%	89%	7%	0%	3%
No earnings	W2 only	201	1.7	19	76	4	1
No earnings	Mixed	16	0.1	8	49	30	13
No earnings	IC only	95	0.8	32	6	6	55
W2 only	No earnings	224	1.9	68	26	2	4
W2 only	W2 only	8,116	67.5	2	94	3	0
W2 only	Mixed	329	2.7	2	53	37	7
W2 only	IC only	39	0.3	17	18	17	49
Mixed	No earnings	13	0.1	52	22	7	19
Mixed	W2 only	275	2.3	2	81	15	2
Mixed	Mixed	326	2.7	1	32	60	6
Mixed	IC only	55	0.5	9	9	19	63
IC only	No earnings	84	0.7	64	8	2	25
IC only	W2 only	36	0.3	7	76	12	5
IC only	Mixed	57	0.5	3	40	38	19
IC only	IC only	515	4.3	10	3	6	81

Notes: "Mixed" status here counts anyone with positive W-2 and positive IC income. Only individuals observed filing in all three years are included.

Appendix Table A-3. Distribution across earning type, by decile

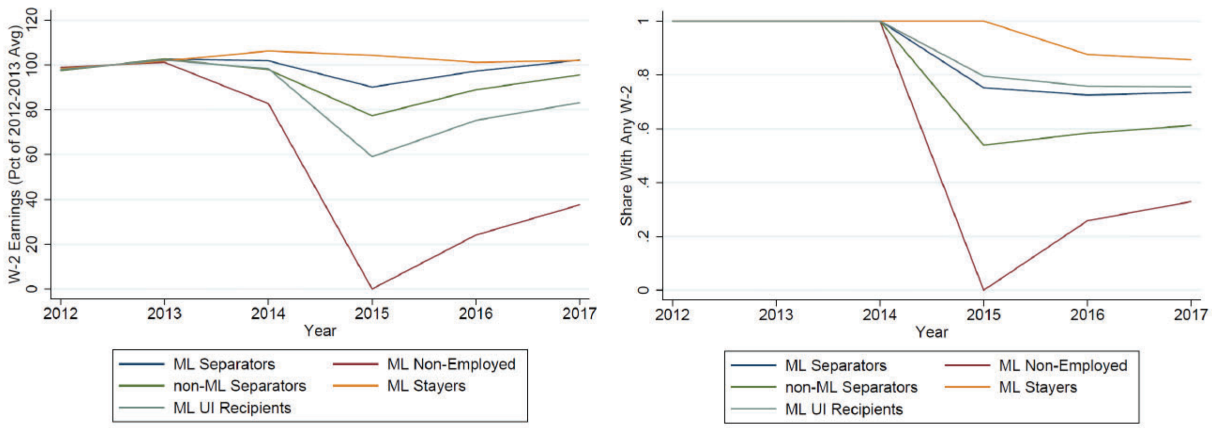
	Share with IC earnings				
	Any IC	Any OPE	Primarily or exclusively W-2	Mixed	Primarily or exclusively IC income
Decile					
1 ($1 - $7,605)	29.0%	2.6%	72.4%	3.7%	23.9%
2 ($7,606 - $14,014)	24.3	2.2	78.6	5.5	15.9
3 ($14,105 - $20,542)	20.1	2.1	83.4	4.5	12.1
4 ($20,453 - $27,561)	13.3	1.8	90.6	2.8	6.5
5 ($27,562 - $35,758)	11.1	1.6	93.2	2.3	4.6
6 ($35,759 - $45,742)	9.6	1.4	94.9	1.8	3.3
7 ($45,743 - $58,984)	8.9	1.1	95.9	1.6	2.5
8 ($58,985 - $78,454)	8.6	0.8	96.5	1.5	2.1
9 ($78,455 - $115,042)	8.7	0.5	96.7	1.5	1.8
10 (> $115,043)	10.8	0.3	95.2	2.3	2.5

Note: Percentages sum to 100 across columns 3-5. Columns 1 and 2 are not mutually exclusive.

Appendix Figures

Appendix Figure B-1
W-2 earnings after job loss

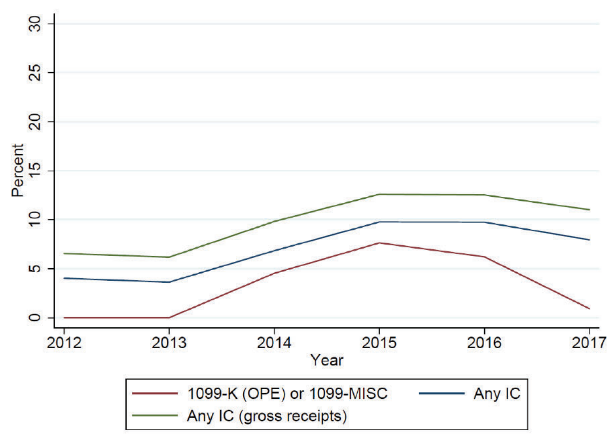
A. W-2 earnings, as percent of 2012-13 average B. Share with any W-2 earnings



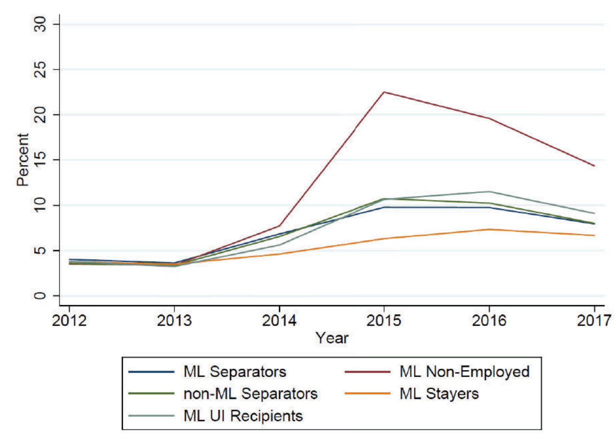
Notes: Samples are defined in the text, and correspond to the columns of Table B-1. All samples except "ML Stayers" received W-2s from the index firm in 2014 but not in 2015.

Appendix Figure B-2
Share of workers with independent contracting earnings after job loss

A. Types of IC earnings, among ML separators



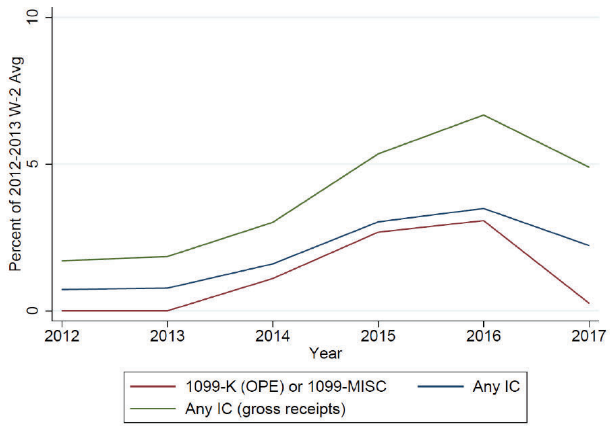
B. Any IC, by separator group



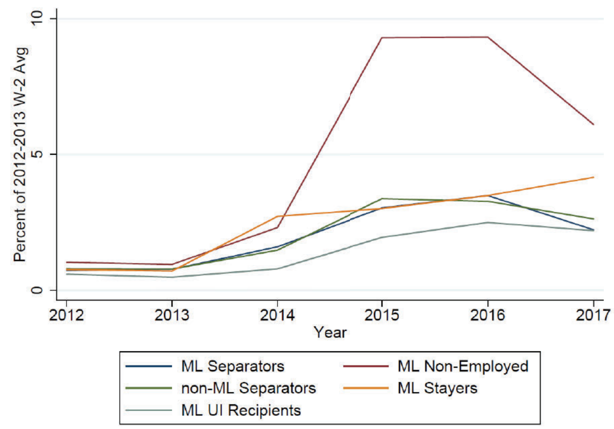
Notes: Panel A shows the share of the 2014 mass layoff separator sample with various indications of independent contracting employment each year. "1099-K (OPE) or 1099-MISC" refers to receipt of either a 1099-K from a firm on our online platform economy list or a 1099-MISC from any employer. "Any IC" and "Any IC (gross receipts)" refer to the presence of net profits or gross receipts, respectively, on a Schedule C or to receipt of 1099s (for profits, in excess of reported Schedule C expenses). Panel B repeats the "Any IC" series across various alternative samples.

Appendix Figure B-3
Amount of independent contracting earnings after job loss

A. Types of IC earnings, among ML separators



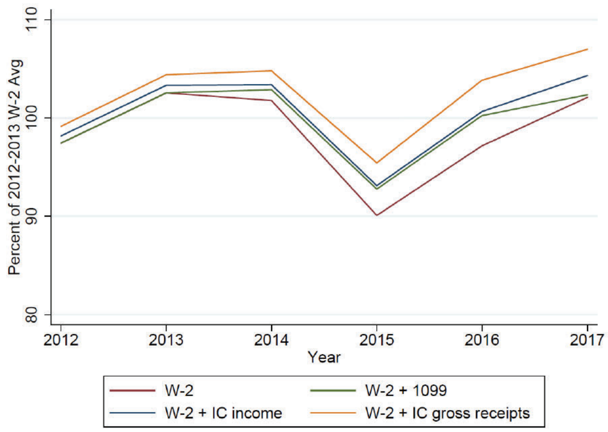
B. Any IC, by separator group



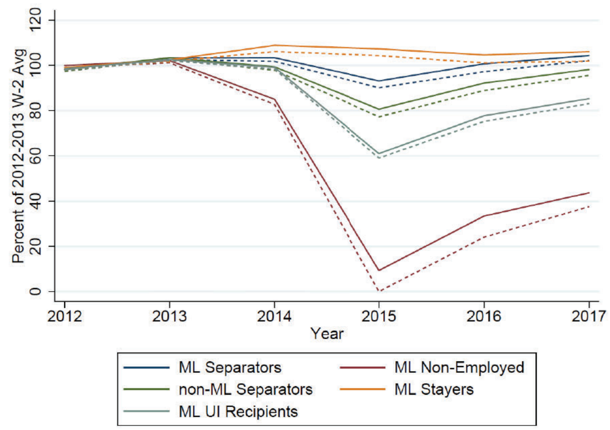
Notes: Figures show the amount of independent contracting earnings, as a share of workers' average pre-displacement W-2 earnings. See notes to Appendix Figure B-2 for explanation of series.

Appendix Figure B-4
Total earnings from W-2 and IC work after job loss

A. Types of IC earnings, among ML separators



B. Any IC, by separator group



Notes: Figures show earnings across various categories as a share of workers' average pre-displacement W-2 earnings. Panel A examines the mass layoff separators sample. Panel B compares samples; dashed lines show W-2 earnings while solid lines show W-2 earnings plus independent contracting earnings (displayed as "W-2 + IC income" in panel A).

Table B-1
Summary statistics for mass layoff samples

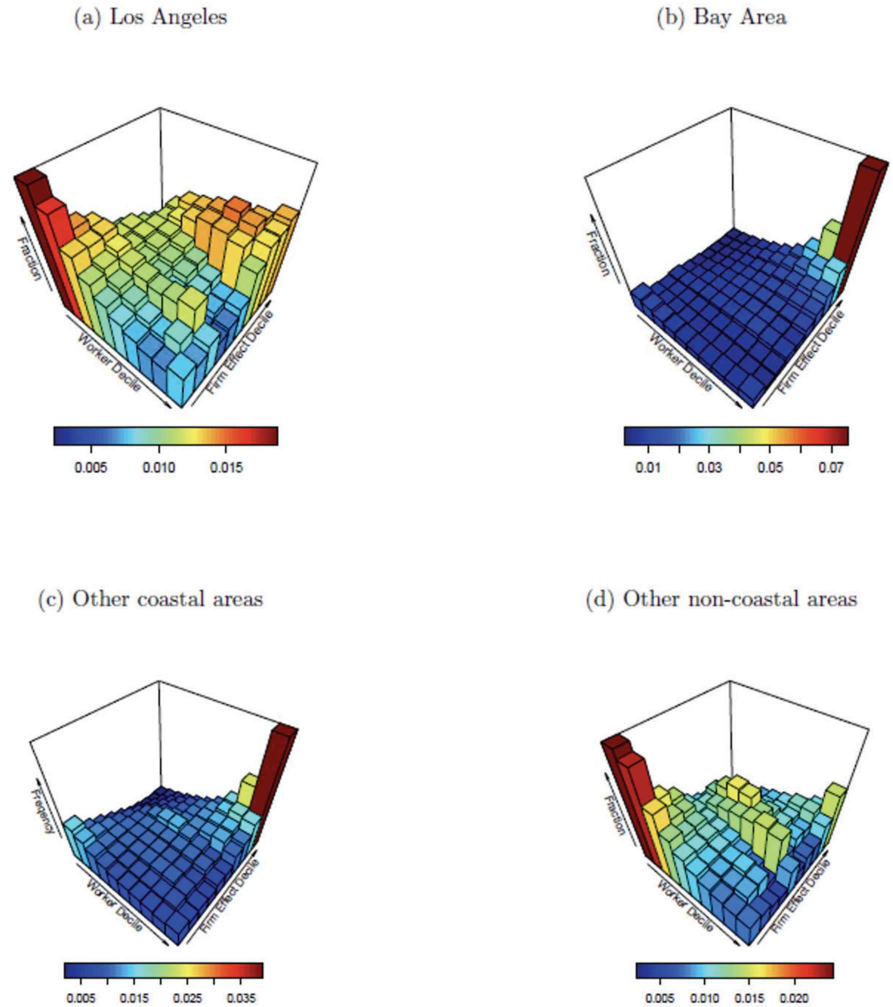
Variable	ML Sep	ML Nonemp	non-ML Sep	ML Stay	ML UI
Demographics					
Imputed Age	45	51	44	46	45
Age 18-25	.03	.014	.05	.028	.026
Age 26-40	.37	.24	.39	.33	.36
Age 41-55	.39	.33	.32	.41	.39
Age 56-64	.16	.25	.16	.18	.17
Over Age 64	.045	.087	.06	.052	.047
Number of Children	.38	.11	.23	.48	.53
Household Size	2.4	1.9	2.1	2.6	2.7
Married	.54	.39	.45	.61	.63
Received UI	.16	.13	.09	.15	1
Prior Schedule C	.09	.089	.081	.083	.09
Above Sample Median Prior Earnings	.49	.46	.46	.52	.46
Filing Rates					
Didn't P/W File in 2015-2017	.68	.5	.58	.76	.8
Filed > Once in 2015-2017	.9	.69	.83	.97	.97
Filed Every Year 2015-2017	.79	.47	.68	.9	.88
Income					
AGI	106,692	86,621	111,961	118,447	81,296
W-2 Earnings	49,030	0	36,238	72,259	36,530
Sched. C Gross Receipts	3,396	5,963	2,871	2,734	2,955
Sched. C Net Profits	1,201	2,499	1,080	475	1,126
UI Amount	847	785	452	767	5,245
Federal EITC Amount	215	114	139	213	467
1(Any W2)	.75	0	.54	1	.8
1(Any Sched. C)	.099	.096	.079	.087	.15
N	53,469	13,855	583,851	96,805	8,632

Notes: Columns 1, 2, 4, and 5 represent subsets of the mass layoff sample, defined in the text. Column 1 is ML separators; column 2 is ML non-employed; column 4 is ML stayers; and column 5 is ML unemployment insurance recipients. Column 3 represents job separators who left firms in our non-ML comparison sample. Statistics pertain to tax year 2015 unless otherwise noted. Median prior earnings are calculated across the entire sample, and are $50,624.

Appendix Figure C-1
Marginal distributions of estimated worker and firm effects, Los Angeles and Bay Area

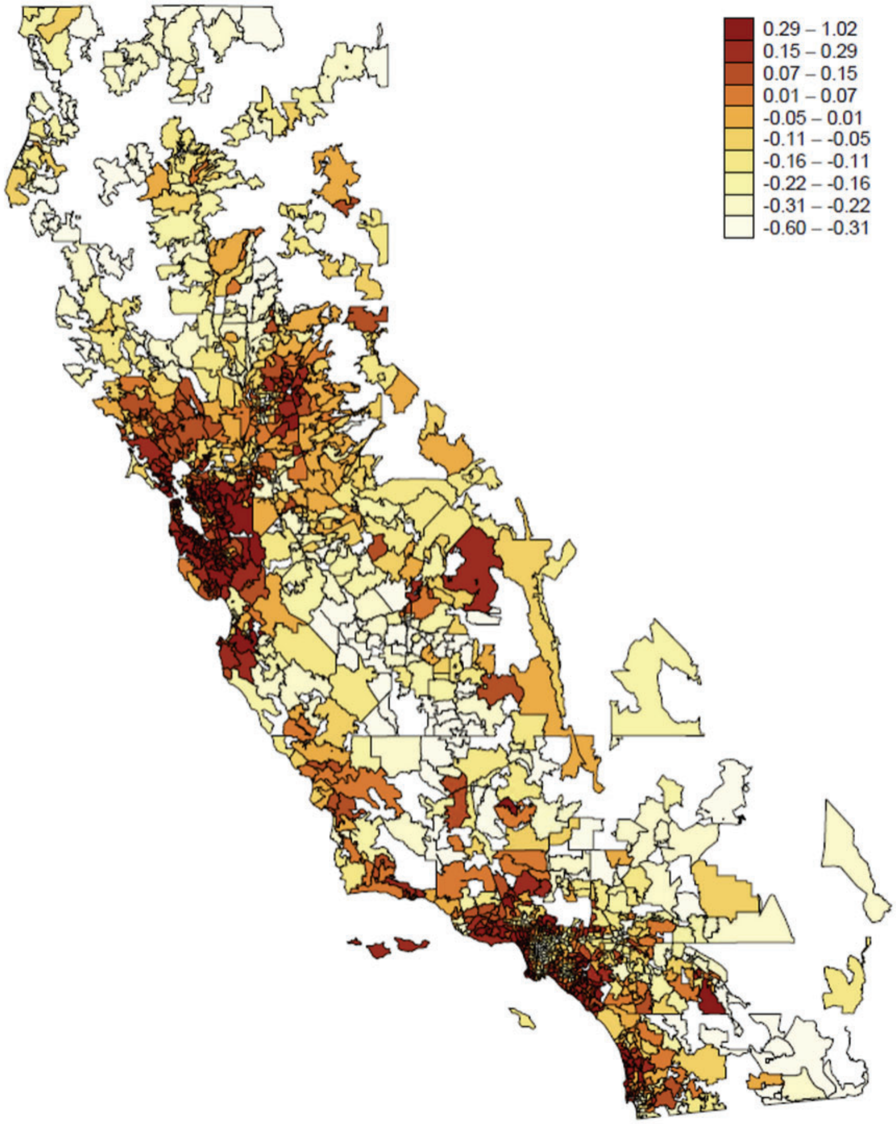
Notes: This figure shows the marginal distributions of each for workers in the Los Angeles and Bay Areas. Estimated worker and firm effects are divided into deciles based on the statewide distribution.

Appendix Figure C-2
Joint distributions of worker and firm effects in four regions of California

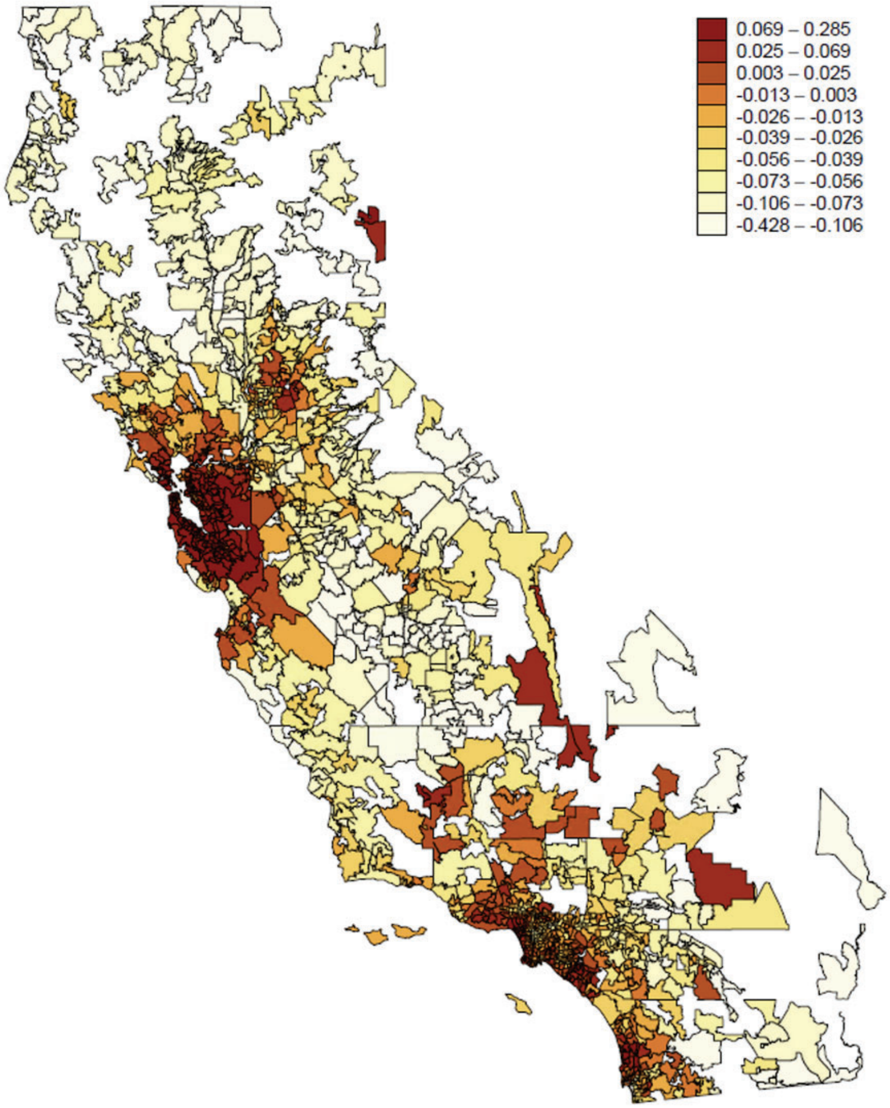


Notes: Estimated worker and firm effects are divided into ten equal sized deciles based on the statewide worker-weighted distributions. Figures show the joint distributions separately for four geographic components of the state. Note that vertical axis scales differ by region.

Appendix Figure C-3
Average worker effect by worker zip code

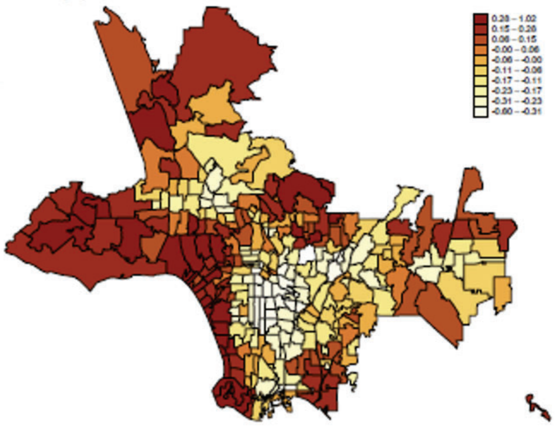


Appendix Figure C-4
Average firm effect by worker zip code

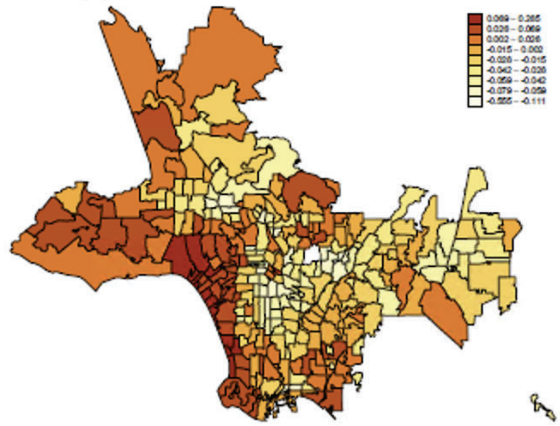


Appendix Figure C-5
Average worker and firm effects by worker zip code: Los Angeles and Bay Area details

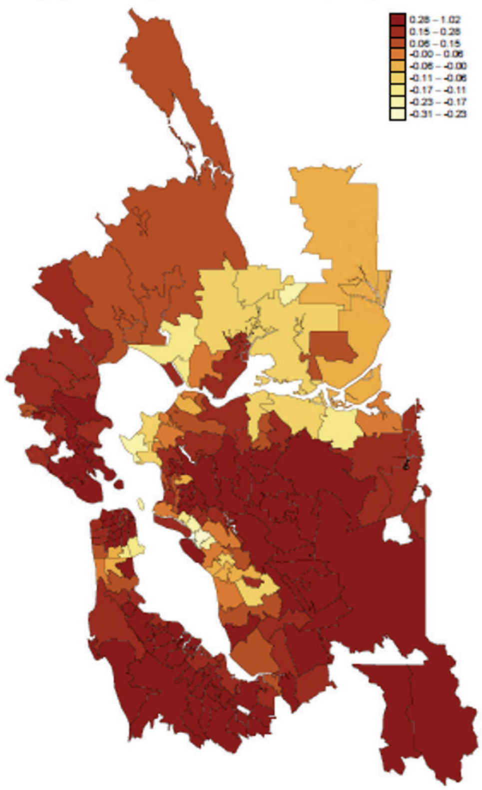
(a) Average worker effect, Los Angeles



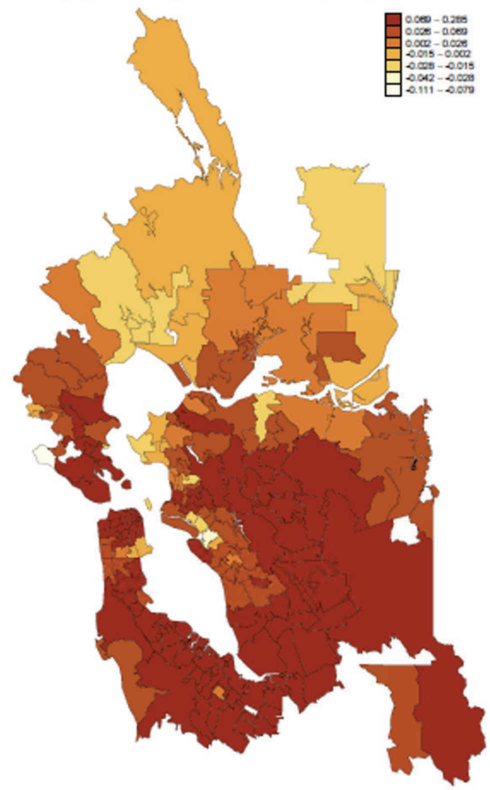
(b) Average firm effect, Los Angeles



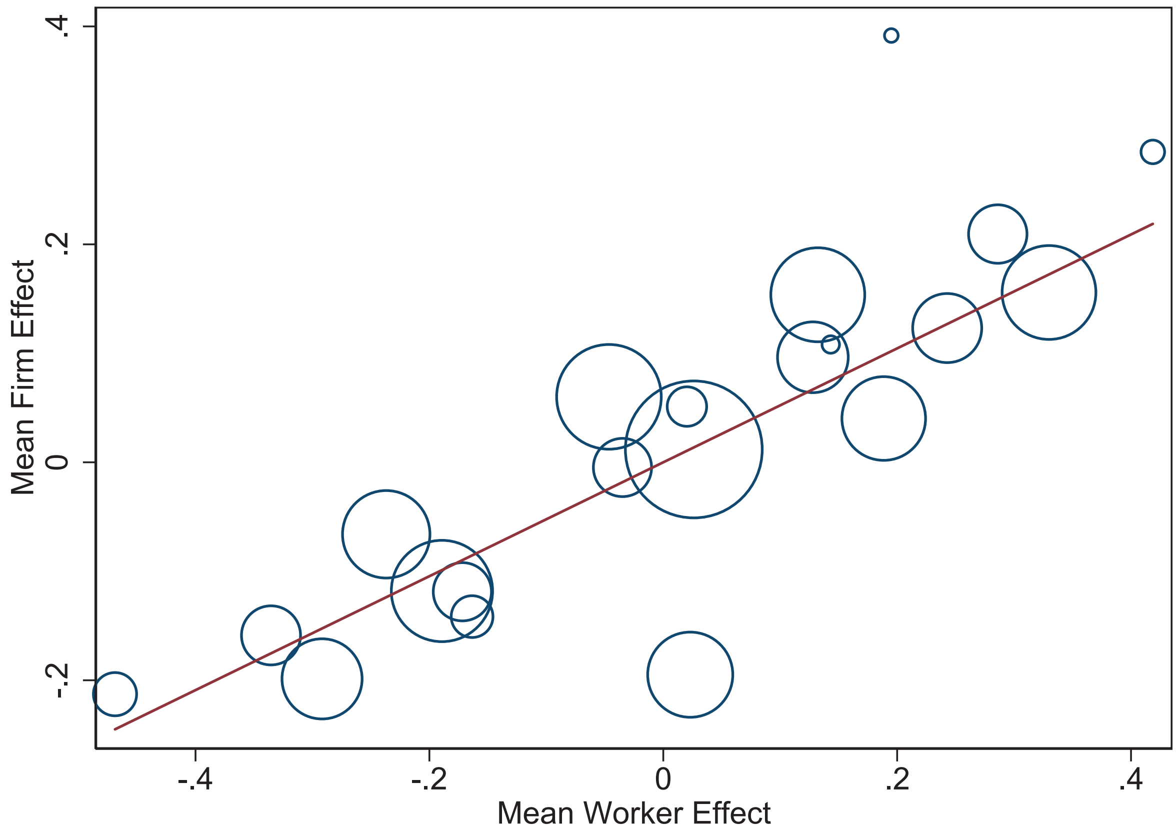
(a) Average worker effect, Bay Area



(b) Average firm effect, Bay Area

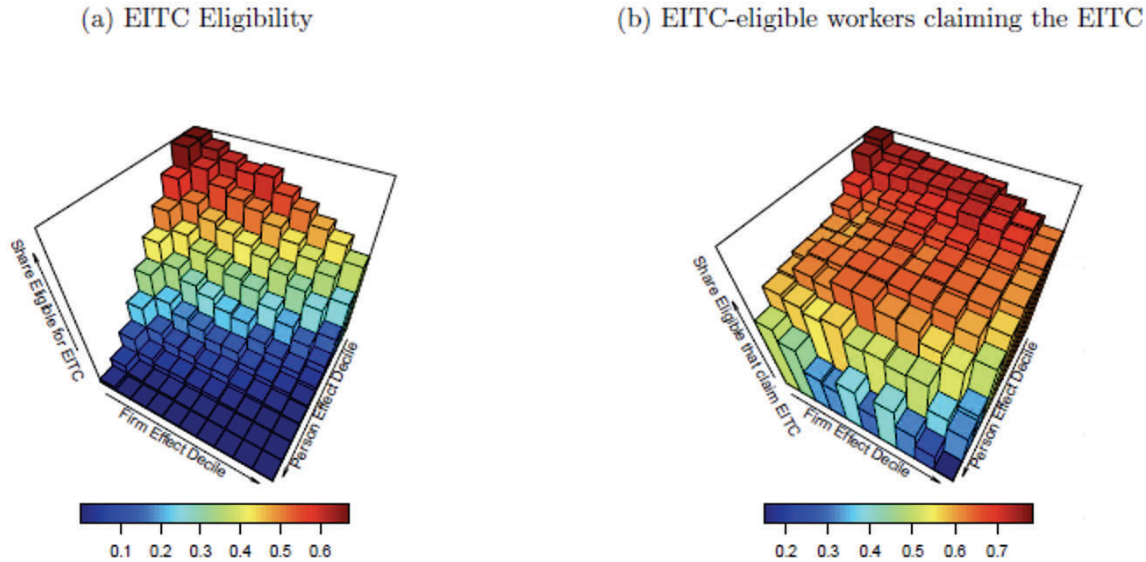


Appendix Figure C-6
Worker and firm effects by industry



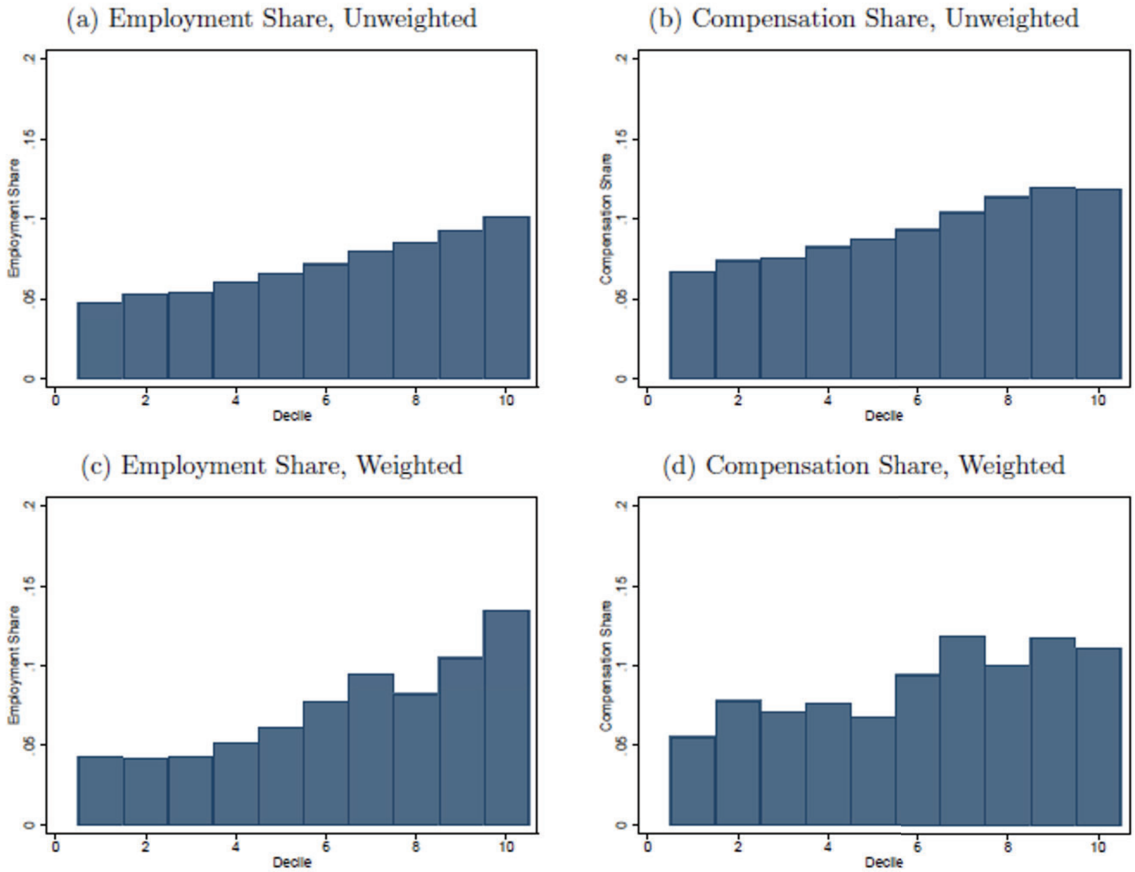
Notes: Marker locations represent average worker and firm effects in each industry. Marker sizes correspond to industry share of employment.

Appendix Figure C-7
EITC eligibility and take-up rates by worker and firm effects



Notes: Figures are based on the worker-level distribution, for individuals with W-2 earnings in TY2017. Tax unit eligibility and take-up are assigned to each worker in the unit. Estimated EITC eligibility is based on tax unit composition and reported AGI and earned income, and on the federal EITC schedule.

Appendix Figure C-8
Firm usage of independent contractors by firm effect



Notes: Figure shows the 1099 share of all workers (receiving either W-2s or 1099s) or of total compensation (the sum of W-2 wages and 1099 gross compensation) at the average firm in each decile of the estimated firm effect distribution. Weighted estimates weight by the number of workers or by total compensation, respectively.

Table C-1
Summary statistics for worker-firm earnings decomposition, by region

	(1) CA	(2) Los Angeles	(3) San Diego	(4) Bay Area	(5) Rest of CA
Log Earnings	10.388	10.324	10.392	10.707	10.326
Log Earnings SD	1.14	1.122	1.09	1.183	1.132
Mean Worker Effect	-	-.047	0	.215	-.037
Worker Effect SD	.818	.812	.782	.834	.812
Firm Effect Mean		-.013	-.001	.078	-.018
Firm Effect SD	.259	.247	.242	.283	.258
$X\beta$ SD	.287	.29	.285	.271	.291
Worker-Firm Effect Covariance	.057	.043	.048	.081	.057
Worker-$X\beta$ Covariance	.014	.013	.015	.021	.011
Firm-$X\beta$ Covariance	.011	.01	.01	.012	.01
AKM Residual SD	.513	.519	.496	.509	.513

Notes: Column 1 presents summary statistics for the full sample, while columns 2-5 divide the sample into four geographic regions. Worker and firm effects are each normalized to have mean zero in the full sample.

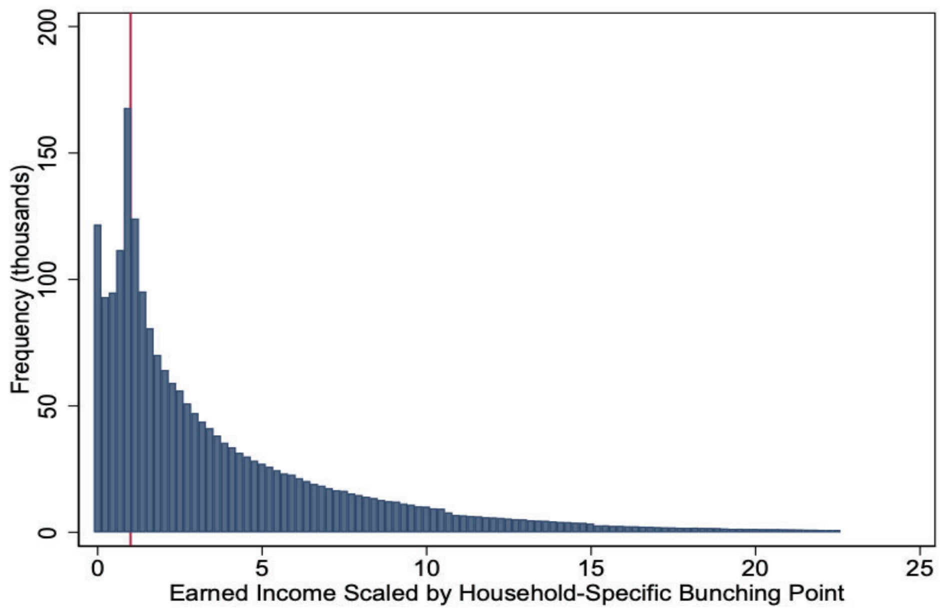
Table C-2
Summary statistics for worker-firm earnings decomposition, by industry

	(1) Log Earnings	(2) Firm Effect	(3) Worker Effect	(4)) % of Observations	(5) % of Firms
22: Utilities	11.22	.28	.42	.48	.19
	[.32]	[.17]	[.2]		
53: Real Estate and Rental and Leasing	10.49	.05	.02	1.35	2.39
	[.58]	[.25]	[.4]		
Missing	10.44	.01	.03	16.21	14.73
	[.64]	[.24]	[.36]		
62: Health Care and Social Assistance	10.43	.06	-.05	9.48	11.29
	[.6]	[.23]	[.36]		
48-49: Transportation and Warehousing	10.38	0	-.03	2.93	2.36
	[.45]	[.19]	[.28]		
61: Educational Services	10.23	-.19	.02	6.27	1.92
	[.35]	[.15]	[.25]		
81: Other Services	10.08	-.12	-.17	2.93	6.8
	[.66]	[.3]	[.42]		
56: Admin. and Support and Waste Management and Remediation Services	9.98	-.07	-.24	6.62	4.93
	[.67]	[.2]	[.4]		
71: Arts and Entertainment	9.98	-.14	-.16	1.51	1.6
	[.72]	[.26]	[.52]		
44-45: Retail Trade	9.98	-.12	-.19	8.87	7.93
	[.48]	[.19]	[.29]		
23: Construction	9.94	-.16	-.34	3.01	3.17
	[.8]	[.33]	[.51]		
21: Mining, Quarrying, and Oil and Gas Extraction	11.02	.39	.2	.16	.11
	[.34]	[.21]	[.29]		
72: Accomodation and Food Services	9.74	-.2	-.29	5.56	10.43
	[.39]	[.2]	[.24]		
11: Agriculture, Forestry, Fishing, and Hunting	9.67	-.21	-.47	1.62	2.16
	[.56]	[.23]	[.34]		
54: Professional, Scientific, and Technical Services	10.91	.16	.33	7.62	11.69
	[.69]	[.26]	[.44]		
51: Information	10.88	.21	.29	2.95	1.82
	[1]	[.29]	[.64]		
52: Finance and Insurance	10.79	.12	.24	4.13	2.77
	[.75]	[.23]	[.47]		
31-33: Manufacturing	10.75	.15	.13	7.64	6.41
	[.6]	[.23]	[.4]		
92: Public Administration	10.7	.04	.19	6.06	.27
	[.31]	[.13]	[.15]		
55: Management of Companies and Enterprises	10.68	.11	.14	.26	.15
	[.59]	[.18]	[.39]		
42: Wholesale Trade	10.67	.1	.13	4.33	6.89
	[.58]	[.24]	[.39]		

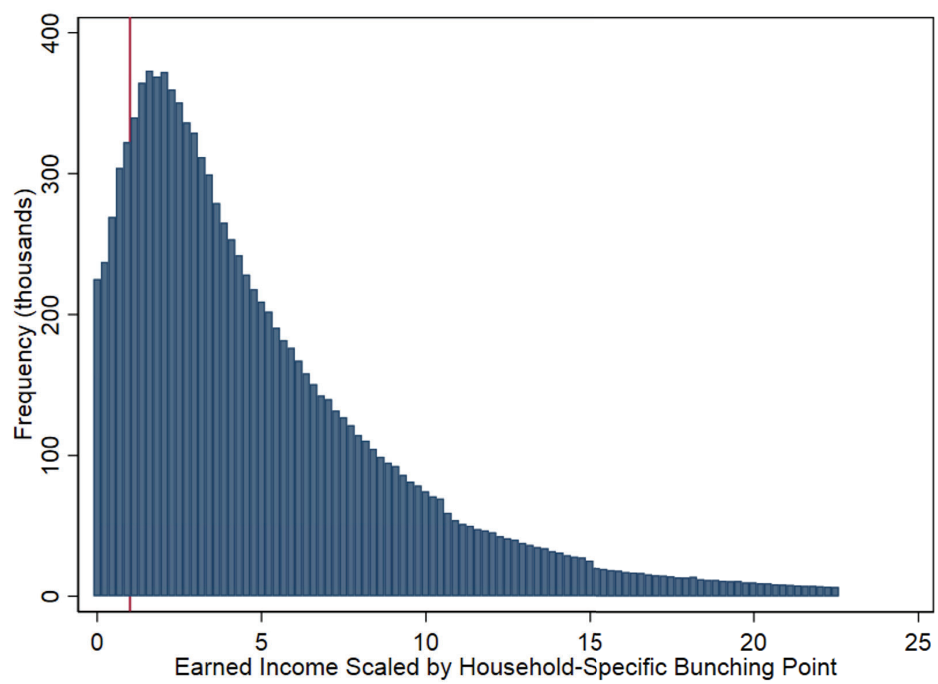
Notes: Columns 1-3 report means and standard deviations (in square brackets) of total earnings and estimated firm and worker effects, by industry. Firm effect distributions are weighted by the number of workers.

Appendix Figure D-1
Distribution of earned income relative to household-specific EITC kink point, by presence of Schedule C

A. Tax units with Schedule Cs



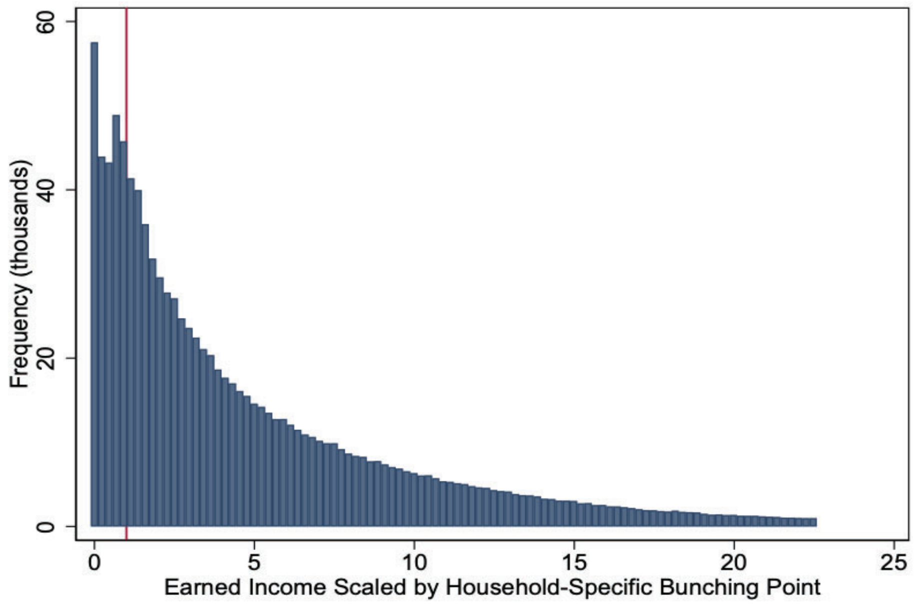
B. Tax units without Schedule Cs



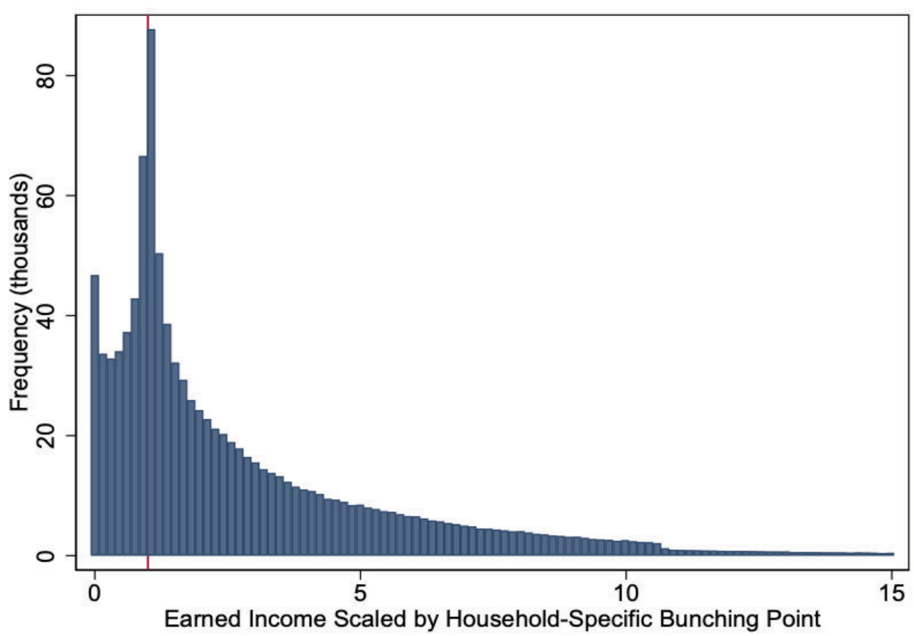
Notes: For each tax unit we use the tax unit size to identify the relevant federal EITC schedule. We then divide total earned income by the first kink point of that schedule, the minimum earnings at which the household would be eligible for the maximum EITC.

Appendix Figure D-2
Distribution of earned income relative to household-specific EITC kink point among Schedule C filers, by presence of dependents

A. Tax units without dependents

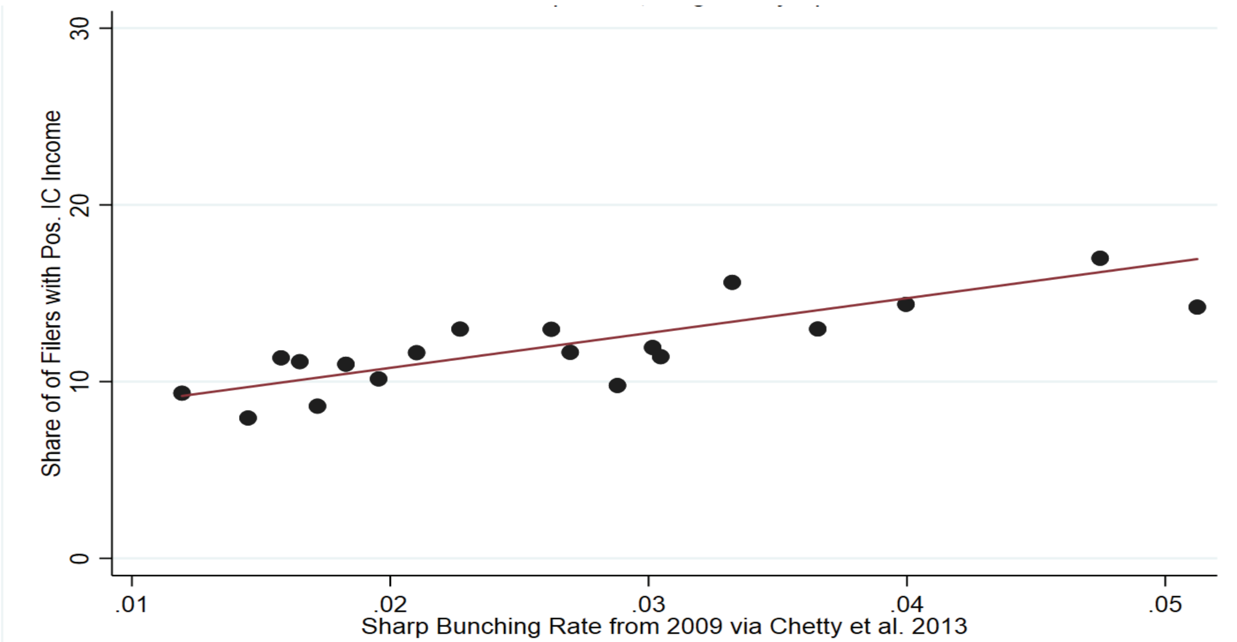


B. Tax units with dependents



Notes: For each tax unit we use the tax unit size to identify the relevant federal EITC schedule. We then divide total earned income by the first kink point of that schedule, the minimum earnings at which the household would be eligible for the maximum EITC.

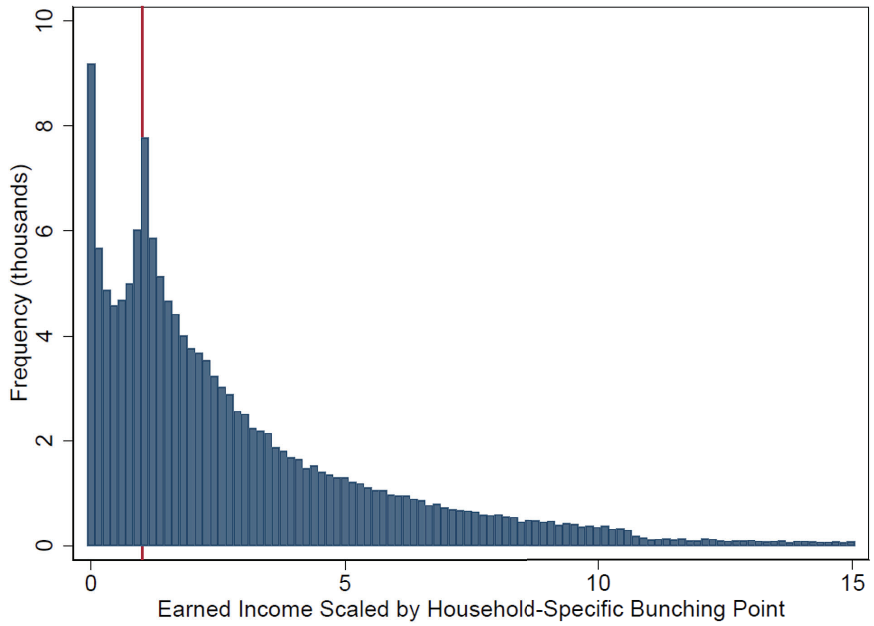
Appendix Figure D-3
Share of filers with positive IC income, by Chetty et al. (2013) sharp bunching rate for 3-digit zip code area



Notes: Each point represents an average for 5% of zip-3 areas, selected based on the Chetty et al. (2013) sharp bunching rate. Vertical axis represents the share of tax units in the area that we classify as having positive IC earnings.

Appendix Figure D-4
Distribution of earned income relative to household-specific kink point among Schedule C filers with dependents, by ratio of total 1099 earnings to reported Schedule C gross receipts

A. Schedule C gross earnings within 10% of total 1099 compensation



B. Schedule C gross earnings not within 10% of total 1099 compensation

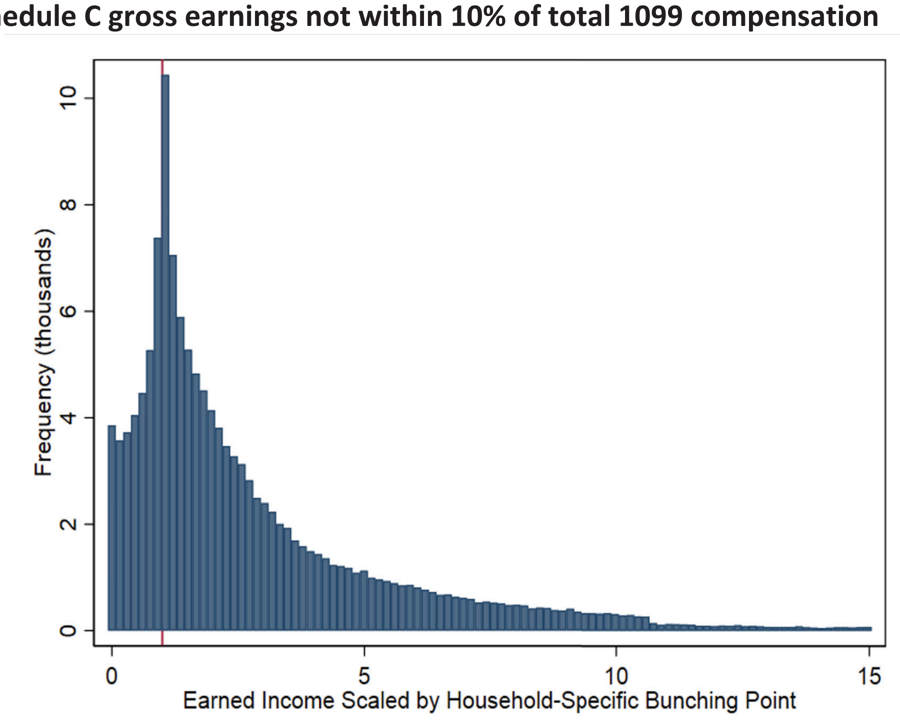


Table D-1. Proportion of earned income from W2 and/or Schedule C, working-age e-filers, 2016

Earned income source	E-filers		E-filers reweighted to remove bunching
	N (1,000s)	%	%
W2 only	11,912	85.6%	86.0%
Primarily (>=85%) W2	581	4.2	4.2
Mixed earners (15-85% W2)	383	2.8	2.6
Primarily (>=85%) Schedule C	67	0.5	0.5
IC Only	979	7.0	6.7
Total (age 18-64)	***13,923***	**100.0%**	**100.0%**

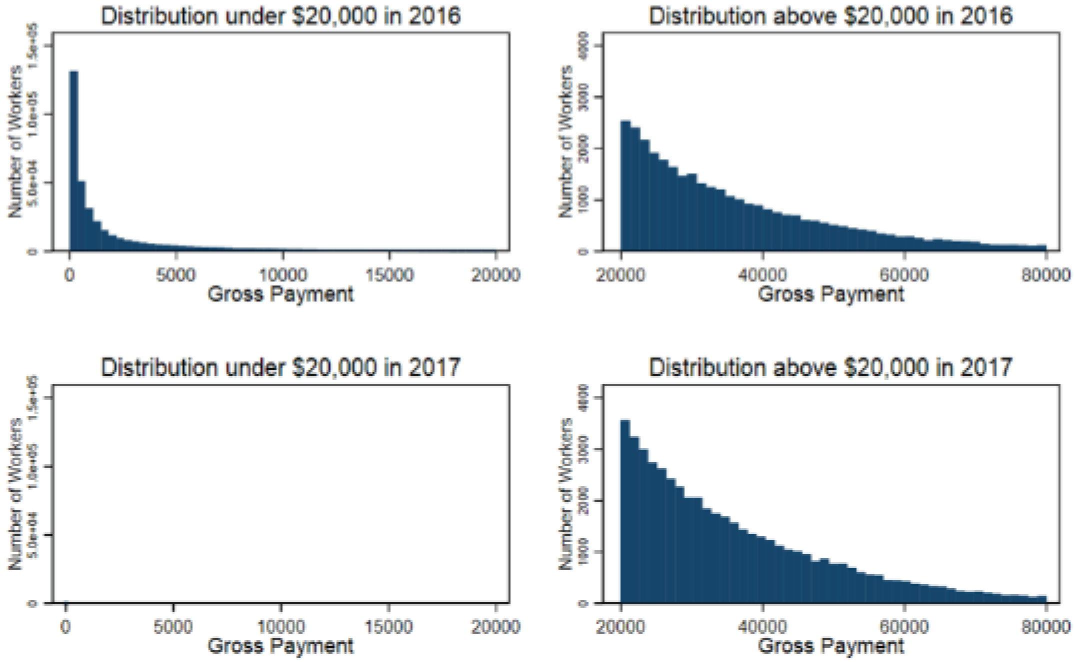
Note: Sample excludes individuals with zero earnings. Schedule Cs with zero or negative net profits are excluded. "Reweighted" column reweights returns with Schedule Cs and earnings near the EITC kink to eliminate the excess density there; see text for details.

Appendix Table D-2. Distribution across earnings deciles, by earnings type, after reweighting to remove bunching

	Distribution across deciles, by earnings type				Distribution across earnings types, by earnings decile		
	Prim. or excl. W-2	Any IC income	Prim. or excl. IC income	OPE wkrs	Any IC income	Prim. or excl. IC income	OPE wkrs
Decile							
1 ($1 - $7,605)	8.1%	20.2%	32.6%	18.3%	28.4%	23.4%	2.6%
2 ($7,606 - $14,014)	8.7	15.2	19.3	14.3	21.8	14.1	2.0
3 ($14,105 - $20,542)	9.3	13.4	15.5	14.4	18.9	11.2	2.0
4 ($20,453 - $27,561)	10.1	9.6	9.2	12.8	13.3	6.5	1.8
5 ($27,562 - $35,758)	10.4	8.0	6.4	11.8	11.1	4.6	1.6
6 ($35,759 - $45,742)	10.6	6.9	4.6	9.8	9.6	3.3	1.4
7 ($45,743 - $58,984)	10.7	6.4	3.5	8.0	8.9	2.5	1.1
8 ($58,985 - $78,454)	10.8	6.2	2.9	5.5	8.6	2.1	0.8
9 ($78,455 - $115,042)	10.8	6.3	2.6	3.4	8.7	1.8	0.5
10 (> $115,043)	10.6	7.8	3.5	1.8	10.8	2.5	0.3

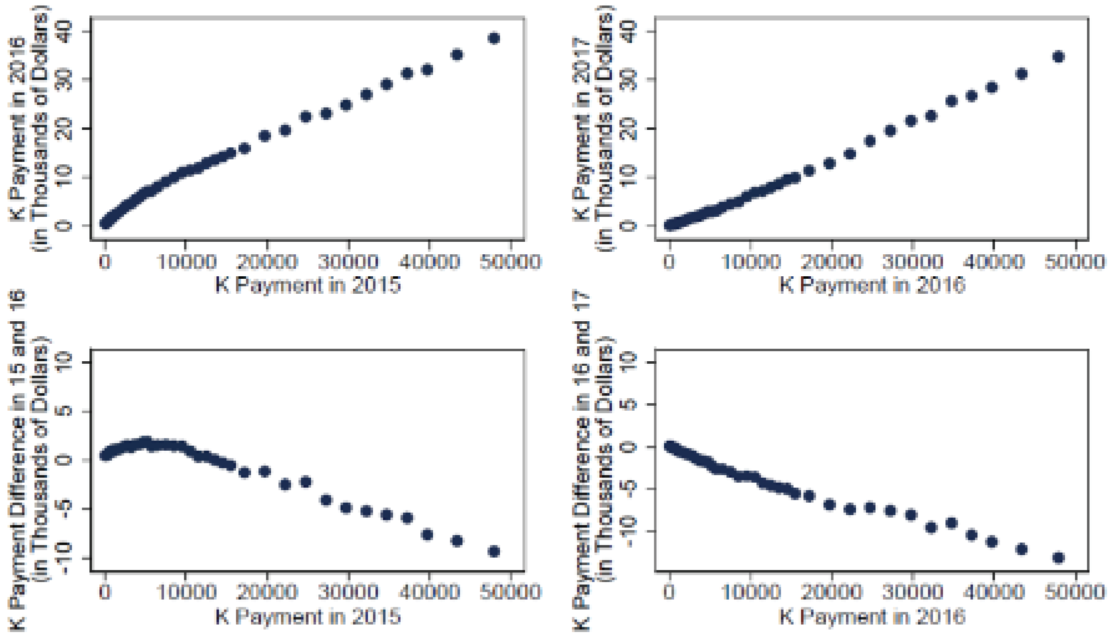
Note: Percentages sum to 100 within each of columns 1-4. Columns are not mutually exclusive. Columns 6-8 show row percentages.

Appendix Figure E-1
Distribution of 1099-K payment amounts in 2016 and 2017, selected OPE firms



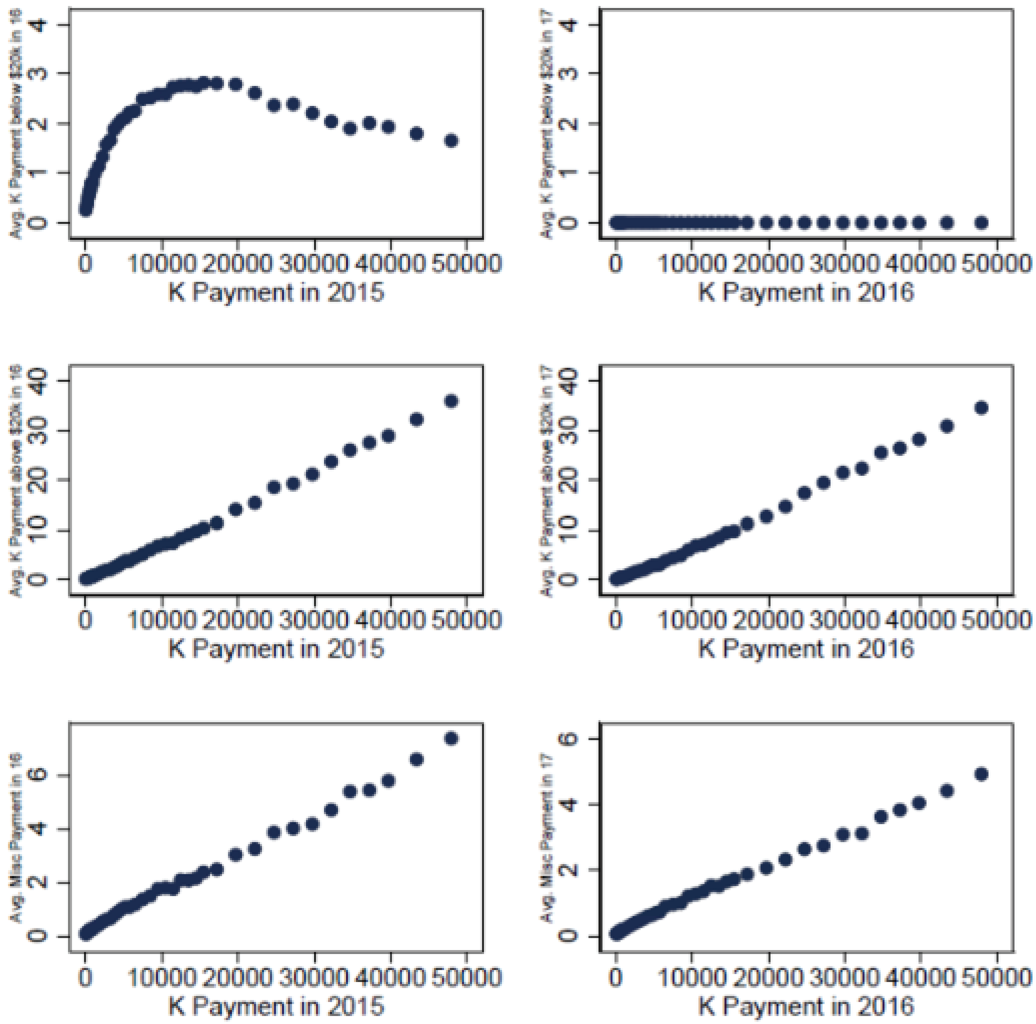
Notes: Frequencies correspond to counts of positive K payment on individual forms.
A worker may receive multiple forms from a firm in a given year.

Appendix Figure E-2
Relationship between 1099-K payment amounts in successive years, selected OPE firms



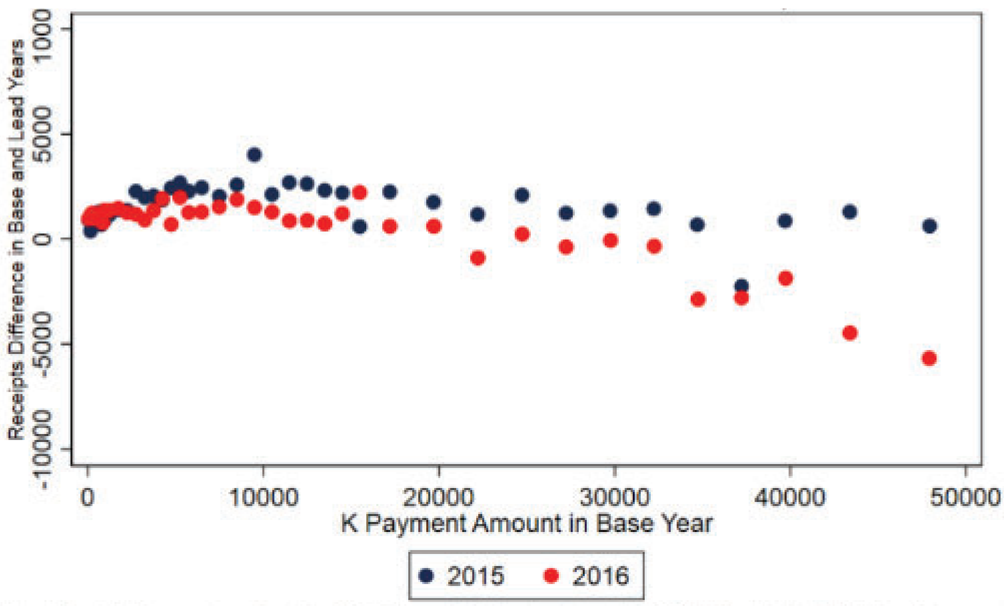
Notes: Sample includes workers with positive 1099-Ks from an OPE firm that adopted the $20,000 K threshold in 2017. K payment values correspond to worker earnings from the single OPE firm. Missing payment values are left missing in base years but coded as zeros in lead years.

Appendix Figure E-3
Relationship between reported 1099-K payment amounts in base year and other 1099 payments in subsequent year, selected OPE firms



Appendix Figure E-4

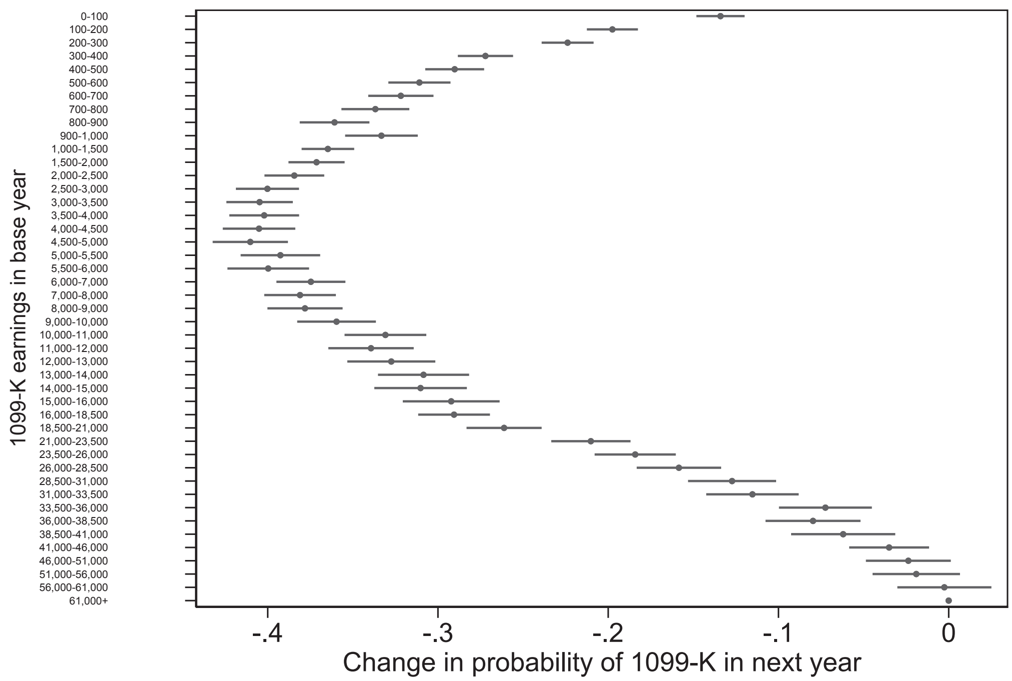
Year-over-year change in Schedule C gross receipts for workers at selected OPE firms in base year



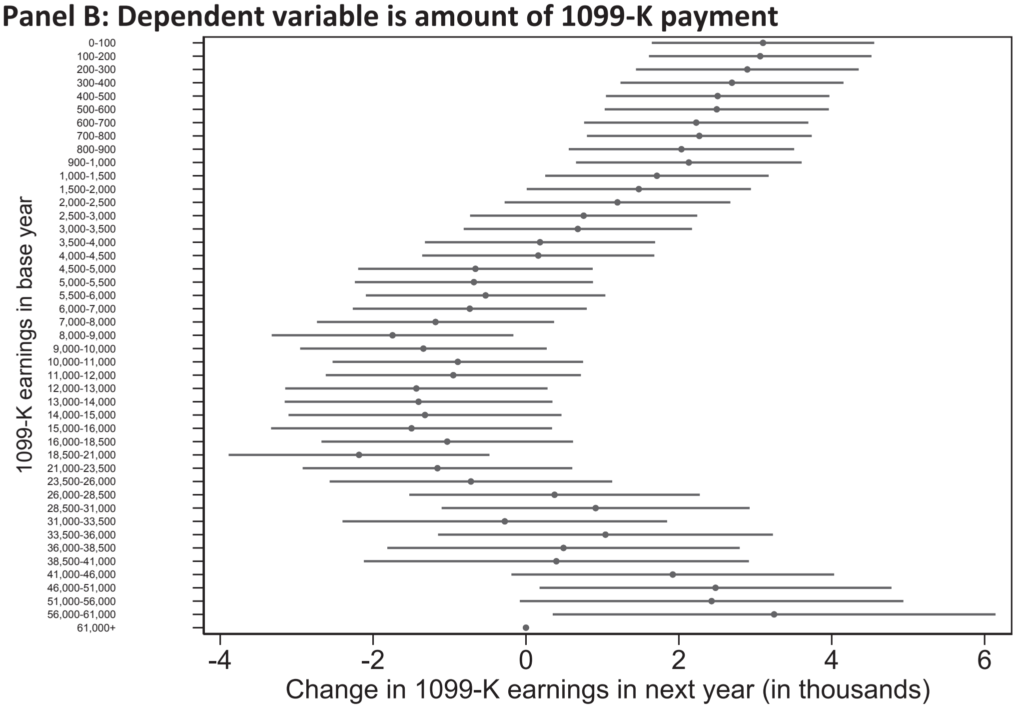
Notes: Sample includes workers with positive 1099-Ks from an OPE firm that adopted the $20,000 K threshold in 2017. Missing K payment values in base years are left missing. Missing Schedule C gross receipts in lead years are coded as zeros.

Appendix Figure E-5
First stage coefficients from 2SLS models

Panel A: Dependent variable is receipt of 1099-K



Panel B: Dependent variable is amount of 1099-K payment



Appendix Table E-1
Estimated effect of 1099-K receipt on tax return measures, 2SLS models

Outcomes	Coefficients and Standard Errors
Filed Schedule C	0.149***
	(0.011)
Schedule C Gross Receipts	5503.840
	(4101.498)
Schedule C Car and Truck Expenses	1994.286***
	(235.583)
Schedule C Net Profit	282.595
	(222.493)
OPE Indicator	0.724***
	(0.005)
W2 Earnings	-1557.471**
	(676.101)
Total Earnings (W2 + C Net Profit)	-1274.876*
	(695.401)
Adjusted Gross Income	3445.136
	(3057.786)
State Tax Paid	215.986
	(304.717)
Self-Employment Tax Paid	38.538
	(35.220)
Federal Tax Paid	817.861
	(720.501)

Notes: For each outcome, our sample includes 565,403 worker-years from a single OPE. Our regression models include a linear 1099-K payment term, 45 K payment indicator bins, and a constant, omitted from output above. The first four sets of 10 bins have the respective width of \$500, \$1000, \$2,500, and \$5,000. The last 5 bins have a width of \$5,000. Standard errors shows in parentheses are clustered at the individual level. $^*p\leq0.10$, $^{**}p\leq0.05$, $^{***}p\leq0.01$.