**Left Out: Measuring minimum wage effects on wage earners and the self-employed using tax data from Washington, DC**

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## Introduction

As the share of the workforce that earns at least some income from self-employment grows, questions about who should—or should not—be eligible for certain labor standards are the subject of important public policy debates. At the state level for example, this is evident from the discussions in California over Assembly Bill 5 and Proposition 22 —measures aimed at establishing which workers should be classified as employees and which workers should be classified as independent contractors. At the federal level, these considerations are present in debates over the Protecting the Right to Organize Act and in the Department of Labor's repeated rulemakings over who is considered an employee or an independent contractor under the Fair Labor Standards Act. Given this, it has become increasingly important to understand different types of work arrangements and how self-employment and independent contracting shape workers' outcomes.

A number of recent studies (Jackson et al, 2017; Abraham et al. 2018; Lim et al. 2019; Collins et al. 2019), provide valuable insight into how many workers are earning income from self-employment, how the advent of online platforms influenced trends in alternative work arrangements, and the labor market outcomes and demographic characteristics of the self-employed. However, because these studies are generally limited to one year of data or rely on cross-sectional data, they are generally not able to track the labor market outcomes of the self-employed across longer periods of time, or provide detailed insight into how self-employment interacts and is affected by labor market policies like the minimum wage. We seek to establish that differences between wage workers and the self-employed observed in these studies are associated with employment type, in addition to other factors.

To our knowledge, this study is the first to use panel tax data to study self-employment in the United States over time. Using individual income tax records from the IRS and employment records from Washington, DC, we construct a panel dataset to analyze the income trajectories of taxpayers who earn the majority of their income from self-employment vis-à-vis taxpayers who earn their income mostly from salaries and wages. This study is also one of a small but growing number examining the relationship between self-employment and the minimum wage. Focusing on earners in the bottom of the distribution, we examine the income trajectories of self-employed taxpayers and wage-earning taxpayers as the District enacted a series of minimum wage increases from 2014-2019.

Self-employed workers—freelancers, gig workers, and other independent contractors—are not covered by the Fair Labor Standards Act, which includes labor protections such as overtime pay for work over 40 hours per week and the minimum wage. Additionally, the self-employed are generally not eligible for social programs such as Unemployment Insurance or Workers' Compensation and are not protected by the National Labor Relations Act, which safeguards workers' right to organize, form and join unions, and bargain collectively. They do not receive employer-provided health insurance and are generally solely responsible for saving for retirement and paying the employer's share of Medicare and Social Security taxes. At the same time, their greater flexibility and control over when, how, and how much to work could act as a compensating differential driving adoption of self-employment. For example, a number of economists have argued that workers primarily look to derive non-pecuniary benefits from self-employment (e.g., Hurst and Pugsley 2017; Bellon et al. 2020).

In this study we examine how earning an important chunk of income from self-employment affects workers' earnings over time, as well as the interaction between self-employment and the minimum wage. Beginning in 2014 the District of Columbia started enacting a series of annual minimum wage increases that lifted the city's wage floor from $8.25 in 2013 to $14.00 in 2019, becoming one of the first U.S. jurisdictions to reach that level (and the first state-equivalent jurisdiction to do so). As of 2022, the DC minimum wage stood at $16.10.

We study if the increase in the District's wage floor had an effect on the economic outcomes of eligible and non-eligible wage-earners and self-employed workers. We also observe the effect of transitions between wage-earning and self-employment for individuals filing taxes in DC. Unlike other minimum wage studies, ours does not focus solely on subsectors of the population such as teenagers or on economic sectors more likely to be directly affected by the policy such as restaurants. Instead, we focus on all low-income DC wage-earning tax filers, the group that is most likely to experience any effects of the minimum wage increases.

Our paper makes two primary contributions to the economic literature: First, we use a novel tax data methodology to examine the relationship between a series of minimum wage increases in Washington DC and the incomes of eligible and ineligible earners. This helps us establish the effect of minimum wage increases on total income and income tax receipts. That we are able to track the income trajectories of workers through time allows us to observe how self-employed taxpayers (vis-à-vis wage-earners) experience the labor market amid a series of minimum wage increases. While tax data comes with some limitations, it allows us to both build a panel and bypass the issues embedded in studying self-employment with survey data.

We find that income increased 34% more for DC low-income taxpayers at minimum wage-covered workplaces than for similar workers who worked in neighboring Maryland or Virginia, for instance. In dollar terms, treated workers gained a median yearly income gain of an additional $3,100 compared to untreated workers in 2018. Yearly tax receipts increased an incremental $63 in the first year and $200 in 2018 for treated versus untreated wage workers. Even though the minimum wage increased steadily every year from 2014-2018, we also find that about half of the relative income gains occurred in the first year of the increase in the city's wage floor.

Our second main finding provides insight into why those who earn a large proportion of their income from self-employment tend to have lower incomes than other earners (Jackson et al. 2017; Bernhardt et al. 2022). Our analysis reveals that most workers experience a sharp drop in income when they become self-employed. Falling income  is not a result of easily observable population or selection effects, but seems to be intrinsically associated with self-employment. By 2018 taxpayers who switched to self-employment had half the income of comparable taxpayers who remained wage workers from 2013-2018. Low- and moderate-income taxpayers who switched from earning most income from wages in 2013 to self-employment had lower incomes in 2018 than they had in 2010. Conversely, those that transitioned from self-employment to wage-earning saw large gains in income. These swings in income were reflected in individual tax receipts such that the Treasury collected -$144 less from each low-to-moderate income taxpayer who switched to self-employment and +790 more for each one that switched to wage-earning.

We also find that self-employed low-income taxpayers have persistently low and stagnant incomes, and we find that the population of people relying on self-employment was increasing prior to 2014. Afterward, this trend reversed. This reversal coincides with the minimum wage increase and is driven by low-income Washingtonians leaving self-employment for wage-earning.

In the following sections we will discuss how this research fits into the economic literature on both the minimum wage and self-employment.  The heart of our analysis consists of descriptive data about wage-earners and the self-employed in Washington DC in a particular policy context. To add depth to the analysis, we perform regression analyses to further validate and elaborate upon our descriptive findings. Finally, in the appendix we have a section describing a triple-difference analysis we use a way to validate our findings on the minimum wage. We also have a section describing in depth the role that the EITC plays in this population.

## Related Literature

### Self-employment: trends and sources of data

Measuring self-employed workers' economic outcomes is increasingly important for the effective design of public policy. According to the theory of compensating differentials, pay increases, flexibility, control, or other job benefits make up for self-employed workers' relative lack of access to employer-sponsored benefits and key labor protections. However, there is evidence that workers are not always compensated for doing work that is dangerous, insecure, or otherwise undesirable (See Weil, 2019, Mishel, 2022). Other studies have noted the low incomes observed for independent contractors and gig workers who earn a large portion of their incomes through self-employment (Jackson et al. 2017).

There is evidence that the number of workers earning income through self-employment or independent contracting has risen over the last two decades (Abraham et al. 2018; Lim et al. 2019; Collins et al. 2019), making questions about how self-employed workers experience the labor market of increasing concern to policymakers..

Academic and public policy discussions about the fissuring of the workplace through domestic outsourcing and subcontracting (Weil 2014), the misclassification of employees as independent contractors (Rhinehart et al. 2021), and the rise of online platforms such as Uber, Lyft, and DoorDash (Lim et al. 2019; Mishel 2018) have all brought new attention to questions about the labor rights and protections non-employees should or should not be entitled to, as well as whether there has been a shift away from traditional employment relationships and towards self-employment. On this latter question, survey data from the Current Population Survey' Annual Social and Economic Supplement (ASEC) finds that the share of the workforce that is self-employed is relatively small and has remained mostly flat over the last two decades (Abraham et al. 2018). Similarly, the Current Population Survey 's Contingent Workforce Supplement (CWS)—the main survey the federal government uses to monitor alternative work arrangements—shows that the share of all workers who are independent contractors[1] declined slightly between 2005 and 2017, dropping from 7.4 percent to 6.9 percent.

Analyses using administrative data, however, generally find that the share of workers who earn income from self-employment and other non-employee work has increased since the late 1990s and early 2000s (Jackson et al. 2017; Abraham et al. 2018; Lim et al. 2019; Collins et al. 2019). Research using tax records from the Internal Revenue Service, for example, finds that a substantial number of workers now combine both wage and self-employment income. Collins et al. (2019) find that between 2000 and 2016 the share of the workers earning income through non-employee arrangements grew by 1.9 percentage points, that they now represent 11.8 percent of the U.S. workforce, and that most of this growth can be attributed to the recent rise of "gig" work mediated through online platforms. Similarly, Jackson et al. (2017) find that in 2014 about 12 percent of all tax filers with earnings paid self-employment taxes—a 32 percent increase from 2001. Lim et al. (2019) focus on tax filers receiving income on Form 1099-MISC/K, and find that the share of workers earning income through independent contracting grew 22 percent between 2001 and 2016.

Abraham, Hershbein, and Houseman (2019) and Abraham et al. (2018) study the discrepancy between surveys and administrative records. They propose that surveys are highly sensitive to how questions are worded and how self-employment is defined, leading many respondents to get miscoded as employees. In addition, household surveys such as the CWS and the CPS-ASEC focus on workers' primary source of income and can fail to capture important information about secondary work activity.

Some scholars have written extensively about the advantages and disadvantages of using tax-return administrative data when studying the labor market (see Slemrod 2016; Saez, Slemrod, and Giertz 2012). On the benefits of employing administrative records such as tax data to study income dynamics among the self-employed, Saez, Slemrod, and Giertz (2012) note that estimates using panel tax data tend to have smaller standard errors, prevent analyses from becoming biased due to composition effects by allowing researchers to follow the same individuals over time, and are needed

[1] CWS makes a distinction between independent contractors and the self-employed (per their definition, ICs can also be wage and salary workers).

to study questions cross-section analyses cannot address, such as how policy changes affect income trajectories. Some of these drawbacks can be present to some extent in most data sources. For example, there is evidence that the self-employed systemically underreport their income to both to tax agencies and U.S. household surveys (Hurst, Li, and Pugsley 2010). Tax data also provide relatively clear definitions of self-employment vis-à-vis wage and salary work and allow researchers to observe how workers combine different sources of income (National Academies of Sciences, Engineering, and Medicine, 2020). In addition, any findings relating to reported income will be informative for both tax scholars and tax agencies.

In the last few years, a number of researchers have used administrative tax data to study the different economic outcomes experienced by self-employed workers and employees. Jackson et al. (2017), for example, find that individuals who earn a substantial share of their income through self-employment are less likely to be covered by health insurance or participate in a retirement account than individuals with only wages. They also find that workers who make the vast majority of their earnings through self-employment are more likely to have an AGI (Adjusted Gross Income) below $20,000 than workers whose earnings come exclusively from wages or workers who engage in self-employment to supplement their wages. Lim et al. (2019) find that independent contracting has grown most among women, as well as tax filers in the bottom of the income distribution and who are using self-employment as their main source of income (on the latter point by Lim et al., we find the opposite trend following DC's 2013 minimum wage increase). These studies also show there is considerable income heterogeneity in self-employment. For instance, taxpayers with partnership income earn substantially more than the wage-only earners, while those earning income through online platforms earn substantially less.

Especially relevant to our study, Slemrod (2016) argues that differences in compliance rates between employees and self-employed means that comparisons between the two groups can be problematic. On heterogeneity in noncompliance, previous research finds thar underpayments of tax compliance are especially large in the higher-paying occupations of vehicle sales, investors, informal suppliers, lawyers and judges, and doctors and dentists (Erard and Ho 2003). Though they also find that workers in vehicle sales, tip earners, and informal suppliers rank highest in terms of the taxes unpaid as a share of their tax liability. The US Treasury reports that much of the tax gap is driven by income that is subject to little or no third-party reporting (US Treasury, 2021). This category includes most self-employment income. Treasury reports that 18-55% of this income is misreported. We take seriously that some portion of the income differences we find between wage-earners and the self-employed is likely driven by misreporting or outright tax evasion.

Even as a number of studies have examined the economic outcomes and profile of the self-employed, as well as determinants that shape individual workers' preference for self-employment (e.g. Brown et al. 2018; Hall and Krueger 2016), how this group of workers interact and are affected by broad economic dynamics and labor market institutions is less well understood. For instance, scholars have suggested that fluctuations in the business cycle, public policy changes, or other trends influencing the demand or supply of labor can lead firms to shift from hiring employees to hiring contractors as a way to reduce labor costs associated with wage employment (Abraham et al. 2018; Abraham and Taylor 1996; Dube and Kaplan 2010; Goldschmidt and Schmieder 2017). In addition, changes in economic conditions or the benefits associated with traditional employment could lead workers to choose to enter or exit traditional employee-employer relationships (Fairlie 2013; Fossen 2020). Fossen (2020), for example, examines whether recessions and booms affect entry rates into self-employment, finding that during the Great Recession high unemployment rates led to an increase in self-employment as those who found themselves jobless looked for alternative avenues for work.

Minimum wages: uncovered workers and spillover effects

In one of the only other studies examining the relationship between minimum wages and uncovered workers, Glasner (forthcoming) finds that while wage floors have little effect on traditional self-employment, they have a substantial effect on online platform work. The reason is that as a greater minimum wage pushes workers into gigs to compensate for lost hours or longer job-seeking spells. Glasner uses state and county-level variations in the minimum wage from 2000 to 2018 to estimate the effect of minimum wages on nonemployer establishments[2], and examines how these effects vary by local labor market concentration and the timing of the deployment of Uber. Glasner finds that for every 10 percent increase in the minimum wage, the number of transportation and warehousing services nonemployer establishments increased by 2.7 percent between 2010 and 2018. These findings suggest that "Uber, and other forms of platform work, are able to effectively take up the slack from excess labor supply in the covered labor market resulting from minimum wage increases."

This and other studies therefore show that individuals not directly affected by minimum wage increases can nonetheless experience employment, income, or wage effects from the policy. If the minimum wage rises it is most likely to directly affect jobs and workers that were previously below the new wage floor, but researchers have also found evidence of positive wage spillovers for jobs slightly above the new minimum as employers raise pay to temper wage compression among workers (Dube 2013; Lopresti et al 2015; Cengiz et al. 2019). Recently, Cengiz et al. (2019) studied more than a 130 state-level minimum wage increases between the late 1970s and the late 2010s, finding that in the five years following a wage floor increase, the overall number of low-wage jobs remained largely unchanged, the affected low-wage workers experienced a 7 percent increase in wages, and spillovers from the policy extended up to $3 above the new wage floor, representing about 40 percent wage increase stemming from the higher minimum wage.

Another set of studies focuses on the effects of citywide minimum wage increases (Dube et al. 2007; Schmitt and Rosnick 2011; Jardim et al. 2017; Fahimullah et al. 2017). Using administrative data from Washington State, Jardim et al. (2017) find that a minimum wage increase in the City of Seattle led to a decline in net payroll expenses, employment, and employee earnings. They note, however, that their estimates could be overstating the decline in employment if, as a response to the minimum

[2] Defined as businesses that do not have paid employees, and that are mostly comprised of the unincorporated self-employed and independent contractors.

wage, employers "respond to the minimum wage by shifting some jobs under the table or outsourcing workers on payroll to contractor positions." Like other studies using administrative data to examine the effects of minimum wage increases (e.g. Jardim et al. 2017; Rinz and Voorheis 2018) we are able to examine the District of Columbia's entire tax reporting, low-wage labor market, rather than examining only lower-wage industries such as the restaurant and retail sectors.

**Policy landscape**

In 2013 there was a contentious political debate around minimum wage policy in the District of Columbia, which involved the mayor vetoing a City Council-passed measure designed to force large retail employers to pay above the general $8.25 minimum wage. Following that, in December 2013 the City Council passed, and in January 2014 District of Columbia Mayor Vincent Gray signed, the Minimum Wage Amendment Act of 2013 into law. The law provided for a general increase in the hourly wage floor for all non-tipped employees from $8.25 to $9.50 on July 1, 2014. Between 2014 and 2016 the jurisdiction's wage floor rose by $1 every July. Stating in 2017 the Fair Shot Minimum Wage Amendment Act of 2016 went into effect, which raised the minimum wage to $15 per hour in 2020, with further increases tied to the Consumer Price Index for Washington's Metropolitan Area (DOES). Inflation increases have pushed the minimum wage to $16.10 per hour in 2022. An estimate projected that in 2021, about 61,000 District of Columbia residents were impacted by the Fair Shot Minimum Wage Amendment Act of 2016 through an increase in wage income or job loss (Fahimullah et al. 2017).

**Table 1. Schedule of minimum wage increases at the federal level and in DC**

| Date | Federal minimum wage | District of Columbia minimum wage | Yearly income in DC |
|---|---|---|---|
| Prior to July 1, 2014 | $7.25 | $8.25 | $17,160 |
| July 1, 2014 | $7.25 | $9.50 | $19,760 |
| July 1, 2015 | $7.25 | $10.50 | $21,840 |
| July 1, 2016 | $7.25 | $11.50 | $23,920 |
| July 1, 2017 | $7.25 | $12.50 | $26,000 |
| July 1, 2018 | $7.25 | $13.25 | $27,560 |
| July 1, 2019 | $7.25 | $14.00 | $29,120 |
| July 1, 2020 | $7.25 | $15.00 | $31,200 |

Note: Yearly income estimated assuming a 40-hour workweek, 52 weeks per year

To build our empirical specification, we take advantage of the fact that this series of increases to the minimum wage floor did not apply to all District of Columbia residents. Only about 24 percent of all jobs in the Washington DC metro area are located in the District. In both 2014 and 2019 about 25 percent of wage and salary employees working in DC were employed by the federal government

(DC CFO 2020). State and local government minimum wage laws are not binding on the federal government, so these workers were not affected by the minimum wage increases of 2014–2021. Similarly, there are important employment flows between DC and other jurisdictions, especially the states of Maryland and Virginia. Per one estimate, in 2014 almost 70 percent of all workers in DC did not live in the city, with that study projecting that the rise of the District's minimum wage would exacerbate commuting incentives among neighboring jurisdictions (Fahimullah et al. 2017). Our data indicates that about half of DC wage workers work for the federal government or in Maryland or Virginia, with the other half working at a private sector establishment in DC or for the DC government. Those two groups will be our treatment and control in the minimum wage study.

While in Virginia the wage floor was never higher than the federal minimum at any point in our study period (it rose from $7.25 to $9.50 in 2021), Maryland did engage in a series of hikes, though they lagged behind DC. Maryland's minimum wage was lifted four times between 2015 and 2019, climbing from $7.25 to $10.10 during that period. Starting in 2018, in some counties, and for employers with more than 14 employees, the increase was greater. Our study assumes DC residents working outside DC were unaffected by rising wage floors. This is an important caveat to our study, though these outside wage increases could only bias our estimates downward.

### Data

To our knowledge, ours is the first study combine administrative tax and employment data to measure the relationship between minimum wage increases and the income trajectories of the self-employed. We are also the first to track the income of  self-employed workers over time using tax data, and one of the only to use US tax data to measure the effects of a minimum wage increase. Our main data source is the population-level individual income tax (IIT) database from the District of Columbia's Office of Revenue Analysis. It contains all individual-level IRS Form 1040 and schedule C records (from 2006-2020) and DC tax records from District form D-40 (from 2001-2020) of all DC tax filers for those years. We focus on wage-earners, as well as those filing a Schedule SE (used to report labor income earned outside of a traditional employment relationship) and Schedule C (used to report income or losses from a business operated or profession practiced as a sole proprietor).[3]

We focus on a decade of post-Great Recession tax returns from 2010 and 2018, giving us time to establish pre-trends before the introduction of the minimum wage increase in 2014. We provide descriptive statistics for the entire population, but our main sample is restricted to single taxpayers with positive earnings. DC's ITT database allows us to construct a panel and track the trajectories of the same tax-filers through time. In addition to information about income and source of income, the data also allows us to observe household size, whether the taxpayer is an Earned Income Tax Credit

[3] Some individuals may file a Schedule C but not have Schedule SE income, since their profits fell below the $400 Schedule SE filing threshold. Other taxpayers with no Schedule C but with partnership income will pay self-employment tax on Schedule SE, if they were actually employed in performing services for the partnership. In keeping with IRS definitions, we consider both to be indicative of self-employment.

(EITC) recipient, a Child Tax Credit (CTC) recipient, as well as their age and zip code of residence. In addition, these data allow us to observe the industries in which Schedule C filers work.

We also connect the IIT data to data from the District of Columbia Department of Employment Services (DOES). The DOES gathers employer-reported wage data for District of Columbia government employees and private-sector employees for use in administering the District's Unemployment Insurance and Paid Family Leave programs. Each quarter, employers have to maintain and report records on the wages paid to all employees each pay period, including information on the cash value of other renumeration, gratuities and tips, and expenses incurred by each employee for which a deduction from wages is paid.

Importantly, the DOES data allows us to separate the workers in the IIT database who were subject to minimum wage increases from those who were not. While all low-income Washingtonians can be said to be part of the labor market affected by a minimum wage increase, the law only applies to workers in the DC private sector or who work for the District government. Those are also the populations contained in the DOES database. The law does not apply to IIT filers who work in Maryland or Virginia, who work for the federal government, or who are self-employed, though those workers may experience spillovers from the wage policy.

Finally, we use a probabilistic matching program to generate a gender indicator for first names that are likely to belong to one gender over another. This is an important advantage given that excluding online platform work, since 2000 independent contracting has grown more among women than among men (Collins et al. 2019).

**Table 2: District of Columbia taxpayers by employment type**

**Type of District of Columbia taxpayers (number and as a share of all taxpayers) 2010, 2013, 2018**

| Year | Number of taxpayers | | | | | Share of taxpayers | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Wage-earners | Self-employed | Both wage-earners and self-employed | Neither wage-earners nor self-employed | Total | Wage-earners | Self-employed | Both wage-earners and self-employed | Neither wage-earners nor self-employed |
| 2010 | 212,766 | 12,787 | 32,376 | 27,541 | 285,470 | 74.5% | 4.5% | 11.3% | 9.6% |
| 2013 | 220,972 | 14,978 | 37,260 | 25,694 | 298,904 | 73.9% | 5.0% | 12.5% | 8.6% |
| 2018 | 235,785 | 14,678 | 44,791 | 24,558 | 319,812 | 73.7% | 4.6% | 14.0% | 7.7% |

Notes: Numbers capture all taxpayers with positive income.
Wage-earners: Reports W-2 income on tax return. Self-employed: reports income on Schedule C or files Schedule SE, Self-employment tax

Before performing any analysis we classify taxpayers in the IIT database as either wage earners (they report wage income on form 1040), self-employed (they file Schedule C: Sole proprietorship or Schedule SE: Self-employment tax), both, or neither (Similar to Jackson et al, 2017).[4] Table 2 presents a cross-sectional look at DC taxpayers during the period in which we will construct our panel. We can see that the population of DC taxpayers is growing over this period. In 2010, 2013, and 2018, approximately 74 percent of taxpayers reported earning wages and no self-employment income. Those self-employed with no wage income grew both in number and as a share of all taxpayers from 2010-2013 and then shrunk by 2018. Taxpayers meeting both definitions grew

[4] Self-employed people can report income on Schedule C or as profit or loss from a partnership or on Schedule S. This income is often comingled with passive rents or with dividend income in tax returns. We therefore use Schedule SE reported self-employment tax payments to identify filers who are actively self-employed and not drawing passive income.

throughout this period, from 11.3% to 14% of all taxpayers. Taxpayers who met neither criteria were likely to have an older median age, and often Social Security or capital gains were their primary income sources. This population shrunk throughout the study period.

Careful attention must be paid when constructing a tax dataset to study trends among independent contractors and online platform workers. For example, Collins et al. (2019) find that a large share of Form 1099-MISC/Ks recipients do not file a Schedule C or Schedule SE, in many cases because they fail to report their income in the correct form. In addition, many self-employed individuals may not receive any 1099-MISC/K forms and nonetheless correctly file with Schedule C or SE on their return. Saez (2010) shows that self-employed taxpayers bunch at the first kink point of the EITC, which is driven by the misreporting of self-employment income. In this study we are careful to control for the receipt of refundable tax credits like the CTC and EITC in order to control for bias from these dynamics. Additionally, Washington DC had more strict reporting requirements for Form 1099 than the IRS during key years of our study period, which gives us more confidence that self-employment income was being reported correctly.

## Methods

Similar to Jackson et al. (2017), we further refine our tax filers depending on what share of income they earn from wages and what share of income they earn from self-employment. Our focus is on workers we classify as "primarily wage earners" and "majority self-employed" whom we define like so:

- **Majority self-employed**: Files a Schedule C or SE Wages comprise less than 50% of total AGI.
- **Primarily wage-earning**: Wage income is at least 85% and no more than 115% of the AGI total.

Our analysis generally excludes tax filers those who meet neither criteria, such as those who only report passive income or Social Security income, and also excludes those with very mixed sources of wage and self-employment income, in order to have cleanly differentiated study groups. Because of the inherent difficulty of assigning income and labor classifications between married filers, and therefore the difficulty of interpreting results from them, we exclude married filers from our analysis.

After narrowing the data to unmarried taxpayers and identifying the majority-self employed and primarily wage-earning (there is no overlap), we see a distribution like in Table 3 (below). About three-quarters of unmarried taxpayers are primarily wage-earning and this number is growing during our study period. In contrast, the "majority self-employed" grew in number and as a proportion of all taxpayers from 2010-2013, but then this trend reversed from 2013-2018. As we will show, this self-employment decline was concentrated among low earners.

**Table 3: Unmarried District of Columbia taxpayers by narrowed employment type**

| Type of District of Columbia taxpayers (number and as a share of unmarried taxpayers) 2010, 2013, 2018 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Number of unmarried taxpayers | | | | Share of unmarried taxpayers | | |
| Year | Primarily Wage-earners | Majority Self-employed | Neither | Total | Primarily Wage-earners | Majority Self-employed | Neither |
| 2010 | 173,642 | 14,687 | 54,088 | 242,417 | 71.6% | 6.1% | 22.3% |
| 2013 | 181,954 | 17,620 | 52,473 | 252,047 | 72.2% | 7.0% | 20.8% |
| 2018 | 209,685 | 16,776 | 41,851 | 268,312 | 78.1% | 6.3% | 15.6% |

Note: Numbers capture all single taxpayers with positive income.
Primarily wage-earners: wages are between 85% and 115% of AGI; Majority Self-employed: Files Schedule C or Schedule SE and wages are less than 50% of AGI

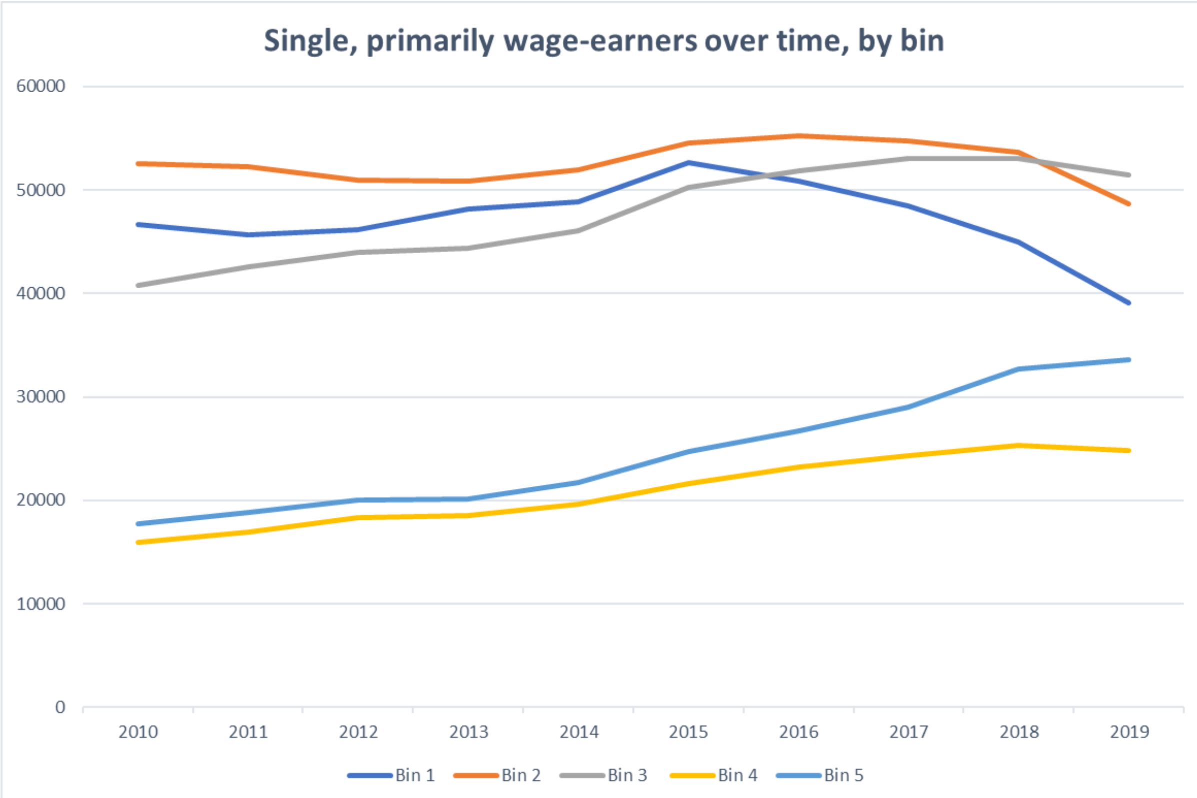
We also construct five Adjusted Gross Income bins, where Bin 1 is selected to identify the lowest-earners, who are most likely to be minimum wage-affected after our base year (2013). As seen in Table 1, a full-time, year-round worker earning the minimum wage at the start of our period ($8.25/hour) would earn $17,160 in annual income and workers making slightly more than the minimum wage (but who could still experience wage spillovers from the policy) will also be included in Bin 1. For a minimum wage worker, the increase over our study period would be very significant, amounting to a 61 percent wage increase. However, our data does not allow us to observe hours worked, so we cannot determine if a taxpayers is working full-time, part-time or working two jobs. Bin 1 is therefore necessarily inexact and constructs a population that is minimum wage-affected as an intent-to-treat measure.

**Table 4. AGI bins used in study**

| Bin | Adjusted Gross Income (AGI) **in 2013** |
|---|---|
| Bin 1 | $1-22,000 |
| Bin 2 | $22,000-$45,000 |
| Bin 3 | $45,000-$75,000 |
| Bin 4 | $75,000-$100,000 |
| Bin 5 | $100,000+ |

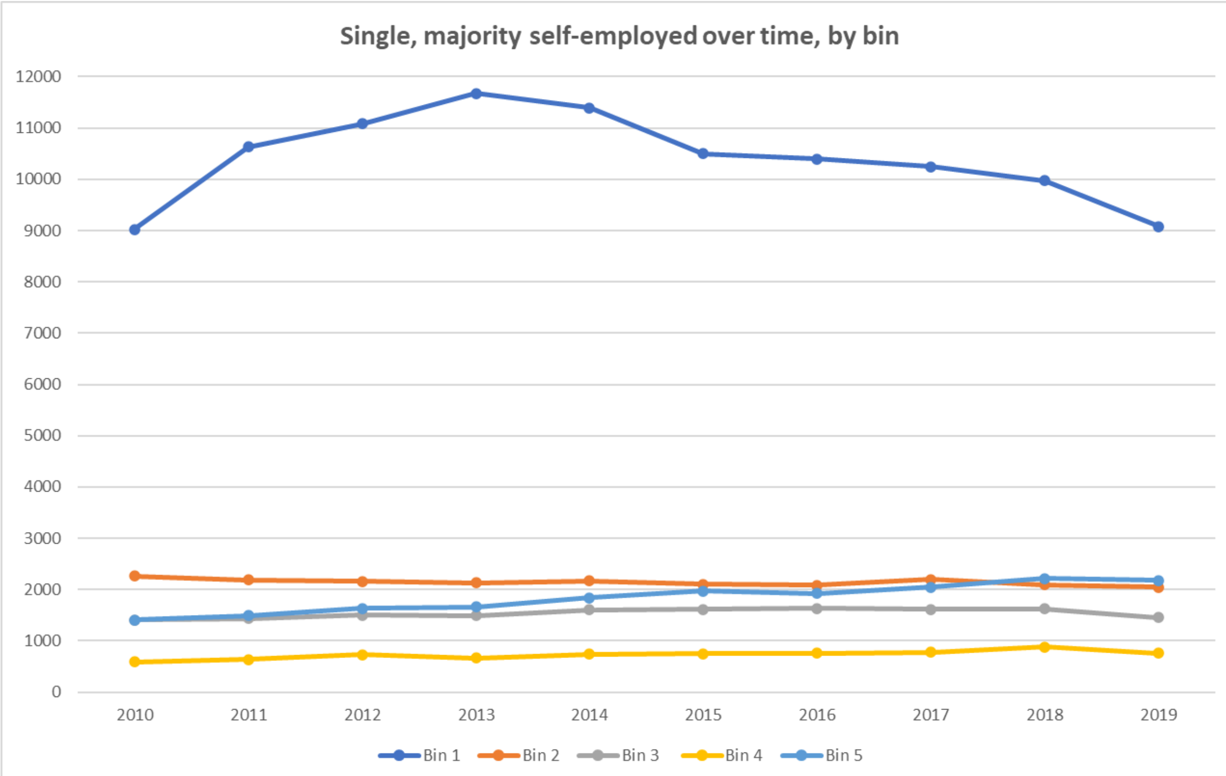
Overall, the number of filers in Bin 1 decreases over this time period, reflecting increasing incomes in the District. In the initial years of our study period, Bins 1 is the largest by number of taxpayers, but by 2018 there are approximately equal numbers of unmarried taxpayers in Bins 1, 2 and 3 (62,000-67,000). A cross-sectional analysis (see Figure 2) shows that incomes are rising in the District among primarily wage-earning Washingtonians. The number of single tax filers making almost their entire AGI from wages in Bin 1 falls, especially between 2015 and 2018, while the corresponding number in Bin 5 steadily increases. The decrease of taxpayers in Bin 1 could indicate that rising wage-rates are pushing them into higher income bins over time.

**Figure 2: Primarily Wage-Earners over time by Income Bin**




There were two distinct trends in the overall number of majority self-employed taxpayers during our study period. Majority self-employment was increasing before the minimum wage was introduced in 2014. Beginning in 2014 the number of majority self-employed began to shrink. This trend is especially visible in Bin 1, which contains a majority of the taxpayers who were majority self-employed. The number of self-employed in the highest-earning Bin5 steadily increased over this time period.

**Figure 3: Majority Self-employed over time by Bin**




**Panel Construction**: We construct the panel by matching taxpayers across years using social security numbers (SSNs). For our primary analysis, we exclude taxpayers who select that they are "married filing jointly" because of the inherent difficulty in assessing from return-level data the extent to which one of the couple could be self-employed, likely subject to the minimum wage, or participating in the labor market at all. Our panel is comprised of all taxpayers who filed taxes in DC in 2010 (to establish pre-trends), 2013 (as our base year when Income Bins are set), and in at least one year from 2014-2018. We also match the panel to their incomes in 2011 and 2012 to fill in the pre-trend analysis.

We experience steady attrition each year of the panel as taxpayers die, move away from DC, get married, or fail to file taxes. In 2010 we begin with 242,417 single taxpayers with positive income. There are 80,778 taxpayers who "survive" in our panel until 2018. Attrition is a potential source of bias in our estimates, we expect lower survivorship rates among those in Bin 1 since previous research using panel data has found that lower-income individuals have greater rates of attrition than higher-income individuals (Fitzgerald, Gottschalk, and Moffitt, 1998). This is due to a variety of factors including higher rates of marriage, divorce, migration, death, or inconsistent tax filing because very low earners do not have an obligation to file. Attrition rates are an unavoidable challenge, but they will not challenge our estimates unless attrition between groups accelerates or decelerates after 2013. That is, attrition introduces bias into our estimates if there is evidence that our main instrument, the minimum wage increases, causes workers to drop out of the labor force or pushes workers to move away from DC, as some of the literature suggests it could (See Neumark, 2019; Clemens and Strain, 2021). If that is the case, our income estimates could be biased upward by survivorship bias.

Our analysis suggests that even though low-income taxpayers are more likely to fall out of the sample overall, attrition among taxpayers in Bin 1—those more likely to be affected by the minimum wage increases and changes in self-employment—does not present a serious challenge to our estimates. After controlling for attrition trends in 2010–2013 we continue to observe higher survivorship rates in Bin 2 (1.3%), Bin 3 (1.7%), Bin 4 (3.7%), and Bin 5 (3.6%) with respect to Bin 1. However, none of these estimates are statistically significant at the 95% confidence level. We also observe that majority self-employed taxpayers experience a higher survivorship rate (1.8%) than primary wage earners throughout our complete panel, though these estimates are not statistically significant at the 95% confidence level either.

Finally, taxpayers are matched by SSN to their employment records in the DOES database in 2013 and every subsequent year, if such records exist. Our data access currently grants us access to 1-2 full quarters of employment data per year, which we use to. We tag taxpayers with a binary indicator variable if they are employed at an employer subject to the minimum wage increase in quarter 2 or 3 of each year. With a fuller data universe we could perform more advanced analysis in the future.

For our panel analysis, taxpayers are classified by income Bin in 2013. Income is allowed to vary on either side of that year, but for the analysis, "taxpayers in Bin 1" are those taxpayers who were in that income Bin in 2013 (making from $1-$22,000).

**Observational analysis**

In the first part of our analysis, we simply track income by bin and employment type over time. Again, we exclude "married filing jointly" filers because of the difficulty of interpreting results for a tax unit consisting of multiple workers. These are the employment groups we track:

- **Majority self-employed**: Files a Schedule C or pays Self-employment tax. Wages&Salaries line is less than 50% of AGI total.
- **Primarily wage-earning**: Wage income is within 15% of total AGI. So, wages are at least 85% and no more than 115% of the AGI total.
    - This group is further subdivided into two groups based on their exposure to the minimum wage increase.
        - **Minimum wage eligible**: works for either the DC government or for a private sector employer in Washington DC. Is contained in the DOES database.
        - **NOT minimum wage eligible**: works for any other employer (the federal government, employers in Maryland, Virginia or another state). Not present in the DOES database.

- **Other taxpayer**: Any other mix of income or employment. "Other" taxpayers who are not wage-earners, self-employed, or have a mix of wages and other income sources are generally not included in our analyses.

The first thing to note is that this was a time of rapid income growth for most of our taxpayer panel. Tables 5 and 6 (below) show that the median income growth from 2013-2018 was 19 percent, a bit more than double the median growth from 2010-2013 of 8 percent. Mean income increase figures are heavily affected by outliers, which can reach into the thousands of percent positive and negative. Therefore, we bind our percent change variable at -100 percent and +1,000 percent. This binds approximately 2 percent of the population. All percent change figures in this paper have those bounds.

**Table 5: Overall Aggregate Gross Income (AGI) change from 2013-2018, Washington DC**

| Mean | N | 1st Pctl | 5th Pctl | Lower Quartile | Median | Upper Quartile | 95th Pctl | 99th Pctl |
|---|---|---|---|---|---|---|---|---|
| 49% | 80,778 | -100% | -67% | 0% | 19% | 53% | 236% | 993% |

Note: Excludes taxpayers who were married filing jointly in 2010, 2013 or 2018

**Table 6: Overall Aggregate Gross Income (AGI) change from 2010-2013, Washington DC**

| Mean | N | 1st Pctl | 5th Pctl | Lower Quartile | Median | Upper Quartile | 95th Pctl | 99th Pctl |
|---|---|---|---|---|---|---|---|---|
| 40% | 80,778 | -100% | -60% | -5% | 8% | 34% | 223% | 966% |

Note: Excludes taxpayers who were married filing jointly in 2010, 2013 or 2018

Appendix Figures 5 and 6 elaborate on the above to show that income growth varied considerably by employment type and starting income bin in 2013. As those figures show, primarily wage-earners saw the fastest income growth from 2013-2018. Among them, the fastest-growing group was those who began in the lowest-earning Bin 1. If a Bin 1 taxpayer worked at an employer covered by the minimum wage increase (a private sector employer in DC or the DC District government), then that taxpayer could expect to see a 79 percent median income increase from 2013-2018. Even taxpayers working in Maryland, Virginia or for the federal government (and therefore not directly affected by the minimum wage increase) saw a 56 percent median income increase.

The fastest growing group were those who switched from self-employment to wage-earning between 2013-2018. Switchers in Bin 1 saw their median income increase by 101 percent, and other switchers to wage-earning also posted strong income gains. Some of this fast income growth is surely due to demographics. As shown in Appendix Table 2, Primarily Wage Earners are younger than the Majority Self-Employed. Younger adulthood is correlated with faster income growth, both in our regression and in the literature (see Lee et al, 2014).Younger age was also a correlated with likelihood to switch employment type.

The only group whose median members faced an absolute income decline over six years were those that moved from wage-earning to self-employment. Becoming self-employed was associated with an immediate decline in income for every income bin in this specification. This decline in income was not reversed even after six years, with the median switcher to self-employment in still having an income 3-51% less in 2018 than they had in 2013. This is despite the fact that switchers were more likely to be younger adults, who generally see high income growth. As the analysis below will confirm, switching from being a primarily wage earner to being majority self-employed is associated with a reduction in income (See: Switching Employment type 2013-2019). It is unclear if the income drop associated with becoming self-employed is caused by self-employment per se, or if people with falling incomes are drawn to self-employment (ie the recently unemployed, or new parents).

Taxpayers who were continuously majority self-employed saw moderate 9-11 percent median income growth over these six years.

Minimum wage

Appendix Figures 1-3 show the median income for our different Bin and employment groups from 2010-2018. This helps to establish the parallel trends assumption for our later regression. The income trajectories of the people who would be classified into Bin 1 in 2013 were broadly parallel from 2010-2012 no matter their employment type. Trends for wage-earners who would later become eligible for the minimum wage increase are essentially identical to wage-earners who would not be covered by the minimum wage increase.

Slightly more women than men were in jobs that would theoretically be eligible for the minimum wage increase, but their age profiles are nearly identical.

The year 2013 sees a slight acceleration in income among wage-earners relative to the self-employed. Because the DC Council passed a series of minimum wage bills in 2013 (one of which was vetoed before the next was passed and signed), we think 2013 could be considered a treatment year due to the fact that employers may have started raising wages in anticipation of the coming minimum wage increase (as in Jardim, 2017). We retain 2013 as our base pre-treatment year because the policy was not technically in effect in that year, but this decision could bias our estimates of the minimum wage's effects downward.

Moving away from pre-trends and demographic composition, Appendix Figures 1-3 show that there is a clear inflection point for primarily wage-earning taxpayers in Bin 1 in 2013. This inflection point is not present for any other group. After 2013 median income growth accelerates for wage-earners but not the self-employed, especially so for those wage-earners covered by the minimum wage. After tracking each other closely from 2010-2013, minimum wage-eligible workers in Bin 1 have a median income $1,848 higher than non-minimum wage eligible counterparts in 2014. The gap between workers at DC establishments and those at Maryland, Virginia or federal government establishments grows to $3,100 by 2018.

This income acceleration is exactly what we would expect to see if the minimum wage was working as intended and increasing low-earners' incomes.

In other income bins, we do not see a similar divergence among wage-earning taxpayers. In Bins 2 and 3, wage-earners' median earnings closely track each other whether or not they were at a minimum wage-covered establishment before and after the minimum wage. Self-employed taxpayers in the higher income bins to not experience the same income stagnation that their low-income counterparts do, and the divergence between them and primarily wage-earners is less noticeable.

See Appendix: Triple Difference Analysis for discussion of different methods we used to test the minimum wage findings.

Self-employment

One of our main findings is that low-wage self-employed earners have persistently low and stagnant incomes. This dynamic is most clearly evident among those in Bin 1. Over half of the Washingtonians who rely on self-employment for their income are in this lowest-income bin (See Figure 3, above). As such, understanding the income trajectories and labor market outcomes of low-earners is key to understanding how self-employment is experienced overall.

Of the 17,620 single majority self-employed taxpayers (Table 2) in Washington DC in 2013, 11,672 were in the lowest-earning bin. As workers in this bin move away from relying on self-employment earnings over time, the total number of self-employed also falls. Gains in other bins are not enough to make up for the net loss of 1,700 self-employed from the lowest bin. As a result, in the context of a growing population and the rise of gig economy platforms, the number of single taxpayers relying on self-employment dropped by 844 from 2013-2018. While outside the scope of this research, an important share of workers who are self-employed do so as a secondary source of income, with evidence that these workers earn substantially higher incomes, on average, than those who rely more heavily on self-employment as their primary source of income (Jackson 2017). In D.C., the share of taxpayers with both wage and self-employment income increased from 11.3 percent in 2010 to 14 percent by 2018 (Table 2). These workers have higher incomes, on average, than those who rely solely on wage-earnings or self-employment.

Washington DC's drop in self-employment was at least partially driven by low earners becoming less likely to choose self-employment and more likely to leave self-employment for wage earning (see Table 4, below). From 2010-2013, 6.4 percent of Bin 1 taxpayers switched from being primarily a wage earner to be majority self-employed, more than double the rate in the overall population (3.0%). Then from 2013-2018, the proportion of Bin 1 taxpayers making this transition dropped to 5.9 percent, even as among the overall population more switched into self-employment in the later period than in the first. We also find that the lowest earners are more likely to switch the opposite way, into wage-earning, and that this trend is accelerating faster for them than for higher-income taxpayers.. Nearly half (42.9%) of the taxpayers who were majority self-employed in 2013 had become primarily wage-earners by 2018, a sharp uptick from the earlier period. These changing flows could suggest that self-employment became comparatively less attractive than wage-earning over this time period. Overall after 2013 transitions from wage-earning to self-employment slowed down during our study period and transition to wage-earning sped up among low-earners.

**Table 7: Percent Switching Employment type, before and After Minimum Wage Increases**

| Percent of one employment type switching to another, by period and income bin | 2010-2013 | | 2013-2018 | |
|---|---|---|---|---|
| | **Bin 1** | **All Bins** | **Bin 1** | **All Bins** |
| **Majority Self-employed to Primarily Wage-Earner** | **31.3%** | **20.3%** | **42.9%** | **26.3%** |
| **Primarily Wage Earner to Majority Self-employed** | **6.4%** | **3.0%** | **5.9%** | **4.2%** |

Appendix figures 3, 4, 5 and 6 show the starkly different income patterns that result when taxpayers switch employment type. Those that become wage earners realize a large increase in income. Despite similar pre-switch income trends, leaving self-employment for wage earning was associated with having an income $10,100 higher just five years later, among the lowest earners. In Bin 2, the difference between the switchers was even wider, $34,473 for the median switcher.

Switching Employment type 2013-2019

We perform robustness checks to test our findings on the income penalty of switching to self-employment and of the income boost from switching to wage-earning. The panel analyses above use 2013 as the base year to form a panel because that is the year before the minimum wage increases began. Though we track tax filers who switch classifications in later years in those analyses, our use of 2013 as the base year could lead to anomalous findings. We therefore expand our analysis to include all tax filers who switch employment classifications in our study period.

First, we identify every tax filer from 2012-2019 who was of a single employment type, Majority Self-employed or Primarily Wage Earner, for **two years in a row and who then switched to the other employment type in the next year.** See Appendix Table 5 for an illustration of this process. We form a panel of all these tax filers and examine the income change they experienced from year before to the year after their switch in employment type.

In this analysis of all employment type switchers (reported in Table 8, below) we see that most taxpayers who switched from wage earning to self-employment from 2013-2019 saw income declines. Middle earners saw sizeable declines in income, while those at the top and bottom of the income distribution saw smaller median declines. Because some switchers experienced very large increases in income, the mean income growth was positive for earners in Bin 1 and Bin 5.

Tax filers who left self-employment for wage-earning experienced income increases the next year, except among the highest earners. Mean and median income change tell directionally similar stories among switchers to wage-earning, but with different magnitudes. Tax filers in all Bins experienced more positive income growth from switching to wage earning than from switching to self-employment, except for the highest earners. Unmarried earners making above $100,000 were seemingly better off switching to self-employment than the other way around.

**Table 8: Next year income change for employment switchers 2011-2019**

| | Observations | Mean income % change | Median income % change |
|---|---|---|---|
| Bin 1 x Switched WE to self-employment | 3541 | 37.8% | -5.3% |
| Bin 2 x Switched WE to self-employment | 1702 | -28.8% | -43.0% |
| Bin 3 x Switched WE to self-employment | 984 | -12.6% | -33.5% |
| Bin 4 x Switched WE to self-employment | 432 | -12.2% | -26.9% |
| Bin 5 x Switched WE to self-employment | 1255 | 12.9% | -5.3% |
| Bin 1 x Switched SE to wage-earning | 3150 | 93.1% | 23.7% |
| Bin 2 x Switched SE to wage-earning | 396 | 48.4% | 35.0% |
| Bin 3 x Switched SE to wage-earning | 230 | 25.0% | 19.5% |
| Bin 4 x Switched SE to wage-earning | 85 | 11.9% | 8.6% |
| Bin 5 x Switched SE to wage-earning | 153 | -12.3% | -7.5% |

Notes: Population is tax filers who were WE or SE for two years and then switched to the other employment the next year,
Percent change in income from the year before employment type switch to the year of the switch.
WE= wage-earning, SE= self-employed.
Bin 1: Base AGI from 0-$22,000, Bin 2: Base AGI from $22,000-45,000, Bin 3: Base AGI from $45,000-75,000
Bin 4: Base AGI from $75,000-100,000, Bin 5: Base AGI above $100,000

Tax Collections Analysis

There are several tax implications from these observations about the self-employed. Appendix Table 4 shows the net gain or loss to the Treasury that results from taxpayers switching classification. From 2013-2014 tax receipts dropped by -$144 for every taxpayer making less than $75,000 who switched to self-employment. They rose by +$790 for each taxpayer who switched to primarily wage-earning from self-employment. While we are unable to measure the extent to which these results might stem from a higher propensity to underreport income or engage in tax evasion among the self-employed, or from genuinely changing economic circumstances, employment type appears to have a substantial effect on tax receipts.

**Regression analysis**

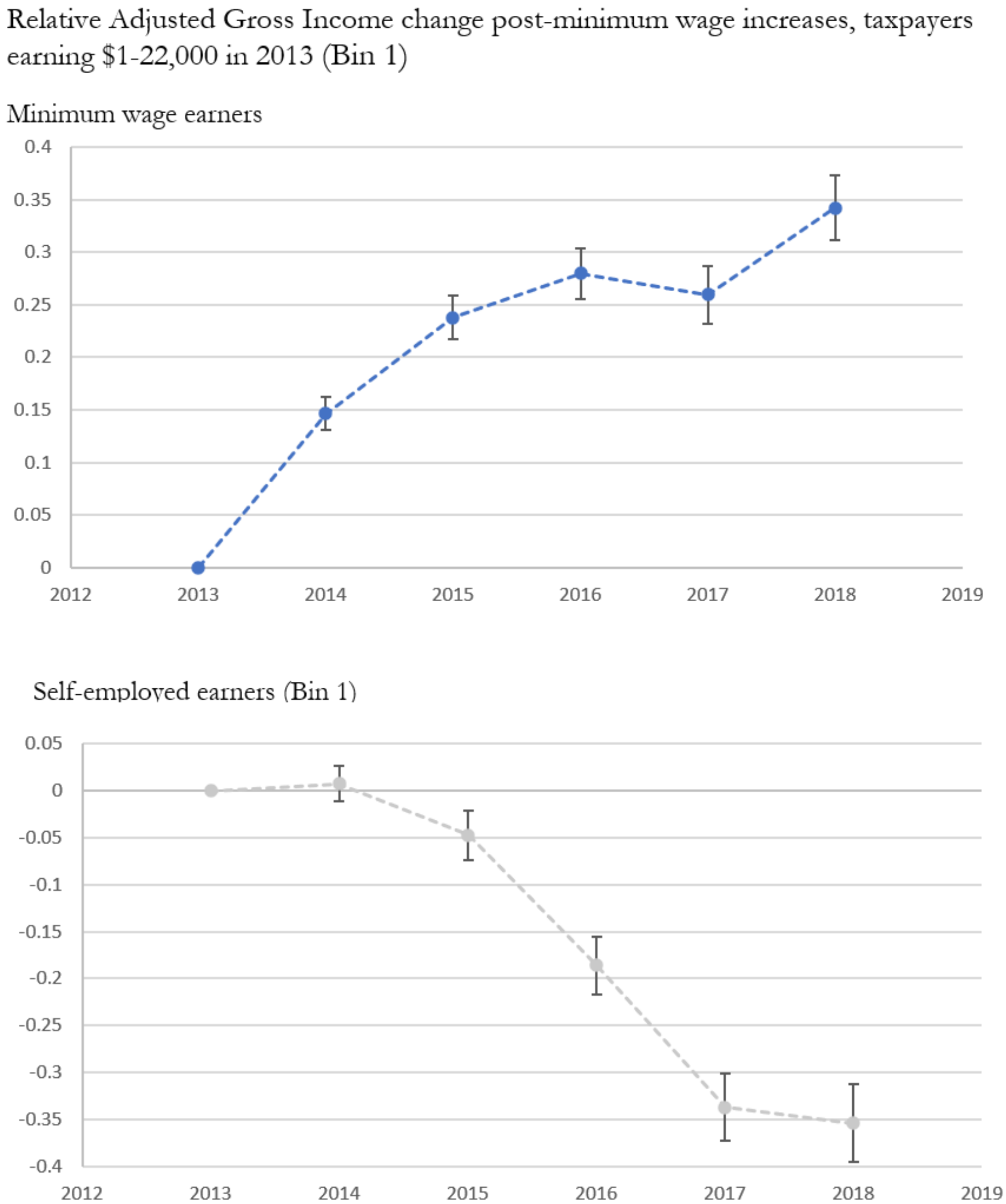
Though from the descriptive analysis it is clear that there are very different income trajectories for filers with different employment types in DC, a regression can help to control for certain observable factors and more closely quantify the differences in income growth between different employment types and income Bins.

Our outcome of interest is the percentage change in AGI from 2013-2018. This outcome variable is bounded to avoid outliers, which otherwise can be quite extreme in panel income tax data (see discussion above or Saez and Slemrod, 2014). Without bounding, outliers see their income change by thousands of percentage points (positive or negative) over even a few years. Extreme outliers are especially common among the self-employed, but are certainly not restricted to them. Percent change in income is bounded at -1 to +10, which binds 2% of the sample from 2013-2018, and less for shorter panel time spans.

We choose a narrow reference group to produce an estimate the direct effect of the minimum wage policy, and also produce estimates of the relative income growth of other employment types in DC over this time period. We add terms for employment types of interest, that is: majority self-employed taxpayers, primarily wage-earners, and people who switched classifications, by Bin. Our omitted reference group in this regression is Bin 1, primarily wage-earners, who were not covered by the minimum wage. The reference group earns wages as their primary form of income but at an employer in Maryland or Virginia or for the federal government, so were not subject to DC's minimum wage increase. We view this group as the most comparable to the minimum wage-affected population and thus most likely to give us a counterfactual, minimum wage unaffected population. However, caveats about spillovers apply to this group, as much if not more than the others. The regression results are in Appendix Table 3.

The regression results show that the minimum wage-eligible had income growth 34 percent faster than their non-eligible counterparts (See Figure 4, below). Signs for their higher-earning counterparts in Bins 2 and 3 were quite large and negative, relative to the reference group, giving us confidence that this is not due to secular differences between employers in DC and neighboring jurisdictions, but to a policy that affected only Bin 1.

**Figures 4 and 5: Regression results**




Note: the coefficients represent percentage change in income relative to the reference group (Bin 1 wage earners not subject to the DC minimum wage) for categorical, binary variables. Error bars represent the 95% confidence interval of the regression estimate.

We also produce estimates for other groups in DC, relative to our reference. Self-employed taxpayers in Bin 1 saw much slower income growth than the reference group, beginning in 2015. They grew 35 percent slower than their wage-earning, minimum wage ineligible counterparts, while self-employed taxpayers in higher Bins saw growth that was noticeably slower than the reference group, but faster than some of the wage-earners at similar income levels. This indicates that there could be factors specific low-wage self-employment that make for very little economic mobility, rather than factors related to self-employment generally. After controlling for co-variates, it seems that income growth for middle earners may have been stronger among the self-employed than among wage-earners.

Even though we have approximately isolated the group to which the minimum wage applies directly, it is important to note that all low-income, labor-involved taxpayers exist in a similar labor market. A rising minimum wage for one segment of the market could be expected to affect the wages of the rest of this population. However, it seems that workers outside of DC's jurisdiction are not able to internalize the wage increase like those directly subject to it. Only 24 percent of jobs in the Washington DC metro area are inside DC city limits, and a quarter of those are federal government jobs, so the District government's ability to affect the overall labor market in the region is limited. However, the likely existence of positive spillovers from this policy to our reference group would mean our estimate of the minimum wage's effects is biased downward.

Taxpayers who switched from wage-earning to self-employment saw large relative income drops in all bins. Switching from being primarily wage-earning to majority self-employment was associated with income growth 79 percent slower than in the reference group in Bin 1 and 158 percent lower in Bin 2. Switching the opposite way (toward being primarily wage-earning) was associated with growth up to 77 percent faster than the reference in Bin 1. Switchers to wage-earning in Bin 1 recorded the fastest growth of any group in the study. This strong growth held for Bin 2 switchers to wage-earning, who only grew 25 percent slower than the reference.

We control for covariates that may affect income mobility and how income is earned or reported. For instance, we control for Earned Income Tax Credit (EITC) and Child Tax Credit (CTC) receipt, and the amount of EITC receipt, which may influence income dynamics especially among the self-employed (See Saez, 2010). The self-employed in our study seem to have a tendency to cluster around the first kink point of the EITC for a single earner with one child similar to Saez, 2010. This tendency may explain some of the stagnant incomes of the self-employed.

Because life-cycle effects also greatly affect earnings trajectories (income increases quickly from a person's 20s-40s and less later in life), we control for age and for the effect of a person being age 25 or under in 2013, in the case of non-linear effects from early adulthood. Finally, past income and income trends are one of the greatest determinants of future income, so we control for a person's absolute and percent past income trend from 2010-2013, as well as actual income in 2010. People with negative income in base year 2013 are not included in the regression.

We find that being under age 25 is associated with relatively fast income growth, while older age is associated with lower income growth. Our past income controls are also strong predictors of future income growth. However the signs on past income variables are negative, indicating that income is demonstrating mean-reversion characteristics in this population. Receipt of the Child Tax Credit was associated with slower income growth, while receipt of the Earned Income Tax Credit was associated with stronger income growth. However, the higher one's level of EITC receipt, the slower income growth was.

It does seem that overall, incomes are mean-reverting and many filers could experience low incomes for a year and then revert to a higher income level. Because incomes are so low in Bin 1 it may be relatively easier to experience a large percentage point increase in AGI (say, a 200% increase from 10,000 to 30,000) than it would be for someone starting with a higher AGI to experience the same percent increase (for instance, going from $50,000 to $150,000). For instance, recent research finds that low- and moderate-income self-employed workers are substantially more likely to experience unexpected income declines, as well as income volatility (Social Policy Institute, 2022). Finally, general economic trends were good over this time period, and especially good for workers at the bottom of the income distribution at the end of the period, so faster relative economic growth at the bottom than at the middle could be driving some of the strong growth we see.

**Discussion and conclusion**

We find evidence that for low-income individuals who file taxes in the District of Columbia, self-employment is associated with lower income growth relative to those who primarily earn their income through wages and salaries. We also find evidence that among wage-earners, wages grew 32-35% faster for those subject to a series of minimum wage hikes from 2013 and 2018. In addition, we find that transitions between wage-earning and self-employment are associated with income penalties and premiums: those who were self-employed in 2013 but switched to being primary wage earners in 2018 saw faster income growth while those who earned the vast majority of their income from wages in 2013 and switched to being primarily self-employed experienced much slower income growth. Self-employment activity grew among the population over this period, but taxpayers engaged in it less intensely (as a percentage of their income) after 2013. Low-earners in particular were more likely to leave self-employment for wage-earning after the minimum wage increase passed. Overall, these trends suggest that self-employment became comparatively less attractive than wage-earning to low-income taxpayers over our study period. These findings do not seem to be seriously biased by differences in attrition rates in the panel among our study groups.

It is difficult to assess how much of the gap in income growth between people who switch to self-employment and people who switch to wage-earning is caused by taxpayers making an unlucky choice(i.e. making a career change to become self-employed), only to experience a significant and long-lasting hit to their income. It could also be the case that life circumstances which have an adverse effect on income push people into relying on self-employment. If job loss or having a child are major drivers of switching to self-employment, then that could explain why income drops so precipitously. Tax evasion or misreporting could also be a significant factor in the estimates we observe, though that certainly cannot explain all of the observed differences between the self-employed and wage-earners. Future analysis in this paper will more fully extend our analysis from low and middle income workers to high-earners as well.

# Appendix

## Appendix table 1: Count of Taxpayers by Bin and Employment type, 2013

| Primarily wage earners and majority self-employed tax filers, by Aggregate Gross Income Bin (2013) | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Majority self-employed** | **Primarily wage earners** | **Bin 1 ($1-22,000)** | **Bin 2 ($22,001-$45,000)** | **Bin 3 ($45,001-$75,000)** | **Bin 4 ($75,001-$100,000)** | **Bin 5 ($100,001+)** | **Total (positive income)** |
| **0** | **0** | 20771 | 14781 | 11241 | 5347 | 13319 | 65459 |
| **0** | **1** | 49378 | 53891 | 47676 | 21429 | 38605 | 210979 |
| **1** | **0** | 12342 | 2494 | 1829 | 973 | 4780 | 22418 |
| **Total** | | 82491 | 71166 | 60746 | 27749 | 56704 | 298856 |

## Appendix table 2: Demographics by Employment type

| Age, AGI and Gender of District of Columbia tax filers, by employment type, 2013 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **2013- full population** | **Age** | | **AGI ($)** | | **Gender (count)** | | |
| | **mean** | **median** | **mean** | **median** | **female** | **male** | **unknown** |
| **Majority Self-employed** | 46 | 43 | $93,129 | $16,042 | 8,593 | 10,088 | 4,432 |
| **Will switch to pWE in 2014** | 37 | 34 | $30,074 | $13,414 | 665 | 420 | 382 |
| **Primarily Wage-earner (MW)** | 37 | 33 | $67,515 | $45,033 | 45,581 | 43,634 | 18,572 |
| **Primarily Wage-earner(no MW)** | 37 | 33 | | | 38,662 | 48,609 | 15,957 |
| **Will switch to mSE in 2014** | 35 | 32 | $70,026 | $22,128 | 679 | 563 | 341 |
| **Other** | 55 | 58 | $76,369 | $40,295 | 29,645 | 29,224 | 8,868 |

### Appendix Table 3: Regression results Percent Income change, 2013-year

Reference group: Bin 1, wage earners, not minimum wage eligible

| | In 2014 | In 2016 | In 2018 |
|---|---|---|---|
| Bin 1 x Primarily WE x MW eligible | 0.14666*** | 0.27982*** | 0.34236*** |
| | 0.01564 | 0.02401 | (0.03051) |
| Bin 2 x Primarily WE x MW eligible | -0.40716*** | -0.70261*** | -0.91056*** |
| | 0.0145 | 0.02272 | (0.02887) |
| Bin 3 x Primarily WE x MW eligible | -0.45622*** | -0.72912*** | -0.90896*** |
| | 0.01699 | 0.02668 | (0.03420) |
| Bin 2 x Primarily WE x not MW eligible | -0.43552*** | -0.76522*** | -0.96874*** |
| | 0.01582 | 0.02527 | (0.03211) |
| Bin 3 x Primarily WE x not MW eligible | -0.46562*** | -0.74276*** | -0.91836*** |
| | 0.01763 | 0.02772 | (0.03549) |
| Bin 1 x Switched to self-employment | 0.04422 | -0.45789*** | -0.78555*** |
| | 0.04347 | 0.05639 | (0.06550) |
| Bin 2 x Switched to self-employment | -0.80030*** | -1.27884*** | -1.58008** |
| | 0.07632 | 0.06820 | (0.07593) |
| Bin 3 x Switched to self-employment | -0.80940*** | -1.29932*** | -1.42342*** |
| | 0.10403 | 0.08892 | (0.09491) |
| Bin 1 x Switched to wage-earning | 0.43795*** | 0.73716*** | 0.77270*** |
| | 0.03383 | 0.03833 | (0.04488) |
| Bin 2 x Switched to wage-earning | -0.15826 | -0.03613 | -0.25502*** |
| | 0.10083 | 0.09792 | (0.11072) |
| Bin 3 x Switched to wage-earning | -0.37142* | -0.54053*** | -0.67483*** |
| | 0.13763 | 0.13709 | (0.16136) |
| Bin 1 x Self-employed | 0.00727 | -0.18627*** | -0.35435*** |
| | 0.01891 | 0.03112 | (0.04123) |
| Bin 2 x Self-employed | -0.28139*** | -0.48179*** | -0.59722*** |
| | 0.03208 | 0.05315 | (0.06980) |
| Bin 3 x Self-employed | -0.40751*** | -0.56234*** | -0.64111*** |
| | 0.03617 | 0.05728 | (0.07388) |
| AGI in 2010 | 0.0000035*** | 0.0000032*** | 0.00000187*** |
| | 2.43378E-7 | 3.626964E-7 | 4.55E-07 |
| AGI trend, 2010-2013 | -0.01303*** | -0.02644*** | -0.03981*** |
| | 0.00148 | 0.00229 | 0.00297 |
| EITC binary | 0.51364*** | 0.82045*** | 0.92395*** |
| | 0.01274 | 0.01878 | 0.02362 |
| CTC binary | -0.1938*** | -0.32766*** | -0.41754*** |
| | 0.01015 | 0.01486 | 0.01862 |
| EITC $ amount | -0.000184*** | -0.000301*** | -0.0003510*** |
| | 0.00000354 | 0.00000519 | 6.50E-06 |
| Age 25 and under, binary | 0.07338*** | 0.26767*** | 0.35154*** |
| | 0.01372 | 0.02058 | 0.02637 |
| AGE in 2013 | -0.0057*** | -0.01329*** | -0.0194*** |
| | 0.00029632 | 0.000453 | 5.88E-04 |
| Adjusted R squared | 0.1013 | 0.1782 | 0.2098 |
| # of observations | 61679 | 49745 | 42034 |

Notes: ***indicates p<.001, *indicates p<0.05.
MW= minimum wage, WE = wage-earner, SE = self-employed

Note: the coefficients represent percentage change in income from 2013-2018 relative to the reference group for categorical, binary variables. The reference group for the triple difference regressions is primarily wage-earning taxpayers with 2013 income $1- $22,000 who were not covered by the minimum wage increase. Percent change in income variable bounded at -100% to +1,000%.

### Appendix Table 4: Per person tax change, by Bin and employment type

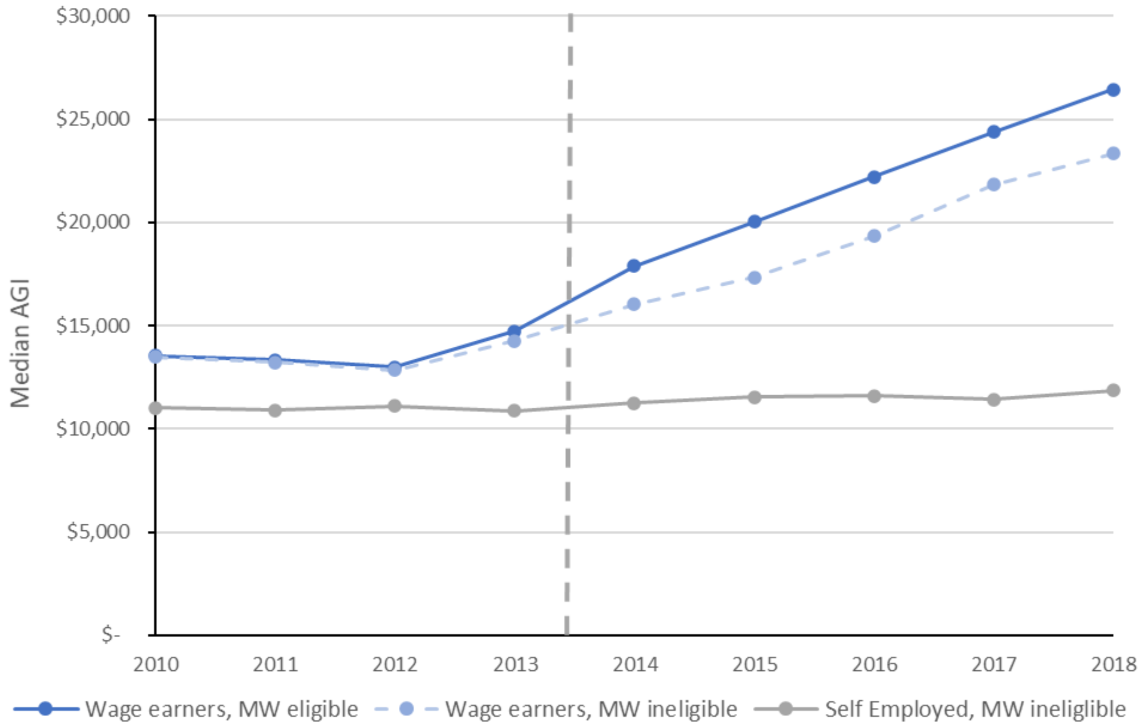
**Change in federal taxes collected 2013-2014, single filers by employment type and bin**

| | Observations | Mean Tax $ change | Median Tax $ change |
|---|---|---|---|
| Bin 1 x Primarily WE * MW eligible | 6382 | $305 | 0 |
| Bin 2 x Primarily WE * MW eligible | 12499 | $365 | $18 |
| Bin 3 x Primarily WE * MW eligible | 9424 | $818 | $453 |
| Bin 1 x Primarily WE * not MW eligible | 5341 | $242 | 0 |
| Bin 2 x Primarily WE * not MW eligible | 7455 | $283 | 0 |
| Bin 3 x Primarily WE * not MW eligible | 7745 | $804 | $515 |
| Bin 1 x Switched WE to self-employment | 406 | $68 | 0 |
| Bin 2 x Switched WE to self-employment | 125 | -$26 | 0 |
| Bin 3 x Switched WE to self-employment | 67 | -$1645 | -$2888 |
| Bin 1 x Switched SE to wage-earning | 714 | $522 | 0 |
| Bin 2 x Switched SE to wage-earning | 71 | $2211 | $623 |
| Bin 3 x Switched SE to wage-earning | 38 | $3165 | $2490 |
| Bin 1 x Majority Self-employed | 3296 | $205 | 0 |
| Bin 2 x Majority Self-employed | 838 | $1057 | 0 |
| Bin 3 x Majority Self-employed | 683 | $1428 | $104 |

Notes: WE= wage-earning, SE= self-employed, MW = minimum wage
Tax change= (2014 Total Tax – 2014 Self-Employment Tax) – (2013 Total Tax – 2013 Self-Employment Tax)
Bin 1: 2013 AGI from 0-$22,000
Bin 2: 2013 AGI from $22,000-45,000
Bin 3: 2013 AGI from $45,000-75,000

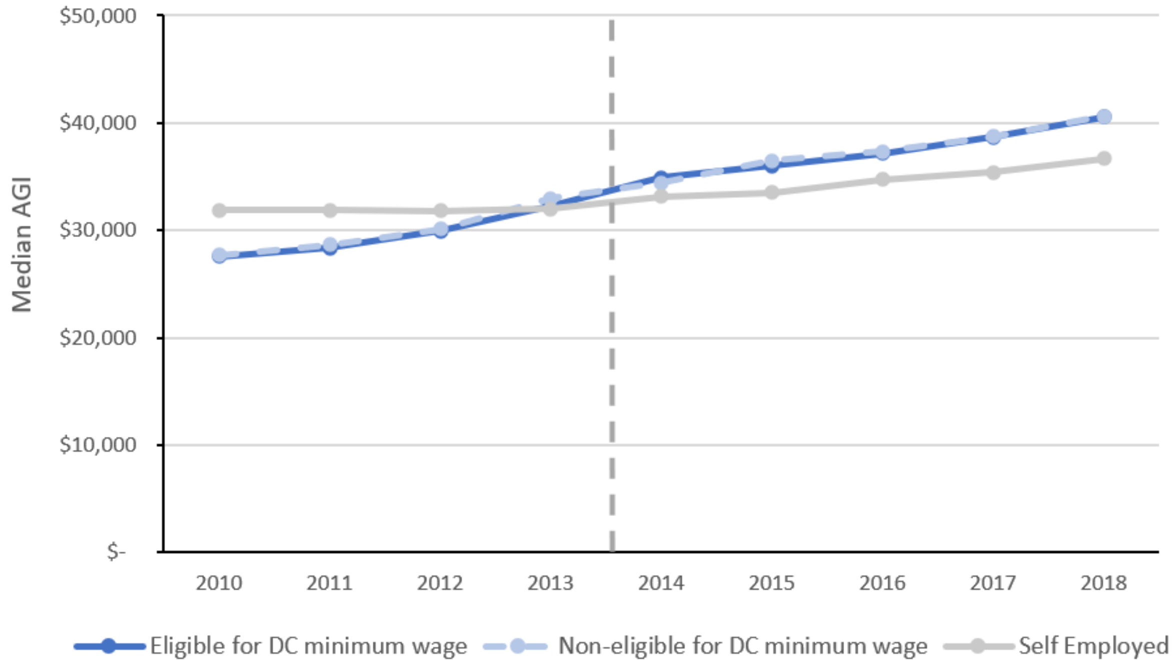
## Appendix Figures 1, 2, 3, 4: Income trends in Bins 1 and 2

Median Adjusted Gross Income for panel of low-income Washington DC taxpayers, by employment type 2010-2018




Note: Dashed line represents when the first minimum wage in our study period went into effect. Wage earners are those who report W-2 income on tax return and for whom wages represent between 85% and 115% of AGI. The self-employed are those who report income on Schedule C or files schedule SE and for whom wages represent less than 50% of AGI. All earners have an AGI of $1-$22,000 in 2013 (Bin 1).

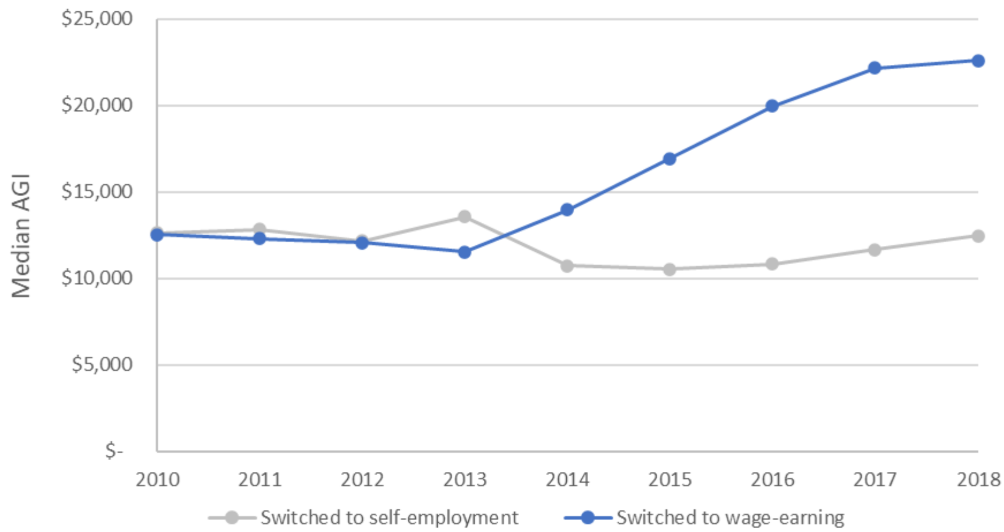
Median Adjusted Gross Income for panel of moderate income Washington DC taxpayers, by employment type 2010-2018




Note: Dashed line represents when the first minimum wage in our study period went into effect. Wage earners are those who report W-2 income on tax return and for whom wages represent between 85% and 115% of AGI. The self-employed are those who report income on Schedule C or files schedule SE and for whom wages represent less than 50% of AGI. All earners have an AGI of $22,000-$45,000 in 2013 (Bin 2).

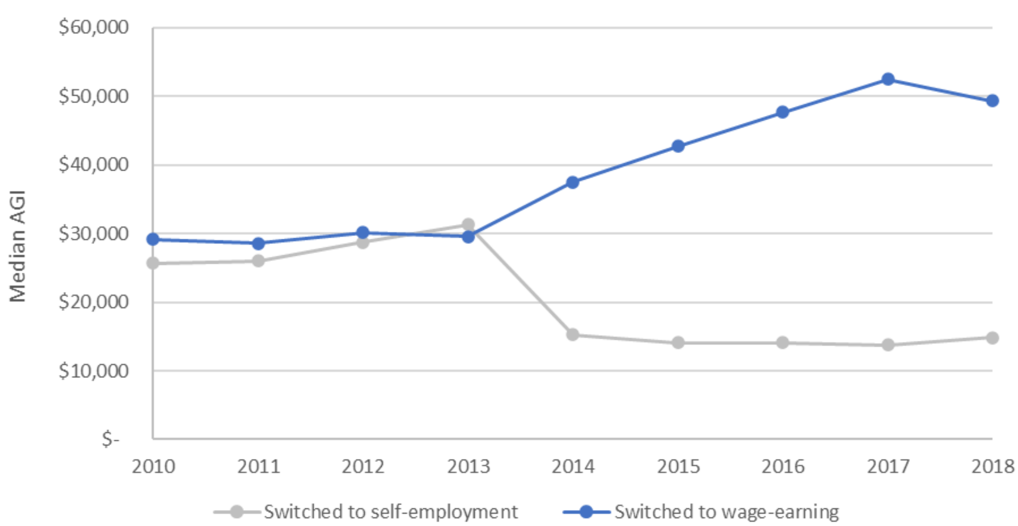
Note: Bins are set in 2013 and income is allowed to vary both before and after 2013.

Median Adjusted Gross Income for single taxpayers, income $0-22,000 in 2013, and who switched between wage earning and self employment, 2010-2018




Note: Dashed line represents when the panel allows the switch to other source of income to occur (post-2013). Wage earners are those who report W-2 income on tax return and for whom wages represent between 85% and 115% of AGI. The self-employed are those who report income on Schedule C or files schedule SE and for whom wages represent less than 50% of AGI. All earners have an AGI of $1-$22,000 in 2013 (Bin 1).

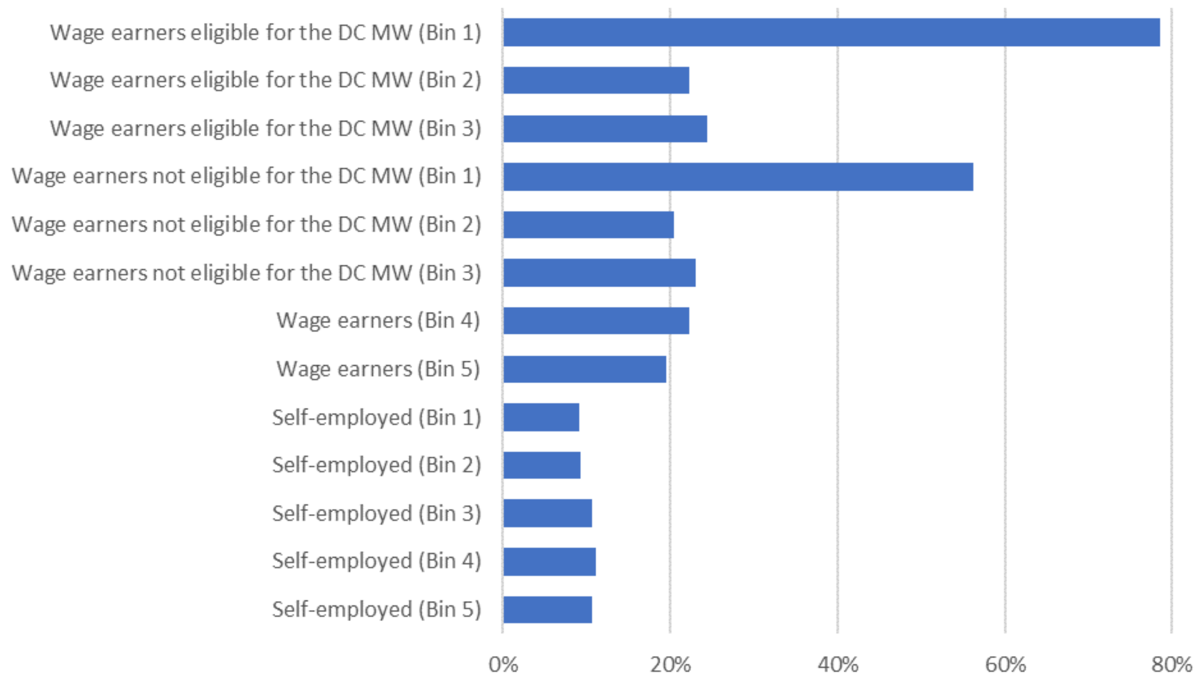
Median Adjusted Gross Income for single taxpayers, income $22,000-45,000 in 2013, and who switched between wage earning and self employment, 2010-2018



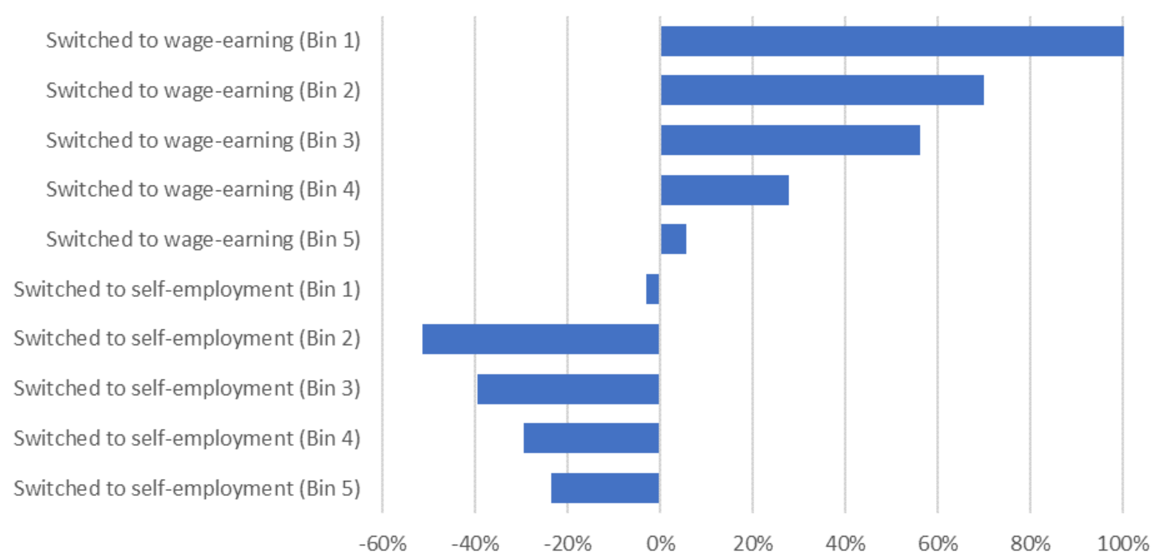

Note: Dashed line represents when the panel allows the switch to other source of income to occur (post-2013). Wage earners are those who report W-2 income on tax return and for whom wages represent between 85% and 115% of AGI. The self-employed are those who report income on Schedule C or files schedule SE and for whom wages represent less than 50% of AGI. All earners have an AGI of $22,000-$45,000 in 2013 (Bin 2).

## Appendix Figures 5 and 6:

Percent change in median Adjusted Gross Income, 2013-2018




Percent change in median Adjusted Gross Income, 2013-2018




Note: Earners who switched to wage-earning represent those who were majority self-employed (filed Schedule C or SE and wage income represents less than 50% of AGI) in 2013 and transitioned to being primarily wage-earners (report W-2 income on tax return and for whom wages represent between 85% and 115% of AGI) by 2018.

## Appendix Table 5

**Switchers panel construction example**
Based on employment classification by year

| 2015 | 2016 | 2017 | 2018 | 2019 | Included in 1-year panel? |
|---|---|---|---|---|---|
| pWE | pWE | mSE | mSE | mSE | Yes |
| missing | mSE | mSE | mSE | pWE | Yes |
| mSE | other | pWE | pWE | pWE | No |
| mSE | pWE | mSE | pWE | mSE | No |

Notes: pWE = primarily wage-earning, mSE = majority self-employed
Rows represent a single tax filer's employment classifications by year

## Appendix Section: Triple Differences Regression

**Triple-Difference (DDD) analysis**

This allows us to disentangle the drivers of income growth and examine what effect the minimum wage increase had on income growth. To accomplish this, we divide single, head of household, and "married filing separately" taxpayers with positive income into several different employment types depending on the source of their income (described above in the "Methods" section) The groups are:

- **Majority self-employed**: Files a Schedule C or pays Self-employment tax. Wages line is less than 50% of AGI total.
- **Primarily wage-earning**: Wage income is within 15% of total AGI. So, wages are at least 85% and no more than 115% of the AGI total.
    - This group is further subdivided into two groups based on their exposure to the minimum wage increase.
        - **Subject to the minimum wage**: works for either the DC government or for a private sector employer in Washington DC. Is contained in the DOES database.
        - **NOT subject to the minimum wage**: works for any other employer (the federal government, employers in Maryland, Virginia or another state). Not present in the DOES database.
- **Other**: Any other mix of income or employment. Taxpayers who do not meet these definitions in either 2013 or 2018 are not included in the regression.

We exclude taxpayers with an AGI above $75,000 in 2013 from the regression, focusing on Bins 1-3. There is a not-insignificant population of labor market participants who we are purposely excluding from our analysis in order to draw contrasts, have a high differentiation between our study populations and for ease of interpretation. For instance, married taxpayers are excluded because it would be impossible to tell if a tax unit filing a Schedule C and also having 40 percent of its income from wages was made up of two self-employed people, one self-employed person with a non-working spouse, or if it contained a person with wage income subject to the minimum wage and a spouse who was self-employed. That is a fairly straightforward population to exclude.

We also exclude taxpayers with very mixed income sources, who have perhaps 75% of their income from wages, but also other sources of income, like capital gains or self-employment. This is a choice to construct our populations conservatively and to increase our ability to interpret our results and elimination possible confounding factors in our analysis. We believe these decisions will tend to bias downward of our estimates of the minimum wage's effect as we eliminate many people who are affected by the minimum wage, but who also have other sources of income.

For the triple-difference estimation we calculate income growth for taxpayers who were (1)in the lowest-income bin in 2013, (2) primarily wage earners in both 2013 and 2018, and (3)in jobs covered by Washington DC's minimum wage law in 2018. This population is compared to the other employment groups among those with incomes $1-$75,000 (Bins 1-3).

Our identifying assumption is that all groups in our analysis have similar income characteristics and vary only in whether they are legally subject to the minimum wage ordinance. To wit, all taxpayers in our analysis live in the same jurisdiction, are involved in the labor market, subject to the same general local economic forces, and have similar income and income trends. However, one segment of the population was covered by a statutory minimum wage increase, depending on which type of employment they have, while their neighbors were not subject to it. Our analysis therefore differs from other studies that divide states or counties by whether they were covered by a minimum wage law or not, and instead we compare people *within the same jurisdiction* by whether their job was covered by the minimum wage or not.

Our first triple-difference regression is as follows:

$$\%AGI\ Change_{y1\text{-}y2} = \beta + \gamma\,\mu\,\sigma + \gamma\,\mu + \mu\,\sigma + \gamma + \mu + \sigma + \nu + \text{(error term)}$$

Our outcome of interest is again the percent change in AGI from y1 (2013) to y2 (2018). The primary regressor is our interaction term for taxpayers who met these criteria: in the lowest income Bin in 2013 (represented by $\gamma$), who were primarily wage earners in both 2013 and 2018 (represented by $\mu$), and who worked at an employer subject to the minimum wage in 2018 (represented by $\sigma$). We also control for the effects of the component parts of this term, partial interaction terms, and use a broad set of controls for past income, age and refundable tax credit receipt, represented by $\nu$ (the same set on controls as in the regression above). In this equation we are measuring the income growth of our minimum wage-affected population against both other employment types (and people who switch employment types) in Bins 1-3. We also run the regression without controls.

In this regression (reported in Appendix Table 6, below) we can see that income increased 32 percent faster for low-wage workers who were directly subject to the minimum wage, relative to their neighbors who were not directly subject to it. The component parts of our interaction term show that just being in Bin 1 continued to be a strong predictor of rising income, separate from the direct minimum wage effect. Being at an employer subject to Washington DC's labor laws was associated with a 27 percent greater increase in income overall, indicating that there could be spillover effects from the minimum wage increase, even for higher income workers.

In order to have higher confidence in the results of this regression, and our minimum wage findings in general, we perform another analysis on a slightly different treatment population. In general we have been using income level in 2013 to divide people into Bins to identify the population who would be affected by the minimum wage hike in the next year, 2014. While we do control for past income in 2010 and calculate past income trends, this method could be imperfect for tax filers with extremely volatile incomes.

Therefore, in this alternate analysis, we condition membership in Bin 1 not only on 2013 AGI being from $1-$22,000, but also on 2012 income. In this alternate analysis, filers must have been in or near Bin 1 for two years in a row in order to qualify for the treatment population. Income in 2012 was allowed to vary slightly, to avoid cutting off edge cases, so for this analysis, income would have to be between $1-$24,000 in 2012 and between $1 and $22,000 in 2013. Results are reported in Appendix Table 5. We find that in this triple difference analysis that income increased by 31.5 percent for our treatment population.

The magnitude of the 5-year income change attributable to the minimum wage increase treatment is 27.6-31.5 percent in this triple difference analysis. This compares to an increase of 34.2 percent in our preferred specification (Appendix Table 2). Though not quite as large in these regressions, these results are comparable and give us confidence in the robustness of our findings.

**Appendix Table 6: Triple Difference Regression Results**

| | 2010-13 base years | Alternate 2012-2013 base years |
|---|---|---|
| Bin 1 x Primarily WE x MW eligible | 0.27606*** | 0.31595*** |
| | 0.03473 | 0.03286 |
| Primarily WE x Bin 1 | 0.19986*** | 0.24891*** |
| | 0.03652 | 0.0356 |
| Primarily WE x MW eligible | -0.30875*** | -0.33679*** |
| | 0.02455 | 0.02538 |
| Bin 1 (AGI $1-22K) | 0.85632*** | 0.60084*** |
| | 0.02945 | 0.03296 |
| Primarily Wage Earner, 2013 | -0.45359*** | -0.38951*** |
| | 0.027 | 0.02887 |
| Primarily Wage Earner, 2018 | 0.2753*** | 0.30522*** |
| | 0.02063 | 0.0213 |
| Minimum Wage eligible, 2018 | 0.3861*** | 0.37422*** |
| | 0.02219 | 0.02281 |
| AGI in 2010/2012 | -0. 00000328*** | -0.00000755*** |
| | 4.4052E-7 | 5.89948E-7 |
| Past AGI % trend, 2010/2012-2013 | 0. 08316*** | -0.08748*** |
| | 0. 00487 | 0.00571 |
| Age # | -0.01831*** | -0.01743*** |
| | 5.92E-04 | 0.00060576 |
| Under age 25 in 2013, binary | 0.38243*** | 0.3581*** |
| | 0.02611 | 0.0223 |
| CTC binary | -0.34588*** | -0.33604*** |
| | 0.01865 | 0.01971 |
| EITC binary | 0.8521*** | 0.66714*** |
| | 0.02312 | 0.02409 |
| EITC, $ | -0.00035555*** | -0.00036091*** |
| | 6.42E-06 | 0.0000065 |
| Adjusted R squared | 0.2256 | 0.2335 |
| # of observations | 42034 | 46786 |

Notes: ***indicates p<.001, **indicates p<0.05.
MW= minimum wage, WE = wage-earner, SE = self-employed

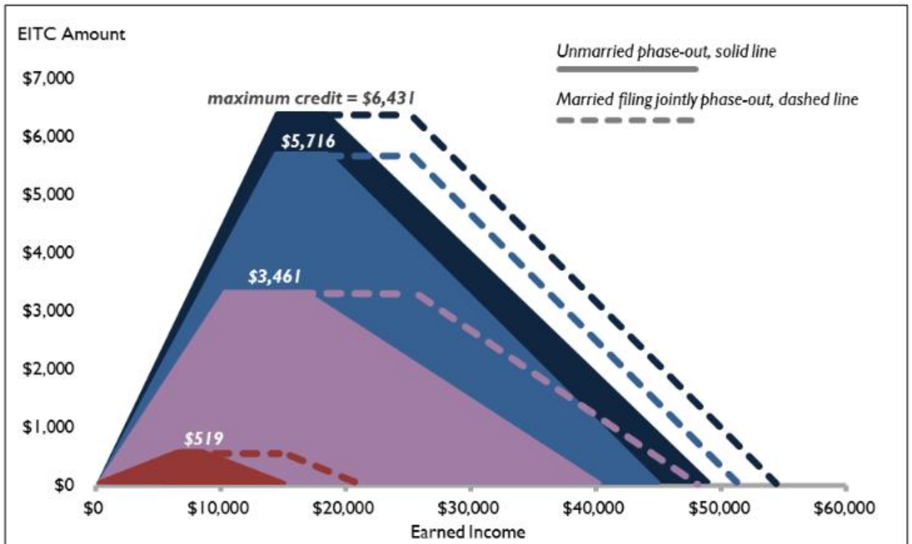
## Appendix Section: EITC Analysis

The federal Earned Income Tax Credit (EITC) is the largest federal cash transfer program for the nation's lowest income workers. It is credited for lifting nearly 5.6 million people above the poverty line in 2018, as well as pushing millions further above the poverty line.[5] Consequently, the policy is hailed by many as a reasonably effective anti-poverty and work-encouragement program.

[5] Center on Budget and Policy Priorities (2019) Policy Basics: The Earned Income Tax Credit. https://www.cbpp.org/research/federal-tax/the-earned-income-tax-credit

As shown in Figure 1, the EITC schedule is based on income levels and number of dependents claimed. It is also structured to have three distinct credit amount segments: 1) a phase-in segment where the federal credit amount increases at a fixed rate for the lowest range of incomes (to encourage work); 2) a plateau segment with a constant amount for an income range just above the lowest incomes; and 3) a phase-out segment of the program where the federal credit gradually decreases in value to zero at a fixed rate as income increases.

**Appendix Figure 7**




| Income when: | Maximum credit begins | Phase-out begins, Unmarried | Phase-out begins, Married | Credit reaches $0, Unmarried | Credit reaches $0, Married |
|---|---|---|---|---|---|
| No Children | $6,780 | $8,490 | $14,170 | $15,270 | $20,950 |
| 1 Child | $10,180 | $18,660 | $24,350 | $40,320 | $49,010 |
| 2 Children | $14,290 | $18,660 | $24,350 | $45,802 | $51,492 |
| 3 or more | $14,290 | $18,660 | $24,350 | $49,194 | $54,884 |

Source: Congressional Research Service

While this study finds that both DC's minimum wage policy and switching between wage employment and self-employment tend to cause large changes in income for respective city residents between 2013 and 2018, this section examines how switching between wage employment and self-employment tended to affect EITC amounts received by respective claimants in this study.

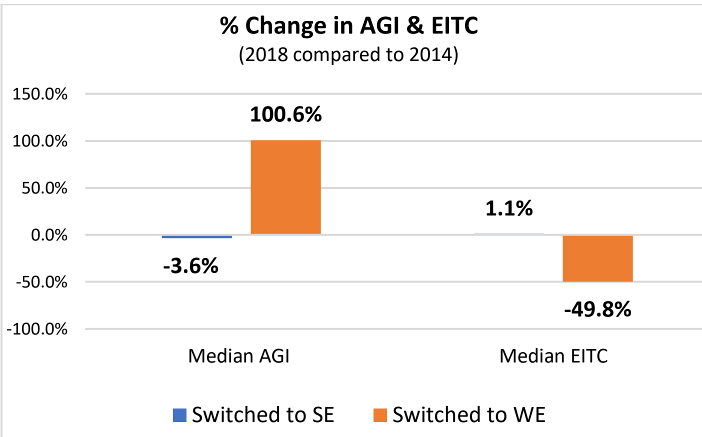
This analysis is limited to workers in Bin 1 because they are most affected by the city's minimum wage policy and the EITC amounts they receive are most consequential. Therefore, we also limit this analysis to a subset of working tax filers receiving near the maximum amount of EITC.

Appendix Table 7 shows the federal adjusted gross income (AGI) and EITC for switchers who were present in years2010, 2013, 2014 and 2018. There was not a significant change in income or EITC for the median worker that switched from wage to self-employment. But for the median worker that switched from self- to wage employment, their income doubled while their EITC decreased considerably (Appendix Figure 8). We find that the latter attained an additional $12,706 in income in 2018 but relinquished $1,639 in EITC because of the decision to switching from self- to wage employment.

## Appendix Table 7

| | N | 2014 | | | | 2018 | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | AGI | | Fed EITC | | AGI | | Fed EITC | |
| | | Mean | Median | Mean | Median | Mean | Median | Mean | Median |
| Primarily WE to Majority SE | 221 | $ 13,366 | $ 12,622 | $ 2,973 | $ 3,305 | $ 11,997 | $ 12,164 | $ 2,822 | $ 3,341 |
| Majority SE to Primarily WE | 911 | $ 14,083 | $ 12,626 | $ 2,875 | $ 3,290 | $ 29,566 | $ 25,332 | $ 2,224 | $ 1,651 |

## Appendix Figure 8




The effect of the EITC on workers' labor supply has been well studied over the past three decades. There is a general consensus that the EITC encourages work because it is a "work bonus" that increases the compensation per additional hour worked (particularly in the phase-in segment of the policy), reduces workers' federal tax liability, provides a cash payment and thus increases after-tax income.[6] [7] Another general finding in the literature is that low income self-employed EITC recipients tend to bunch around the first kink point of the EITC because it is the point of the schedule that maximizes the tax credit/refund.[8] The self-employed tend to have more flexibility in hours worked and more say in the total amount of reported earnings.

Bunching around the first EITC kink point by low-income self-employed recipients also exists in the District of Columbia (Upadhyay and Muhammad, 2017).[9] But whereas the literature focused on the change in the number of hours worked (as indicated by the change in annual income) by the self-employed, we more specifically examine the interaction between the EITC received and the decision of low-income workers to switch from self-employment to wage employment in a city that increased its minimum wage 60.6 percent between years 2014 and 2018.

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[6] Congressional Research Service. (2018). The Earned Income Tax Credit (EITC): An Economic Analysis. R44057. https://crsreports.congress.gov/product/pdf/R/R44057/13

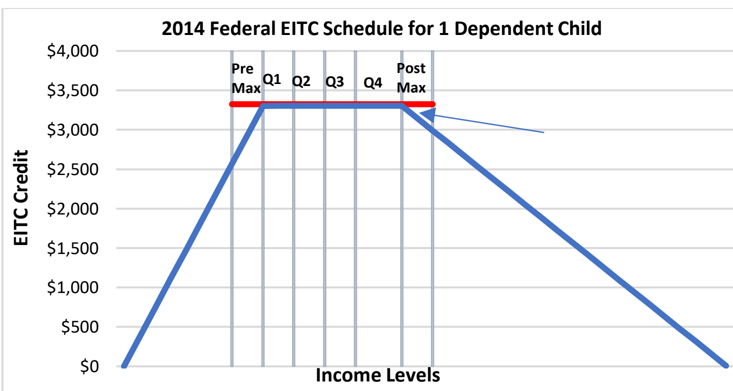
[7] Chetty, R., Friedman, J., & Saez, E. (2013). Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings. The American Economic Review, 103(7), 2683-2721.

[8] Saez, E. (2010). Do Taxpayers Bunch at Kink Points? American Economic Journal: Economic Policy, 2(3), 180-212.

[9] Muhammad, Daniel and Ameesh Upadhyay. (2017) The Labor Supply Effects of the District of Columbia Earned Income Tax Credit. District of Columbia Office of Revenue Analysis.

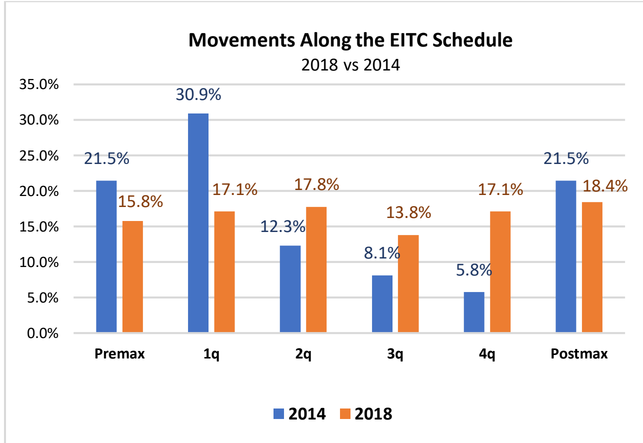
To start, we take all workers in this study that were majority self-employed in 2014 but primarily wage-earners in 2018, EITC claimants with 1 dependent child in both years and received the maximum or near maximum EITC of $3,305 in 2014. (The majority of city EITC claimants have one dependent.) We then divide these EITC claimants into six groups. The first group is for claimants that earned $5,450 and $6,450 in annual income.  This group (referred to as Pre Max) represents claimants that earned income a just little shy of the amount that would entitle them to the maximum credit in 2014. The second group (Q1) are claimants that earned between $6,455 and $6,875 in income and a credit of $3,305. This is the quartile with the lowest incomes that earned the maximum credit. The third group (Q2) are claimants that earned between $6,875 and $7,300 in income and a credit of $3,305. This is the quartile with the second lowest incomes that earned the maximum credit. The fourth group (Q3) are claimants that earned between $7,300 and $7,725 in income in 2014 and a credit of $3,305. This is the quartile with the second highest incomes that earned the maximum credit. The fifth group (Q4) are claimants that earned between $7,725 and $8,150 in income and a credit of $3,305. This is the quartile with the highest incomes that earned the maximum credit. And lastly, the sixth group (Post Max) are claimants that earned between $8,150 and $9,150 in income and a credit a little less than the max credit of $3,305.  These groups are represented by the segmented red line in Appendix Figure 9.

**Appendix Figure 9**




Appendix Figure 10 shows the relative change in distribution of EITC claimants described above along the 2014 EITC schedule (blue bars) compared to their relative distribution along the comparable 2018 EITC schedule (orange bars). This Figure only represents claimants that received the maximum credit or near maximum credit amounts in 2014 and 2018. The figure shows that in 2014 there was indeed a significant degree of bunching around the first kink, which is consistent with the literature. But, the significantly higher incomes stemming from the switch from self-employment to wage employment amidst rising annual minimum wages appear to have caused many of the bunched claimants to more equally disperse along the EITC schedule to the right in 2018.

**Appendix Figure 10**




But the data also indicates (not shown) that in 2018 there were 40 percent more claimants that received the EITC but were at income and credit levels beyond the Post Max endpoint or red line. And furthermore, the systemically large income increases caused 22.4 percent of the claimants in this subgroup in 2014 to be practically ineligible for the EITC in 2018, mostly wage-earners.

There are over 14,000 majority self-employed tax filers in the city over the study period. These workers, presumably, are benefiting from self-employment because of non-pecuniary benefits such as, but not limited to, greater job flexibility and control over when, how, and how much to work. However, in terms of annual income, their earnings remain relatively stagnant, has not kept up with inflation (Appendix Table 8).

**Appendix Table 8**

| | 2014 | | | 2018 | | | % Change in |
|---|---|---|---|---|---|---|---|
| | Median AGI | Median EITC | Total After-tax Income | Median AGI | Median EITC | Total After-tax Income | Total After-tax Income |
| Primarily WE to Majority SE | $ 12,622 | $ 3,305 | $ 15,927 | $ 12,164 | $ 3,341 | $ 15,505 | -2.6% |
| Majority SE to Primarily WE | $ 12,626 | $ 3,290 | $ 15,916 | $ 25,332 | $ 1,651 | $ 26,983 | 69.5% |

Thus, it appears that the city's minimum wage policy and choosing to engage in full-time wage-employment have robust positive effects on the economic welfare of affected workers. So much so that the economic advantages of full-time wage employment dwarf the anti-poverty effects of the EITC. Prior to the city beginning to increase its' minimum wage, the ranks of Schedule C filers were growing steadily. But when the minimum wage began in increasing in 2014, the ranks began to steadily shrink. We interpret these dynamics as indicating that since 2014 many workers in the city are choosing to forego some, and in some cases all, of the EITC in exchange for the much larger positive income effects of full-time wage employment in a city with a high minimum wage that increases annually to adjust to inflation.