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THE EVOLUTION OF PLATFORM GIG WORK, 2012-2021

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ABSTRACT

We document the dynamics of tax-based measures of work mediated by online platforms from 2012 through 2021. We present a measurement framework to account for high reporting thresholds on some information returns using returns from states with lower reporting thresholds to provide a more complete estimate of total platform work. Updating data through 2021 allows us to provide the most comprehensive estimates of the COVID-19 pandemic on tax filing behavior. We find that the number of workers receiving information returns not subject to the 1099-K gap increased dramatically during the pandemic, with least 5 million individuals receiving information returns from platform gig work by 2021, nearly all from transportation platforms. We present evidence that the availability of expanded unemployment insurance benefits resulted in many individuals who were platform workers in 2019 not reporting any self-employment income in 2020-2021. At the same time, other services done by platform gig workers increased dramatically by at least 3.1 million people between 2019 and 2021. Interestingly, the broader 1099-contract economy follows a different trend, declining during this period, suggesting the challenges for tax administration are largely concentrated among platform gig workers, at least through 2021.

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1 Introduction

Work mediated by online platforms has emerged as a widespread phenomenon over the last decade. An expansion of work that is mediated by platforms rather than by employers has important implications for both tax administration and policy more broadly: As self-employed independent contractors, platform workers are not subject to tax withholding, are responsible for determining their tax liability, and are not subject to labor laws mandating minimum wages, overtime, or sick leave, and do not pay into state unemployment insurance systems. These millions of new workers engaging in platform work may not fully realize the tax implications of their work decisions. The COVID-19 pandemic has only put further policy and popular attention on platform work.

The first step in understanding the platform economy is having an ability to measure it. Earlier work by Collins, Garin, Jackson, Koustas, and Payne (2019) documented trends in freelance work reported on 1099 returns from 2000 to 2016 with particular focus on the role of gig work mediated by online platforms.[1] That work found that the prevalence of income from platform-based driving work—typically small annual amounts supplementing other employment—–expanded dramatically between 2012 and 2016, but no increase in the prevalence of other types of freelance work. Yet, the platform economy was still relatively nascent in 2016, and it is possible that platform gig work has continued to rise dramatically since then. More recently, the COVID-19 crisis and subsequent changes in the policy and economic landscape may have led to sweeping changes in the extent and nature of gig work. It is therefore important to extend measurement of platform work and gig work more broadly through present day.

This paper extends the analysis of Collins, Garin, Jackson, Koustas, and Payne (2019), focusing on the evolution of platform work between 2016 through 2021. A central challenge in measuring platform work after 2016 is the shift towards reporting platform payments on 1099-K subject to much higher \$20,000 reporting threshold beginning in 2017. Previous work has examined the introduction of the 1099-K on tax reporting, but has not focused on platform gig work specifically. Many platform gig workers are part-time self-employed and/or new to self-employment, which may provide new challenges for tax administration (Slemrod, Collins, Hoopes, Reck, and Sebastiani, 2017; Adhikari, Alm, and Harris, 2021; Adhikari, Alm, Collins, Sebastiani, and Wilking, 2022). In order to assess the size of any

[1] Other recent empirical research drawing on tax return data and other survey or administrative data sources has made strides in measurement of platform work (Jackson, Looney, and Ramnath, 2017; Farrell and Greig, 2016, 2018; Bracha and Burke, 2021; Lim, Miller, Risch, and Wilking, 2019; Greig and Sullivan, 2020), and we now have more research examining how and why workers use the platform economy (Koustas, 2018, 2019; Garin, Jackson, Koustas, and McPherson, 2020; Jackson, 2020).

resulting reporting gap, we merge state 1099-K information returns from Massachusetts and Vermont that are subject to a lower reporting threshold to the federal tax return data. We use the information available from these two states to estimate the national trend in platform work beyond 2016 and to explore the spillovers of changes in 1099-K reporting to individual reporting of self-employment earnings on Form 1040 Schedules C and SE.

A second key goal of our work is to document how the platform economy and tax reporting behaviors of gig workers evolved around the COVID-19 pandemic. We find that the number of workers with platform-based gig work payments grew dramatically around the pandemic, while the composition of platform workers shifted significantly. We document both widespread exit from and entry into platform-mediated work, with a net increase of 3 million workers (approximately 150% growth). One potential contributing factor to dramatic changes in platform work and tax filing during the pandemic was the Pandemic Unemployment Assistance program, which extended unemployment insurance (UI) benefits to platform workers excluded from regular UI systems. We present evidence that the availability of new PUA benefits resulted in many individuals who were platform workers in 2019 not reporting any self-employment income in 2020 and 2021. We show that this appears to be a real labor supply response rather than more activity falling below 1099-K reporting gaps. At the same time, platform gig work increased dramatically, driven by record levels of new entry. The surge in platform work among new entrants is driven almost entirely by nonemployee compensation payments from platforms on 1099-NEC rather than payments on 1099-K, consistent with a shift from ride-hailing work to delivery work observed in other data sources. We discuss the how this shift in activity has impacted the composition of the platform workforce and implications for tax compliance.

This paper is organized as follows: In the next section, we discuss the data used in this paper, introducing new state-level returns that have not been previously used to study the platform economy. We next show raw trends, and introduce our methodology to impute the overall size of platform work in the U.S. in Section 3. Section 4 outlines an empirical strategy to estimate the impacts of the 1099-K gap on self-employment tax filing, and presents results. Section 5 provides a detailed study on platform work during the COVID pandemic. We present raw trends and discuss sources of entry and exit. Section 6 examines the role of unemployment insurance extensions to platform gig workers, and the implications for tax administration. Section 7 places trends in platform gig work in line with trends in components of the workforce including other 1099-contract work broadly defined. Section 8 concludes with a discussion of future research directions.

2 Data and Imputation Methodology

In this section, we first discuss the federal and state tax data we rely on in this paper. State returns allow us to see platform activity that may be missing from federal returns after 2016. After describing these data and the various reporting requirements, we then describe how we combine the federal and state datasets to impute national estimates of platform work.

2.1 IRS data

In this work, we focus on gig workers who supply labor on platforms that primarily mediate labor activity, as opposed to selling or leasing platforms. For tax purposes, platform-based gig-economy workers are technically self-employed independent contractors. Crucially for our work, payments by *firms*–including online platforms—to self-employed contractors are reported directly to the IRS on 1099 information returns. Collins, Garin, Jackson, Koustas, and Payne (2019) provides an in-depth discussion of these forms and how they can be used to measure activity in the gig economy.

We measure participation in platform work based on receipt of an information return from a payer known to be an online platform. Updating Collins, Garin, Jackson, Koustas, and Payne (2019) to include platforms operating at any point through 2021, we focus on a list of over 90 different labor platforms that account for the overwhelming majority of payments to gig workers over the period studied. We observe payments to gig workers on three different types of information returns. First, firms have been required to report all compensation of \$600 or more to self-employed independent contractors in Box 7 of Form 1099-MISC ("nonemployee compensation") through 2019 and on its successor, the new Form 1099-NEC, beginning in 2020. Until 2011, all "freelance" or "gig" work done for firms or for clients through online intermediaries was reported as nonemployee compensation on 1099-MISC. In 2011, a new law went into effect requiring companies that processed credit cards, electronic payments, or other transactions to report each recipient's payments on Form 1099-K. Subsequently, several large platforms began issuing Form 1099-K instead of Form 1099-MISC non-employee compensation. We track the total payments individuals receive from these companies that are reported on either a 1099-K or on a 1099-MISC/NEC as non-employee compensation.

A potentially important limitation to studying the Form 1099-K is that platform companies classifying themselves as third party networks are only required to file this form if the total amount of such transactions exceeds \$20,000 and the aggregate number of such transactions exceeds 200. In practice, this did not impact our previous analysis through 2016, as most of the major platforms voluntarily issued 1099-Ks to all platform participants, regardless of the earnings level, prior to 2016, and/or issued a 1099-MISC. Beginning in 2017, however, some large platforms have announced changes in their reporting policies and have moved to only report income on the 1099-K if it met the higher reporting threshold legally required for the 1099-K. This problem of platform work no longer being measured due to it being below the reporting threshold is known as the "1099-K" gap. The American Rescue Plan Act of 2021 lowered the 1099-K reporting threshold to $600 with no minimum number of transactions beginning in tax year 2022, effectively bringing reporting back in line with the 1099-MISC. However, it was announced in December 2022 that implementation of this new rule would be delayed.

Despite the high reporting thresholds for Federal 1099-K reporting, several states have passed laws requiring state-level 1099-K reporting subject to lower thresholds. In the past five years, at least 9 states have introduced legislation to reduce state filing requirements for third-party settlement organizations who make payments to in-state residents, which would include online platforms. These states include California, Illinois, Massachusetts, Maryland, New Jersey, and Virginia. Details differ slightly across states, and we list these states and the detail of their policies in Appendix B.

One important note is that in most cases, these federal and state laws affect a broader swath of economic activity beyond just platform gig work. Most activity captured on the 1099-K is not platform gig labor income, but instead reflects credit card transactions by small businesses. However, for the most part, these laws affect reporting equally. The one exception is California, which explicitly lowered the reporting threshold only for "app-based drivers."

To learn about trends for 2017 and 2018, we examine state-level 1099-K data from Massachusetts and Vermont, states which have entered into data-sharing agreements with the IRS. Starting in 2017, both states require platforms to file state-level 1099-Ks to all payees with $600 or more in revenues. We use these state-level returns to examine how rates of gig platform work changed in those states over time. We then estimate how national platform work rates would have changed from 2016 onwards if the rates grew at the same pace as in these two states (MA/VT); we discuss our methodology below.

The scope of the 1099-K reporting gap is illustrated in Figure 1, which compares state-level 1099-K reporting and federal 1099-K reporting by online platforms to workers in MA/VT to other states. Through 2016, the distribution in MA/VT looked similar to the rest of the country. This changes beginning in 2017. While the distributions of both types of returns is nearly identical above the $20,000 threshold, there is a sharp drop in the number of federal returns—but not state returns—below the threshold. The fact that there is any mass below $20,000 reflects some platforms voluntarily reporting below the $20,000 threshold.

By 2018, some federal reporting still voluntarily occurs below \$20,000 in MA/VT, but not elsewhere in the country. The difference between the two data series represents the federal reporting gap resulting from the higher threshold.

3 Raw and Imputed Trends in Platform Work Since 2012

3.1 Trends in Federal and State 1099 Data

Panel A of Figure 2 plots the number of individuals with payments for work on gig platforms reported on information returns for each year 2012 through 2021. The blue line plots total counts of individuals with any payments on 1099-K or on 1099-MISC Box 7 (1099-NEC for 2020–2021), while the red line excludes payments on 1099-K less than \$600, the reporting threshold for non-employment compensation on 1099-MISC/NEC and the 1099-K threshold in MA and VT. The blue line documents the same rapid early growth of platform work through 2016 previously described in Collins, Garin, Jackson, Koustas, and Payne (2019). However, there is an abrupt shift in the trend in 2017 when platform companies largely ceased reporting any amounts below \$20,000 on 1099-K. One will note that the blue series ceases to be distinct from the red series, as we only observe 1099-Ks with amounts less than \$600 prior 2017 when major platforms still issued 1099-K below the \$20,000 threshold. Moreover, the red series hits a sudden plateau in 2017 and 2018——as will become clear below, this is because the most rapid growth prior to 2017 occurred among workers with small amounts of earnings.

Despite the widespread adherence to the higher reporting threshold, the red series in Panel A plateaus and never *declines*—and rises dramatically again beginning in 2020. Panel B of Figure 2 provides insight as to why this is the case by breaking down gig payments by form type. The Figure shows that while there *is* a decline in the number of workers getting 1099-Ks, there is growing number of workers with platform income reported as nonemployee compensation on 1099-MISC or NEC. One reason for this rise in nonemployee compensation reporting is because many platforms that issue 1099-Ks to workers also issue 1099-MISCs in certain circumstances. For example, while a ride-hailing platform might report processed payments from riders to drivers on 1099-Ks, any bonus payments to drivers that come from the company and are not paid for by any particular rider must be reported as non-employee compensation on a 1099-MISC—such payments have become more common over time.[2] Another reason is a dramatic shift towards gig work that is only reported on 1099-

[2] From 2018 onward, Panel B of Figure 2 shows that most platform workers with large amounts of earnings

MISC (for example, delivery driving) around the COVID-19 pandemic in 2020 and 2021; we discuss this in more detail below.

Figure 3 further breaks down the platform workers in Figure 2 Panel A by their primary activity and earnings amount. A striking finding is that in all years, the overwhelming majority of platform workers are primarily engaged in transportation and delivery work—note that the y-axis scale in Panel A of Figure 3, which plots the number of such workers, is an order of magnitude different than the scale in Panel B, which plots all other categories of gig workers. Moreover, we find that even after the 1099-K reporting thresholds become binding, only a small minority of platform workers earn more than $20,000 in annual gross platform earnings. These findings are is consistent with the findings in Collins, Garin, Jackson, Koustas, and Payne (2019), which documented that the vast majority of platform workers made small gross amounts and even smaller net profits after the typical 40-60 percent expensing rate. This patterns continues to hold through 2021.

A key question raised by the raw data is how much of the platform workforce is missing from the federal 1099 data due to the high 1099-K reporting thresholds. One way to learn about the size of the reporting gap is using available state-level 1099-K return data from MA and VT, which are subject to a $600 threshold consistent with the 1099-MISC/NEC. We explore these data in Figure 4, which compares the share of the tax workforce—individuals with any labor income—with platform earnings in excess of $600 reported on 1099s in MA and VT in comparison to the rest of the US.[3] Outside of MA and VT, we measure the prevalence of platform work using just the federal information return data, displayed in the solid black line. For MA and VT residents, we measure the prevalence of platform work using both the federal data and the 2017 and 2018 state-level 1099-K data. To examine the bite of the 1099-K reporting thresholds, we break out the subset of individuals in each year who receive at least one 1099-MISC/NEC from a platform or have a 1099-K with more than $20,000, whose would be counted as platform worker irrespective of the $20,000 1099-K threshold.

The dashed lines in Figure 4 show that that in both MA/VT and the US more broadly there was steady growth in the share of workers with platform earnings not affected by 1099-K reporting thresholds (either because their 1099-K earnings exceeded the threshold or because their platform earnings were reported on 1099-MISC). While this share was always

still reported on 1099-K also receive a misc. At the same time, many workers on platforms that issue 1099-Ks get a 1099-MISC from the platform but not a 1099-K——-this occurs if workers get bonus payments from firms but do not have receipts from clients in excess of the 1099-K reporting threshold.

[3]Following Collins, Garin, Jackson, Koustas, and Payne (2019), we define the tax workforce as all individuals with labor earnings reported on a W-2 return or on 1040 Schedule SE as well as 1040 filers with contract work payments on 1099 returns. The components of the tax workforce through 2021 are provided in Tables 1a-1b.

slightly larger in MA/VT than the rest of the country, the shares grew at similar rates in both regions between 2014 and 2018. However, when examining overall reporting of platform work (the solid lines), shares in MA/VT grow in parallel to the rest of the US (albeit at a higher level) through 2016, after which there is a clear divergence—–while the share of workers with platform payments reported on 1099 returns plateaus in 2017 in the broader US, there is continued growth in MA and VT where the 1099-K reporting threshold is $600. The observed trend in MA and VT after 2016 suggests that, had platforms consistently reported payments under $20,000 in the broader US, one would likely also have observed continued growth in the share of workers with platform earnings throughout the US beyond 2016. The similarity of the growth rates (thought not the levels) of the shares in MA/VT and the rest of the US through 2016 suggests one might obtain a reasonable estimate of the national prevalence of platform work in 2017 and 2018 by extrapolating the observed 2017 and 2018 growth in the platform worker share in 2017 and 2018 to the rest of the US, which we explore next.

3.2 Imputation of National 1099-K Gap: Methodology

We leverage the lower reporting threshold in MA and VT on State 1099-K forms in 2017-2018 to impute how these trends would have continued nationally if all states were subject to a lower $600 reporting threshold. In Figure A.1a, for Massachusetts and Vermont, we show trends in the receipt of 1099 forms (1099-MISC from any payer or 1099-K from an OPE platform) as a share of the overall tax workforce, which is defined as individuals with wages and/or self-employment on Schedule SE, or individuals filing a 1040 with a 1099-MISC or 1099-K from a gig platform. First, the share of the workforce with either a Federal 1099-K (from OPE platforms) and/or a Federal 1099-MISC is shown in black. In red, we restrict to individuals receiving a 1099-K of greater than $600. In practice, this restriction appears to only be binding in years 2014 and later, when some gig platforms start issue forms starting at $1. Finally, in the dashed red line we additionally include individuals who receive a state 1099-K from MA or VT. Starting in 2017 and 2018, the State 1099-K forms capture an additional fraction of the workforce who are earning between $600-$20,000 from gig platforms that no longer appear on Federal 1099Ks, as seen by the divergence of the red and dashed red line in Figure A.1a.

Our exact methodology for imputing national trends builds on the sub-components plotted in Figure A.1a and works as follows. When considering trends in OPE as a share of the workforce, the receipt of a 1099-K affects both our numerator (the 1099 workforce) and the denominator (the overall tax workforce); therefore, we must adjust both components accordingly. This affects the overall tax workforce (the denominator) because we include individuals in our tax workforce definition if they file a tax return, Form 1040, and have 1099 earnings even with no wages (W-2) nor self-employment profit (Schedule SE). Thus, absent the receipt of a 1099, we are not capturing them in the tax workforce definition, and so we need to account for both the change to the 1099 and tax workforce.

We define two groups of states: (1) those with state 1099-Ks, i.e. Massachusetts and Vermont (denoted "MA" for short in all equations that follow), and (2) all states nationally (denoted "NAT" in all equations). Our calculation proceeds in two steps. First, for 2017 and 2018, we impute how much the 1099 workforce grew relative to 2016. Second, we impute how much the "gig only" subgroup of the overall tax workforce grew —these are the only individuals that would not otherwise be counted (i.e. individuals with only a 1040 and gig 1099-K, and no W-2s, 1099-MISCs nor SE) —denote these $TWmultiplier^{NAT}_{2017}$ and $TWmultiplier^{NAT}_{2018}$. For both parts, we assume the groups grew nationally at the same rates in 2017 and 2018 as we observed in MA and VT.

3.2.1 Imputation Part 1: Adjust 1099 Workforce

First, we impute and adjust the 1099 workforce. In both MA/VT and nationally at baseline (in 2016), we calculate the ratio of the overall 1099 workforce including those receiving 1099-Ks (from OPE platforms) to the overall 1099 workforce excluding those receiving 1099-Ks (from OPE platforms). By calculating this at baseline, this flexibly allows for the possibility that 1099-Ks account for a different fraction of the 1099 workforce in MA and VT than they do nationally. These multipliers can be interpreted as how much times larger would the 1099 workforce be when you include 1099-Ks (from gig platforms) versus exclude them.

$$1099multiplier^{NAT}_{2016} = \frac{\text{1099 Workforce including 1099-Ks}^{NAT}_{2016}}{\text{1099 Workforce excluding 1099-Ks}^{NAT}_{2016}}$$
$$1099multiplier^{MA}_{2016} = \frac{\text{1099 Workforce including 1099-Ks}^{MA}_{2016}}{\text{1099 Workforce excluding 1099-Ks}^{MA}_{2016}}$$
$$1099multiplier^{MA}_{2017} = \frac{\text{1099 Workforce including 1099-Ks}^{MA}_{2017}}{\text{1099 Workforce excluding 1099-Ks}^{MA}_{2017}}$$
$$1099multiplier^{MA}_{2018} = \frac{\text{1099 Workforce including 1099-Ks}^{MA}_{2018}}{\text{1099 Workforce excluding 1099-Ks}^{MA}_{2018}}$$

At the national level, we can only calculate this ratio in 2016 due to the K-gap, however we can calculate this ratio in all years for MA and VT. We then assume that the share of the 1099 workforce receiving 1099-Ks grows nationally at the same rate as in MA/VT. We also account for different baseline (in 2016) 1099 multipliers in MA/VT and nationally in case

1099-Ks made up a different share initially. Therefore, nationally, we estimate the 1099-K workforce multiplier in 2017 or 2018 as the following:

$$1099multiplier_{2017}^{NAT} = \left(\frac{1099multiplier_{2017}^{MA}}{1099multiplier_{2016}^{MA}}\right) * 1099multiplier_{2016}^{NAT}$$
$$1099multiplier_{2018}^{NAT} = \left(\frac{1099multiplier_{2018}^{MA}}{1099multiplier_{2016}^{MA}}\right) * 1099multiplier_{2016}^{NAT}$$

Finally, we use the actual observed 2017 and 2018 national data on the 1099 workforce (excluding 1099-Ks), and our above multipliers to back out the size of the national 1099 workforce including 1099-Ks:

$$\textbf{Adjusted } \text{1099 Workforce including 1099-Ks}_{2017}^{NAT} =$$
$$1099multiplier_{2017}^{NAT} * \text{1099 Workforce excluding 1099-Ks}_{2017}^{NAT}$$
$$\textbf{Adjusted } \text{1099 Workforce including 1099-Ks}_{2018}^{NAT} =$$
$$1099multiplier_{2018}^{NAT} * \text{1099 Workforce excluding 1099-Ks}_{2018}^{NAT}$$

3.2.2 Imputation Part 2: Adjust Tax Workforce

In this second step, we account for the under-counting of the tax workforce size when we add in additional 1099-K recipients through the imputation. In practice, this change to the tax workforce is quite small as it only affects an already small subset of the tax workforce, the group we denote as gig only: individuals with only a 1040 and gig 1099-K or 1099-MISC, and no wages (W-2) or self-employment profits (Schedule SE). Our methodology is identical to above when we calculate the 1099 workforce multipliers. We compare the ratio of the gig only subset of the tax workforce when you include 1099-Ks to when you exclude the 1099-Ks. This multiplier tells you how much larger the gig-only tax workforce group is when you include 1099-Ks versus exclude them at baseline (in 2016).

$$TWmultiplier_{2016}^{NAT} = \frac{\text{Gig Only including 1099-Ks}_{2016}^{NAT}}{\text{Gig Only excluding 1099-Ks}_{2016}^{NAT}}$$
$$TWmultiplier_{2016}^{MA} = \frac{\text{Gig Only including 1099-Ks}_{2016}^{MA}}{\text{Gig Only excluding 1099-Ks}_{2016}^{MA}}$$
$$TWmultiplier_{2017}^{MA} = \frac{\text{Gig Only including 1099-Ks}_{2017}^{MA}}{\text{Gig Only excluding 1099-Ks}_{2017}^{MA}}$$
$$TWmultiplier_{2018}^{MA} = \frac{\text{Gig Only including 1099-Ks}_{2018}^{MA}}{\text{Gig Only excluding 1099-Ks}_{2018}^{MA}}$$

Again in 2017 and 2018, we observe in MA and VT how this multiplier grows relative to 2016. We assume similar growth nationally in this "gig only" group as we observe in MA and VT. We also account for baseline (in 2016) differences in the multipliers. Then in a similar method to above, we then can calculate the national multiplier for this gig only group in the tax workforce:

$$TWmultiplier_{2017}^{NAT} = \left(\frac{TWmultiplier_{2017}^{MA}}{TWmultiplier_{2016}^{MA}}\right) * TWmultiplier_{2016}^{NAT}$$
$$TWmultiplier_{2018}^{NAT} = \left(\frac{TWmultiplier_{2018}^{MA}}{TWmultiplier_{2016}^{MA}}\right) * TWmultiplier_{2016}^{NAT}$$

Finally, we can estimate the size of the gig only tax workforce in 2017 and 2018 with by using our multipliers and the actual observed size of the "gig only" group excluding 1099-Ks.

$$\textbf{Adjusted}\text{ Gig only Workforce}_{2017}^{NAT} = TWmultiplier_{2017}^{NAT} * \text{Gig Only excluding 1099-Ks}_{2017}^{NAT}$$
$$\textbf{Adjusted}\text{ Gig only Workforce}_{2018}^{NAT} = TWmultiplier_{2018}^{NAT} * \text{Gig Only excluding 1099-Ks}_{2018}^{NAT}$$

We then calculate the size of the tax workforce using the adjusted "Gig only" workforce above rather than the actual observed "Gig only" workforce counts. In practice, this means we use the measures for Gig only Workforce$_{2017}^{NAT}$ and Gig only Workforce$_{2018}^{NAT}$ in the tax workforce count when we sum up all the subgroups of the tax workforce. This leaves us with the final adjusted tax workforce numbers: **Adjusted** Tax Workforce$_{2017}^{NAT}$ and **Adjusted** Tax Workforce$_{2018}^{NAT}$.

3.2.3 Imputation Part 3: Final Steps to Create Imputed Series

We now combine the imputed values calculated in part 1 and part 2 in order to create our adjusted trends. The first imputed series that we create is the "adjusted 1099 Workforce share" - this is the share of the workforce with a 1099. The second imputed series that we create is the subset of the 1099 workforce that are platform gig workers.

The first imputed series is a simple fraction combining part 1 and part 2. The series demonstrates what share of the tax workforce is a 1099 worker. We take the "**Adjusted** 1099 Workforce inc calculated in part 1, and divide this by the adjusted Tax Workforce, calculated in part 2 using our imputed "Gig Only" workforce group.

$$\textbf{Adjusted}\text{ 1099 Workforce Share}_{2017}^{NAT} = \frac{\textbf{Adjusted}\text{ 1099 Workforce including 1099-Ks}_{2017}^{NAT}}{\textbf{Adjusted}\text{ Tax Workforce}_{2017}^{NAT}}$$
$$\textbf{Adjusted}\text{ 1099 Workforce Share}_{2018}^{NAT} = \frac{\textbf{Adjusted}\text{ 1099 Workforce including 1099-Ks}_{2018}^{NAT}}{\textbf{Adjusted}\text{ Tax Workforce}_{2018}^{NAT}}$$

The end result of our national extrapolation method, the share of the tax workforce who receive a 1099, is reported in Figure A.1b. Appendix C, we discuss alternative imputation procedures for estimates of platform work.

In our second imputed series, we break down the 1099 workforce into the subset who engage with an OPE platform. Recall from section 2, online platforms in the OPE issue 1099-Ks. Thus, 1099 individuals who do not engage in online platform work are not affected by the reporting thresholds as all such work is reported on 1099-MISCs. We accurately observe the 1099 Workforce Share *excluding* OPE workers in all years. Therefore, we can back out the imputed growth in the OPE as a share of the workforce as follows:

$$\textbf{Adjusted } \text{1099 OPE workforce share} = \textbf{Adjusted } \text{1099 Workforce Share} - \text{1099 Workforce Share } \textit{excluding} \text{ OPE}$$

The end result of this series is presented in figure 5, in levels, and is discussed in the next section.

3.3 Imputed Trends in Platform Work, 2012-2018

Panel A of Figure 5 displays our estimates of the size of the platform workforce in 2017 and 2018 in the US, letting the share of the national workforce with platform gig earnings grow at the same rate as in MA and VT from 2016 to 2018.[4] Two important takeaways from these estimates stand out: First, the number of platform workers in the workforce continued to grow through 2018 and exceeded 2 million in that year. Second, 770,000, or nearly one-third of platform workers in 2018, were missing in the federal 1099 data because of the high 1099-K reporting threshold. These individuals would appear in the data if the federal 1099-K had been subject to a $600 threshold.

To shed further light on the nature of platform work, Panel B of Figure 5 breaks down the platform workforce by whether their platform earnings come exclusively from transportation platforms. A striking finding is that nearly all platform work observed in the 1099 data is on transportation platforms, comprising ride-hailing and delivery apps. In each year since 2014, less than 10 percent of the platform-based workforce did something besides transportation-related work.[5] Panel B further breaks down transportation platform workers by whether they

[4]To examine the validity of extrapolating national trends from MA and VT data, we also display the predicted trend using this method going back to 2014 in the dotted line in Panel A of Figure 5. Reassuringly, the prediction prior to 2016 closely matches the observed national growth.

[5]Outside of transportation related platforms, OPE labor platforms include a wide variety of services including home repair services, creative platforms, tutoring, and social media content creation.

make more than \$20,000 in *gross* earnings totaled across all platforms.[6] In each year, only a small minority of workers on transportation apps make more than that amount.[7] Collins, Garin, Jackson, Koustas, and Payne (2019) show in greater detail that typical earnings in the platform economy are small—particularly when one takes into account that the typical platform worker reports expenses equal to 40-60 percent of gross revenues.

We use our imputed series to extend the main trend analysis from Collins, Garin, Jackson, Koustas, and Payne (2019) through 2018 in Appendix Figure A.2. In our analysis, we define the "workforce" as all individuals who receive any wage (W-2) earnings, 1099-reported contract earnings, or Schedule SE self-employment earnings.[8] To highlight the contribution of the online platform economy, the figure breaks out individuals who have 1099-reported contract earnings from online platform companies.[9] Contract workers may also have wage/salary earnings reported on W-2 returns. To highlight which contract workers depend primarily on such work for their livelihoods over the year, we break out contract workers into the subset who are primarily self-employed (i.e. those whose self-employment net profits on Schedule SE exceed their W-2 earnings) and contract workers whose self-employment profits supplement W-2 earnings over the year.[10] The baseline series only include 1099 returns issued to individuals' TINs, but we also display the series including 1099 returns issued to EINs linked to individual TINs using Schedule C for years 2007 onward in dashed lines. Panel A displays the prevalence in the full workforce, while Panel B restricts to individuals in the full-time workforce.

We observe substantial growth in the share of the workforce with earnings from online platform work in both panels of Figure A.2 beginning after 2012. By 2018, over one percent of the overall workforce in Figure A.2 Panel A had received payments for work on platforms.

[6] We utilize our imputed series in calculating this breakdown, and we have to make a couple of assumptions to split the earnings above and below the \$20,000 threshold among transportation related workers. The individuals with any other activity we observe directly. We also observe directly individuals with *gross* earnings over \$20,000 from a single platform. Thus, the remaining individuals come from our imputation in Panel A. All imputed individuals do not have total *gross* earnings below \$20,000 because a subset may work for multiple platforms and have a total of \$20,000 from multiple platforms despite no single platform paying them more than \$20,000. In 2016, we calculate the share of individuals with only 1099-K returns between \$600-\$20,000 *but* had total gross earnings of \$20,000 or more, i.e. they worked for multiple platforms. We impose this breakdown in 2017 and 2018 as a way of splitting the imputed workers across the subgroups.

[7] The number of workers with platform-based income from activities other than transportation tasks who make more than \$20,000 is very small and would be imperceptible in the figure.

[8] Following Collins, Garin, Jackson, Koustas, and Payne (2019), we only include individuals with 1099-reported contract earnings in the workforce when they receive a W-2 or file a tax return.

[9] A minority of online platform economy participants broken out in Figure A.2 also have contract payments on 1099-MISC for work outside the online platform economy.

[10] We cannot directly measure the share of net earnings workers derive from their independent contract work, because 1099 returns only report gross payments and not net income. Net income after expenses is determined on Schedule C; however, revenues reported or not reported on 1099 returns are not broken out separately so it is not possible to isolate the net earnings from 1099-reported contract work.

However, when we break out platform workers by whether their Schedule SE profits exceed their W-2 earnings, we find that in a large majority of cases such workers moonlight in the gig economy and derive the majority of their labor earnings from W-2 work.

4 Effects of the 1099-K Gap on Tax Reporting

In principle, the taxes owed by platform workers are invariant to 1099 reporting rules. Even if they do not receive a 1099, someone who makes profits as a platform worker still is required to report their earnings to the IRS on Form 1040 Schedule C, regardless of whether they receive the 1099 information return. In practice, however, platform gig workers with gross revenues below the 1099-K reporting thresholds might be less likely to report their platform income on a 1040 return—for instance, such workers may not be aware that such income is subject to federal taxes if they do not receive an information return. Thus, an important question for tax policy is whether gaps in 1099-reporting impact taxpayer filing behavior and tax revenues in practice.

In this section, we examine the impact of the 1099-K gap on individual tax filing behavior. To do this, we compare behaviors of workers living in Massachusetts near the state border with workers living on the other side of the border in adjacent states around the introduction of state 1099-K in 2017.[11] On the MA side of the border, workers continued to have all payments from platforms over \$600 reported on an information return, while workers living in adjacent states largely ceased to receive 1099-Ks for their platform earnings starting in 2017. Meanwhile, platform workers close to the border on either side operate in the same labor market and face identical labor conditions. Since states may have other differences in policy, we employ a difference-in-differences border design that compares differential evolution of outcomes on each side of the border around 2017. The identifying assumption is that there are no differential changes in policy or market conditions on opposite side of the border in around 2017 besides the introduction of the state 1099-K reporting.

In our baseline analysis, we focus on individuals in the workforce in 2016 who had earnings less than \$20,000 reported on a federal 1099-K in 2016. This is the group most likely to be impacted by changes in 1099-K reporting in 2017. The MA law does not just affect 1099-K reporting for gig workers, but for a broader set of economic activity, mainly by small businesses. We also conduct a similar analysis on a broader set of workers who had any reported wage or self-employment income in 2016. Massachusetts is a relatively small state with large counties; Figure E.1 shows that, for any county, the largest distance between a

[11] We do not include Vermont in our baseline analysis, given the small counts of total platform workers living near borders. However, we do include it in robustness results in the appendix

zipcode and the border is under 60 miles, but some counties, like Worcester county, extend from the top to the bottom of the state, and clearly reflect different labor markets. In our baseline specification, we restrict to workers who lived in zipcodes with a centroid within 15 miles of the border in 2016 and assign "treatment" status by their state of residence in 2016. Table 2 shows descriptive statistics. Column (1) reports descriptive statistics for 2016 gig workers in our baseline sample, while Column (2) compares descriptive statistics for the broader 2016 tax workforce.

Our main individual-level specification is given as follows:

$$y_{it} = \beta \mathbb{I}\{State_i = MA\} * Post_t + \delta_i + \zeta_{p(i),t} + \epsilon_{it} \tag{1}$$

where the subscript i indexes an individual. The individual fixed effects δ_i captures any fixed difference in policy or sample composition across states. We include county border pair by year fixed effects, $\zeta_{p(i),t}$, which limits our comparisons to sets of individuals in pairs of counties that border each other, but happen to be in different states by absorbing trends common to everyone in the county pair.[12] We conduct our analysis on data from 2014 to 2018, and the "post" period is defined as 2017 and 2018. We also estimate dynamic versions of the same specification with year-specific effects (relative to the omitted year 2016) in order to examine whether there were differential pre-trends across the border. We examine a balanced panel of individuals and code outcomes as zeros whenever no tax information is present.

Panel A of Table 3 reports the "first-stage" effects of the introduction of the low-threshold state 1099-K in Massachusetts in 2017 on the information returns individuals receive from gig platform companies. Incumbent platform workers in Massachusetts are about 20 percentage points more likely to receive a 1099-K, and 18 percentage points more likely to receive any information return from a gig work platform in 2017 and 2018 than individuals on the other side of the border—including zero observations, this amounts to a \$2,100–\$2,500 increase in reported revenues on OPE 1099s on average. Panels A and B of Figure 6 show how these effects evolved over time. Importantly, we observe that the 1099-reported earnings of platform workers trend in parallel until 2017 when a sharp change in reporting occurs around the introduction of the state 1099-K in MA, supporting our identifying assumption.

We examine the downstream implications for individual reporting in Panel B of Table 3. We find that introduction of the state 1099-K and the corresponding 20 percentage increase

[12] Note: one county can appear in more than one matched county pair, so the final dataset used in this analysis expands based on the number of county pairs. Each individual therefore appears once per border county pair their 2016 county of residence is a part of; we cluster at the individual level to account for this potential repetition of individuals.

in the share of individuals getting a 1099-K return resulted in 1.4 and 2.8 percentage point increases in the likelihoods of filing Schedule C and Schedule SE on a federal 1040 return, respectively. We observe that individuals report about $700 more gross receipts on Schedule C—about 30 percent of the increase in 1099-reported receipts. However, affected individuals also increase their reported expenses on Schedule C, resulting in a $420 increase in net Schedule C profits and a $328 increase in Schedule SE profits on average. Reassuringly, we find no estimated effect on third-party reported W-2 earnings, which should not be impacted by 1099-K reporting in any way. Panels C and D of Figure 6 show that these outcomes also evolve in parallel up until 2017, where reporting increases suddenly among individuals on the MA side of the border.

To benchmark the magnitudes of these individual reporting effects to the "first-stage" effects on receiving a 1099-K, we estimate two-stage least squares specifications in which we treat the receipt of a 1099-K or the amount reported on the 1099-K as the explanatory variable using $\mathbb{I}\{State_i = MA\} * Post_t$ as an instrument. The estimates from these specifications, which are presented in Table 4, quantify the pass-through of information return reporting to individual reporting on form 1040. We find that issuing a state 1099-K to an individual increases the probability of filing any Schedule C and Schedule SE by 6.4 and 12.3 percentage points respectively.[13] In dollar amounts, we find that each additional dollar reported on a state 1099-K that would have gone unreported otherwise raises receipts reported on Schedule C by 28 cents, Schedule C net profits after expenses by 17 cents, and Schedule SE earnings by 13 cents.[14] To explore whether these pass-through rates differ across different types of files, we present subgroup analysis in Appendix Tables E.3, E.4, and E.5—these present first-stage, reduced-form, and instrumental-variables estimates, respectively. Interestingly, we find that continuing to have platform payments reported on a state 1099-K had bigger impacts on Schedule C receipts of higher earners with a more established history of filing Schedule C in the past.

These results show that state-level 1099-K reporting made incumbent platform workers more likely to report greater amounts of earnings on Schedule C. However, the increase in Schedule C reporting relative to the increase in 1099-K reporting is fairly small. One likely possibility is that many experienced platform workers outside of Massachusetts continued to file Schedule C despite not receiving any 1099-K (though perhaps reporting lower levels of receipts than they might have otherwise). It is unclear, however, whether new entrants

[13]The impact on Schedule SE filing is larger because higher reported Schedule C profits increase the likelihood of exceeding the $433 Schedule SE filing threshold.

[14]Due to winsorizing of extreme positive values of receipts and expenses—which are only reported in positive amounts—and winsorizing of both positive and negative values of Schedule C net profits, the estimates in Column 4 are slightly different than the difference in the estimates in Columns 2 and 3.

into gig work in 2017 and 2018 who *never* had experience receiving a 1099-K would have the same familiarity with their reporting obligations—in that case, the tax filing behavior of new entrants to platform might be more sensitive to 1099-K reporting than their more experienced counterparts. Moreover, many small businesses received a 1099-K reporting receipts, which could have had broader impacts on tax reporting in MA.

To examine effects of closing the 1099-K gap on this broader population, we re-estimate out main specification on all individuals near the border who were active in the workforce in 2016. Examining the full workforce allows us to capture the entry margin, though the number of workers (and, moreover, the amount of earnings) affected by the changes in 1099-K reporting are likely very small relative to the overall workforce. The first stage results in Panel A of Table 5 show that the introduction of the state-level 1099-K in 2017 increased the share of the workforce with platform work earnings on a 1099 by about 0.4 percentage points amounting to about $40 more in revenues on average. We also find a 2 percentage point increase in individuals receiving a 1099-K from any payer, including non-platform work earnings, which corresponds to about $128 more in revenue. Interestingly, the results in Panel B of Table 5 show that this change increased the share of individuals filing Schedule C by about 0.4 percentage points, indicating that issuing state-level 1099-Ks was highly effective at increasing Schedule C filing—more than 3/4 of individuals getting a platform 1099 only because of the state-level reform were induced to file a Schedule C. However, the $38 increase in firm reported receipts is minuscule relative to approximately $6,000 in average Schedule C receipts in the sample; accordingly, we are underpowered to detect any impact on Schedule C receipts, expenses, or profits, and likewise for Schedule SE profits, among gig platform workers. These results are also consistent with there being limited changes in self-employment tax filing as a result of the additional information returns at low thresholds beyond platform gig work.

In Appendix Table E.1 and Appendix Table E.2, we show robustness to our sample restrictions. For each table, in Panel A we show results using the border counties for Massachusetts, and in Panel B we expand to include Vermont border counties. Comparing Panel A and B illustrates that our results are robust to including individuals in Vermont border counties. Each column shows robustness to restricting individuals to different distances (in miles) from the border. In our baseline specification, we restrict to workers who lived in zipcodes with a centroid within 15 miles of the border in 2016, but Appendix Table E.1 and Appendix Table E.2 show our "first-stage" effects of receiving an OPE 1099 are robust to a wide range of distance restrictions.

Finally, we combine our results in section 3 with our results from the border design to estimate the national tax gap resulting from the 1099-K gap. We estimated that 770,000 workers did not receive an information return due to the 1099-K gap. Multiplying 770,000 by $420, our estimate of increased Schedule C profits reported on the MA side of the border, yields an estimated 323.4 million in national unreported profits due to the 1099-K gap.

5 Platform Work and COVID-19

The COVID-19 pandemic had dramatic effects on many aspects of the U.S. economy. This challenge was met with dramatic policy responses and changes to the tax environment.

We begin exploring trends in platform gig work between 2017-2021. Since COVID was unique in many ways, imputation assumptions made prior to 2020 are unlikely to hold after 2019. Accordingly, in this section we report raw data from the period after 2017, when the 1099-K gap begins to bind. While likely undercounting total platform gig employment, our data series should at least be comparable over time in this period.

Figure 7(a) reports overall counts of gig platform work, with separate breakdowns by major gig industry: transporation and delivery;[15] "creater/influencer," defined as platforms where people are paid for posting original content; and all other platforms, which includes platforms providing online tutoring, tele-health and other professional services. As discussed above, we follow over 90 platforms by 2021.

The first takeaway is that transportation and delivery work remained the largest components of gig work, with other platforms continuing to represent only a small share of the overall gig economy. In 2020, we see a jump in gig work by around 1.2 million workers. Over 1 million comes from transportation and delivery, and an additional 150,000 comes from creator/influencer platforms. Platform gig work again expands dramatically by 1.9 million between 2020 and 2021, with 1.8 million having an information return from a transportation or delivery platform.

A second takeaway is that this was a period of record entry as well as exit. Figure 7(b) examines flows of entry and exit from platform work, showing that nearly 2.1 million new workers entered the gig economy in 2020 who did not do have an information return from the platform gig economy in 2019, a 100% increase over 2019. An additional 3.1 million entered in 2021 who were not participating in 2020. At the same time, exits also jumped. 1.2 million who had a platform gig 1099 in 2020 left by 2021.

Table 1a provides an update of Table 1 from Collins, Garin, Jackson, Koustas, and Payne (2019) with the number of unique individuals engaged in platform work through 2020, broken out by tax filing status. Appendix Tables G.1-G.3 show this same breakdown by state. Raw

[15] We combine these because some transportation platforms are also delivery platforms, and we cannot separately identify the two.

counts by state back to 2012 and Metropolitan Statistical Area (MSA) back to 2014 are provided in Appendix Tables G.5-G.6. As found in Collins, Garin, Jackson, Koustas, and Payne (2019), many platform workers do not file Schedule C/SE, or even file a tax return at all.[16] In 2018, just under 70 percent of platform gig 1099 recipients filed a Schedule C. This has fallen to approximately 60 percent by 2020. One reason for the low Schedule C filing rates may be small amounts of profits, after expenses.

The age and gender distribution pre COVID (2019) and post (2021) is shown in Figure 8. The platform economy is disproportionately comprised of prime-age workers ages 30-55. Even before COVID, the demographic composition of the platform economy has been changing, particularly for transportation and delivery work. More women have participated in platform work over time. First, looking at platform and delivery work, the distribution became much younger post-COVID, possibly reflecting lower perceived COVID risk among younger workers compared to older workers. The transportation and delivery workforce also became more female, with women now comprising 44 percent of this work by 2021. Among all other platforms, this workforce became even more female (66%), mainly shifting to women in their early 20s and 30s.

These trends in new entry and demographic changes suggest that many new entrants are doing self-employment for the first time, while many incumbent workers exit. Previous research has shown that many workers enter gig platform work following an economic shock, such as unemployment (see, for instance Koustas (2018, 2019); Jackson (2020)). We provide brief suggestive evidence on the economic shock channel in Tables E.7a-E.7b for wage-only workers in 2019. By the nature of the COVID shock, different industries were differentially affected: in some industries, like grocery stores, very few workers had slack demand, whereas demand fell dramatically for hospitality and restaurants industry. Industries that are more affected by COVID, as evidenced by higher UI receipt, are industries with *more* new entry into platform gig work, which is suggestive that entry was related to the size of the shock.[17]

[16] Not all taxpayers are required to file tax returns. Filing requirements vary by filing status and age. For tax year 2020, a taxpayer under the age of 65 filing as "single" must file a return if gross income is at least $12,400. However, the filing requirement for independent contractors is $400 for anyone with net earnings from self-employment of at least $400.

[17] Because our data are annual, we cannot determine whether individuals participated in gig work while simultaneously receiving UI.

6 The Role of Pandemic Unemployment Assistance (PUA)

In this section, we examine how COVID and the associated policy response interacted with tax administration opportunities and challenges for the gig economy. In particular, we examine the impact of unemployment insurance (UI) expansions to include self-employed workers, in a program known as Pandemic Unemployment Assistance (PUA). To what extent did extending UI to previously ineligible workers impact the gig economy trends and tax compliance in the above section?

Despite not paying into state UI systems, self-employed workers, as well as other ineligible workers, have sometimes received UI on a limited basis during times of natural disasters, through a federal program known as Disaster Unemployment Assistance (DUA).[18] Pandemic Unemployment Assistance (PUA), passed in March 2020, was modeled after the existing DUA program, but was on a much larger scale.

To qualify for PUA, a worker must not have been covered by traditional UI from a wage job. Eligibility included the self-employed impacted by COVID, as well as new entrants to the workforce, and even job-leavers who could provide evidence that they left their job due to a COVID-related reason, such as caregiving responsibilities for a child impacted by a COVID-related shutdown. The weekly PUA benefit was at minimum one-half the state average weekly UI benefit amount, but could be up to the maximum state benefit if a worker provided proof of earnings to justify a higher benefit amount. PUA recipients were also eligible for a weekly top up: first, the $600 Federal Pandemic Unemployment Assistance (FPUC), available from March-July 2020, and later the weekly $300 in "Lost Wages Assistance" (LWA) for up to six weeks for the rest of 2020.

While PUA was a federally funded program, the practical administration of the program was left up to the states. States first needed to verify that a worker was not eligible for traditional UI. Once that was verified, they also needed to determine whether someone could not work due to COVID. Unlike for traditional UI during COVID, states had much more discretion for eligibility determinations for PUA at this stage. Various guidance and directives were issued by DOL to try to clarify eligibility. For instance, on April 5, 2020, DOL released guidance that explicitly mentions ridesharing, which was the largest component of platform gig work prior to 2020: "a driver for a ridesharing service who receives an IRS Form 1099 from the ride sharing service... may still qualify for PUA benefits if he or she has been

[18] In Appendix F, we conduct a comparable analysis of the DUA program on self-employed workers after Hurricane Katrina. We see similar takeup, but considerably lower levels of annual benefit.

forced to suspend operations as a direct result of the COVID-19 public health emergency."[19] While attempts like this were made to clarify eligibility, DOL guidance remained vague and left considerable discretion to the states to determine eligibility, a point we will return to below.

While aggregate data on PUA claims by state are available, there are few sources of comprehensive and comparable microdata on PUA across states. Moreover, self-employed, and gig workers especially, to whom UI was extended can be particularly difficult to capture in survey data. We build on Larrimore, Mortenson, and Splinter (2021) and rely on UI as measured in IRS administrative tax records. In the tax data, annual unemployment insurance receipt is reported by states on Form 1099-G information returns (note: receipt of a 1099-G, like all information returns, does not depend on tax filing). However, these payments do not specify whether an individual receives PUA or regular UI. We next proceed to identify key groups of workers that would have received eligibility under PUA, rather than traditional UI.

Self-employed workers with a U.S. tax filing requirement are expected to file a tax form known as Schedule C to report their self-employment receipts and expenses. We link W2 information returns reporting any wage income, and focus on those who had negligible wage earnings in 2019, to ensure that UI eligibility would come from PUA and not traditional UI. We also restrict to self-employment profits less than $60,000 (approximately the 99th percentile for platform gig workers, and the 90th percentile for other self-employed), since higher earning self-employed may also be eligible for the Paycheck Protection Program (PPP). Self-employment encompasses many occupations and industries, which may have been impacted differentially by the pandemic. For this reason, we also zoom in on several industries as identified via self-reported NAICS codes on Schedule C. As a point of comparison outside of self-employment and a check for external validity, we also examine the cohort of graduating high-school seniors, who we identify as those turning 18 between September 2019 and May 2020.[20] In order to determine location and household circumstances, we restrict to such individuals who were claimed as a dependent on a tax return in 2018 or 2019. While we do not see high school attendance or graduation, high school graduation rates are quite high, giving us confidence that most of the individuals we identify would be graduating in 2020.

Note that unlike traditional UI, which is based on the location of your employer, PUA eligibility was determined by state of residence. We determine assignment of PUA based on the address in 2019 tax filings and information returns. For graduating seniors, we use

[19] See https://wdr.doleta.gov/directives/attach/UIPL/UIPL_16-20.pdf

[20] We do not examine graduating college students, since we would not know what labor market to assign them to after graduation for our research design.

the parents filing address in 2019, and if unavailable, we look back to 2018. We also study mortality based on the date of death as reported via a link with data from the Social Security Administration. Mortality is important to examine because COVID was of course a public health crisis and differential mortality could affect the interpretation of our results. For our 18 year olds, we also examine college attendance as proxied by receipt of a 1098-T information return, which are required to be filed by educational institutions for each student they enroll and for whom a reportable transaction is made.

We report descriptive statistics on our main groups of interest, their earnings pre-COVID, and UI receipt, in Table 6. We compare workers primarily working in the platform economy (Col 1), to those who had primary earnings from wage work (Col 2), to new entrants to gig platform work from wage work (Col 3) and to other primary self-employed (Col 4). We make a distinction between primary versus secondary earnings in platform work since those who were primarily engaged in platform work in 2019 were most likely eligible for new Pandemic Unemployment Assistance (PUA) benefits, compared with traditional UI.

We find that both lower rates of C filing for continuing platform workers, the increase in the share who are secondary platform workers, and new entrants, pulls down the overall SE filing rate among platform workers seen in Table 1a.

Column (3) tells us the baseline rates of Schedule C filing for new entrants in the year. C filing rates for new entrants are under 60 percent. Moreover, new entrants expanded dramatically, doubling between 2019 and 2021, and increasing by a similar amount again between 2020 and 2021.

Tax filing falls for all groups between 2019 and 2020. Schedule SE filing in the subsequent year falls more for primary gig workers than it does for secondary gig workers. This reflects more exit from platform work for primary gig workers, but also lower rates of SE filing in the next year, even conditional on still receiving gig platform income. This could reflect lower profits due to the COVID-19 pandemic.

Even in 2019 prior to COVID, a large share of workers have reductions in their primary source of earnings (defined as self-employment profits for primarily gig platform workers, and wages for all other workers) from year to year. Around half of those who were primarily platform workers had reductions in their earnings between 2018-2019. Platform work is often short-term, and participation is correlated with other negative income shocks, so part of this reduction in earnings from year to year reflects these other shocks. The share with year-to-year earnings losses rose 17 percentage points to 66.9 percent between 2019-2020. These numbers are similar for other primary self-employed.

In 2019, the economy was strong, and rates of UI receipt were quite low. Platform workers were not eligible for UI, unless they had eligibility from a wage job, and just 0.5 percent of primary platform workers in 2018 received UI in 2019. The highest rate of UI claiming was among new platform gig entrants in 2019, with 5.2 percent receiving UI in 2019. We see a completely different story for 2020, however. Over half of the 2019 primary platform workers received UI in 2020, compared with 37 percent of those with supplemental platform gig work in 2019, 32 percent of new gig entrants in 2020, and 25 percent of other primary self-employed. In terms of the targeting of this UI, while workers with earnings losses are more likely to receive UI, the rate of receiving UI without any primary earnings losses ranged from 15.3 percent among other primary self-employed, to 29.7 percent among 2019 platform workers.[21]

Conditional on receiving UI, the median amount of UI received in 2020 was 1.42 times 2019 platform earnings. This ratio was close to 1 for other primary self-employed, and 0.67 and 0.64 for secondary platform earners and new entrants, respectively. These ratios largely reflect differences in the earnings distribution across these workers. As shown in Appendix Table D.1, the amount of UI received in 2020 varied little with income: the average benefit received by primarily platform gig workers making less than $2,500 in 2019 was over $17,300, whereas the average benefit for those making between $30,000-$60,000 was around $19,700. As shown in the second to last row of Table 6, UI in 2020 dramatically lowered the share of workers with earnings reductions. Among new platform gig entrants, UI reduced the share with a primary earnings loss by 34.6 percentage points to 32.3 percent, lower than than 49.9 percent rate in 2019.

In Figure D.1, we examine the full distribution of earnings changes for each of these groups. We show that earnings losses were more extreme between 2019-2020 than between 2018-2019, especially for platform gig workers. After accounting for UI, the earnings distributions shift to the right, but this shift is much larger for those who were primarily platform workers.

While we examined earnings changes from 2018-2019 in Table 6, a more apt comparison might be to compare 2020 to past crises. While gig work is a relatively recent phenomenon, in Appendix F, we examine UI experience among self-employed, independent contractors broadly defined, and W2-only workers in two past crises: the 2007-9 Great Recession and in 2005 following Hurricane Katrina. The latter was notable because Disaster Unemployment Assistance (DUA) extended UI to self-employed workers. We show that UI takeup among self-employed workers in 2005 following Hurricane Katrina was almost as high as PUA, around 35 percent of self-employed and independent contractors took up UI. Despite these similar takeup rates, one important difference was that the amount of benefits received during

[21] This could partly reflect differences in timing, if someone receives UI early in the year and found better earnings opportunities later in the year.

COVID was much higher. This is because DUA only paid at most the maximum weekly benefit amount in Louisiana. As a result, the average amount of annual benefits received at the time was only around \$1,000.

Additional descriptive statistics on UI takeup across states and industries are provided in Table E.8. Row 1 refers to the 514 thousand workers we identified as primarily platform gig workers in 2019. Conditional on receiving UI, they received an average of \$18,400. This was substantially higher than median earnings for this group in 2019, which was around \$11,400.

If we examine the broader population who were primarily self-employed in 2019, around 25 percent of these self-employed-only workers received UI. However, we see variation across self-employment industries. For instance, 68 percent of those self-employed in personal care services in 2019 received UI.

A second takeaway of Table E.8 is that the share and amounts of UI received varied dramatically across states. Appendix Table E.9 presents the full distribution across states for gig platform workers, self-employed, and the cohort of graduating high-school seniors. For primarily platform gig workers, 75 percent received UI in MA, compared with 15 percent in Utah. Among other services, we see variation ranging from 19 to 70 percent. In industries like construction and general freight trucking, the variation across states ranges from 5 percent to 77 percent.

What generates the large differences in the share and amount of UI received across states? We hypothesize that these differences reflect two major factors: 1) the size of the pandemic shock faced by the state, and 2) differences in UI screening, program administration, and the interpretation of PUA eligibility across states, which we will refer to loosely as "PUA generosity."

To separate out these two hypotheses, we again employ the border design empirical approach, will allow us to separate out the role of PUA generosity from economic and pandemic conditions. Our main specification is run at the individual level and given as follows:

$$y_i = \beta G_{s(i)} + \delta X_i + \zeta_{p(c(i))} + \epsilon_i \tag{2}$$

where the i subscript indexes individuals, the $c(i)$ is i's county of residence, $s(i)$ is i's state of residence, and $p(c(i))$ is the border county pair of residence.[22] In our baseline estimation, we restrict to workers in county-border pairs, living in zipcodes that are at most 25 miles from a zipcode in the county-border pair on the opposite side of the border. We will show in our

[22]Note: one county can appear in more than one matched county pair, so the final dataset used in this analysis expands based on the number of county pairs. We two-way cluster standard errors at the county-pair as well as state to account for this.

robustness checks that our results are not sensitive to the choice of spatial bandwidth.[23] The key object of interest is β, which tells us the effect of G_s, a measure of state UI generosity, on y. Previous work studying UI generosity during the Great Recession has focused on measures like the number of weeks of extended benefits (Hagedorn, Karahan, Manovskii, and Mitman, 2013; Boone, Dube, Goodman, and Kaplan, 2021), the maximum weekly benefit, and maximum replacement rates (Marco and Kermani, 2013). As our main measure of genosity, we examine the (county-leave-out) state average annual UI benefit received (denote the county-leave-out $G_{s(-c(i))}$). We construct a county-leave-out measure to remove any mechanical correlation that may result from unobserved differences in the severity of the shock specific to that county. Using our measure, the interpretation of β is an ITT effect of the average differences across county border pairs, for every dollar increase in average UI compensation paid in the state.

Our specification also includes a set of county-level controls, including the log population of the county, the log area of the county, the percent of the county classified by the BLS as urban, and the percent of the population living in an urban area. In some specifications, we also consider individual-level controls for age, gender and presence of children.

Our main specification assumes that individuals living anywhere within 25 miles of each other are comparable. We also consider a spatial RD version of our specification. This specification has limitations. Particularly large population centers that may still have comparable workers may be located closer or further from the border, which is a problem in finite samples.[24] Nevertheless, if our results are robust to an RDD, specification, this provides some assurance our results are coming from sharp differences at state borders. The set up of our spatial RDD is as follows: Consider a border county pair indexed by $\{j, k\}$. Without loss of generality assume $G_{s(-c_j)} > G_{s(-c_k)}$, i.e. county j is on the more generous side. Define the differential generosity as $diff = G_{s(-c_j)} - G_{s(-c_k)}$, and an indicator for being on the "high"

[23]Note that our main specification is equivalent to the regression common to the literature run at the county-level weighted by the number of incumbent workers in the county:

$$y_c = \beta G_{s(-c)} + \delta' X_c + \zeta_{p(c)} + \epsilon_c \tag{3}$$

There are significant advantages to running our specification at the individual level. First, we are able to restrict the spatial bandwidth in the way described. Second, we will examine heterogeneity by individual-level variation by running our regression separately by demographic group (age terciles, gender, has children under 18 years old, has child under 6 years old, female and has child under 6 years old), and 2019 earnings. Third, we also consider IV estimates, as discussed below.

[24]There is disagreement on how to deal with this in the literature. For instance, Boone, Dube, Goodman, and Kaplan (2021) treat each county equally, whereas Dieterle, Bartalotti, and Brummet (2020)'s specifications are population weighted. Our baseline specifications are population weighted, but we also show our results are robust to weighting counties equally.

side as $high = \mathbb{I}\{G_{s(-c_j)} > G_{s(-c_k)}\}$. We now define our RDD specification:

$$
\begin{aligned}
y_c = {} & \alpha high + \beta diff \times high + \gamma_1 distance + \gamma_2 distance \times high \\
& + \delta' X_c + \zeta_{p(c)} + \epsilon_c
\end{aligned}
\tag{4}
$$

The coefficient β will identify a jump at the border, scaled by the size of the difference across border county pairs. We also consider a version allowing the linear trend to differ for every border-county pair.

For our border design to be valid, there have to be no omitted variables correlated with our measures of UI generosity and our outcomes, i.e. $\mathbb{E}[\epsilon_i | G_{s(-c(i))}, X_i, \zeta_{p(c(i))}] = 0$. Violations could take the form of contemporary or static differences across places. We can test for the latter by considering "placebo" versions of our outcomes, lagged by one year so that they refer to the period prior to COVID, to test they are unrelated to UI generosity in 2020. An example of a violation of the contemporaneous assumption would be that if states that had more generous UI also had other more generous benefits, such as food stamps or rental assistance. We do not have data on all these other state programs that we can link to our workers; however, based on the descriptive statistics described above, we believe PUA was first order. In a further robustness check, we also add in indicators for state and county-level policies related to COVID shut downs.[25]

In addition, spillovers across borders could affect the interpretation of our estimates to be the causal effect of UI policy in the state. Suppose one state is very generous compared with a neighboring state and labor supply responses to UI are large so that many workers in the generous state exit; this could increase demand and wages for workers in the least generous state, thus exacerbating differences across the two neighboring counties. To test for these spillover effects, we examine the following specification:

$$
y_i = \beta^{spillover} NG_{p(c(i))} + \delta' X_i + \gamma_s + \epsilon_i \tag{5}
$$

where $NG_{p(c(i))}$ is the generosity of the border-county's *neighbor*, and γ_s is a state fixed effect, hence absorbing state generosity. $\beta^{spillover}$ will estimate any differential effect depending on the bordering county's generosity.

The estimates from our main specification given in equation (2) are reduced form estimates of the effect of average state UI generosity. These reduced form estimates are the correct estimate for considering the effect of state generosity on average behavior. Another object of interest is the effect of *receiving* UI on an individual's behavior. To estimate

[25]Data are from the National Association of Counties (NACO) County Explorer, available at: https://ce.naco.org/?dset=COVID-19&ind=Emergency%20Declarations%20Type

this object, we also consider IV estimates of receiving an additional dollar of UI. Our IV specification is given as follows:

$$\begin{aligned} y_i &= \beta^{IV}\widehat{UI_i} + \delta' X_i + \zeta_{p(c(i))} + \epsilon_i \\ UI_i &= bG_{s(-c(i))} + d' X_i + z_{p(c(i))} + u_i \end{aligned} \tag{6}$$

We instrument the amount of UI received with the (county leave-out) state average amount of UI. The interpretation of our IV estimates is the effect on compliers, i.e. those who receive an additional dollar in UI because the state pays out more in UI. The same identifying assumptions in our ITT specification are required to interpret our IV estimates as causal, plus the the standard exclusion restriction, which would require that state PUA generosity impacts UI claiming only through receiving UI. One violation would be spillover effects of PUA generosity that increase demand for gig work, which we will be explicitly testing for. One source of comparison with our estimates of earnings responses to increases in UI are estimates of the Marginal Propensity to Earn out of unearned income (MPE). Receiving income from UI in a given week is typically conditional on not working in that week; therefore, our estimates in (6) are a combination of the MPE plus any moral hazard effects leading to a reduction in annual labor supply.

For disclosure purposes, we restrict our regressions to counties that had at least 10 workers of a particular group in 2019. This is most binding for primary platform workers, since these workers tend to be more concentrated in urban counties. There are 276 counties with at least 10 platform workers in 2019; these counties are shown in the map in Figure E.2. We exclude New York City for our baseline estimates, since institutions differed (some rideshare drivers were eligible for traditional UI). As discussed above, our baseline estimates restrict to individuals in zipcodes whose centroid is within 25 miles of a zipcode on the opposite state border, but we will also examine robustness to other spatial bandwidths.

6.1 Results

6.1.1 Balance Checks

We begin with a series of balance checks. Table E.10 reports results from running our main specification (where the measure of generosity is the county leave-out unconditional state average of UI received by the group, in thousands of dollars) on outcomes at baseline: age, sex, presence of children, and 2019 measures of wages and adjusted gross income. We do this separately for our three main groups of interest: primary platform workers, all other self-employed, and the high-school graduation cohort. Platform workers look similar on most dimensions, including 2019 earnings. Platform workers in states with more UI generosity appear slightly older but the difference is small– the point estimate implies for each $10,000 difference in UI, platform workers are less than 1 year older, and we interpret this as likely coming from sampling variability. Other self-employed workers in states where UI was more generous appear to have slightly lower 2019 adjusted gross income, but the difference is not statistically significant. Our approach will be to examine these outcomes in *changes* to net out any of these pre-existing differences. Table E.13 examines balance by selected self-employment industries and finds similar results. The final column examines high-school graduation cohorts. Instead of 2019 earnings, we examine 2019 parental AGI. We find no statistically significant differences.

6.1.2 ITT effects

Our baseline results from running Specification 2 are reported in Tables 7a-7e, for primary platform workers, other self-employed, and the cohort of graduating high-school seniors, respectively.

We begin by examining outcomes for platform gig workers in Table 7a. We examine 1099 receipts, Schedule C receipts, Schedule C profits, Total Earnings (wage + profits), any indicators for any Schedule C in 2020 and 2021.

Our key finding is that for each dollar increase in UI given by the state, reported receipts fall by between 50-60 cents, and self-employment profits fall by 22 cents for primary platform workers. Total earnings, the sum of profits plus wages, falls only slightly more, around 24 cents, suggesting that most of the effect comes from reductions in reported profits. Column (3) of the bottom panel reports the first stage: $1 in average UI paid out by the state to platform workers predicts 50 cents of UI received, after conditioning on border county pair fixed effects and controls. Given our instrument is the state average UI, the first stage should be mechanically close to 1 if we exclude the county-border pair fixed effects and controls. The fact that the first-stage relationship between the individual values and average state values have a slope closer to 0.5 suggests about half of the predicted relationship is due to common factors across border country pairs and our controls. Combining the behavioral effect of the reductions in total earnings with the direct increase in income (plus changes in EITC receipt) means that for every dollar in UI paid out, average income increased by around 25 cents. Since we are examining reported Schedule C earnings, these earnings are subject to changes in tax reporting behavior. We examine additional reporting outcomes around self-employment and find most of the reduction in reported Schedule C receipts is confirmed by firm-reported 1099s. Further, we do not see any evidence of differential expensing of self-employment income on either side of state borders. The effect on Any Schedule C in 2021 is a rough proxy for exiting self employment. Given the unconditional average UI amount was around 10,000, the point estimate of -0.005233 implies that exits increased by 10*(0.005233), or about 5 percentage points, due to PUA, a relatively modest decline given the size of entry.

Panel (b) examine our results for a subset of platform gig workers with more substantial profits greater than $15,000 in 2019. We find our results are even stronger. An important question is whether our estimates are interacting with the 1099-K gap described above. For instance, if an individual with receipts greater than $20,000 in 2019 fell below $20,000 in 2020 due to slack demand, this could result in less reported on a 1099 and lower profits reported to tax authorities. We investigate this in Panel C. In Columns (1)-(2) we interact our measure of generosity with a MA/VT indicator. Column (2) narrows the bandwidth to 10 miles, as we did above. By 2020, three other states implemented similar laws lowering reporting thresholds. In Column (3), we interact generosity with this broader set of states. We find no statistical difference in states with lower 1099-K reporting thresholds, suggesting this is a real labor supply response and not due to the 1099-K gap.

Moving on to other self-employed, we find somewhat smaller reductions in reported receipts, but similar reductions in total profits or 0.21. The ITT response for high school seniors is also very similar, 0.22. However, note that the first stage is stronger for these groups, 0.7 cents for self-employed workers and 1 for graduating high-school seniors, suggesting that the border county pair fixed effects and controls account for little of the variation. For graduating high school seniors, our estimated effect comes almost entirely from a reduction in W2-reported wage work, rather than self-employment profits reported to IRS, providing additional evidence of a true labor supply response rather than a change in tax reporting.

6.1.3 IV effects

We now turn to IV responses. For gig platform workers, the first-stage relationship was about 0.5, and our IV estimates are approximately double the magnitude of our reduced form estimates. The IV estimate implies that for every dollar in UI received, total earnings fell by 48 cents. The related IV estimates for other self-employed are -28 cents and -22 cents for high school seniors.

We next examine heterogeneity in our IV estimates by demographic groups for primary platform workers and other self-employed in Figure E.6a. We consider the following groups: bottom tercile of age (age <33); middle 50 percent of age (ages 33-53); top tercile of age (ages 54+); sex (as recorded by the SSA); presence of a spouse on a 2019 return; presence of a working spouse, defined as a spouse who had W2 earnings in 2019; having a child under 18 (based on SSA birth records); having a child under 6; being female and having a child under 6; and 2019 earnings bins (<$7,500, $7,500-$15,000, and $15,000+). For the most part, the results are fairly similar across different demographic groups. For other self-employed, but especially for gig platform workers, effects are largest for those who had more earnings in 2019. The effect size grows in magnitude to around -30 cents for self-employed earning between $7,500-$15,000. For gig platform workers, the reduction in earnings is around 80 cents for earners making more than $15,000 in 2019. This pattern is opposite of the direction of the replacement rate. However, our results are consistent with patterns observed in Golosov, Graber, Mogstad, and Novgorodsky (2021) among lottery winners.

In Table E.6b, we break self-employment by industry and calculate IV estimates and compare results to the control complier means (CCMs)— the counterfactual change in earnings in the absence of UI. We see some heterogeneity across industries that appears correlated with the CCMs. Industries like real estate, finance and insurance, wholesale trade, and retail trade all show the largest declines, and have the largest counterfactual earnings in the absence of UI.

This seems consistent with what we saw above for gig workers. The number of platform gig workers actually grew dramatically, driven by waves of new entrants. These new entrants were primarily engaged in food and grocery delivery work, which saw demand expand rapidly during 2020. In contrast, the incumbent platform workers were mainly rideshare drivers that saw demand for their services contract sharply. Switching/search costs to delivery may have been low for incumbent rideshare drivers. In the language of the search and matching literature, the job finding rate per unit of search for other gig jobs may still have been high. Similarly, high school grads commonly take part-time jobs in grocery stores, which had high demand during 2020.

6.1.4 Robustness

Table E.11 examines additional robustness of our estimates. In row 2, we add in policy controls for state and local policies on COVID emergency orders and state at home policies. Our main specification included gig workers with secondary wage earnings. Row 2 excludes these workers. In row 3, we add in individual controls (age, presence of children). Our results are stable in all these specifications. In row 4, we weight each county equally instead of population weighted. Our results are noisier but the point estimates are similar.

The next set of robustness checks test the assumptions regarding our spatial research design. Our default spatial bandwidth was to restrict to zipcodes within 50 miles of the county border. The key identifying assumption is that UI generosity changes sharply at the border. In row 5, we do the Dieterle, Bartalotti, and Brummet (2020) correction of controlling for the average distance of the population center for each state border. In rows 6 we report results from the spatial RDD following specification 4. In Figure D.3, we examine the robustness of our main results to alternative spatial bandwidths, ranging from no restrictions, to up to 10 miles to the border. Our results are stable up to 10 miles to the border.

In row 7, we report our test for spillovers from specification 5. We find no evidence of large spillovers from neighboring counties, except possibly for high school graduates, although the result is imprecisely estimated.

What makes the COVID crisis unique from prior economic shocks is that it was also a public health crisis. We next examine an admittedly extreme health outcome, mortality, as a check that mortality effects are not driving our results. There are two main channels by which UI could reduce mortality: by reducing workplace exposure if a worker reduced their labor supply, or through income effects.

We report ITT estimates for mortality, and we scale the independent variable to be in *thousands* of dollars for readability. Thus, the results are interpretable as the mortality effect for every additional $1,000 in UI benefits issued by a state.

We begin by examining results for gig platform workers for whom we saw the largest reductions in labor supply. We do see a mortality reduction, concentrated among the oldest ages (ages 54+, the oldest quartile for platform workers). We report the exact point estimates for workers aged 54+ in Column (1) of Table E.12a. To provide more context on magnitude, our result implies that going from the 25th to 75th percentile in state average UI ($6,000→$11,000) reduced mortality of older gig platform workers by -0.00069*5=0.3 p.p., or (0.003*100,000 gig workers 52+)=300 deaths. In Column (2), we examine outcomes including controls for state and local policies, and find our results unchanged. Placebo outcomes lagged by one year show no statistically significant effects (Column 3). In contrast to gig workers, we do not see any estimates of the same magnitude for self-employed more broadly. There is a statistically significant reduction for the youngest quartile of workers, but the point estimate of -0.0001 is 1/7 of the size for older gig workers.

We examine heterogeneity in Tables E.6a-E.6b. The only statistically significant result is among the platform gig workers ages 54+.

Since we saw in Figure E.6a that UI reduced gig worker labor supply proportionally across age groups, and we know that COVID was more virulent for older individuals, the differential reductions in mortality for older gig workers seems most plausibly driven by COVID, as opposed to alternative explanations such as reductions in work-related injuries (including car accidents) or income effects that might be expected to affect workers of all ages in a more equal manner. We investigate this channel further in Table E.12b and Figure D.4 by interacting our mortality finding with whether someone had a wage-earning spouse (spouse and wage-earning status are defined as of 2019). Having a wage-earning spouse likely provided more opportunities to bring workplace exposure home, even if a gig worker reduced their own labor supply. We first check that we do not find any differential reduction in individual or household labor supply by presence of a working spouse (Columns 1-2). We find our mortality reduction is entirely driven singles and those with non-working spouses. The estimated own mortality reduction is nearly completely mitigated by the presence of a spouse who worked (Column 3). We do not see any evidence of mortality reductions among SE workers overall, or in SE industries with small reductions in labor supply, suggesting that the mortality reduction is through the reduction in labor supply, rather than income effects alone. Perhaps the closest result in the literature comes from Sullivan and von Wachter (2009), who find increases in mortality across all age groups following job displacement.

7 Experience of Platform Work Compared to Other Components of the Workforce During COVID

So far, we have mainly examined raw counts of gig work during COVID. How did contract work evolve as a share of the tax workforce? How does the experience of platform work compare to other components of the workforce, in particular, other 1099 contract work?

A natural comparison would be to examine trends in the immediate years pre/post COVID. Table 1b provides raw counts including 2019, and Figure A.3 shows raw trends as a share of the workforce. An issue that arises measuring non-employee compensation during this period is that that, due to administrative complications related to the pandemic in 2020, paper 1099 MISC returns for tax year 2019 (filed in 2020) were not fully processed.[26] This is readily apparent in A.4, which shows that although there was a sharp drop in 1099-MISC returns filed, there was no drop whatsoever in electronically-filed returns and thus the drop was entirely due to paper returns (the residual category). As nearly all gig platform firms and large employers file electronically, this mainly effects smaller non-platform 1099 firms that issue 100 or fewer 1099s. 2019 drops precipitously because of the incomplete processing of paper returns.

We make progress in two ways. One simple solution is to ignore 2019 and compare trends in contract work with 2018. Table 8a reports counts by NAICS 2 industries as self-reported on Schedule C. Interestingly, we see that other 1099 contract work declined, by 12.5 percent between 2018 and 2020 and 22.9 percent between 2018 and 2021. We find that other 1099 contract work declined quite broadly across all NAICS 2 industries. In panels (b) and (c), we examine workers with above and below 15,000 in profits, and find results that are qualitatively similar for low and higher earners.

[26] See "IRS Statement – Information Returns," May 13, 2022. https://www.irs.gov/newsroom/irs-statement-information-returns

A second approach is to estimate the undercount in 2019 directly. Figure A.4 shows that the share of 1099 returns with non-employee compensation that were filed electronically was growing time before 2019—specifically, the ratio of all returns (paper and electronic) to electronically filed returns declined linearly from 2014 to 2018, with 2020 returning exactly to the 2014–2018 trend line. If all electronic returns were processed but not all paper returns, and the true ratio if all returns were processed remained on the trend line, then the true total number of 1099 returns should be given by the observed count of electronic returns in 2019 times the predicted ratio of all returns to electronic returns. This gives a total number of 1099 returns with nonemployee compensation that is approximately 1.3 times the observed total. We therefore estimate 2019 levels by inflating the number of individuals with 1099 nonemployee compensation by a factor of 1.3

We implement our fix in Figure 9 to provide a consistent series on platform and other contract work as a share of the tax workforce. Outside of platform gig work, contract work was very stable between 2018 and 2019. During 2020 and 2021, platform gig work grew dramatically, both as a share of the tax workforce and as a share of contract gig work. As of 2021, platform gig work comprised 3.15 percent of the workforce, and 30 percent of all 1099 contract work. However, other 1099 contract work declined, resulting in overall decline in gig contract work broadly defined. Putting our trends together, the broader 1099-gig economy, inclusive of platform gig work and other contract work, fell from 10.8 percent of the workforce in 2018 (11.1 percent in 2019, according to our imputation), to 10.3 percent in 2020, rising slightly to 10.5 percent in 2021.

8 Conclusion

One of our contributions in this paper was to incorporate state tax data with lower reporting thresholds to overcome the 1099-K gap that becomes more binding in 2017. We use federal and state tax data to document the dramatic increase in platform work since 2012, reaching more than 2 million workers by 2018. We estimate that more than 1/3 of these workers did not receive any information-reporting of their gross receipts.

A second contribution was to examine the evolution of platform gig work during the COVID-19 pandemic. COVID saw another dramatic increase in platform work, with around 3 million new workers, most of whom worked for a transportation or delivery platform. We also saw growth to a lesser extent among creator and influencer platforms. The pandemic accelerated a shift in platform worker towards young workers and especially women, who have become more represented among platform workers over time. Most workers engage part-time with platform work, and only around 60 percent file self-employment taxes in recent years, conditional on having information-reporting of their activity.

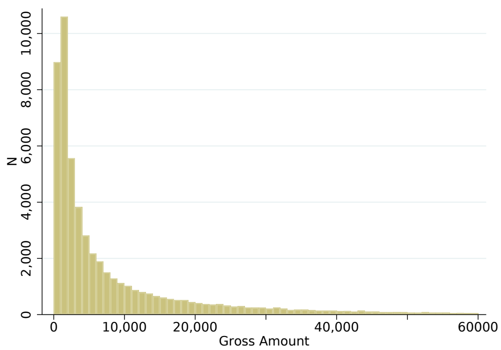
Whether COVID-19 represents a permanent change in platform work or we will return to previous trends remains to be seen. However, many new workers engaged in self-employment and platform work for the first time. Interacted with the 1099-K gap, this may have prompted new compliance issues for 2020-2021 for platform gig work. Comparing to broader trends in 1099 contract work, the picture is mixed on whether COVID was a watershed moment for the gig economy. While platform gig work increased, COVID does not appear to have fundamentally shifted the overall prevalence and nature of contract/SE work—and may have decreased it.

Figures

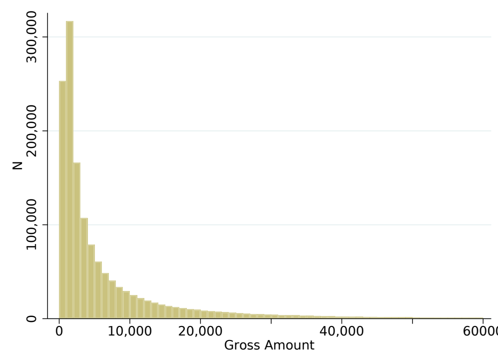
Figure 1: Distribution of Online Platform Economy 1099-Ks Issued to MA/VT Residents, Federal versus State Data

2016

(a) MA/VT

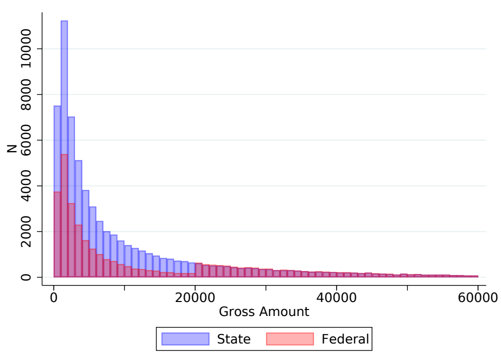


(b) All Other

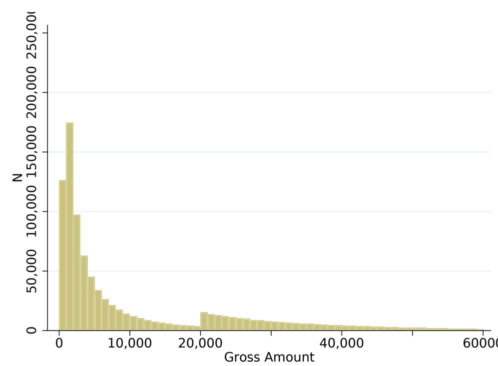


2017

(c) MA/VT

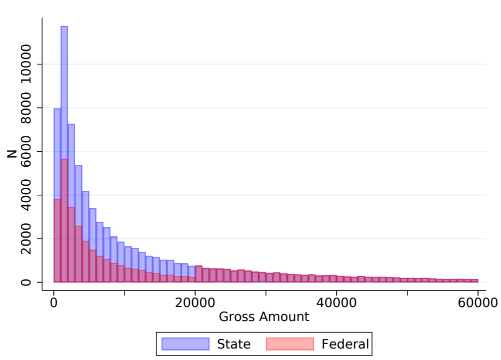


(d) All Other

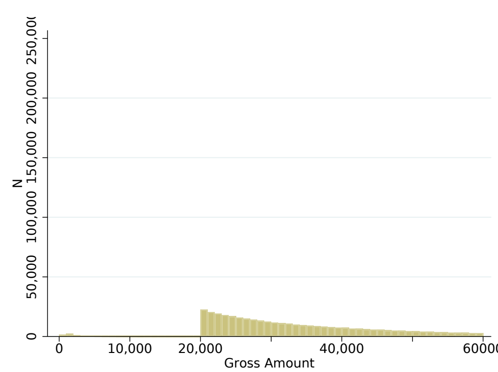


2018

(e) MA/VT



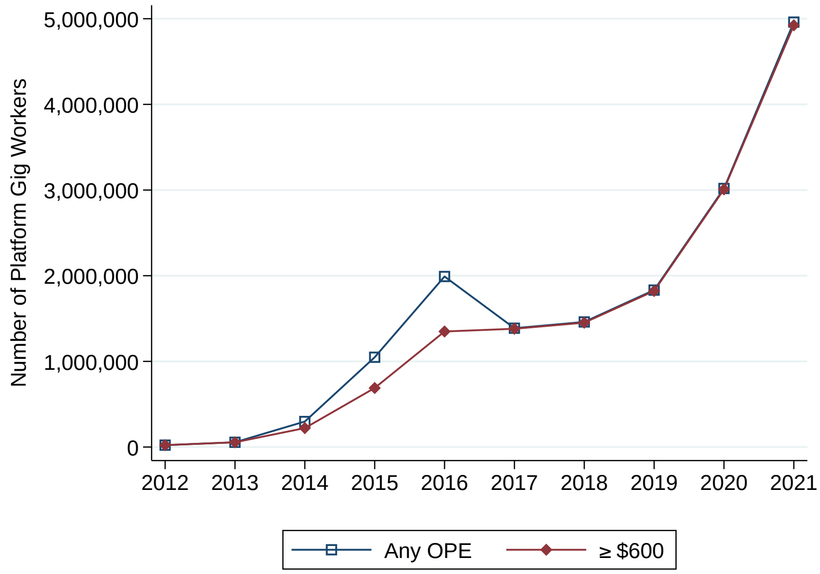
(f) All Other



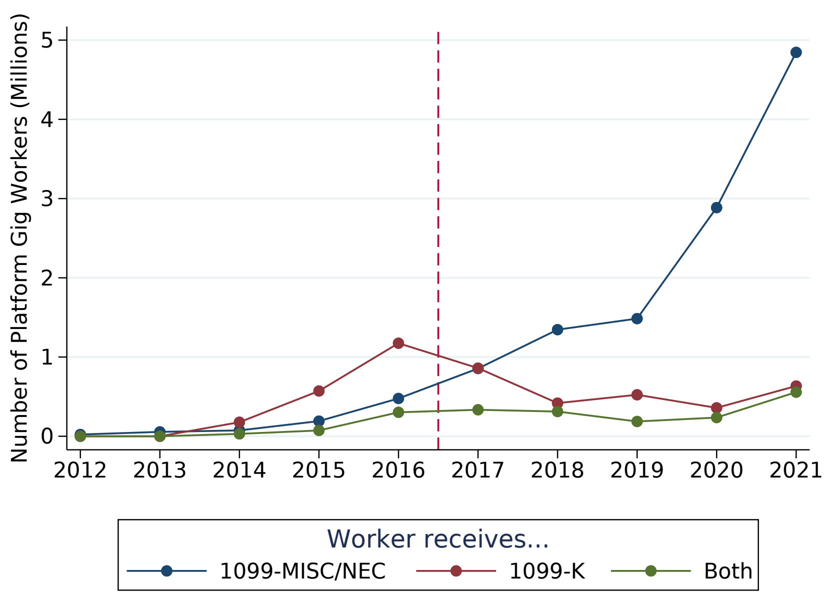
Note: The histograms document the distribution of 1099-K amounts $\geq$ \$600 in 2016-2018 for platform gig payers. Left-hand panels restrict to the states of Massachusetts and Vermont. The red distribution represents the Form 1099-Ks issued at the Federal level, while the blue distribution represents those issued by the states of Massachusetts and Vermont in 2017-2018. All other panels show federal 1099-K data only.

Figure 2: Raw Trends, Platform Gig Work, 2012-2021

(a) Individuals with Any Payments for Platform Work



(b) Number of Individuals by Information Return Received

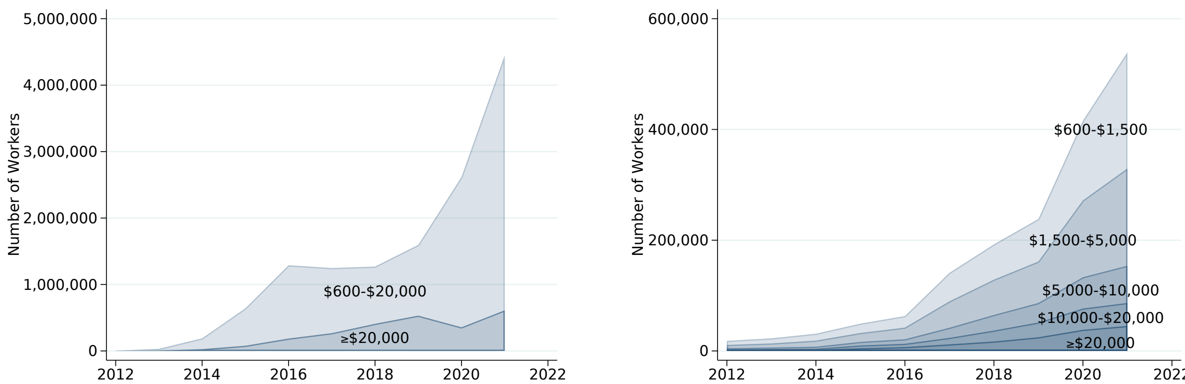


Note: B restricts to $\geq$ \$600 in gross receipts.

Figure 3: Gross Earnings in Platform Gig Work

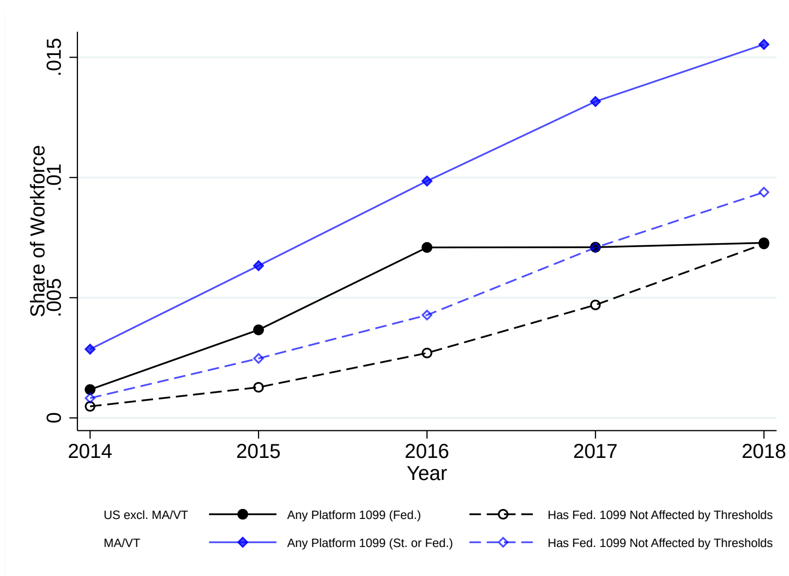
2012-2018

(a) Transportation & Delivery Platforms (b) All Other Platforms



Restricts to ≥ $600 in gross receipts. Not additive. People in both are in each of the other series.

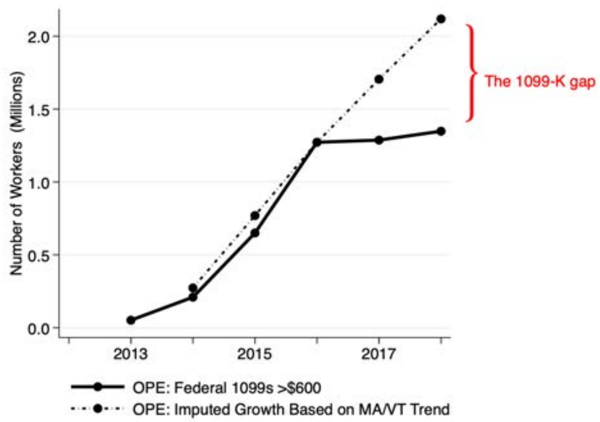
Figure 4: Share of Workforce with Platform 1099, MA and VT Versus Rest of US



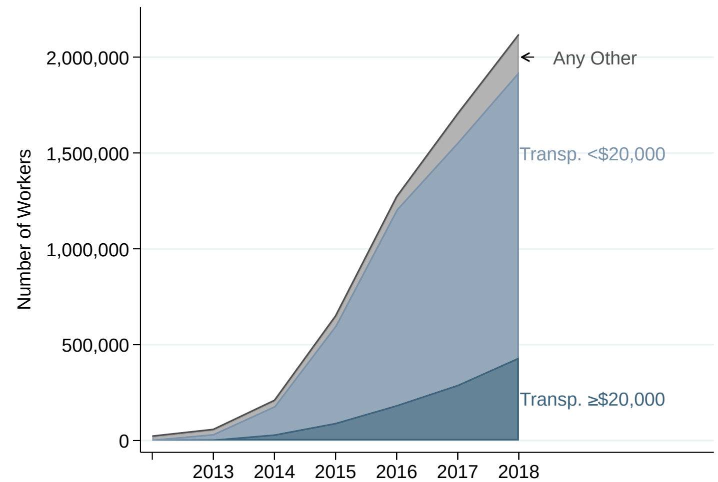
Mention workforce definition. Restricts to ≥ 600.

Figure 5: The Rise of Online Platform Work

(a) Measures Using Federal and State Data



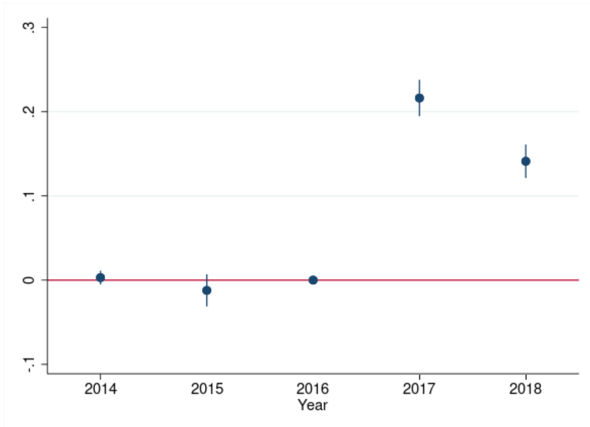
(b) Breakdown by Activity and Amount



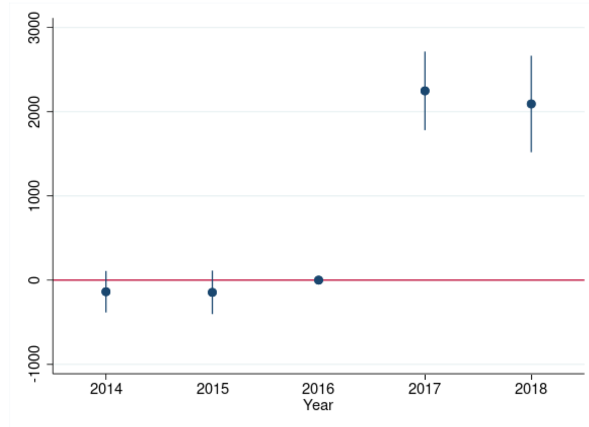
Note: Subfigure (a) shows the number of individuals participating in online platform work with at least $600 in payments from an online platform firm on a 1099-K or 1099-MISC form. The solid line displays the count of such individuals in the federal 1099 return data. The dashed line imputes growth in the share of the workforce with OPE income after 2016 based on observed growth in Massachusetts and Vermont incorporating the state-level 1099-K returns subject to a lower $600 threshold in those states. The difference between the solid and the dashed black lines in 2017 and 2018 represents the estimated size of the 1099-K gap. Additionally, we show prior to 2016 how closely the imputation tracks with the actual federal data during the period where the 1099-K is not a problem. Subfigure (b) breaks down the OPE participants in Subfigure (a) based on whether their OPE earnings were solely from transportation work. The individuals whose OPE earnings solely come from transportation work are further subdivided based on whether their total OPE gross earnings are above or below $20,000.

Figure 6: Event Studies Around Introduction of M-1099K

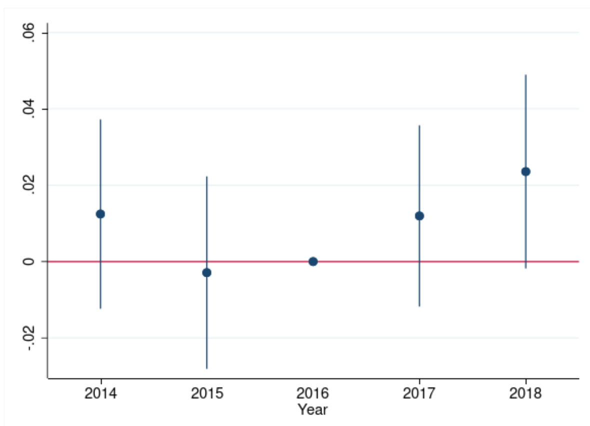
(a) Has OPE Gig 1099 (MISC or K)



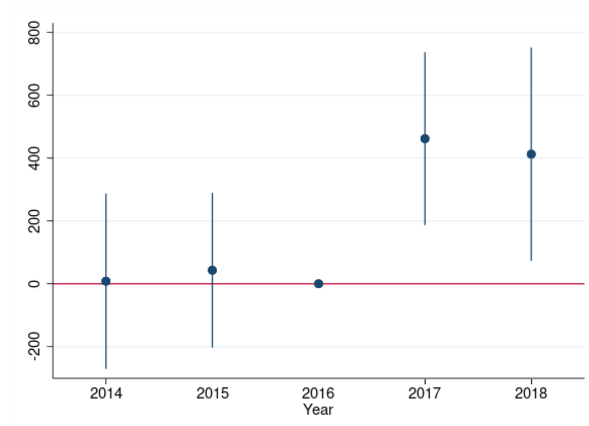
(b) OPE Gig 1099s $ Amount



(c) Files Schedule C

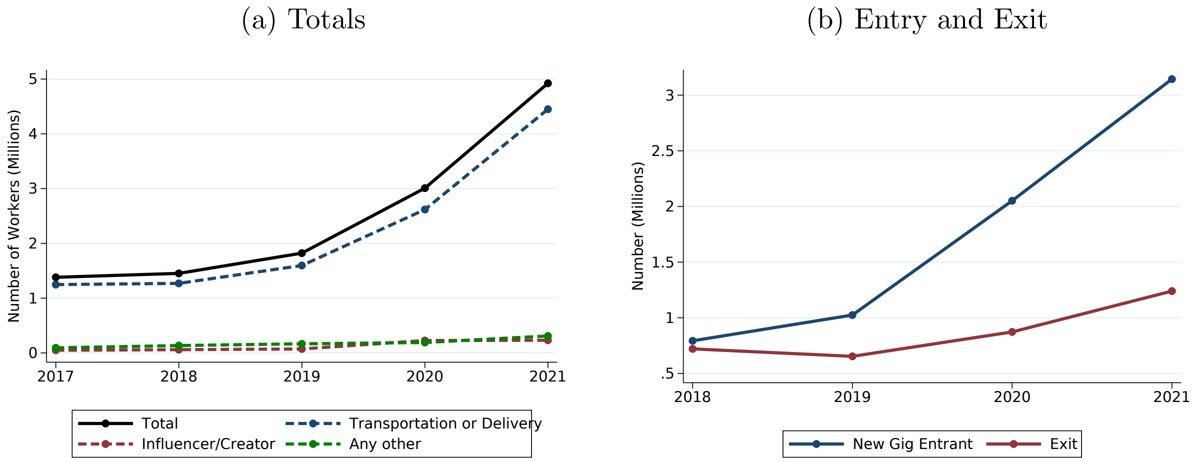


(d) Schedule C Profits/Loss



Note: Note: Figures report coefficients from running a county border regression around the introduction of the M-1099-K in 2017. The sample is restricted to the border-county pairs between Massachusetts, and the following states: Connecticut, New York, New Hampshire, and Rhode Island. Within border-counties we restrict to individuals living zipcodes within 15 miles of the border. All regressions include individual fixed effects, and border-pair x year fixed effects. Results are clustered at the individual level. The sample is a balanced panel of all individuals who were OPE gig workers in 2016 in one of the border counties, and we hold constant their 2016 border county for all years.

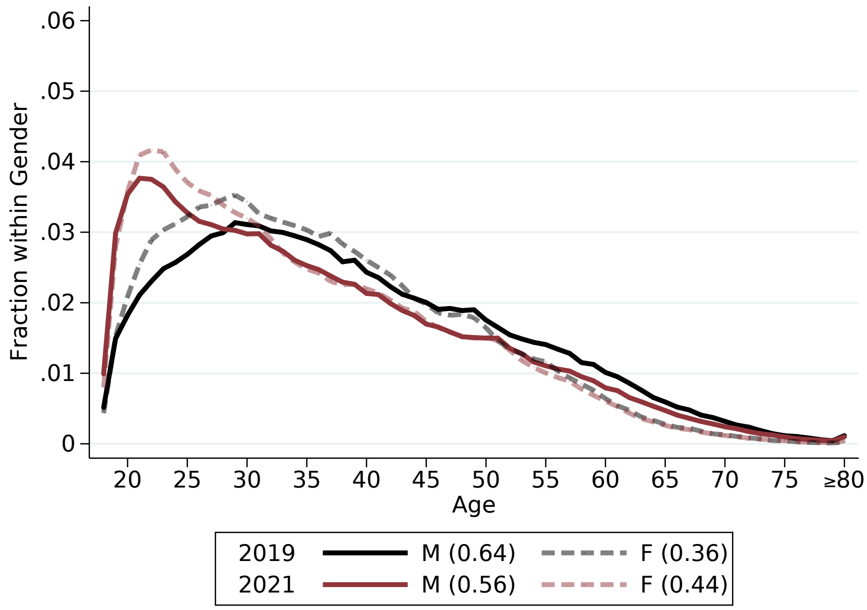
Figure 7: Platform Gig Work, 2017-2021



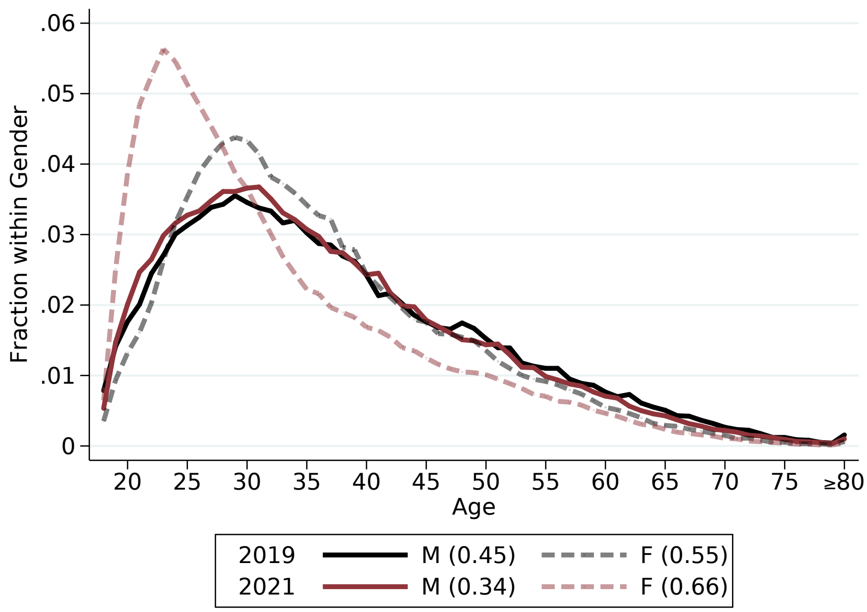
Notes: Left-hand figure shows total number of workers, in millions, active at some point in the year indicated on the x-axis. Right-hand panel shows flows, in millions, of new entry and exit. "New Entrant" is defined as someone with a 1099 from a platform gig company who had no 1099 from a platform gig company in the previous year in the previous year. "Exit" is defined as having a 1099 from a platform gig company in the current year, but no 1099 in the next year.

Figure 8: Age Distribution of Platform Gig Work, by Year and Gender

(a) Transportation & Delivery Platforms

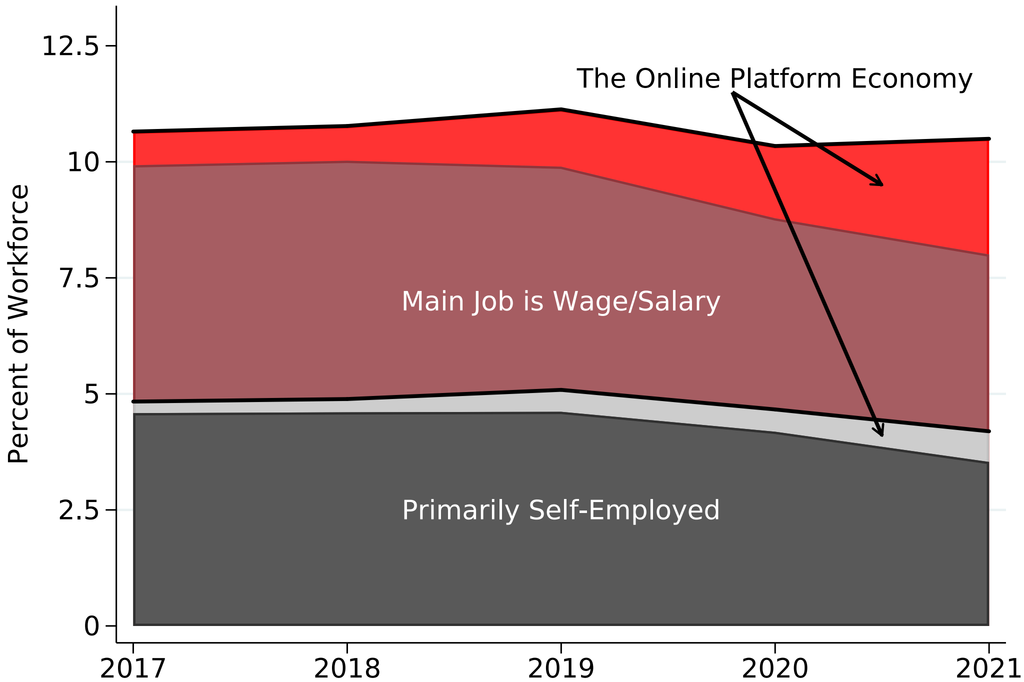


(b) All Other Platforms



Notes: Figure shows the age distribution of platform gig workers separately by year and gender as recorded in SSA data. The share of the gender share of platform gig workers in each year is reported in parentheses in the legend.

Figure 9: Broader Trends in Contract Work



Notes: Figure shows the share of individuals in the workforce with firm-reported payments for contract labor are reported on a 1099 Information Return. The workforce is defined as all individuals appearing on a 1040 return in a year who have labor income reported on a W-2 return, a 1099 return, or on Schedule SE as well as individuals individuals with positive earnings on either a W-2 who do not file Form 1040. Following the method in Collins, Garin, Jackson, Koustas, and Payne (2019), we separately break out the subset of independent contractors with 1099-reported payments from online platform economy firms. "Earnings Primarily from Self-Employment" defined as having the majority of wage plus Schedule SE earnings coming from Schedule SE; "Earnings Primarily from Wages" is defined as the complement. 2019 values for contract work outside of platform gig work are imputed following the methodology described in Section 7. Raw trends are reported in figure A.3.

Tables

Table 1: Components of the Tax Workforce, 2012-2020 (Thousands)

(a) Platform Gig 1099s

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1040 Filers								Non-Filers	
	Has SE and C		Has SE, No C		Has C, No SE		No C or SE		-	-
	Has W2	No W2	Has W2	No W2	Has W2	No W2	Has W2	No W2	Has W2	No W2
2012	6,389	7,333	323	140	2,190	982	2,160	586	666	1,352
2013	15,115	20,354	512	262	7,085	2,370	4,218	1,022	1,570	2,988
2014	72,915	65,374	1,696	746	57,861	11,387	56,056	6,282	13,044	14,853
2015	231,384	150,705	5,142	2,006	231,573	36,416	260,058	21,292	61,700	54,618
2016	432,500	258,441	6,733	3,232	423,723	68,586	502,051	40,251	148,121	116,242
2017	387,257	268,933	5,078	2,549	263,646	60,329	178,620	19,301	109,121	99,132
2018	414,285	323,399	5,472	2,716	230,573	62,410	180,373	20,414	117,119	110,581
2019	482,500	385,477	6,568	2,990	268,638	76,624	347,315	72,995	103,093	93,494
2020	823,940	483,871	13,111	5,151	452,958	121,359	586,704	77,432	260,624	208,664
2021	1,269,446	695,847	17,488	6,440	661,685	136,258	1,019,908	100,411	640,641	427,668

(b) All 1099 MISC/K/NEC Contract Work and Other Components of Tax Workforce

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Tax Filers											Non Tax Filers		
	No 1099					Has 1099						No 1099	Has 1099	
	No SE or C	Has SE		Has C, No SE		Has SE		Has C, No SE		No C or SE		-	-	-
	Has W2	Has W2	No W2	Has W2	No W2	Has W2	No W2	Has W2	No W2	Has W2	No W2	Has W2	Has W2	No W2
2012	125,200	3,653	5,973	3,452	1,711	4,974	5,061	1,910	922	2,123	632	12,234	673	1,385
2013	126,368	3,688	5,980	3,537	1,728	5,031	5,135	1,976	934	2,100	615	12,846	720	1,440
2014	127,556	3,783	5,956	3,583	1,699	5,353	5,286	2,064	935	2,105	589	13,585	802	1,528
2015	128,814	3,763	5,893	3,673	1,700	5,567	5,390	2,272	957	2,324	588	14,165	905	1,624
2016	128,690	3,714	5,834	3,715	1,726	5,813	5,539	2,449	992	2,552	607	15,286	1,072	1,790
2017	130,529	3,809	5,880	4,106	1,759	5,802	5,576	2,400	1,011	2,493	808	15,789	1,091	1,889
2018	131,072	3,845	5,894	4,490	1,789	5,913	5,697	2,431	1,028	2,578	828	16,484	1,156	1,964
2019	135,748	5,192	7,388	5,107	2,043	4,562	4,283	1,995	821	2,335	968	13,918	715	1,249
2020	131,087	3,708	6,268	4,898	2,290	5,365	5,349	2,339	1,048	2,670	711	15,795	1,171	1,910
2021	124,180	4,204	6,589	4,725	1,874	5,623	4,966	2,299	818	2,777	553	22,921	2,010	2,507

Notes: Tables report individual counts in thousands. 1099 refers to individuals who have any of the following: Non-employee compensation reported on 1099-MISC Box 7 (2012-2019), 1099 NEC (2020-2021), or 1099-K from a gig economy platform. Panel (a) is restricted to individuals receiving at least one 1099 return from the platform gig economy, while panel (b) includes all 1099s. The sum of columns (1)-(13) in Panel (b) corresponds to the "tax workforce" as defined in Collins, Garin, Jackson, Koustas, and Payne (2019). Tax filings as of December 2022.

Table 2: Summary Statistics for MA Border Sample

	(1)	(2)
	Gig Workforce 2016 Sample	Tax Workforce 2016 Sample
Age	39.03	42.15
Female	0.20	0.49
Has a OPE Gig 1099 ANY	1.00	0.01
Has a OPE Gig 1099-K	1.00	0.01
Has a OPE Gig 1099-MISC	0.12	0.00
$ Amount OPE 1099-K	4,732.20	45.58
$ Amount OPE 1099-MISC	196.38	4.73
$ Amount OPE 1099	4,948.86	50.75
Files Schedule C	0.68	0.12
# Schedule Cs	0.79	0.13
Schedule C Receipts	6,632.39	6,192.54
Schedule C Expenses	5,134.38	4,373.63
Schedule C Profits/Loss	1,497.87	1,803.19
Files Schedule SE	0.43	0.10
Schedule SE Earnings	2,115.21	2,505.86
W-2 Wages	24138.61	39689.75
Total Earnings	26279.05	42180.39
Files Form 1040	0.89	0.93
Observations	16,465	3,515,253

Notes: Table reports summary statistics in 2016 for the samples in our county border regression around the introduction of the M-1099-K in 2017, specification 1. The sample is restricted to the border-county pairs between Massachusetts, and the following states: Connecticut, New York, New Hampshire, and Rhode Island. Within border-counties we restrict to individuals living zipcodes within 15 miles of the border. Column (1) includes the sample of all individuals who were OPE gig workers in 2016 in one of the MA border counties. Column (2) includes the sample of all individuals in the tax workforce in 2016 in one of the MA border counties.

Table 3: Border Design Regression Results Around Introduction of M-1099-K
2016 Gig Workforce Sample

(a) Effects on Receipt of 1099Ks

	(1) Has OPE Any 1099	(2) Has OPE 1099-K	(3) Has OPE 1099-MISC	(4) K Amount OPE	(5) All OPE Amount	(6) Has Any 1099-K	(7) K Amount Any
Post x MA	0.182***	0.206***	0.0305***	2107.1***	2264.2***	0.226***	2491.5***
	(0.00980)	(0.00955)	(0.00736)	(228.5)	(250.6)	(0.00976)	(247.1)
Distinct i	10363	10363	10363	10363	10363	10363	10363
Distinct c	22	22	22	22	22	22	22
Dep. Means							
MA Pre	0.4178	0.4140	0.0713	2,110	2,250	0.4371	2,357
MA Post	0.4353	0.4210	0.2068	5,953	6,590	0.4499	6,466
Oth Pre	0.4234	0.4218	0.0330	2,123	2,190	0.4432	2,397
Oth Post	0.2498	0.2037	0.1489	3,677	4,158	0.2126	3,986
R^2	0.574	0.589	0.311	0.343	0.351	0.565	0.374

(b) Effects on Schedule C and Schedule SE Filing

	(1) Files Sched C	(2) # Sched Cs	(3) Receipts	(4) Expenses	(5) Profits/Loss	(6) Files SE	(7) SE Earnings	(8) W2 Wages	(9) Files 1040
Post x MA	0.0146	0.0184	692.8^{a}	214.4	420.0**	0.0279**	328.3*	-250.9	0.00180
	(0.00954)	(0.0124)	(381.0)	(308.8)	(132.7)	(0.00865)	(128.9)	(411.6)	(0.00697)
Distinct i	10363	10363	10363	10363	10363	10363	10363	10363	10363
Distinct c	22	22	22	22	22	22	22	22	22
Dep. Means									
MA Pre	0.3652	0.4191	4,942	3,691	1,217	0.2419	1,638	25,561	0.8530
MA Post	0.4235	0.5077	9,571	7,477	2,095	0.2749	2,694	28,099	0.8359
Oth Pre	0.3859	0.4459	4,825	3,597	1,190	0.2517	1,603	23,903	0.8631
Oth Post	0.4226	0.5051	8,804	7,154	1,638	0.2569	2,328	26,838	0.8472
R^2	0.455	0.484	0.596	0.582	0.499	0.394	0.555	0.753	0.484

Note: Table reports results from running a county border regression around the introduction of the M-1099-K in 2017, specification 1. The sample is restricted to the border-county pairs between Massachusetts, and the following states: Connecticut, New York, New Hampshire, and Rhode Island. Within border-counties we restrict to individuals living zipcodes within 15 miles of the border. All regressions include individual fixed effects, and border-pair x year fixed effects. Results are clustered at the individual level. The sample is a balanced panel of all individuals who were OPE gig workers in 2016 in one of the border counties, and we hold constant their 2016 border county for all years. Panel A presents outcomes related to the receipt of 1099s. Columns (1)-(5) are restricted to 1099-Ks and 1099-MISCs from gig platforms. Columns (6) and (7) refer to 1099-Ks issued by all payers. Panel B presents outcomes related to the effect on filing Schedule C, Schedule SE, W-2 Wages, and filing F1040.

Table 4: IV Estimates: Pass-through of 1099-K Reporting to Amounts Reported by Tax Filers
2016 Gig Workforce Sample

	(1) Files Sched C	(2) # Sched Cs	(3) Receipts	(4) Expenses	(5) Profits/Loss	(6) Files SE	(7) SE Earnings	(8) W2 Wages	(9) Files 1040
Has Any K									
= (Post x MA)	0.0644	0.0813				0.123***			0.00795
	(0.0409)	(0.0532)				(0.0366)			(0.0307)
All K Amount									
= (Post x MA)			0.278*	0.0861	0.169**		0.132**	-0.101	
			(0.141)	(0.120)	(0.0513)		(0.0493)	(0.163)	
Distinct i	10363	10363	10363	10363	10363	10363	10363	10363	10363
Distinct c	22	22	22	22	22	22	22	22	22
Dep. Means									
MA Pre	0.3652	0.4191	4,942	3,691	1,217	0.2419	1,638	25,561	0.8530
MA Post	0.4235	0.5077	9,571	7,477	2,095	0.2749	2,694	28,099	0.8359
Oth Pre	0.3859	0.4459	4,825	3,597	1,190	0.2517	1,603	23,903	0.8631
Oth Post	0.4226	0.5051	8,804	7,154	1,638	0.2569	2,328	26,838	0.8472
R^2	0.0415	0.0398	0.131	0.0530	0.0603	0.0494	0.0763	0.0180	0.0000754

Note: Table reports results from running a county border regression around the introduction of the M-1099-K in 2017, specification 1. We instrument for either an indicator for having received a 1099K from any firm or the $ Amount reported on a 1099K with the instrument being an indicator for living in Massachusetts in the post 2016 period. The sample is restricted to the border-county pairs between Massachusetts, and the following states: Connecticut, New York, New Hampshire, and Rhode Island. Within border-counties we restrict to individuals living zipcodes within 15 miles of the border. All regressions include individual fixed effects, and border-pair x year fixed effects. Results are clustered at the individual level. The sample is a balanced panel of all individuals who were OPE gig workers in 2016 in one of the border counties, and we hold constant their 2016 border county for all years. Panel A presents outcomes related to the receipt of 1099s. We presents IV outcomes related to the effect on filing Schedule C, Schedule SE, W-2 Wages, and filing F1040.

Table 5: Border Design Regression Results Around Introduction of M-1099-K
2016 Tax Workforce Sample

(a) Effects on Receipt of 1099Ks

	(1) Has OPE Any 1099	(2) Has OPE 1099-K	(3) Has OPE 1099-MISC	(4) K Amount OPE	(5) All OPE Amount	(6) Has Any 1099-K	(7) K Amount Any
Post x MA	0.00398***	0.00470***	0.000603***	38.48***	39.42***	0.0208***	127.5***
	(0.0000914)	(0.0000802)	(0.0000675)	(1.716)	(1.975)	(0.000151)	(11.90)
Distinct i	2380981	2380981	2380981	2380981	2380981	2380981	2380981
Distinct c	22	22	22	22	22	22	22
Dep. Mean	0.0048	0.0040	0.0020	45	53	0.0146	510
R^2	0.326	0.325	0.274	0.406	0.409	0.424	0.655

(b) Effects on Schedule C and Schedule SE Filing

	(1) Files Sched C	(2) # Sched Cs	(3) Receipts	(4) Expenses	(5) Profits/Loss	(6) Files SE	(7) SE Earnings	(8) Files 1040
Post x MA	0.00381***	0.00420***	-33.74	-47.72^{a}	1.756	0.00193***	-4.851	0.00277***
	(0.000300)	(0.000333)	(34.02)	(28.78)	(10.66)	(0.000282)	(14.18)	(0.000398)
Distinct i	2380981	2380981	2380981	2380981	2380981	2380981	2380981	2380982
Distinct c	22	22	22	22	22	22	22	22
Dep. Mean	0.1174	0.1247	6,056	4,295	1,743	0.0942	2,431	0.8821
R^2	0.696	0.694	0.841	0.833	0.786	0.652	0.820	0.464

Note: Table reports results from running a county border regression around the introduction of the M-1099-K in 2017, specification 1. The sample is restricted to the border-county pairs between Massachusetts, and the following states: Connecticut, New York, New Hampshire, and Rhode Island. Within border-counties we restrict to individuals living zipcodes within 15 miles of the border. All regressions include individual fixed effects, and border-pair x year fixed effects. Results are clustered at the individual level. Sample is a balanced panel of all individuals who were in the tax workforce in 2016 in one of the border counties, and we hold constant their 2016 border county for all years. Panel A presents outcomes related to the receipt of 1099s. Columns (1)-(5) are restricted to 1099-Ks and 1099-MISCs from gig platforms. Columns (6) and (7) refer to 1099-Ks issued by all payers. Panel B presents outcomes related to the effect on filing Schedule C and Schedule SE.

Table 6: Descriptive Statistics, 2019-2021

	(1)	(2)	(3)	(4)
	Primarily Platform Gig in $Year-1$	Secondary Platform Gig $Year-1$	New Gig Entrant in $Year$	Other Primary SE in $Year-1$
N (Thousands), 2019	449.1	1,011.3	1,041.5	13,060.9
... 2020	553.4	1,298.8	2,075.4	13,005.3
... 2021	696.4	2,322.3	3,201.4	12,603.6
% with Schedule C, 2019	83.8	45.9	59.1	80.9
... 2020	80.9	41.3	57.6	78.7
... 2021	73.2	37.3	51.3	74.2
% with Platform Gig, 2019	70.0	47.1	100.0	-
... 2020	61.8	47.2	100.0	-
... 2021	71.2	54.4	100.0	-
% with Schedule C, conditional on gig platform, 2019	91.3	63.7	59.1	-
... 2020	89.8	61.2	57.6	-
... 2021	84.2	54.4	51.3	-
% with earnings loss, 2019	49.9	34.9	45.2	54.2
% with earnings loss, 2020	66.9	41.1	49.4	62.6
% with UI, 2019	0.5	4.2	5.2	0.3
% with UI, 2020	52.1	37.1	32.4	25.3
... and has earnings loss	63.1	51.8	44.4	31.4
... and no earnings loss	29.7	26.7	20.7	15.3
% with UI, 2021	26.9	22.3	23.7	14.2
2020 UI, % of 2019 earnings, Median (Conditional on UI)	142.0	67.3	64.2	98.2
% with 2020 earnings $+$ UI $<$ 2019 earnings	32.3	26.1	35.8	49.1

Note: Table reports descriptive statistics on earnings changes and UI generosity for platform gig and other self-employed workers in the indicated years. Earnings is defined as the sum of Schedule C profits and W2 wages.

Table 7: Border Design Regression Results, State PUA Generosity

(a) Platform Gig Work, All

	(1) ΔMISC/K Receipts	(2) ΔTot Sched C Receipts	(3) ΔTot Sched C Profits	(4) ΔTotal Earnings 2020	(5) ΔTotal Earnings 2021	(6) Any Sched C 2020	(7) Any Sched C 2021
State Avg. UI, $	-0.527***	-0.617***	-0.219***	-0.240***	-0.0141		
(County l.o.)	(0.135)	(0.122)	(0.0324)	(0.0320)	(0.0361)		
State Avg. UI, $1000s						0.000521	-0.005233**
(County l.o.)						(0.00125)	(0.001656)
Dep. Mean	-15,673	-16,669	-4,931	-2,115	3,724	0.798	0.632
Distinct individual	88,305	88,305	88,305	88,305	88,305	88,305	88,305
Distinct county	276	276	276	276	276	276	276

	(1) Δ Profits 2019-2020	(2) Δ Total Earnings 2019-2020	(3) UI $ 2020	(4) Δ Total Income 2019-2020	(5) Δ Total Earnings 2019-2020	(6) UI $ 2021
State Avg. UI $	-0.219***	-0.240***	0.500***	0.250***		0.595***
(County l.o.)	(0.0324)	(0.0320)	(0.0665)	(0.0498)		(0.102)
UI $ 2020					-0.479***	
					(0.0498)	
OLS/IV	OLS	OLS	OLS	OLS	IV	OLS
K-P F-stat	-	-	-	-	56.445	-
N individuals	88,305	88,305	88,305	88,305	88,305	88,305
N counties	276	276	276	276	276	276
Dep. Mean	-4,931	-2,115	9,561	6,931	-2,115	5,751

(b) Platform Gig Work, 2019 Earnings > $ 15,000

	(1) Δ1099 MISC/K Receipts	(2) ΔTot Sched C Receipts	(3) ΔTot Sched C Profits	(4) ΔTotal Earnings 2020	(5) ΔTotal Earnings 2021	(6) Any Sched C 2020	(7) Any Sched C 2021
State Avg. UI, $	-0.778***	-0.868***	-0.370***	-0.375***	-0.022		
(County l.o.)	(0.209)	(0.226)	(0.081)	(0.061)	(0.065)		
State Avg. UI, $1000s						-0.000624	-0.006412*
(County l.o.)						(0.00179)	(0.002443)
Dep. Mean	-20,258	-22,756	-9,857	-7,047	4,054	0.859	0.713
Distinct individual	32,394	32,394	32,394	32,394	32,394	32,394	32,394
Distinct county	271	271	271	271	271	271	271

(c) Interactions with State 1099-K Laws

	(1) Δ Total Earnings 2020	(2) Δ Total Earnings 2020	(3) Δ Total Earnings 2020
State Avg. UI $	-0.184***	-0.163**	-0.182***
(County l.o.)	(0.048)	(0.065)	(0.058)
$\times$ MA/VT	0.025	-0.589	
	(0.224)	(0.518)	
$\times$ MA/VT/VA/MD/IL			0.020
			(0.086)
MA/VT	-1,331	9,713	
	(3,594)	(8,709)	
MA/VT/VA/MD/IL			-1,000
			(1,087)
Spatial Bandwidth	25	10	25
N individuals	88,305	44,869	88,305
N counties	276	220	276
Dep. Mean	-2,115	-2,175	-2,115

(d) All Other Self-Employed

	(1) ΔTot Sched C Receipts	(2) ΔTot Sched C Profits	(3) ΔTotal Earnings 2020	(4) ΔTotal Earnings 2021	(5) Any Sched C 2020	(6) Any Sched C 2021
State Avg. UI, $	-0.265***	-0.173***	-0.209***	-0.0476*		
(County l.o.)	(0.0594)	(0.0305)	(0.0272)	(0.0211)		
State Avg. UI, $1000s					-0.00321*	-0.00220
(County l.o.)					(0.00136)	(0.00148)
Dep. Mean	-7,332	-3,196	-994	1,344	0.769	0.629
Distinct individual	2,397,349	2,397,349	2,397,349	2,397,349	2,397,349	2,397,349
Distinct county	1,058	1,058	1,058	1,058	1,058	1,058

	(1) Δ Total Earnings 2019-2020	(2) UI $ 2020	(3) Δ Total Earnings 2019-2020	(4) Δ Total Earnings 2019-2020	(5) Δ Total Earnings 2019-2020	(6) UI $ 2021
State Avg. UI $	0.209***	0.701***				0.497***
(County l.o.)	(0.0272)	(0.0613)				(0.0656)
UI $ 2020			-0.299***	-0.294***	-0.276***	
			(0.0320)	(0.0385)	(0.0293)	
OLS/IV	OLS	OLS	IV	IV	IV	OLS
K-P F-stat	-	-	130.945	114.164	157.138	-
N individuals	2,397,349	2,397,349	2,397,349	1,872,229	2,397,349	2,397,349
N counties	1058	1058	1058	276	1058	1058
Dep. Mean	-994	3,892	-994	-989	-994	2,033
Border Counties	All	All	All	Gig	All	All
Border-pair FE	X	X	X	X	X	X
Border-pair × Industry FE					X	

(e) High School Graduation Cohort

	(1) Δ Total Earnings 2019-2020	(2) UI $ 2020	(3) Δ Total Earnings 2019-2020	(4) Any 1098-T 2020-2021	(5) UI $ 2021
State Avg. UI $ (County l.o.)	-0.221*	1.023***			0.611***
	(0.0980)	(0.179)			(0.151)
UI $ 2020			-0.216*		
			(0.103)		
State Avg. UI $1000s (County l.o.)				-0.009	
				(0.0211)	
OLS/IV	OLS	OLS	IV	OLS	OLS
K-P F-stat	-	-	32.669	-	-
N individuals	950,732	950,732	950,732	950,732	950,732
N counties	1037	1037	1037	1037	1037
Dep. Mean	2,502	1,024	2,502	0.566	590

Note: Table reports results from estimating Specification 2 in the text. The dependent variable is is indicated by the column header. All results control for the log population of the county, the log area of the county, the percent of the county classified by the BLS as urban, and the percent of the population living in an urban area.

Table 8: Trends in Platform Gig v. Other Contract Work, 2018, 2020, 2021

(a) Counts (Thousands) of 1099 Contract Workers who File Schedule C

	(1) 2018	(2) 2020	(3) 2021	(4) % Change, 2018-2020	(5) % Change, 2018-2021
1. Platform Gig	954.7	1788.5	2708.3	87.3	183.7
2. Other (Non-Platfom Gig) Contractors	13,678.7	11,973.6	10,769.6	-12.5	-21.3
By NAICS 2:					
11: Agriculture	119.8	111.2	92.3	-7.2	-22.9
21: Mining	52.4	39.6	35.2	-24.5	-32.8
23: Construction	1205.1	1111.9	881.2	-7.7	-26.9
31-33: Manufacturing	102.4	88.5	75.3	-13.6	-26.5
42: Wholesale Trade	112.4	97.1	80.9	-13.6	-28
44-45: Retail Trade	677.6	647.4	574.7	-4.5	-15.2
48-49: Transportation/Warehousing	621	559.3	473.8	-9.9	-23.7
51: Information	177.3	152.5	149.7	-14	-15.6
52: Finance/Insurance	465.3	450.9	411.7	-3.1	-11.5
53: Real Estate	846.4	824.4	752	-2.6	-11.2
54: Professional Services	1,858.3	1,683.7	1,542.7	-9.4	-17
56: Admin Support/Waste Mgmt	941.3	870.8	762.9	-7.5	-18.9
61: Education	426	316.9	311.6	-25.6	-26.9
62: Health Care/Social Assist.	813.8	744.5	698.1	-8.5	-14.2
71: Arts/Entertainment/Recreation	806.2	592.5	599.6	-26.5	-25.6
72: Accomodation/Food Services	110.9	82.9	85.3	-25.2	-23.1
81: Other Services	1,378.8	1,182.4	1,029.9	-14.2	-25.3
All other, excluding platform gig	2,963.8	2,417	2,212.7	-18.5	-25.3

(b) Counts (Thousands) of 1099 Contract Workers with Schedule C Profits <15,000

	(1) 2018	(2) 2020	(3) 2021	(4) % Change, 2018-2020	(5) % Change, 2018-2021
1. Platform Gig	846.2	1,563.3	2,335.9	84.8	176.1
2. Other (Non-Platfom Gig) Contractors	8741.9	7606.7	6726.4	-13	-23.1
By NAICS 2:					
11: Agriculture	76.8	71.0	59.1	-7.5	-23.1
21: Mining	30.7	25.1	20.8	-18.2	-32.2
23: Construction	563.4	519.8	407.4	-7.7	-27.7
31-33: Manufacturing	64.0	56.0	46.5	-12.5	-27.3
42: Wholesale Trade	66.8	59.0	48.4	-11.6	-27.5
44-45: Retail Trade	551.8	529.9	465.5	-4.0	-15.6
48-49: Transportation/Warehousing	233.1	214.6	171.5	-8.0	-26.4
51: Information	120.8	106.6	102.0	-11.7	-15.6
52: Finance/Insurance	196.2	191.8	174.5	-2.3	-11.1
53: Real Estate	339.1	317.5	272.3	-6.4	-19.7
54: Professional Services	1,114.6	1,017.4	915.4	-8.7	-17.9
56: Admin Support/Waste Mgmt	676.1	626.0	538.1	-7.4	-20.4
61: Education	366.9	269.9	261.6	-26.4	-28.7
62: Health Care/Social Assist.	501.7	454.8	414.7	-9.3	-17.3
71: Arts/Entertainment/Recreation	652.0	493.7	486.8	-24.3	-25.3
72: Accomodation/Food Services	86.9	65.0	65.0	-25.2	-25.2
81: Other Services	944.7	844.1	689.2	-10.6	-27.0
All other, excluding platform gig	2,156.4	1,744.5	1,587.5	-19.1	-26.4

(c) Counts (Thousands) of 1099 Contract Workers with Schedule C Profits $\geq$ 15,000, Thousands

	(1) 2018	(2) 2020	(3) 2021	(4) % Change, 2018-2020	(5) % Change, 2018-2021
1. Platform Gig	108.5	225.2	372.4	107.4	243.1
2. Other (Non-Platfom Gig) Contractors	4936.9	4366.8	4043.2	-11.5	-18.1
By NAICS 2:					
11: Agriculture	42.9	40.2	33.2	-6.4	-22.6
21: Mining	21.7	14.4	14.4	-33.5	-33.6
23: Construction	641.7	592.1	473.8	-7.7	-26.2
31-33: Manufacturing	38.5	32.5	28.7	-15.4	-25.3
42: Wholesale Trade	45.7	38.1	32.5	-16.5	-28.8
44-45: Retail Trade	125.8	117.5	109.2	-6.6	-13.2
48-49: Transportation/Warehousing	387.9	344.8	302.2	-11.1	-22.1
51: Information	56.5	45.8	47.7	-18.8	-15.5
52: Finance/Insurance	269.1	259.2	237.2	-3.7	-11.8
53: Real Estate	507.3	506.9	479.7	-0.1	-5.4
54: Professional Services	743.7	666.3	627.3	-10.4	-15.6
56: Admin Support/Waste Mgmt	265.2	244.7	224.8	-7.7	-15.2
61: Education	59.1	47	50	-20.4	-15.4
62: Health Care/Social Assist.	312.1	289.7	283.4	-7.2	-9.2
71: Arts/Entertainment/Recreation	154.1	98.9	112.8	-35.9	-26.8
72: Accomodation/Food Services	24	18	20.3	-25.2	-15.6
81: Other Services	434.2	338.3	340.7	-22.1	-21.5
All other, excluding platform gig	807.5	672.5	625.1	-16.7	-22.6

Notes: Table reports raw counts (in thousands) of Schedule C filers with non-employee compensation reported on 1099 MISC Box 7 (2018), 1099 NEC (2020-2021), or a 1099-K issued by a gig economy platform. Individuals are assigned the NAICS industry self-reported on Schedule C, with the exception of platform gig workers, who are identified by having at least one 1099 issued by a gig platform.

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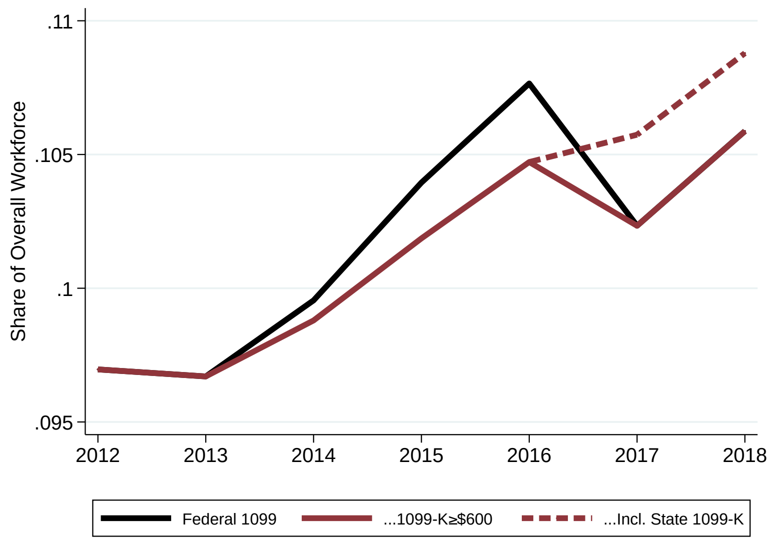
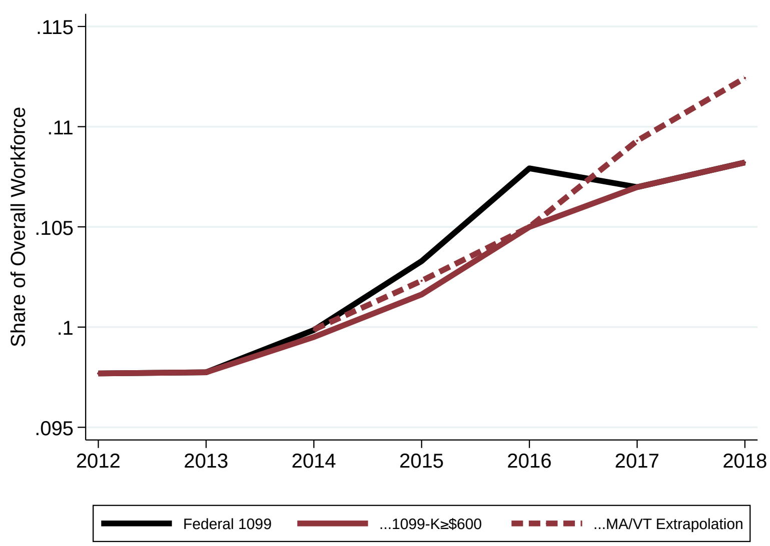
A Appendix Figures

Figure A.1: Estimating National Prevalence of all Contract work in 2017 and 2018, Using MA and VT

(a) **MA and VT, Actual Data**



(b) **National, Extrapolation Method for Platform Work:**

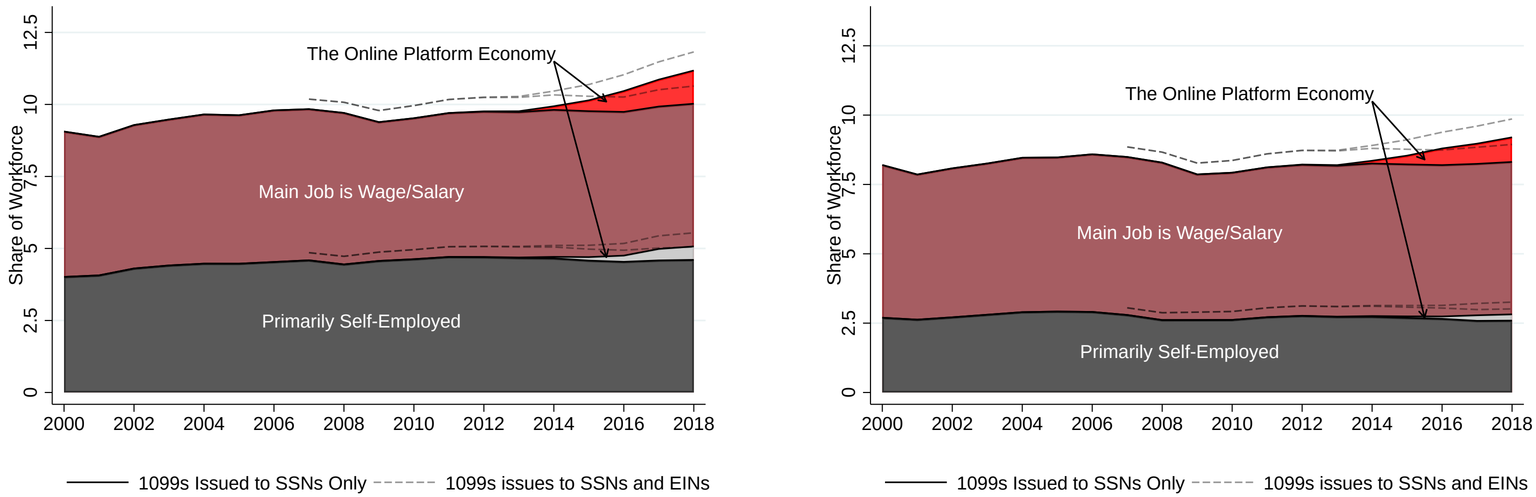


Note: Subfigure (a) shows data only for MA and VT. In solid black, we show the share of the workforce receiving a any 1099-MISC or an OPE 1099-K. In solid red, we exclude individuals with less than $600 in payments from an online platform firm on a 1099-K. The dashed red line displays the share of such individuals in the State MA-1099-K data in 2017 and 2018. In subfigure (b) we show similar trends at the national level. Here the dashed line imputes growth in the share of the workforce with 1099 work after 2016 based on observed growth in Massachusetts and Vermont.

Figure A.2: Overall Prevalence of Contract Work through 2018, With Platform Economy Imputation in 2017 and 2018

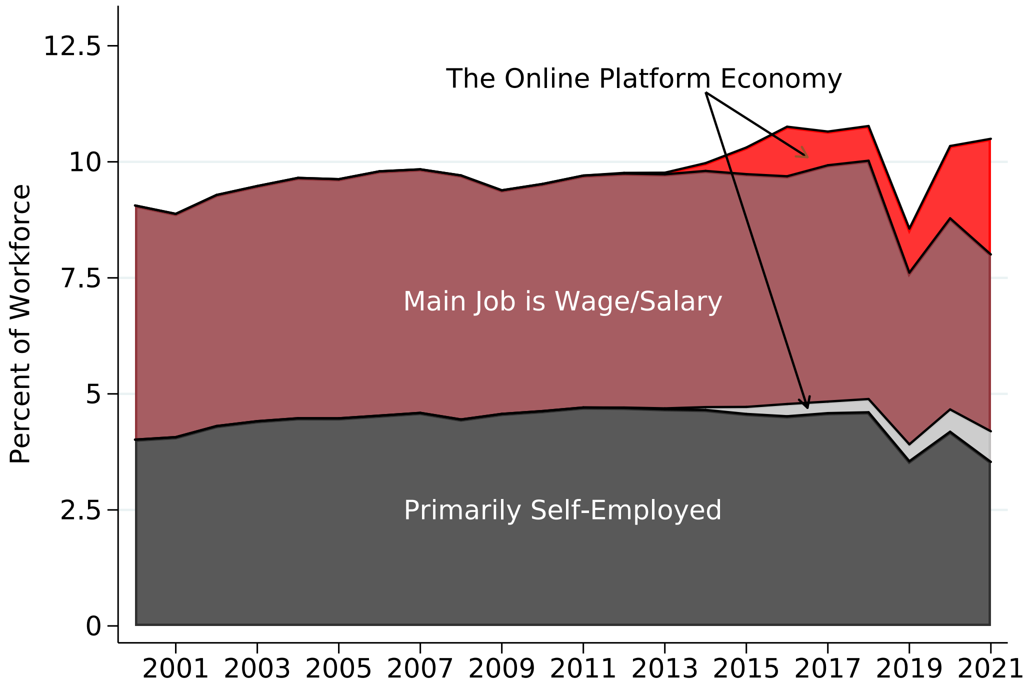
(a) All Workforce Participants

(b) With Earnings $\geq$ \$15,000 (\$2015)



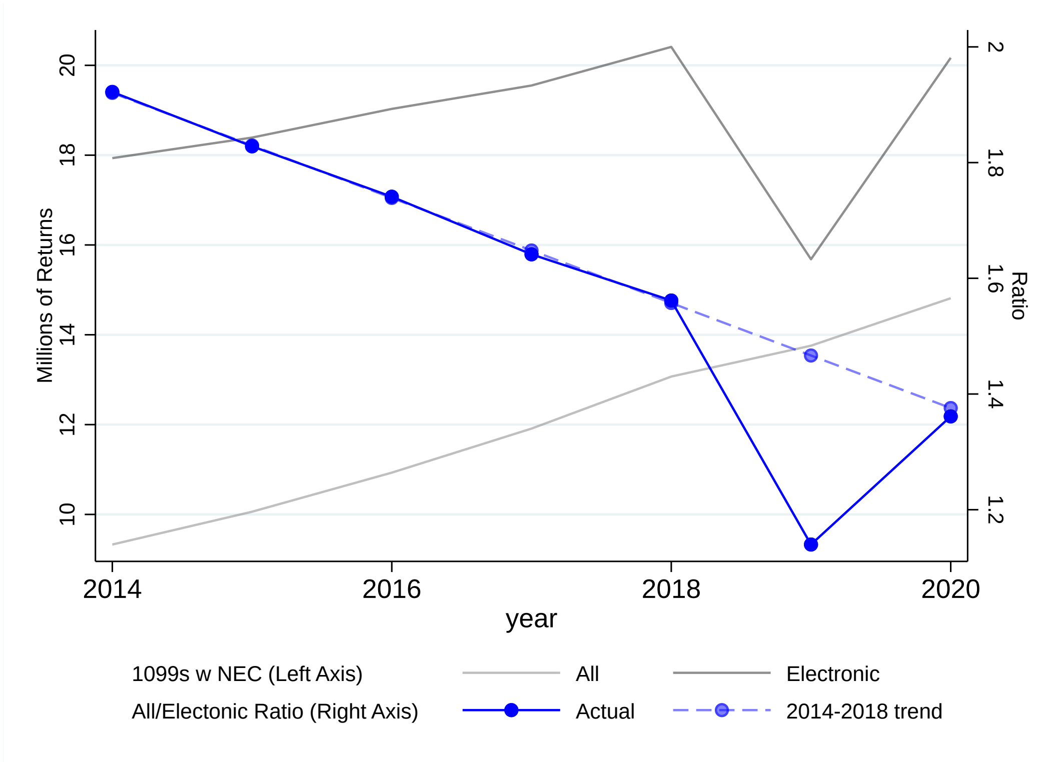
Notes: Figure shows the share of individuals in the workforce with firm-reported payments for contract labor are reported on a 1099 Information Return. The workforce is defined as all individuals appearing on a 1040 return in a year who have labor income reported on a W-2 return, a 1099 return, or on Schedule SE as well as individuals individuals with positive earnings on either a W-2 who do not file Form 1040. Panel A shows rates in the total workforce, while Panel B restricts to the workforce with at least \$15,000 in labor earnings reported on Form W-2 and Schedule SE combined. Following the method in Collins, Garin, Jackson, Koustas, and Payne (2019), we separately break out the subset of independent contractors with 1099-reported payments from online platform economy firms. "Earnings Primarily from Self-Employment" defined as having the majority of wage plus Schedule SE earnings coming from Schedule SE; "Earnings Primarily from Wages" is defined as the complement. The baseline series only includes 1099 returns issued to individual SSNs; for years beginning 2007, we also display each series including all 1099s issued to EINs listed on individual Schedule Cs in dashed lines.

Figure A.3: Raw Trends, 1099 Contract Work, as a Share of Tax Workforce, 2000-2021



See notes for Figure 9.

Figure A.4: 1099 Returns with Nonemployee Compensation, Electronically Filed Versus All



Note: Plot displays counts of all 1099 returns with nonemployee compensation greater than $600 filed in each year (1099-MISC through 2019 and 1099-NEC in 2020) with count of electronically filed returns broken out. Plot also displays ratio of all returns to electronically filed returns, along with 2014-2018 trend line. The predicted ratio in 2019 is 1.3 times the observed ratio; thus, if all electronic returns were processed but not all paper returns, and true ratio if all returns were processed remained on the trend line, the true total count of returns should be 1.3 times the observed count.

B State Policies Related to 1099-K Reporting

Table B.1: State 1099-K Reporting Requirements

State	Minimum Transaction Value	Minimum Transaction Count	Date Effective/Applicable
Vermont	Gross payments exceed or are equal to $600 in calendar year	No minimum	Applies to all payments on or after January 1, 2017
Massachusetts	Gross payments exceed, or are equal to $600 in calendar year	No minimum	Applies to all payments on or after January 1, 2017. May be filed using MA-1099-K.
Illinois	Gross payments exceed $1,000 in the calendar year	AND 4 or more transactions	New de minimis thresholds effective January 1, 2020. 1099-Ks required to be filed with IL from January 1, 2019.
Virginia	Gross payments exceed or are equal to $600	No minimum	January 1, 2020.
Maryland	Gross payments exceed or are equal to $600	No minimum	June 1, 2020
Missouri	Gross payments exceed or are equal to $1,200	No minimum	Timing uncertain.
Arkansas	Gross payments exceed or are equal to $2,500	No minimum	Timing uncertain.
California	App-based driver, gross payments of $600 or more	No minumum	January 1, 2021
New Jersey	Gross payments exceed or are equal to $1,000	No minimum	January 1, 2021.

States with mandatory 1099-K reporting, but no change in minimum reporting threshold: Florida (effective 2021), Kansas, Tennessee, Iowa, Connecticut, and Oregon.

C Imputation Procedure as a Share of the Tax Workforce

In this Appendix, we provide multiple alternative imputation methodologies for measuring platform work, and the 1099-K gap. Some alternative imputations are more sophisticated and require more assumptions than others, and so we present all alternatives here for completeness. These alternatives highlight the potential range of values that the true underlying trends may exhibit.

C.1 Alternative Imputation 1

Our main alternative imputation leverages raw counts of 1099 OPE work and the gross amounts on the 1099-Ks rather than utilizing the share of the workforce engaged in 1099 work. We build on our imputation methodology described in section 3.2, and incorporate a third key component: 1099-K dollar *gross* amounts.

We combine the 1099-K returns based on the *gross amounts* into two groups: amounts of \$600-20,000 and more than \$20,000, as we observe the latter group in all years for all states. Thus, we calculate the ratio of 1099-Ks with gross amounts $\in [600, 20,000)$ to gross amounts $\geq 20,000$ in the base year 2016, and for both types of states (MA and VT, versus all other states). Note that we normalize all of our count measures, C_y, to be counts of 1099-Ks per 1,000 population in year y to make them comparable across state groups (MA and VT, versus all other states). We will later re-inflate the counts per 1,000 population to a total count. We use 2016 as a base year, since it's the closest year to our imputed years and therefore we think most comparable.

We define the following ratio R_{2016}, where C_y is defined to be counts of 1099-K per 1,000 population in year y:

$$R_{2016} = \frac{C_{2016}^{(MA,600-20k)}}{C_{2016}^{(MA,20k+)}} * \frac{C_{2016}^{(Other,600-20k)}}{C_{2016}^{(Other,20k+)}}. \tag{7}$$

For each year y (where $y \in 2017, 2018$) the value for other states can be imputed using ratio R_{2016} as follows:

$$C_y^{(Other,600-20k)} = \frac{1}{R_{2016}} * \frac{C_y^{(Other,20k+)} * C_y^{(MA,600-20k)}}{C_y^{(MA,20k+)}} \tag{8}$$

Finally, since C_y is a count per 1,000 population in year y, we use state populations to aggregate these counts to a total state level count rather than a per 1,000 population measure:

$$[\textbf{Imputed Count of 1099K}]_y^{(Other,600-20k)} = C_y^{(Other,600-20k)} * \frac{\text{population}}{1000} \tag{9}$$

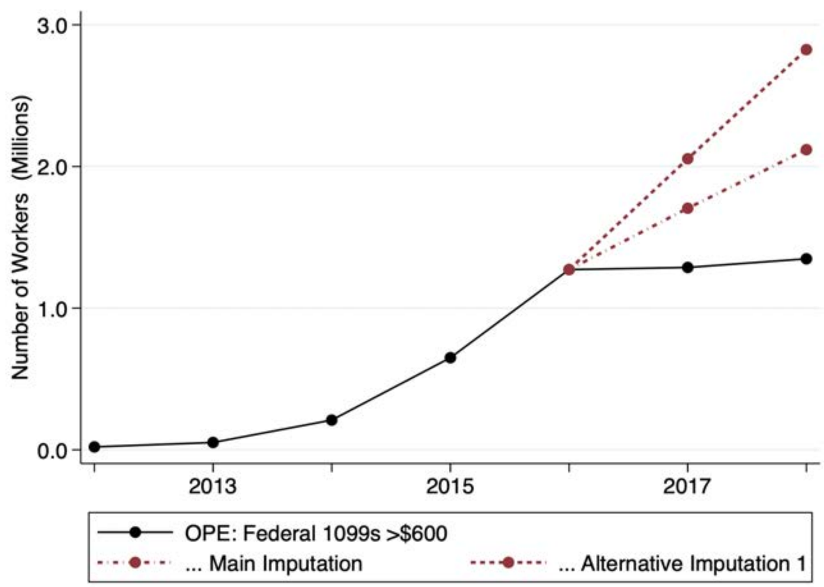
In summary, for years where we have complete information we use the available data, and for years where we are missing data then we use the imputation. Thus, for all years we use true counts for 1099-Ks $\geq \$20,000$, and from 2017 onwards we use our imputed values for 1099-Ks $\in [600, 20000)$ in states for which we do not have state 1099-K data (i.e. all states other than MA and VT). We are then able to fill in the missing components of our imputation.

Finally, when considering how these imputed 1099-K measures translate into new platform work counts at the individual level, we need to consider that some of the individuals we are imputing to have 1099-Ks between [600,20000) may have also received a 1099-MISC from a platform and thus are already accounted for on the extensive margin. We calculate this share in 2016, our base year. Only 25.56% of individuals with 1099-Ks also had a 1099-MISC. Thus to get the overall number of individuals with OPE work, we discount our 1099-K imputed count by (1-.2556) and add this to the OPE 1099-MISC counts. Putting this all together, we get a final adjusted number of OPE works as follows:

$$\begin{aligned}\textbf{Adjusted}\text{ Count of OPE}_y = &(\text{Count with OPE MISC})_y^{All} + (1-.2556) * [(\text{Count of 1099K})_y^{(MA,20k+)} \\ &+ (\text{Count of 1099K})_y^{(MA,600-20k)} + (\text{Count of 1099K})_y^{(Other,20k+)} \\ &+ (\textbf{Imputed Count of 1099K})_y^{(Other,600-20k)}]\end{aligned}$$

In Figure C.1, we present the trend of this alternative imputation, labeled "Alternative Imputation 1", and compare it with our main imputation described in Section 3.2, labeled "Main Imputation". This alternative specification predicts a larger K-gap, and suggests our main imputation is more conservative.

Figure C.1: Alternative Specification for MA/VT Imputation



Note: We show trends in the number of individuals participating in online platform work with at least $600 in payments from an online platform firm on a 1099-K or 1099-MISC form. The solid line displays the count of such individuals in the Federal 1099 return data. The two dashed lines impute growth in the share of the workforce with OPE income after 2016 based on observed growth in Massachusetts and Vermont incorporating the state-level 1099-K returns subject to a lower $600 threshold in those states. The "Main Imputation" is described in Section 3.2 and "Alternative Imputation 1" is described in Append Section C.

C.2 Various Other Imputation Alternatives

We also present two simple imputations as a comparison to our main imputation. While these imputations require less assumptions, as we will show, they do not perform as well in terms of pre-trends.

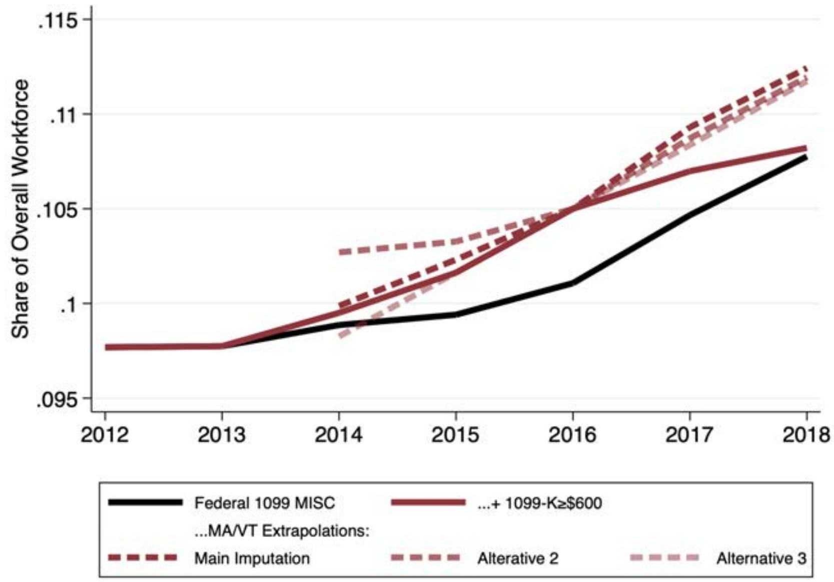
In our “Alternative 2” imputation, we assume that the 1099 workforce grew in parallel to the Federal 1099 MISC series, which is the subset of the 1099 workforce who does not receive an OPE 1099-K. This methodology imposes what share of the 1099 workforce receives an OPE 1099-K in the base year (2016), and inflates the Federal 1099 MISC series accordingly. In Figure C.2a, one can see that the “Alternative 2” line is parallel to the Federal 1099 MISC series.

In “Alternative 3”, we impute the 1099 workforce in 2017 and 2018 by assuming that the 1099 Workforce grows linearly, the solid red line. We extrapolate a linear trend from 2015 to 2016 forward into 2017 and 2018.

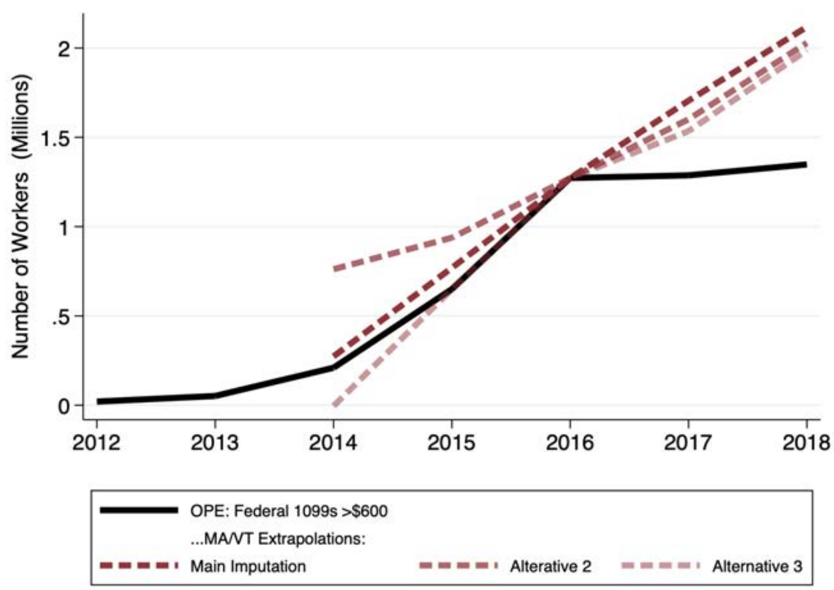
In figure C.2a, we show these two alternative imputations along with the main imputation to highlight the potential range of values that the true underlying trends may exhibit. Despite these alternative imputations being calculated as a share of the workforce, we also present these alternative series with OPE counts in Figure C.2b.

Figure C.2: Measures of the 1099 Workforce: Alternative Imputations

(a) As a Share of the Workforce



(b) In Counts



Note: We show trends in the number of individuals participating in online platform work with at least $600 in payments from an online platform firm on a 1099-K or 1099-MISC form. The solid line displays the count of such individuals in the Federal 1099 return data. The two dashed lines impute growth in the share of the workforce with OPE income after 2016 based on observed growth in Massachusetts and Vermont incorporating the state-level 1099-K returns subject to a lower $600 threshold in those states. The "Main Imputation" is described in Section 3.2 and "Alternative 2" and "Alternative 3" are described in Appendix Section C. In Panel B, we transform the imputations in Panel A which are measured as a share of the workforce to be in counts of individuals with OPE work.

D Border Design: Additional Results

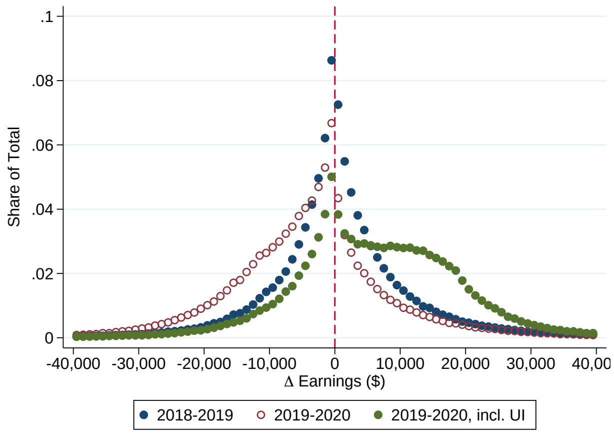
Table D.1: UI Earnings Gradient

Earnings in Year from Primary Source	Platform Gig, 2019 UI Cond. Mean 2020	Platform Gig, 2019 Share	Self-Employed, 2019 UI Cond. Mean 2020	Self-Employed, 2019 Share	Wage-Only, 2019 UI Cond. Mean 2020	Wage-Only, 2019 Share	Wage-Only, 2018 UI Cond. Mean 2019
0-2,500	17,279	0.11	15,449	0.09	12,536	0.04	2,295
2,500-7,500	17,397	0.19	14,942	0.17	10,661	0.09	2,022
7,500-15,000	18,064	0.32	14,703	0.30	11,182	0.15	2,669
15,000-30,000	19,350	0.30	15,039	0.27	12,103	0.28	3,654
30,000-60,000	19,772	0.06	15,176	0.11	12,452	0.30	4,899
60,000-100,000	19,097	0.00	15,373	0.03	11,814	0.10	5,496
100,000+	17,062	0.00	14,307	0.02	11,459	0.04	5,962

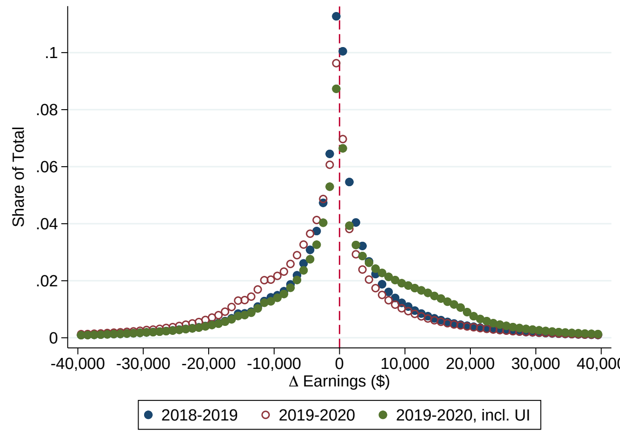
Note: "UI Cond. Mean" is the UI compensation received, conditional on receiving UI in the indicated year. "Share" is the share of UI recipients in each earnings bin. Earnings based on Schedule C profits.

Figure D.1: Earnings Changes, Pre/Post COVID

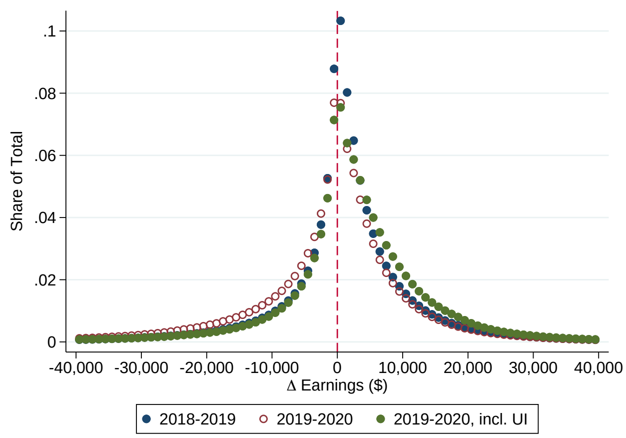
(a) Primary platform gig workers



(b) Other primary self-employed workers

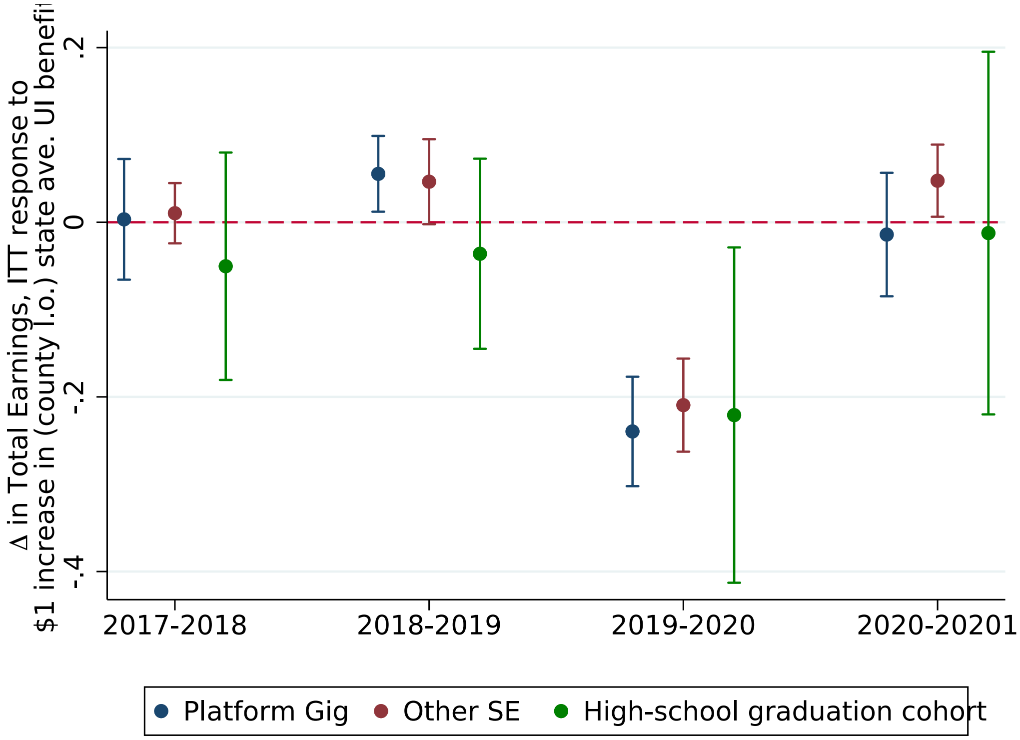


(c) Wage-only workers



Note: Figure shows the distribution of earnings changes between 2018-19 (navy) and 2019-2020 (maroon), for the indicated group, where the group is classified as of the base year of the earnings change. We also report earnings changes inclusive of UI for 2019-2020 (green).

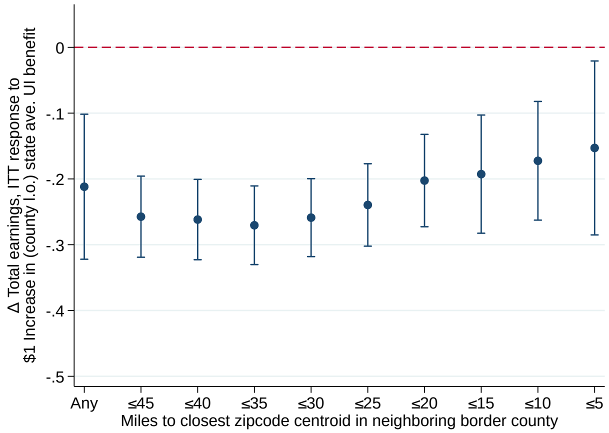
Figure D.2: ITT Earnings Response to $1 Increase in State Average UI Benefit



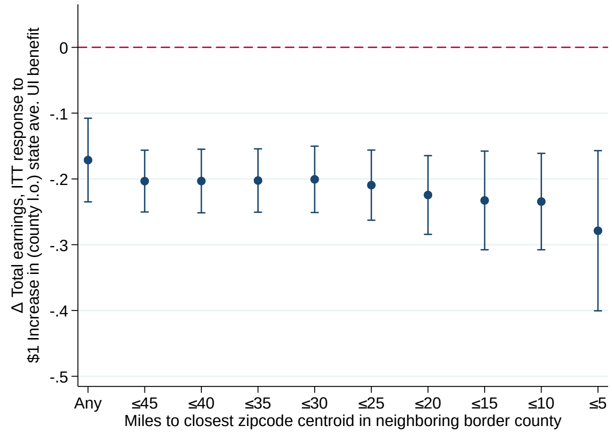
Notes: Figure shows results from separate regressions of change in total earnings on (county l.o.) state average UI benefit in 2020.

Figure D.3: Robustness to Spatial Bandwidth

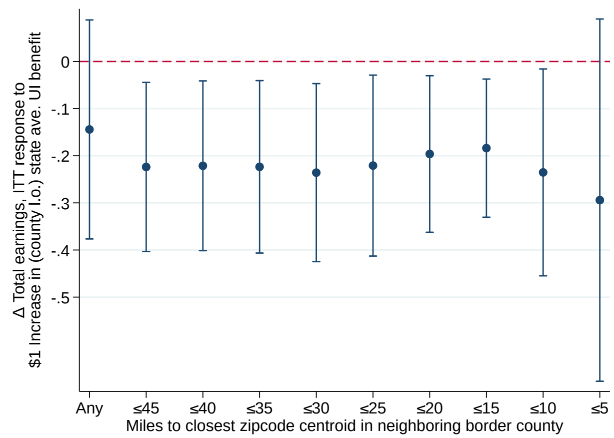
(a) Primary Platform Gig



(b) Other Primary Self-employed

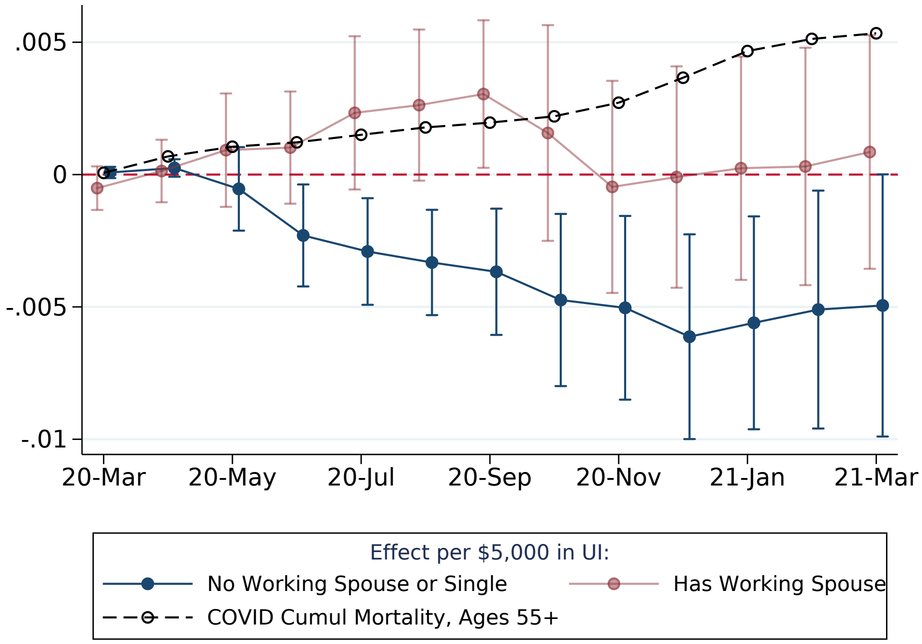


(c) High-School Graduation Cohort



Notes: Figure shows the robustness of main results to the spatial bandwidth indicated on the x-axis.

Figure D.4: Platform Gig, Cumulative Monthly Mortality Response to $5,000 of UI



Notes: Figure shows results from separate regressions.